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The Impact of Climate Change on Catastrophe Risk Model

Implications for Catastrophe Risk Markets in Developing Countries

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Abstract

Catastrophe risk models allow insurers, reinsurers and governments to assess the risk of loss from catastrophic events, such as hurricanes. These models rely on computer technology and the latest earth and meteorological science information to generate thousands if not millions of simulated events. Recently observed hurricane activity, particularly in the 2004 and 2005 hurricane seasons, in conjunction with recently published scientific literature has led risk modelers to revisit their hurricane models and develop climate conditioned hurricane models. This paper discusses these climate conditioned hurricane models and compares their risk estimates to those of base normal hurricane models. This comparison shows that the recent 50 year period of climate change has potentially increased North Atlantic hurricane frequency by 30 percent. However, such an increase in hurricane frequency would result in an increase in risk to human property that is equivalent to less than 10 years' worth of US coastal property growth. Increases in potential extreme losses require the reinsurance industry to secure additional risk capital for these peak risks, resulting in the short term in lower risk capacity for developing countries. However, reinsurers and investors in catastrophe securities may still have a long-term interest in providing catastrophe coverage in middle and low-income countries as this allows reinsurers and investors to better diversify their catastrophe risk portfolios.

This paper—a joint product of the Global Facility for Disaster Reduction and Recovery Unit, Sustainable Development Network Vice Presidency, and the Global Capital Markets Development Department, Financial and Private Sector Development Vice Presidency—is part of a larger effort in the department to is part of a larger effort to disseminate the emerging findings of the forthcoming joint World Bank-UN Assessment of the Economics of Disaster Risk Reduction. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at john@fcm.com and omahul@worldbank.org respectively. We are grateful to Apurva Sanghi and participants of the seminar at the World Bank held on this topic for their suggestions and constructive comments.

The Impact of Climate Change on Catastrophe Risk Models: Implications for Catastrophe Risk Markets in Developing Countries[1]

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[1] This paper, a product of the Global Facility for Disaster Reduction and Recovery (GFDRR) Unit, Sustainable Development Network Vice Presidency, is part of a larger effort of the GFDRR to disseminate the emerging findings of the forthcoming joint World Bank-UN Assessment of the Economics of Disaster Risk Reduction. We are grateful to Apurva Sanghi and participants of the seminar at the World Bank held on this topic for their suggestions and constructive comments.

1. Introduction

Catastrophe models are complex and almost completely inaccessible to the non-specialist. Yet, these models tell policymakers what are the economic risks to society and form the basis of rate making for billions of dollars in insurance premiums per year in the United States alone. We summarize two important results from US hurricane catastrophe models: one for base normal (BN) hurricane risk and one for climate conditioned (CC) hurricane risk. Summary results are presented in Loss Exceedance Curve (LEC) form, which is a kind of cumulative distribution function and thus gives considerable summary information about what hurricane catastrophe models are saying about hurricane risk, both in the absence and in the presence of climate conditioning.

This paper presents a simple method for the comparison of catastrophe model outputs based on a so-called intensity profile (IP) and residual intensity profile (RIP). The IP and RIP are used to compare the catastrophe model risk estimates of BN hurricane risk versus CC hurricane risk. CC hurricane models were implemented by catastrophe modeling companies in 2006 after a series of academic papers and the heightened hurricane activity of 2004 and 2005 gave impetus to the notion that tropical cyclones occur more frequently in the current climactic regime. CC catastrophe models offer the darkest view of U.S. hurricane risk that can be justified from historical observations of North Atlantic hurricanes. Therefore, a comparison of BN versus CC catastrophe models offers a glimpse into the assumed causes and costs of climatically driven increases in hurricane activity. Using our simple method of comparison, we show that CC catastrophe models imply that the recent 30 to 50 years' worth of climate change has increased North Atlantic hurricane frequency to a level approximately 30% greater than normal. While a significant increase, we put this increase in perspective by pointing out that increases in U.S. coastal property density have exhibited a long-term secular trend of 50% real growth per decade. This means that the total impact of up to 50 years' worth of climate change on U.S. Hurricane risk is worth less than 10 years' worth of U.S. coastal property growth. The potential impact on non-U.S. reinsurance markets is a decline in coverage capacity.

2. Catastrophe models are not pricing models

Before going on to discuss catastrophe models, it is important to emphasize that catastrophe models are not pricing models. The results of catastrophe models do not lead directly to insurance and reinsurance prices, mainly because of the cost of the capital which must be put-up against systemic insurance risks.[2] An in-depth discussion of the issues and reasons behind the incomplete linkage between actuarial estimates of risk and market prices for risk transfer is beyond the scope of this report; however, the reader can gain some understanding to the issue through a simplified example of a reinsurance price function. A reinsurance broker might summarize for insurance clients the cost of reinsurance in a given year with something like the following formula:[3]

$$ROL = LOL + 5\%, \qquad (1)$$

[2] Cummins, J.D. and Olivier Mahul (2009): "Catastrophe Risk Financing in Developing Countries: Principles for Public Intervention." The International Bank for Reconstruction and Development / The World Bank.

[3] Cummins and Mahul (2009). See in particular Figure 2.2 on p.35.

where ROL is "rate on line," the reinsurance premium divided by the limit of coverage, and LOL is "loss on line," the average annual loss (AAL) of a reinsurance contract divided by the limit of coverage. The AAL is the expected annual loss averaged over a long period of time. It is typically gotten from a catastrophe model, which performs detailed, stochastic scenario analyses, as will be discussed further in the next section below. Putting aside taxes, overhead, and other transactional costs, if reinsurance premiums were purely determined by actuarial risk, the additional 5% term in (1) would not exist: ROL would equal to LOL in a world with no cost of capital and no transaction costs.

