Modelling insurance markets: value of seasonal weather forecasts

Trevor Maynard

Phd Student at LSE (on the train) and Head of Exposure Management at Lloyd's. But…

…these comments are personal views and do not necessarily reflect those of Lloyd's

Not published yet, intend to present at Hurricane conference in June.

Some facts and stats

x 7

- 1960 - 1990 number of natural catastrophes doubled…
  …. **insured losses increased nearly seven times**.
- Due (in part) to increased population in risky areas…
  …but also due to an increase in the level of risk.
- 2005 was the worst year ever for property insurers
  - USD 95 bn dollars relates to the US hurricanes alone
  - the Lloyd's incurred claims of USD 6 bn to help people hit by Hurricanes Katrina, Rita, and Wilma.

Table 12

The 40 most costly insurance losses 1970–2009

Insured loss[10] (in USD m, indexed to 2009)	Victims[11]	Date (start)	Event	Country
71163	1836	25.08.2005	Hurricane Katrina: floods, dams burst, damage to oil rigs	US, Gulf of Mexico, Bahamas, North Atlantic
24479	43	23.08.1992	Hurricane Andrew; floods	US, Bahamas
22767	2982	11.09.2001	Terror attack on WTC, Pentagon and other buildings	US
20276	61	17.01.1994	Northridge earthquake (M 6.6)	US
19940	136	06.09.2008	Hurricane Ike: floods, offshore damage	US, Caribbean: Gulf of Mexico et al
14642	124	02.09.2004	Hurricane Ivan: damage to oil rigs	US, Caribbean: Barbados et al
13807	35	19.10.2005	Hurricane Wilma: floods	US, Mexico, Jamaica, Haiti et al
11089	34	20.09.2005	Hurricane Rita: floods, damage to oil rigs	US, Gulf of Mexico, Cuba
9148	24	11.08.2004	Hurricane Charley: floods	US, Cuba, Jamaica et al
8899	51	27.09.1991	Typhoon Mireille/No 19	Japan
7916	71	15.09.1989	Hurricane Hugo	US, Puerto Rico et al
7672	95	25.01.1990	Winter storm Daria	France, UK, Belgium, NL et al
7475	110	25.12.1999	Winter storm Lothar	Switzerland, UK, France et al
6309	54	18.01.2007	Winter storm Kyrill: floods	Germany, UK, NL, Belgium et al
5857	22	15.10.1987	Storm and floods in Europe	France, UK, Netherlands et al
5848	38	26.08.2004	Hurricane Frances	US, Bahamas
5242	64	25.02.1990	Winter storm Vivian	Europe
5206	26	22.09.1999	Typhoon Bart/No 18	Japan
4649	600	20.09.1998	Hurricane Georges: floods	US, Caribbean
4369	41	05.06.2001	Tropical storm Allison: floods	US
4321	3034	13.09.2004	Hurricane Jeanne: floods, landslides	US, Caribbean: Haiti et al
4074	45	06.09.2004	Typhoon Songda/No 18	Japan, South Korea
3988	135	26.08.2008	Hurricane Gustav: floods, offshore damage	US, Caribbean: Gulf of Mexico et al
3740	45	02.05.2003	Thunderstorms, tornadoes, hail	US
3637	70	10.09.1999	Hurricane Floyd: floods	US, Bahamas, Columbia
3631	167	06.07.1988	Explosion on platform Piper Alpha	UK
3530	59	01.10.1995	Hurricane Opal: floods	US, Mexico, Gulf of Mexico
3482	6425	17.01.1995	Great Hanshin earthquake (M 7.2) in Kobe	Japan
3372	25	24.01.2009	Winter storm Klaus	France, Spain
3093	45	27.12.1999	Winter storm Martin	Spain, France, Switzerland
2917	246	10.03.1993	Blizzard, tornadoes, floods	US, Canada, Mexico, Cuba
2755	38	06.08.2002	Severe floods	UK, Spain, Germany, Austria et al
2680	26	20.10.1991	Forest fires which spread to urban areas, drought	US
2667	–	06.04.2001	Hail, floods and tornadoes	US
2575	4	25.06.2007	Heavy rainfall, floods	UK
2540	30	18.09.2003	Hurricane Isabel	US, Canada
2488	39	05.09.1996	Hurricane Fran	US
2454	20	03.12.1999	Winter storm Anatol	Denmark, Sweden, UK et al
2448	4	11.09.1992	Hurricane Iniki	US, North Pacific Ocean
2361	–	29.08.1979	Hurricane Frederic	US

