The value of seasonal weather forecasting

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Introduction

The insurance industry exposes itself annually to losses from hurricanes. To date the most costly year was 2005 when hurricanes Katrina, Rita and Wilma caused insurance losses of USD83bn (source, Swiss Re Sigma). Seasonal weather forecasting methods are becoming more sophisticated [1] and the time may eventually come when useful forecasts can be made about possible landfall events in the coming year. It is likely that the skill and capabilities of these forecasts will increase over the coming decades. This paper seeks to investigate whether 'limited information forecasts' are of use to a hypothetical insurer and how allowance for climate trends affects profitability. The paper notes that, with very deep uncertainty, it is very difficult to distinguish between an underwriter who is good or just lucky.

Figure 1: Hurricane model

Experimental design

For a hurricane to cause a major loss the following has to occur: (1) a hurricane forms; (2) it makes landfall; (3) it is intense, and finally; (4) the landfall location occurs where exposure density is high (i.e. it hits a major urban or commercial centre). This is illustrated in figure 1.

The basic simulation examined in this paper is as follows:

- Simulate the number N_B of hurricanes that form in the North Atlantic Basin;
- Simulate the number $N_L|N_B$ of these that make landfall;
- Simulate the number $N_C|N_L$ of these which hit a major city or commercial centre;
- Simulate the saffir simpson strength of each storm that makes landfall (see table 2 for assumed proportions) assume this is independent to landfall location,
- Uniformally sample N_C of these, which are deemed to be the city hits, assume a 1-1 correspondence between strength of a city hit and financial loss. Assume losses arise of $S_1, S_2, \ldots S_{NC}$ – see table 2;
- Calculate the Premium charged P ;
- Calculate the insurance (underwriting) profit as $P - \sum_{i=1}^{N_C} S_i$

Parameters

Table 1: Hurricane model

Process	Variable name	Distribution	Parameter
Frequency of generation	N_B	Poisson(λ)	$\lambda = 7$
Landfall number	$N_L \mid N_B$	Binomial(N_B, q)	q = 0.24
City Hit number	$N_C \mid N_L$	Binomial(N_L, c)	c = 0.25
Kreps reluctance			30%
Exposure/Premium scalar	$\beta 1, \beta 2, \beta 3, \beta 4$		10%

Table 2: Severity and loss model

Saffir Simpson	Proportion (1955-2010) Stationary %	Assumed loss (Stationary) USD bn	Proportion (1995-2010) Non-stationary %	Assumed loss (Non-stationary) USD bn
	(A)	(B)	(C)	(D)
1	38.2	1.0	34.8	1.4
2	24.7	3.0	25.1	5.0
3	28.4	15.0	28.7	22.0
4	6.2	70.0	8.8	75.0
5	2.5	130.0	2.6	132.0

Pricing methods

The following subsections describe various pricing methods which were investigated. These are all based on the work of Rodney Kreps [2] they do not pretend to be actual pricing methods used by individual insurers and reinsurers which are likely much more sophisticated. They do, however, capture the essence of pricing: the the insurer aims to cover expected losses and provide a return on capital to its investors that is consistent with the size of the risk taken on.

Naïve Pricing: Ignore all forecasts

$$P_0 = E(N_C)E(S) + 30\% \left(E(S)^2 VAR(N_C) + E(N_C) VAR(S)\right)^{\frac{1}{2}}$$

Variant 1: Generation Frequency known approximately - reduce line size. $P_1 = P_0$ +/- 10% according to season strength f.

$$f(n_B) = \begin{cases} high & n_b > E(N_B) + k.\sigma(N_B) \\ medium & n_b \in [E(N_B) - k.\sigma(N_B), E(N_B) + k.\sigma(N_B)] \\ low & n_b < E(N_B) - k.\sigma(N_B) \end{cases}$$

Variant 2: Generation Frequency known approximately - adjust premium rate

$$P_2 = \begin{cases} P_0(1+\beta_1) & f(N_B) = high \\ P_0 & f(N_B) = medium \\ \dfrac{P_0}{(1+\beta_2)} & f(N_B) = low \end{cases}$$

Variant 3: Generation Frequency known accurately

$$P_3 = q.c.N_B.E(S) + 30\% \left(E(S)^2.q.c.(1-q.c).N_B + q.c.N_B.VAR(S)\right)^{\frac{1}{2}}$$