The impact of catastrophe model changes most often has a muted impact on insurance and reinsurance premiums, which is supported well by the form of price functional illustrated by (1). For example, the LOL might vary by up to 30% up or down from model to model (so a 1% LOL in one model might be 1.3% in another, equally valid model[4]), but the excess premium represented by the 5% term in (1) might range anywhere from 3% to 12% year to year, depending on the cost of insurance and reinsurance capital in a given year.[5] This means, especially for catastrophic risks which have a low probability of occurrence, the majority of the year-to-year volatility in reinsurance prices might be attributed to factors outside of the variation in risk estimates produced by catastrophe models.

All of this is not to say that catastrophe models do not matter. They matter a great deal because they form the basis of a market-driven conversation on prices and availability of insurance and reinsurance. Also, too, catastrophe models potentially form a constructive link between science, engineering, and commerce. By their integration into the global insurance and reinsurance market, catastrophe models subject scientific developments in meteorology and seismology to an intense examination, the results of which are disseminated annually into a market that involves hundreds of billions of dollars in premiums worldwide. When this model-based system of commerce functions as intended, risk is taken more deliberately and with the costs and benefits more clearly in mind.

3. Catastrophe models

Catastrophe models are specialized computer models[6] that use probabilistic scenario analysis to provide estimates of the probability of different size losses occurring in well-defined insurance systems. Catastrophe models first emerged in the late 1980s as affordable computing power

[4] The most commonly asked question (what is the characteristic model uncertainty in catastrophe models) is typically unanswered by modeling firms. Generalizations are difficult to come by. Model uncertainty varies according the hazard being modeled. In case of U.S. hurricane risks, a reasonable estimate of model uncertainty is plus or minus 30%. So, for example, if an event is judged to have an annual probability of occurrence of 1% by one modeler, another, equally expert modeler, might estimate the probability of occurrence of the same event at 1.3% and yet another, equally expert modeler, might estimate the probability of occurrence of the same event at .7%. More typically, the variance among expert opinion in U.S. hurricane would be expected to be closer to plus or minus 15%, so the plus or minus 30% range is intended to encompass a wide range of variance in expert opinion.

[5] In the Spring of 2009, in the reinsurance market for US hurricane risks, the ROL is anywhere from 8 to 12% for a 1% LOL.

[6] Commercial models include those from Applied Insurance Research (AIR), EQECAT, Risk Management Solutions (RMS). Public domain models include the FEMA HAZUS model by Applied Research Associates (ARA) as well as the Florida Office of Insurance Regulation's Florida Public Hurricane Model.

became available to those in the insurance industry who wanted to overlay hazard estimates on current estimates of property exposure[7]. Complex, largely non-transparent, and often subject to commercial non-disclosure agreements, catastrophe models nonetheless provide the support for public and private rate setting on billions of dollars of insurance in the United States each year—consider, for example, the Florida Hurricane Catastrophe Fund[8] and the California Earthquake Authority[9]; public statements regarding their necessity and capital adequacy involve the use of catastrophe models.

Catastrophe risk models are well developed for developed economies where there is a demand for such models, for example from insurance and reinsurance companies that offer catastrophe coverage to their clients. In developing countries, where the property insurance market is usually under development (such as most middle income countries) or undeveloped (such as most low-income countries), the demand for catastrophe insurance is almost non-existent and, consequently, catastrophe risk models are scarce. The donor community has been recently sponsoring the development or the enhancement of catastrophe risk models. Hurricane and earthquake risk models have been developed for the Caribbean region under the sponsorship of the Caribbean Catastrophe Risk Insurance Facility. Likewise, donors have financed the development of country-specific catastrophe risk models for the South Pacific Islands. In addition, there have recently been attempts to develop catastrophe risk models on open platform. For example, the Central American Probability Risk Assessment (CAPRA) initiative, supported by the World Bank and other development agencies, is based on an open and modifiable platform which allows governments and institutions to supplement the model with previous and ongoing initiatives (Cummins and Mahul, 2009). Such models are not only useful for insurance purpose, but also they offer policy makers new tools for their country management and mitigation programs. Such models are expensive to develop and the private sector may be reluctant to invest due to uncertainty about generating sufficient business to recover development costs. There is clearly a role for donors to finance such models to help countries better assess their economic and fiscal exposure to natural disasters, and ultimately, help reduce the physical and financial vulnerability of developing countries to natural disasters.

For those unfamiliar with catastrophe models, we describe here a highly simplified hurricane model. To calculate the Average Annual Loss (AAL) from US hurricanes, consider the following landfall model specification, outlined here only for illustration purposes:

$$AAL = \sum_{i=1}^{n} W_i \sum_{j=1}^{5} H_{i,j} D_j \qquad (2)$$

where

i is a coastal segment (CS) index;

[7] Karen Clark (1986): "A Formal Approach to Catastrophe Risk Assessment and Management," *Proceedings of the Casualty Actuarial Society*, vol. LXXIII, no. 139. http://www.casact.org/pubs/proceed/proceed86/86069.pdf

[8] Florida Hurricane Catastrophe Fund (FHCF) website. See in particular the annual reports under the "FHCF Reports" section. http://www.sbafla.com/fhcf/

[9] California Earthquake Authority (CEA) website. See in particular the history of the CEA reports under the "About the CEA" section. http://www.earthquakeauthority.com/

n is the total number of CSs;
j is hurricane intensity given as Saffir-Simpson category 1 to 5.
W_i is the property value in the i^{th} CS;
$H_{i,j}$ is the annual probability of occurrence of a hurricane of intensity *j* in the i^{th} CS; and
D_j is the portion of property value lost to hurricane of intensity *j*.