Chile EQ

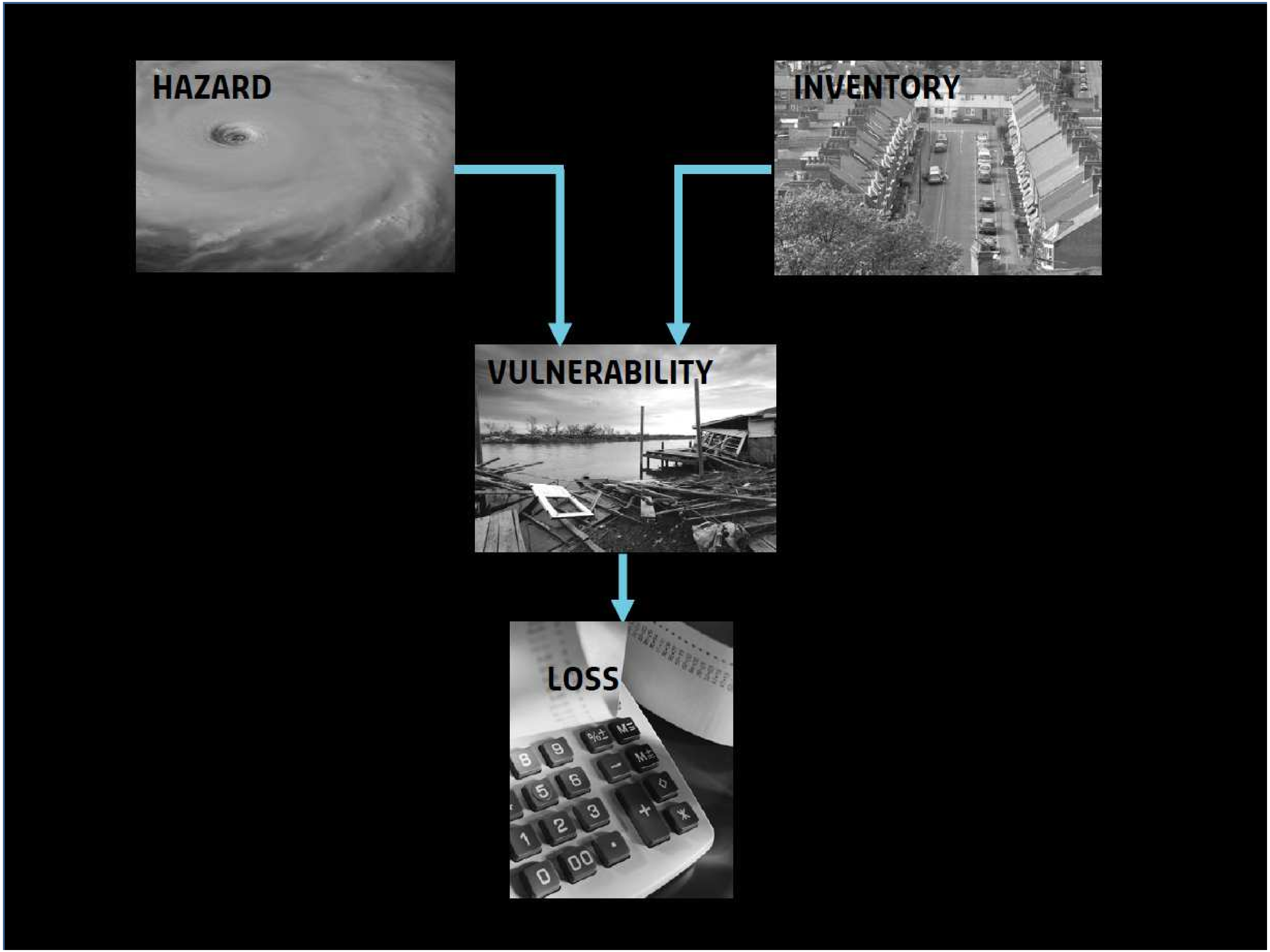
New Zealand EQ

Winter Storm Xynthia

2010 update:

Source Munich RE

Source: Swiss Re, sigma catastrophe database


HAZARD
INVENTORY
VULNERABILITY
LOSS

The “near term” view

- Catastrophe modelling companies have offered conditional models
- Variety of names:
  - “Near term”
  - Warm SST conditioned
  - “Medium term”
- Typically a 5 year average
- Variety of procedures
  - Expert elicitation
  - Internal view
  - Weighted Ensemble Average

Simple model

The basic simulation examined in this paper is as follows:

- Simulate the number (n_B from the random variable N_B) of hurricanes that form in the North Atlantic Basin;
- Simulate the the number (n_L from the random variable $N_L|N_B$) of these that make landfall;
- Simulate the number n_C of these which hit a major city or commerical centre (see simple model below) , from the distribution $N_C|N_L$;
- Simulate the saffir simpson strength of each storm that makes landfall $sa_1, ...sa_{n_L}$ from the iid random variables $SA_1, SA_2, ...SA_{N_L}$ - 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 (sa_i) between strength *of a city hit* and financial loss ($S_i = S(sa_i)$) distribution;
- Calculate the Premium charged (using a Krepps [1] formula) as $P_0 = E(N_C)E(S) + 30\% \left(E(S)^2 VAR(N_C) + E(N_C) VAR(S)\right)^{\frac{1}{2}}$;
- Calculate the insurance (underwriting) profit as $P_0 - \sum_{i=1}^{n_C} S_i$.

In the control we'll assume that $N_B \sim poisson(\lambda)$, where $\lambda = 7$, this is the average number of hurricanes per year since 1955 rounded up (to very approximately allow for over-dispersion, the true mean is 6.1 with a variance of 6.8). See the plot below which compares histogram of actual hurricane numbers to a poisson(7) distribution sample:

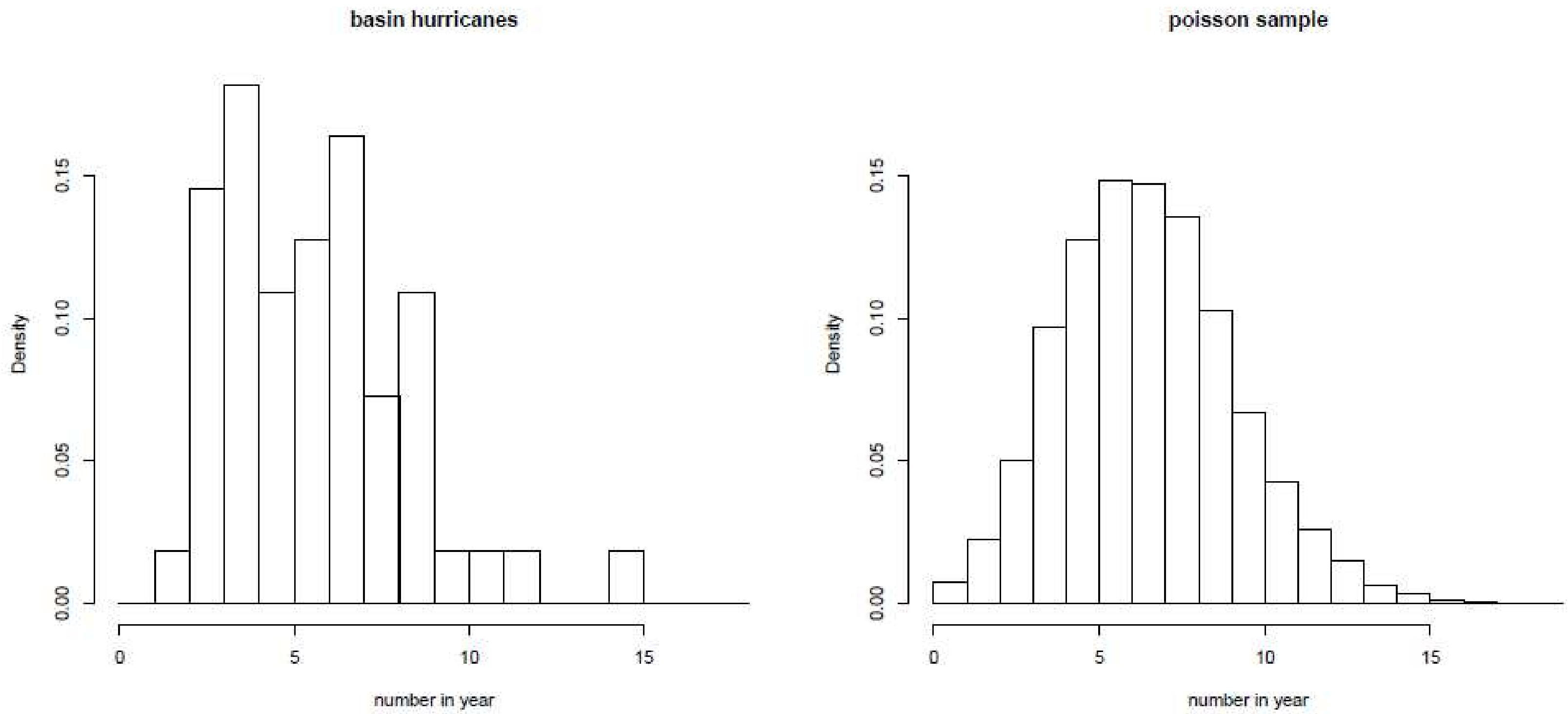


Figure 1: Histograms of actual hurricane counts per year (left) and simulated (right)

Assume that $N_L|N_B \sim binomial(N_B, q)$, where q=24% (based on HURDAT data).

A simple model of whether a major city is hit is defined as follows:

- The US east coast is around 12000 miles long;
- Assume that each hurricane falls into a 'slot' exactly 300 miles wide - so there are 40 such slots on the US coast;
- Assume there are 10 major population centres on the coast
- Say that each city is sufficiently far away from the others, so there is a zero probability of a hurricane hitting two - also assume that each city is in the middle of a coastline 'slot' (defined above);
- Assume that a hit on each coastal slot is equally likely, and therefore there is a 10/40 probability (call this 'c' below) that a landfalling storm will hit a major city - assume the loss would otherwise be zero.

Using the above model the number of city hits is $N_C|N_L \sim binomial(N_L, c)$.

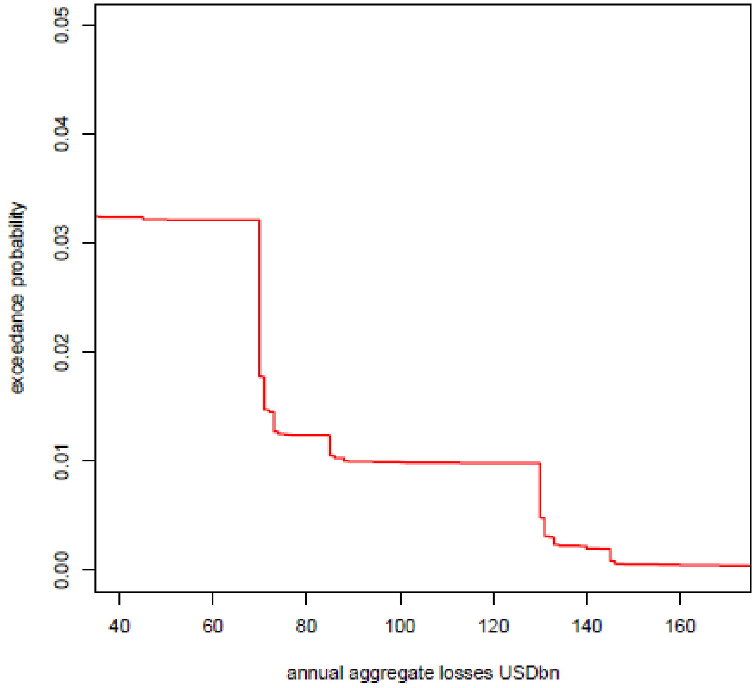
Or equivalently $N_C \sim poisson(\lambda.q.c)$