Variant 4: Landfalling Frequency known accurately

$$P_4 = c.N_L.E(S) + 30\% \left(E(S)^2.c.(1-c).N_L + c.N_L.VAR(S)\right)^{\frac{1}{2}}$$

Variant 5 Severity (or "Potential Loss" PL) known approximately and 5b (adj line size +/10%)

$$P_5 = \begin{cases} P_4(1+\beta_3) & g(PL) = high \\ P_4 & g(PL) = medium \\ \dfrac{P_4}{(1+\beta_4)} & g(PL) = low \end{cases}$$

Results – stationary climate

As expected, profits are made in the majority of years, with a few years with small losses (i.e. negative profits), and a tiny fraction with very material losses.

The figure below shows the various premium levels that arise under the pricing variants (grey). The average premium level is also shown (black). Note that the average premium for variants 3,4 and 5 are all *lower* than the control (P_0).

Figure 2: Range of premium rates

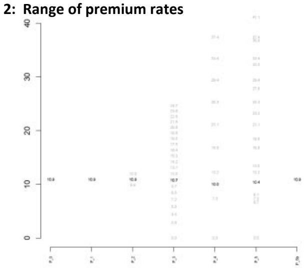
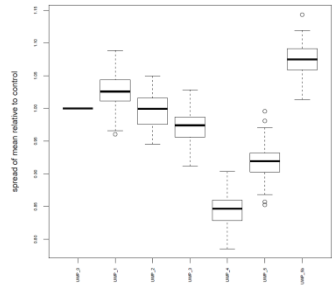


Figure 3 shows the impact on underwriting profit. This was initially surpassing. The methods with more information did worse! However, once you realise that the reduced variance is passed straight to the policyholder through lower prices, this becomes clear.

Figure 3: Profitability levels



The work assumes that insurers hold capital in addition to reserves to be able to survive extreme events. I have adopted UK regulation so that estimated annual aggregate losses with 1in 200 probability must be survived. The impact of ever more information on capital is subtle and varies from method to method. In the simple setting modelled the 1 in 200 year aggregate losses do not necessarily increase when the number of basin hurricanes or landfalls increases. Hence the risk goes up in jumps. However the premium does rise monotonically as the number of storms increases and hence capital actually falls when the premium is rising faster than the risk only to jump up again when the losses "catch up". We see a saw tooth picture in terms of capital held.

Results – non stationary climate

In this section I investigate the impact of a non-stationary climate (as supported by the evidence). I assume the 1995-2010 period is a proxy for "current" levels of risk. This leads to a shift in the proportion of storms of different strength as shown in table 2.

I assume that generation frequency N_B is not changed despite good reasons to assume that it has increased - because I want to focus on shifting strength. I also assume the landfall proportion is fixed. Emmanuel [3] has shown that the PDI has increased in recent times - from his work I have assumed a 40% overall increase in potential destructiveness. The change in severity frequency (table 2, column C) accounts for 16% of this - so an additional uplift of 24% is applied to the severity table (table 2 – column D). This is done in such a way to only slightly increase the cat 4,5 storms on the presumption that they are already close to maximally destructive.

A naive company that does not recognise the climate trend still makes a profit 84.6% of the time - though its expected profits are almost halved. The Naive company will go insolvent twice as often as a company pricing correctly - so the policyholder bears the brunt of their mistake - but pays lower premiums until this happens.

Key messages

- A (very) simple model of hurricane risk and pricing was used to illustrate the impact of forecasting information;
- Some of the results are likely to be an artefact of the pricing method. Other methods are being investigated and conclusions may change;
- A simple line size scaling method performed best over the pricing approaches tested;
- Complex pricing methods tend to pass the benefits to policyholders and return lower expected profits if applied without adjustment;
- An underwriter who is pricing correctly still has a very high probability of returning a less than average return in their career;
- An underwriter who is pricing incorrectly still has a reasonable probability of appearing to provide a decent return over their whole career;
- Forecasting information is valuable, but not as much as you might think. Residual uncertainty for extreme events is very large and dominates results in the medium term;
- Insurance Regulators, Trade Press, Investment analysts and Companies must work hard to avoid being fooled by randomness. [4]

Bibliography

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[3] Emmanuel K. Increasing destructiveness of tropical cyclones over the past 30 years. Nature, 436|4, August 2005.

[4] Nassim Nicholas Taleb. Fooled by randomness. Random House, third edition edition, 2005.