W_i can be described as an *exposure distribution*; $H_{i,j}$ a *hazard distribution*, and D_j a *damage function*. These three elements of a catastrophe model determine annual probability of losses to property. The model underlying (2) above is highly simplified in many respects—for one, it assumes one hurricane, no more and no less, per year. The details of full blown catastrophe model are difficult to summarize into a simple model like this, but to give the reader a general feel for rough numbers, for major hurricanes (j=3,4,5), D_j is roughly 10 percent for insured losses. In a major coastal segment of property, such as around Miami, Florida, total property value, W_i (where i is suitably chosen to select the coastal segment that encompasses the greater Miami area), is effectively around 1 trillion USD[10][11]. Therefore, given these simplified numbers, a major hurricane striking a major urban coastal segment of property is expected to cause an insured loss of property of about 100 billion USD. Such an event (major hurricane striking a major urban coastal segment of property) is expected to occur with annual probability of about 1 percent, or once every 100 years.[12] Therefore, as of 2009 we would say that a 1-in-100 year hurricane insured loss is 100 billion USD. The hazard distribution is considered relatively stable and biased toward higher intensity storms in warmer, southern waters[13]. In an unfortunate, partial coincidence, the US East Coast exposure distribution is sometimes, though not always, peaked where the coastline juts out into the ocean as well[14]. The damage function is relatively stable over time, so the main factor affecting changes in hurricane risk is changes in the exposure distribution. For US hurricane, AAL is currently estimated at about 10 billion USD[15].

Catastrophe models use Monte Carlo techniques to generate 10 thousand years or more of simulated losses. Using the simple model above, a catastrophe model would generate random occurrence of hurricanes in simulated year via $H_{i,j}$, then overlays those random hurricanes on the fixed property distribution, W_i. The damage function D_j then translates the incidence of

[10] FHCF website.

[11] These figures are very high in absolute terms, and represent about 7 percent of the 2008 US GDP. Hurricanes hitting small islands can losses that are several times larger than their GDP. For example, a major hurricane hitting Jamaica could cause losses of more than 200% of GDP.

[12] Note again that these numbers are rough and not consistently defined from researcher to researcher. For example, depending on how strictly one defines a hurricane strike on a particular location (from landfall within 5 miles to bypassing within 90 miles), the probability of a strike on a particular location can vary by a factor of 10 from model to model. Here, an emphasis was placed on giving round numbers that bear a reasonable resemblance to the kinds of numbers used in detailed commercial catastrophe models.

[13] National Hurricane Center website. See in particular the Climatology section.
http://www.nhc.noaa.gov/HAW2/english/basics.shtml

[14] Pielke, Jr., R. A., Gratz, J., Landsea, C. W., Collins, D., Saunders, M. A., and R. Musulin (2008): "Normalized Hurricane Damages in the United States: 1900-2005," *Natural Hazards Review*, vol. 9, no. 1, pp. 29-42.
http://sciencepolicy.colorado.edu/publications/special/normalized_hurricane_damages.html

[15] Karen Clark & Company (2008): "Near Term Hurricane Models: How Have They Performed?"
http://www.karenclarkandco.com/pdf/KCC_NearTermHurricanes.pdf

hurricanes on property into realized losses, the end result being the generation of losses over many simulated years.

The results of catastrophe model loss simulations are most often summarized in the form of a *loss exceedance curve* (LEC). A LEC essentially contains all the information of a cumulative distribution. In particular, it gives the annual probability that a pre-determined loss is exceeded every year. For example, consider a simple LEC as follows:

$$LEC(z) = \begin{cases} 0.6, & z = 0, \\ 27.7, & z = 1, \\ 101.2, & z = 2, \\ 204.0, & z = 3, \\ 325.3, & z = 4, \end{cases} \qquad (3)$$

where this LEC (and any other LEC in this report) is in units of USD billions, $z=Log_{10}(\textit{return period})$, $\textit{return period} = 1/p$, and p is an *annual occurrence probability*. Some terminology is useful here: z is the *log return period*. We would read the above LEC as saying that a 1 billion USD loss or more is expected to occur every year (z=0), a 20 billion USD loss or more is expected to occur on average every 10 years (z =1), a 100 billion USD loss or more is expected to occur on average every 100 years (z=2), and a 180 billion USD loss is expected to occur on average every 1,000 years (z =3). In practice, the LEC available to the user of a catastrophe model has tens of thousands of specified, discrete values. A more complete version of the LEC given above would look like:

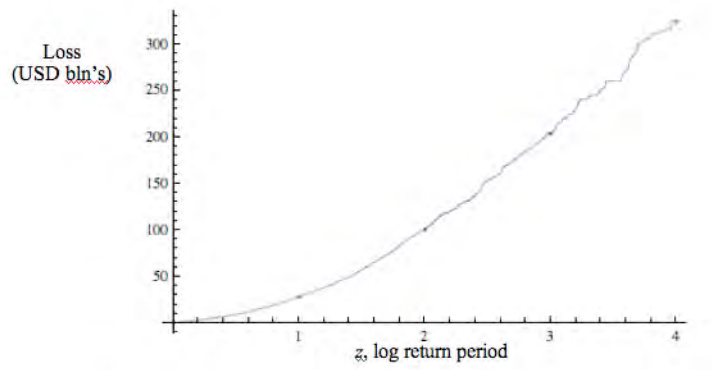

Figure 1. A loss exceedance curve (LEC) versus log return period (z).
Discrete points on the curve correspond to those given in (3) above.