The landfall intensity distribution is calculated from the following table (based on HURDAT data from 1955 to 2009):

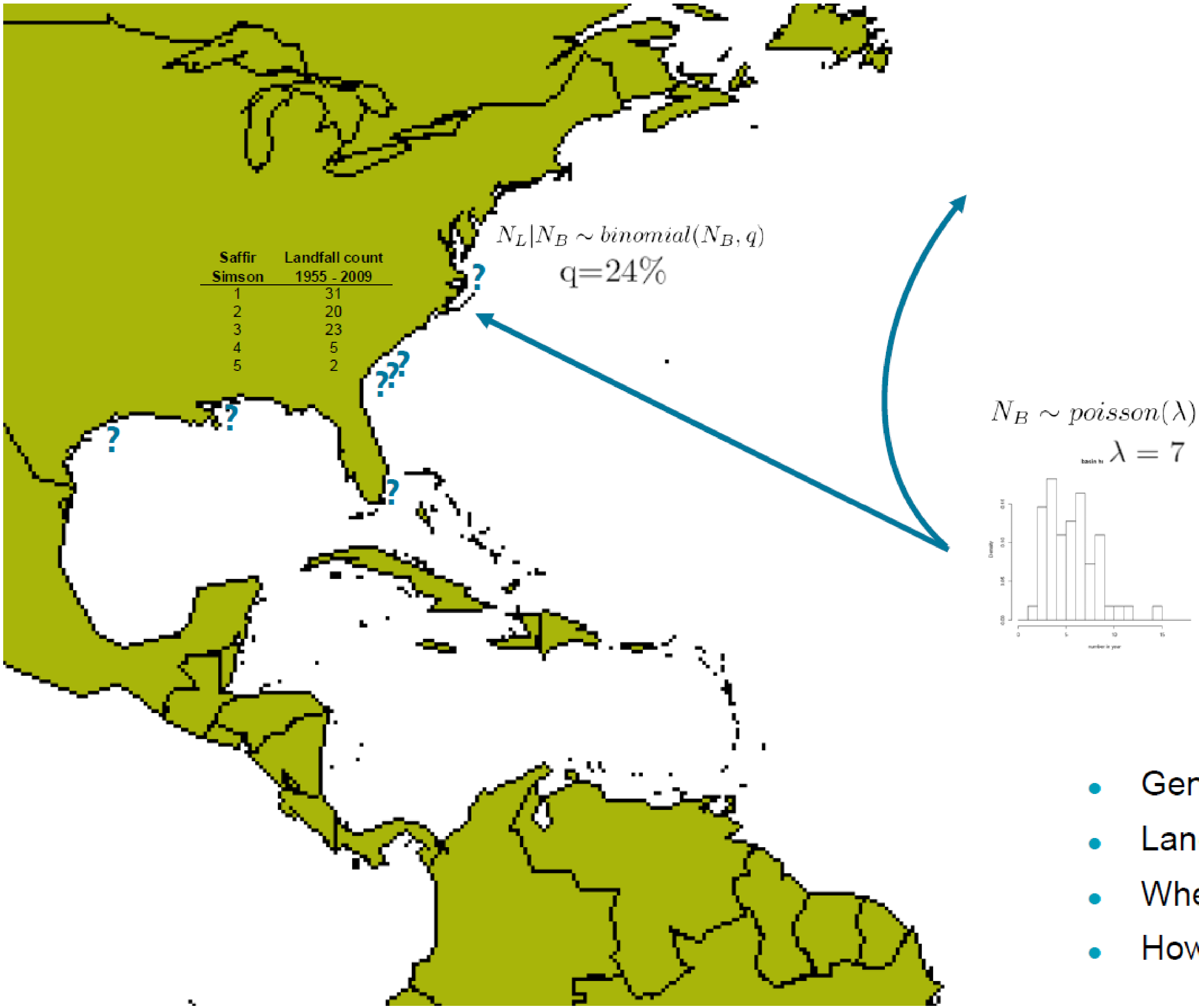
saffir simpson	landfall count since 1955
1	31
2	20
3	23
4	5
5	2

Assume the losses are related to saffir simpson score as follows:

saffir simpson (sa)	loss S(sa) USDbn
1	1
2	3
3	15
4	70
5	110



- 2/3 rds of years have zero loss
- *P(Katrina size loss=USD40bn)* = 3.3%
  ….(cf AIR 3%)
- *P(KRW=USD80bn)* = 1/80



- Generated?
- Landfalling?
- Where?
- How big?

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

Pricing variants:

1. Basin frequency known approximately – reduce line size
2. Basin frequency known approximately – change premium rate
3. Basin frequency known – change premium rate
4. Landfalling frequency known – change premium rate
5. Landfalling known, severity known approximately

1. Basin frequency known approximately – reduce line size

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

σ = standard deviation, k=0.4, so n<6= "low", n>8="high"

season frequency (f)	P(season frequency= f)
low	30 %
medium	43%
high	27 %

Roughly symmetric

Company acts unilaterally….

$$\text{underwriting profit} = \begin{cases} \frac{1}{(1+\alpha_2)}.(P_0 - \sum_{i=1}^{n_L} S_i) & f(n_B) = \text{'}high\text{'} \\ (P_0 - \sum_{i=1}^{n_L} S_i) & f(n_B) = \text{'}medium\text{'} \\ (1+\alpha_1).(P_0 - \sum_{i=1}^{n_L} S_i) & f(n_B) = \text{'}low\text{'} \end{cases}$$

In the experiment $\alpha_1 = \alpha_2 = 10\%$.

2. Basin frequency known approximately
- change premium rate

Market acts together (else write no business?)

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

In the experiment $\beta_1 = \beta_2 = 10\%$.

3. Basin frequency known – change premium rate

Here we assume the N_B is forecast accurately, i.e that the insurer knows the number n_B of basin tropical cyclones in the year. In this case $N_C \sim binomial(n_B, q.c)$ Hence in this case (in a year where $N_B = n_B$ the premium is calculated as:

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

Note in this case that $P_3|N_B$ is a random variable (i.e. varying each year), and that $E(P_3|N_B) \neq P_0$.

- Landfalling frequency known
- change premium rate

In this case we not only know the number of basin storms - but the number of them that go on to make landfall. In this case $N_C \sim binomial(n_L, c)$ and hence the premium is calculated as:

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

5. Landfalling known, severity known approximately

In this variant we assume (as in variant 4) that the number and strength of landfalling hurricanes is known accurately but not which ones (if any) hit a city. Hence a potential lossPL (an upper bound on possible losses) is known and this

$$g(pl) = \begin{cases} \text{`}high' & pl > E(PL) + k_3.\sigma(PL) \\ \text{`}medium' & pl \in [E(PL) - k_4.\sigma(PL), E(PL) + k_3.\sigma(PL)] \\ \text{`}low' & pl < E(PL) - k_4.\sigma(PL) \end{cases}$$

For this simulation we have set $k_3 = 0.63$ and $k_4 = 0.36$.

landfall severity (s)	**P(landfall severity= s)**
low	35 %
medium	34%
high	31 %

Continued….