where the discrete points reported above are plotted as small, filled circles. Often a point of confusion, we must point out that the simple LEC in (3) above only gave sampled points from a fuller LEC. If the LEC in (3) had been the complete story, it would be graphed instead like this

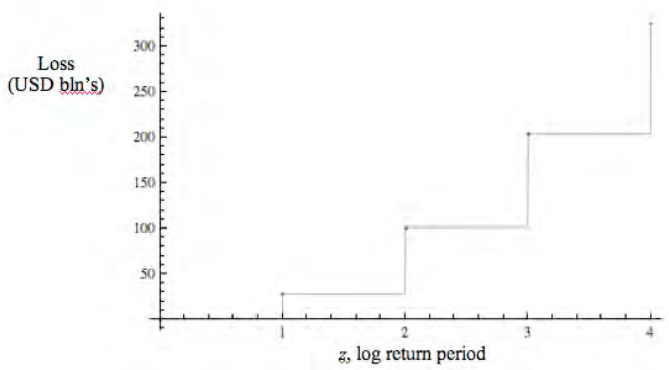

Figure 2. An LEC based only on a handful of specified points.

which can be understood if one recognizes that all discrete LECs may be imagined as being associated with discrete events in a sample space, but each such discrete event may be further subdivided into an equivalent multitude of events, each with the same outcome but with a finer probability measure. For example, if we use the notation $\{x_i; p\}$, were x_i is the outcome of event i and p_i is the probability of event i, the discrete probability distribution {1,0; ½, ½} can be expressed as {1,1,0,0; ¼, ¼, ¼, ¼}, but in both cases, their associated LEC would be the same. If one follows this logic to fill in the gaps of a discrete LEC for a continuous plot, the result will be as seen immediately above.

Despite these considerations, we use a simple polynomial form to approximate a LEC. The results are given as follows for *base normal* (BN) and *climate conditioned* (CC) US hurricane losses:

$$BN(z) = \sum_{k=0}^{6} a_k z^k, 0 \le z \le 4 \qquad (4)$$

$$CC(z) = \sum_{k=0}^{6} b_k z^k, 0 \le z \le 4 \qquad (5)$$

where

$$a_0 = +0.591,\ a_1 = +10.4351,\ a_2 = +6.8906,\ a_3 = +14.5026,$$
$$a_4 = -5.726,\ a_5 = +0.9653,\ a_6 = -0.0675,$$

and

$$b_0 = +1.9547,\ b_1 = +12.8025,\ b_2 = +10.9584,\ b_3 = +11.1832,$$
$$b_4 = -3.8843,\ b_5 = +0.4982,\ b_6 = -0.0257.$$

The log return period, z, is restricted only because reasonable curve fits were not available for higher return periods, as Monte Carlo noise often becomes significant above z=4.[16] To give a reader a feel for the model variances, we note that for a fixed return period, the LEC might vary by approximately plus or minus 10 percent among different models. We end this section by displaying $BN(z)$ and $CC(z)$ versus their corresponding, detailed LECs:

[16] Non-disclosure is considered not to be violated here because these LECs are altered to produce stylized curves for the purposes of this paper. These LECs do not match the LECs from any one modeling firm.

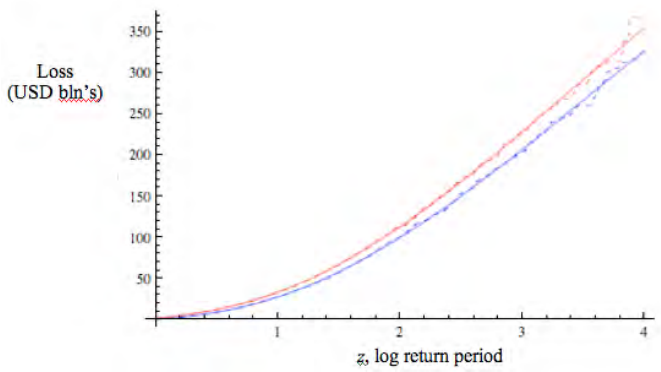

Figure 3. *BN* (solid blue curve) and *CC* (solid red curve) versus their detailed LEC results (dashed curves, same respective color).

Before any notion of climate conditioned hurricane activity was implemented in catastrophe models in 2006, the *BN* curve was the industry standard. Beginning in 2006, the *CC* curve, which utilizes climate-conditioned hurricane statistics, became the industry standard, although not without objection and controversy.[17]

Note that $BN(2) = 100$, and $CC(2) = 113$. In other words, the base normal 1-in-100 year US hurricane insured loss is set to 100 billion USD, and the climate-conditioned 1-in-100 year US hurricane insured loss is set to 113 billion USD. Furthermore, as calculated in the Appendix, the AAL of *BN* is set to 11.4 billion USD, and the AAL of *CC* is set to 14.6 billion USD.[18] Finally, the reader might note that *BN* stochastically dominates *CC* to the first order, which, in the theory of decisions under uncertainty, means that *BN* is preferred to *CC* by all decision makers regardless of their attitudes toward risk.[19]

4. Climate conditioned hurricane models

In 2006, the year following Hurricane Katrina, the three major catastrophe modeling firms—AIR Worldwide (AIR), EQECAT, and Risk Management Solutions (RMS)—introduced "near term" hurricane models that increased hurricane risks under the assumption that warmer than usual sea surface temperature (SST) in the North Atlantic would increase hurricane activity[20]. As already

[17] For example, one of the "big three" modeling firms, AIR, objects to the scientific and statistical justification of CC catastrophe models, so AIR allows its clients to calculate climate-conditioned LECs as an alternative view of risk, while not officially endorsing the use of CC results. See Karen Clark & Company (2008) for further discussion.