Landfalling known, severity known approximately (continued)

5. Adjust pricing

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

Note the use of P_4 in the above formula

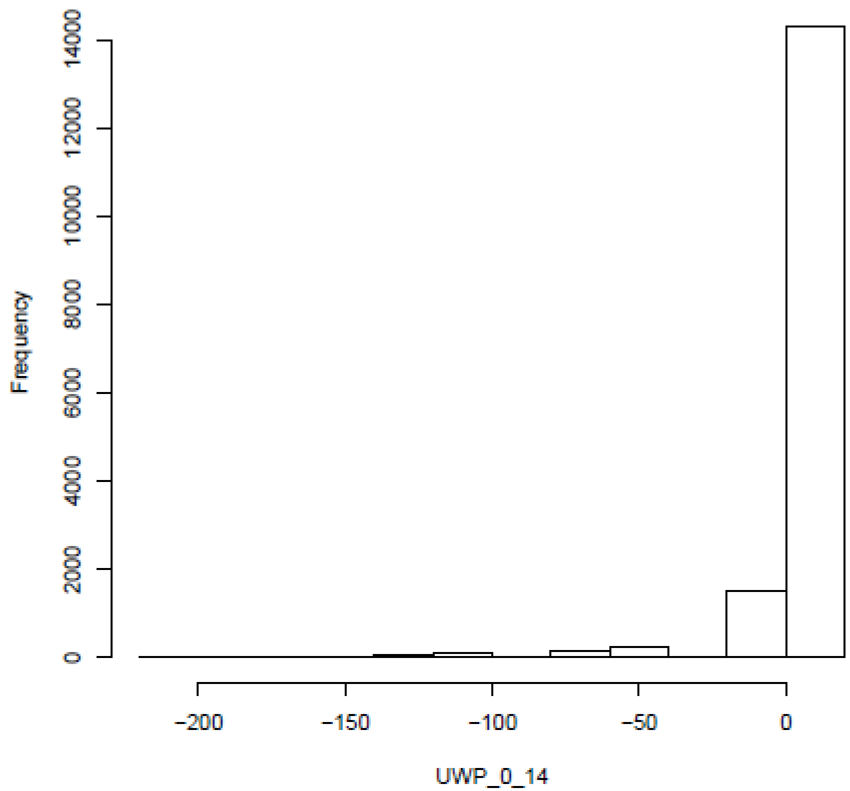
5b. Scale line size

$$\text{underwriting profit} = \begin{cases} \dfrac{1}{(1+\alpha_4)}.(P_0 - \sum_{i=1}^{n_L} S_i) & g(pl) = \text{'}high\text{'} \\ (P_0 - \sum_{i=1}^{n_L} S_i) & g(pl) = \text{'}medium\text{'} \\ (1+\alpha_3).(P_0 - \sum_{i=1}^{n_L} S_i) & g(pl) = \text{'}low\text{'} \end{cases}$$