[18] The technically involved reader might attempt to replicate this result by numerical method by implying the probability distribution implied by the cumulative distribution function represented by *BN* and *CC*. The numerical results for AAL should not deviate significantly from the values given in the Appendix; if they do, it is recommended that the resolution of the numerical method be increased to achieve a reasonable convergence to the analytic results presented in the Appendix.

[19] Quirk, J.P. and R. Saposnik (1962): "Admissibility and Measurable Utility Functions," *Review of Economic Studies*, 29, 140-146; Hadar, J. and W. Russell (1969): "Rules for Ordering Uncertain Prospects," *American Economic Review*, 59, 25-34; Hanoch, G. and H. Levy (1969): "The Efficiency Analysis of Choices Involving Risk," *Review of Economic Studies*, 36, 335-346.

[20] Karen Clark & Company (2008).

hinted at in previous section, we call these near-term models *climate conditioned*. It is necessary to use such general terminology because there is disagreement among scientists about the ultimate causes of elevated hurricane activity in climate conditioned catastrophe models (CC catastrophe models). More specifically, there is disagreement among scientists about the significance of the observed approximate 0.5 ^{o}C rise in SST over the last 30 years. One group of scientists believes that this rise in SST is part of a multidecadal cycle that is signaled by variations in de-trended SST records[21]. Another group of scientists believes that this rise in SST directly drives increases in hurricane activity[22,23]. Since the IPCC has concluded that SST has risen approximately 0.5 ^{o}C over the last 30 to 50 years[24], we might take CC models to reflect the maximum potential increase in hurricane activity that might occur from the last 30 to 50 years' worth of climate change (CC)[25].

In the case of two out of the three major catastrophe modeling firms, both non-climate conditioned and climate conditioned models are available, which allows for a convenient non-CC versus CC study to be made[26]. We already laid the groundwork for this comparative study by giving the LECs *BN* and *CC* at the end of the previous section above. In the following section, we present a simple method for comparing these two different LECs and show how this method is a useful way to understand the differences among LECs in general.

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[21] Goldenberg, S. B., Landsea, C. W., Mestas-Nunez, A. M., and W.M. Gray (2001): "The Recent Increase in Atlantic Hurricane Activity: Causes and Implications," *Science*, 293, pp. 474-479. http://www.sciencemag.org/cgi/reprint/293/5529/474.pdf

[22] Emanuel, K. (2005): "Increasing destructiveness of tropical cyclones over the past 30 years," *Nature*, 436, pp. 686-688. http://www.nature.com/nature/journal/v436/n7051/pdf/nature03906.pdf

[23] Webster, P. J., Holland, G. J. , Curry, J. A., and H.-R. Chang (2005): "Changes in Tropical Cyclone Number, Duration, and Intensity in a Warming Environment," *Science*, 309, pp. 1844-1846. http://www.sciencemag.org/cgi/reprint/309/5742/1844.pdf

[24] IPCC (2007): "Summary for Policymakers. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change," Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M.Tignor and H.L. Miller (editors), Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. http://www.ipcc.ch/pdf/assessment-report/ar4/wg1/ar4-wg1-spm.pdf

[25] In this report, depending on the context, CC stands for both climate conditioned and climate change. The apparent double meaning is tolerable as the underlying intention is the same. Climate change, according to the IPCC's usage (see footnote 1 in [6]), refers to any change in climate over time, whether due to human activity or natural variability. Climate conditioned here means essentially the same thing: CC catastrophe models only gauge potential increase in hurricane activity correlated with past increases or variations in SST. Whether these SST increases or variations are ultimately driven by human-driven changes in SST or natural variability is not decided by CC catastrophe models

[26] Karen Clark & Company (2008).

5. The intensity profile and residual intensity profile of two LECs

Given two LECs, we can compare them by examining what we will call an *intensity profile* (IP). The intensity profile of two LECs, LEC_1 and LEC_2, is simply the ratio between the two as follows:

$$IP(z) = \frac{LEC_1(z)}{LEC_2(z)}, AAL(LEC_1) \geq AAL(LEC_2). \qquad (5)$$

By convention, in this report we ensure that the AAL of the LEC in the numerator of the IP is greater than or equal to the AAL of the LEC in the denominator. For reference, the IP is graphed versus the ratio

$$\Gamma = \frac{AAL(LEC_1)}{AAL(LEC_2)}, AAL(LEC_1) \geq AAL(LEC_2), \qquad (6)$$

where we again maintain the convention that the higher AAL goes in the numerator. We plot IP for *BN* and *CC* in Figure 4 below. Γ=1.28 in Figure 4 and, to be clear, *CC* is the numerator LEC, and *BN* is the denominator LEC.

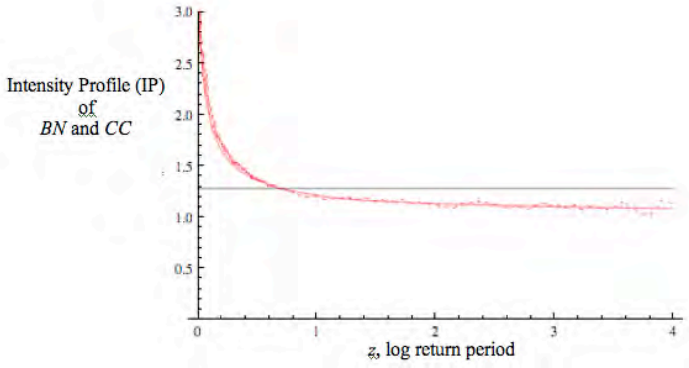

Figure 4. Intensity Profile (IP) of *BN* and *CC* (solid red curve).
As in Fig. 3, detailed results are provided for comparison (dashed red curve).

The Γ reference line is useful in IP graphs because the horizontal axis is not linear in probability, which makes the probability-weighted average intensity profile difficult to gauge at a glance. In Figure 4, the probability-weighted average of the smooth, red curve is equal to the Γ line.

It is common to interpret the migration from the *BN* model to the *CC* model as reflecting an increase in losses per hurricane, presumably from more intense storms. For example, the 1-in-100 year storm, in our case, seems 13% "more intense" when going from *BN* to *CC*, hence the rise from 100 to 113 billion USD loss at the 100 year return period. Certainly, in the absence of further analysis, the IP profile can be interpreted this way. The shift from *BN* to *CC* can be achieved by increasing event losses versus return period of the event in the manner implied by the IP profile: smaller, more frequent events have losses increased roughly 3 times; larger, less frequent events have losses increased roughly 10 percent; overall losses are increased by about 30 percent. This, however, turns out not to be the most fundamental characterization of how *BN* models become *CC* models. To see this, we need to examine a *residual intensity profile* (RIP), which is calculated as follows:

$$RIP(z) = \frac{LEC_1(z)}{LEC_2(z+\Delta z)}, \qquad (7)$$

$$AAL(LEC_1) \geq AAL(LEC_2),$$

$$\Delta z = Log_{10}\Gamma_{freq},$$

Γ_{freq} has a value s.t. $AAL(LEC_2(z+\Delta z)) = AAL(LEC_1(z))$.

Loosely speaking, we are interested in how much of the IP can be explained by a shift in frequency of occurrences of events. Because our LECs are graphed versus log return period, a simple leftward translation of an LEC by amount Δz is equivalent to multiplying the probability of occurrence (that is, the frequency of occurrence) of all underlying loss events by $\Gamma_{freq}=10^{\Delta z}$. Furthermore, when we choose a frequency shift, Γ_{freq}, that eliminates all the difference in AAL between the two LECs being compared, the resulting residual intensity profile has a weighted average value of 1. If the RIP is close to unity, we can say that the difference between two LECs is mainly explained by a frequency shift in events and not by an intensity shift in events. If the RIP varies wildly or in a dramatic way from unity, we would say that the differences between two LECs are not simply explained by a frequency shift in events and that either intensity shifts or a combination of intensity and frequency shifts explains the difference between the two LECs.

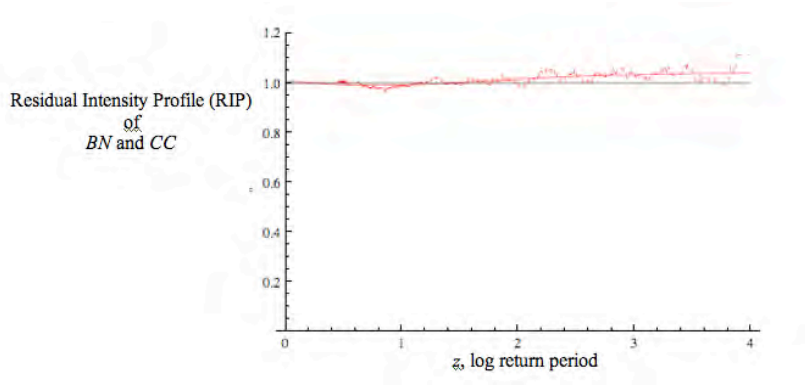

Figure 5. Residual Intensity Profile (RIP) of *BN* and *CC* (solid red curve).
As in Fig. 3, detailed results are provided for comparison (dashed red curve).

As we can see in Figure 5, the shift from BN to CC is largely driven by an increase in frequency of hurricane events. The RIP is not perfectly constant, however, which implies that effective hurricane intensities are being changed a little. In particular, the RIP implies a slight increase in loss intensity for larger events (higher return periods) when going from *BN* to the *CC* models.

Let us review what we have done so far in this report. Hurricane catastrophe models are represented by *BN*(*z*) in the absence of climate conditioning and by *CC*(*z*) in the presence of climate conditioning. The shift from *BN* to *CC* increases annual expected hurricane insurance losses from 11.4 to 14.6 billion USD, which is an approximate 30 percent increase. Because an expectation value is effectively a summation over event probabilities multiplied times respective event losses, we can affect an increase in modeled expected loss by increasing event losses, increasing event probabilities, or both. It turns out that hurricane catastrophe models interpret climate conditioning as mainly involving an increase in hurricane frequency. This results in a signature, nearly constant RIP between *BN* and *CC*.

6. Coastal property increases relative to Climate Change

Normalized historical hurricane damage studies[27] offer important evidence and insight for the estimation of hurricane catastrophe risks. Although these historical studies offer only a sample of risk, the damage normalization process itself offers insight into a kind of Moore's Law, or a secular trend of faster than normal growth, associated with increases in productivity, that underlies the formation of natural catastrophe risks. Historical hurricane losses are normalized when each historical hurricane loss is adjusted for changes in population, per capita wealth, and inflation. The component of change outside of inflation might be referred to as *property density* (property asset real value per unit area). Before the late 1980's, historical hurricane losses were only adjusted by inflation, which grossly understated historical loss experience in present day terms because US coastal property density has been growing rapidly, by about a factor of 1.5 times in real terms per decade. This, in combination with inflation, has conspired to create an approximate doubling of nominal dollar losses every decade for a given hurricane scenario. For example, Hurricane Andrew is estimated to have caused 26.5 billion USD in economic damage in 1992. A replay of the same event in 2005 is estimated to cause a loss of about 54 to 58 billion USD, depending on the normalization methodology used[28].

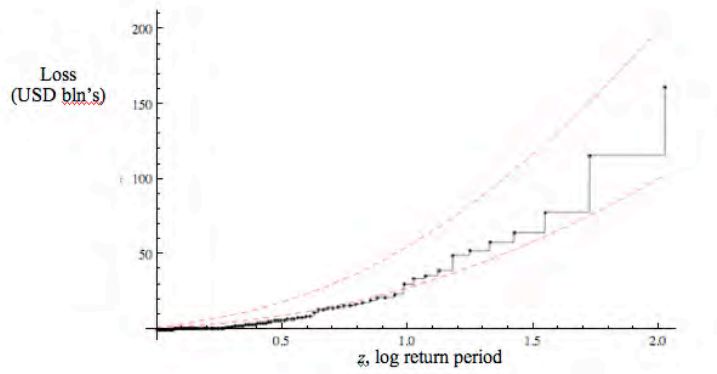

Figure 6. Normalized historical LEC (solid black lines & dots) compared with *BN* and *BN* doubled (dashed red lines).

Using an LEC format, Figure 6 above compares normalized historical losses from 1900 to 2005 to the BN model results. If agreement were perfect, the normalized historical LEC would center on the upper dashed line in Figure 6 because the normalized historical losses are meant to gauge total economic damage. Typically, total economic damages are taken to be roughly double the insured losses[29]. Yet, the agreement in Figure 6 is not bad as far as such historical comparisons to model results go. All of this is meant to say that not only is faster than normal growth in property density a clearly observed phenomenon, but normalizing historical losses for inflation and property density alone does a good job of providing a historical loss record that comes close to reproducing the risk estimates of considerably more sophisticated catastrophe models.

Let us assume for the sake of discussion that increases in US coastal property density, all other things being equal, are uniform across all areas affected by hurricanes and that the rate of real growth in such property density is 1.5 times per decade[30]. This would lead directly to the

[27] Pielke *et al*. (2008).
[28] *Ibid.*
[29] *Ibid.*
[30] *Ibid.*

conclusion that real hurricane losses increase by a factor of 1.5 times every decade. We create a new LEC, $BN_{10yr}(z)=1.5BN(z)$, which we compare with *BN* and *CC* in Figure 7 below.

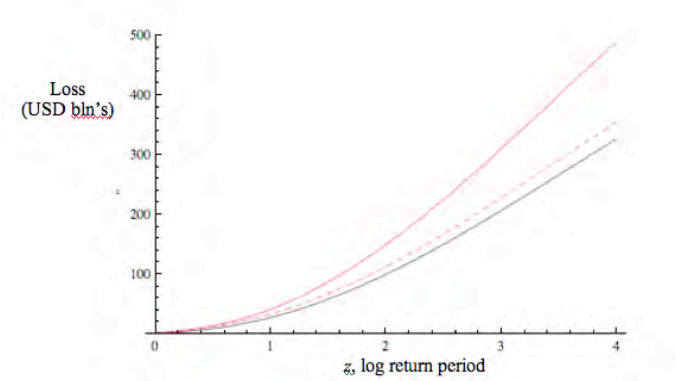

Figure 7. BN_{10yr} (solid red curve), *CC* (dashed red curve), and *BN* (black solid curve).

The result is visually striking because it appears that 10 years' worth of property density growth creates increases in hurricane losses way beyond any potential increases due to recent CC, but the graph is deceptive. As already mentioned above, because the horizontal axes of our graphs are in log return period, visual weighting does not correspond well to probability weighting. The BN_{10yr} versus *BN* intensification profile is flat at 1.5 (not pictured), whereas the *CC* versus *BN* intensification profile starts out at approximately 3 at zero return period and drops down to approximately 1.1 at higher return periods (Figure 4 above). As stated before, the average weighted intensification of CC versus BN in Figure 4 is 1.28. Still, if property density increase were continuous and uniform over time, we would estimate that roughly 6 years of coastal US property growth might yield the equivalent growth in risk seen in CC catastrophe models.[31]

In conclusion, we cannot say that property density increases create the same intensification profile as CC, but we can say that less than a decade's worth of property density increases can have the same or worse impact on hurricane risk than is reflected in current, CC catastrophe models. Therefore, up to 50 years worth of CC impact on hurricane risk is only equivalent to less than a decade's worth of property density increase. Over the next few decades, US coastal property density increases are likely to eclipse any foreseeable increases in hurricane risk from CC, both on an annual average expected loss basis and at a 1-in-100 year exposure level.

7. The arbitrary premium hypothesis

As previously stated above, CC catastrophe models are not free of controversy. More than one industry observer has asked aloud whether or not CC has been used as an excuse to raise insurance and reinsurance premiums. We will call this the Arbitrary Premium Hypothesis (APH). Such behavior is generally difficult to prove[32], especially because intention is difficult to

[31] The growth factor 1.5 per 10 years implies a 4.138 percent real growth in property density per year. Such a growth rate would produce a 28 percent increase in property growth in 6 years.

[32] Duggan, Mark and Steven D. Levitt (2002): "Winning Isn't Everything: Corruption in Sumo Wrestling," *American Economic Review*, v92, 1594-1605.

establish[33]. Although beyond the scope of this paper, it is worthwhile to mention a possible strategy to prove or disprove the APH using some of the techniques of this paper. If one were to compare the LECs for US hurricane across all modeling companies and across all years going back to, say, 1999, it might be possible to see eventually, perhaps by 2016 (ten years after CC models were introduced) that property density growth alone will explain most model changes and that CC models eventually become indistinguishable from a BN model from 1999 trended up every year for property density growth. This would provide a hint that the APH is true. Depending on the actual LEC development versus the property density increase trend, CC models in 2006 might in retrospect be seen as either (i) a convenient way either to catch up on property density growth revealed by the active 2004 and 2005 US hurricane seasons or (ii) a way to get ahead of property density growth increases in the near future.

8. US reinsurance markets and the potential effect on developing countries

What happens in the US reinsurance market (USRM) often affects reinsurance markets abroad, so here we will discuss the USRM. The USRM, like the US insurance market, is the largest in the world[34]; it is estimated that North America (and mainly the USA) absorb 75% of the worldwide catastrophe reinsurance capacity (Cummins and Mahul 2009). Currently, the USRM is experiencing important challenges. Demand for reinsurance coverage is going up, while the ability of the USRM to provide coverage is going down. Models have some part in this. If modeled risk increases, as they have with the transition to CC models, both the insurer and reinsurer need to raise more capital or shed risk. Loss events often harm insurer and reinsurer differently, but model change events affect both in the same way. This year, this awkward dynamic is exacerbated by a potential change in the way rating agencies view the capital adequacy of insures and reinsurers. As of this year, the Florida Hurricane Catastrophe Fund (FHCF), the largest provider of hurricane reinsurance in the world, is considered substantially hampered in its ability to meet its potential obligations. This is because coming into this year the FHCF has relied upon tens of billions of USD in contingent, post-disaster financing to cover losses to the FHCF should the Big One occur. The recent impairment of the credit markets makes such a massive, post-event financing of losses unfeasible. This has caused a 10 to 30 billion USD gap in hurricane reinsurance, which cannot be easily filled. Furthermore, similar to the state of Florida, the rest of the reinsurance and insurance industry had been relying, at least in part, on post-event financing. Before the credit crisis, rating agencies expected that even substantial shortfalls in capital caused by a loss event could be healed over by the rapid mobilization of capital into the reinsurance and insurance markets after a large loss event—as had been the case in the past after Hurricane Andrew, the Northridge Earthquake, the terrorists attacks on 9/11, and Hurricane Katrina. Now, the outlook on post-event capital mobility and formation is uncertain.

We are still watching the situation unfold, but it appears inevitable that USRM premiums are set to dramatically increase in 2009-2010. Unlike increases driven by a loss event, these premium increases are likely to be slower to wash out of the system becuase they are driven by underlying structural trends and not by a single, rare event of loss.

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[33] Transcripts of private conversations are sometimes used to establish that a transaction has been manipulated, but even this form of evidence is not without its issues. One of the authors (JS) has observed that traders will sometimes confess to rigging a price when they in fact did not. Ultimately, expressing only the desire, not the true ability, to gain an edge in a highly competitive market, a trader's confession is often a lie about a lie.

[34] Swiss Re website. See in particular the research and publications of Swiss Re's sigma group. www.swissre.com

In the catastrophe bond market, we are seeing almost a doubling in premiums for 1-in-100 year hurricane risks, which are now approaching 10 to 11 times actuarial levels, versus 4 to 7 times actuarial levels in years past. The expected result is that reinsurance capacity is likely to dry up over the next 2 years for any market abroad that is not a major source of risk and premium. This could manifest itself not so much in rate increases for non-US reinsurance markets, but in non-renewals of coverage or dramatic reductions in coverage in reinsurance coverage for developing countries.

The hardening catastrophe reinsurance market, due to major insurance and reinsurance losses in 2008, and the increased demand for capacity in some developed countries (particularly the US) may reduce the capacity available for middle and low-income countries, particularly in the short term. However, this impact may be limited in the medium term, given the growing interest of investors and reinsurers for non-peak risks, that is, risks that are not correlated with the peak risks (such as US hurricanes and earthquakes), particularly for middle and low-income countries, which contribute to their portfolio diversification.

Appendix: How to calculate the AAL of an LEC

It can be shown that the AAL, which is just an expected loss, can be calculated with the following expression:

$$AAL(LEC) = LEC(0) + \int_0^{z_{\max}} 10^{-z} \frac{dLEC(z)}{dz} dz \qquad (A.1)$$

where z_{max} is the upper bound of the valid range of the argument of LEC. As a reminder, in this report, we used $z_{max} = 4$ throughout.

Because LEC(z) has polynomial form, the integral in (A.1) is solvable in closed form with the following result:

$$AAL(LEC) = a_0 + A - B\left(C_0 + C_1 z_{\max} + C_2 \frac{z_{\max}^2}{2!} + C_3 \frac{z_{\max}^3}{3!} + C_4 \frac{z_{\max}^4}{4!} + C_5 \frac{z_{\max}^5}{5!} \right),$$

$$A = \sum_{l=0}^{6} a_l,$$

$$B = 10^{-z_{\max}},$$

$$C_j = \sum_{l=j+1}^{6} a_l, \qquad (A.2)$$

$$a_k = \frac{a_k}{Ln[10]^k} k!,$$

$$z_{\max} = Ln[10] z_{\max}.$$

□

Substituting into (A.2) the respective parameters of (4) and (5) in the main text, we get AAL(*BN*)=11.4 and AAL(*CC*)=14.6, where AAL is in billions of USD.