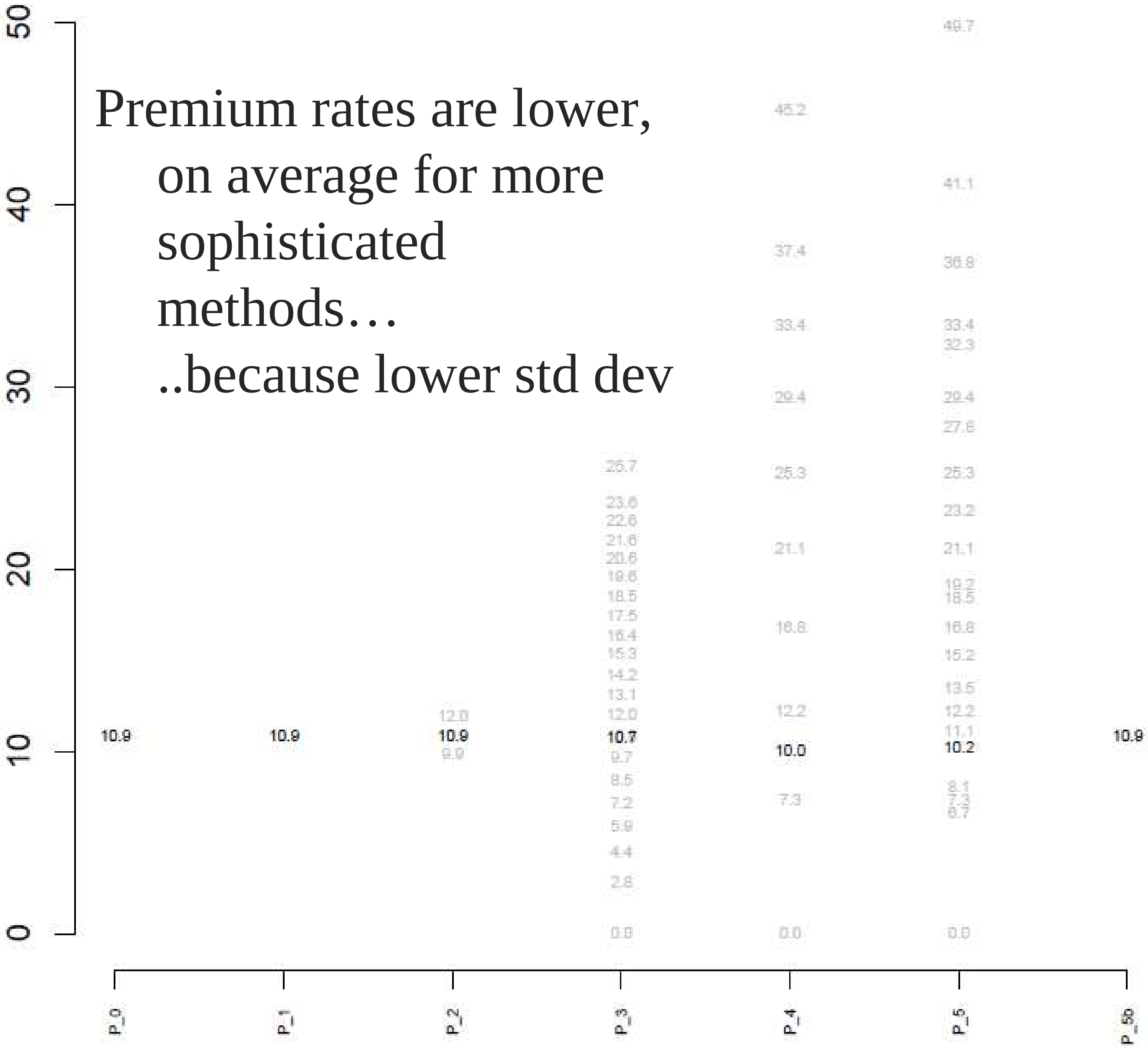
Note the use of P_0 in this case. In the experiment $\alpha_3 = \alpha_4 = 10\%$.

Results

Control experiment – underwriting profits



Premium rates



Premium rates are lower, on average for more sophisticated methods…

..because lower std dev

Premium rates are lower, on average for more sophisticated methods… ..explanation

Consider for example variant 3. The premium formula for the control is:

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

So,

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

Compare this to,

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

So, since $E(N_B) = \lambda$,

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

Now, the term $q.c.\lambda.E(S) = 5.42$, is the same for both expectations and the term involving $E(S)^2$ is clearly lower for (P_3) (due to the $(1-q.c)$ term). In the specific simulation we have:

$$30\% \left(E(S)^2.q.c + q.c.VAR(S)\right)^{\frac{1}{2}} = 2.061$$

, compared to

$$30\% \left(E(S)^2.q.c.(1-q.c) + q.c.VAR(S)\right)^{\frac{1}{2}} = 2.047$$

In the particular simulation we have $E(N_B^{\frac{1}{2}}) = 2.59$ compared to $E(N_B)^{\frac{1}{2}} = 2.64$ but it is generally true that $E(N_B^{\frac{1}{2}}) < E(N_B)^{\frac{1}{2}}$.

In the particular simulation we therefore have:

$$E(P_0) = 5.42 + 2.061 * 2.65 = 10.88$$

compared to

$$E(P_3) = 5.42 + 2.047 * 2.59 = 10.72$$

Therefore it is clear that the reason for the premium difference is due to the capital loading (the standard deviation part of the equation). In the case when we have more information (variant 3) the standard Kreps formula gives credit for the lower variance and hence calculates a lower premium.

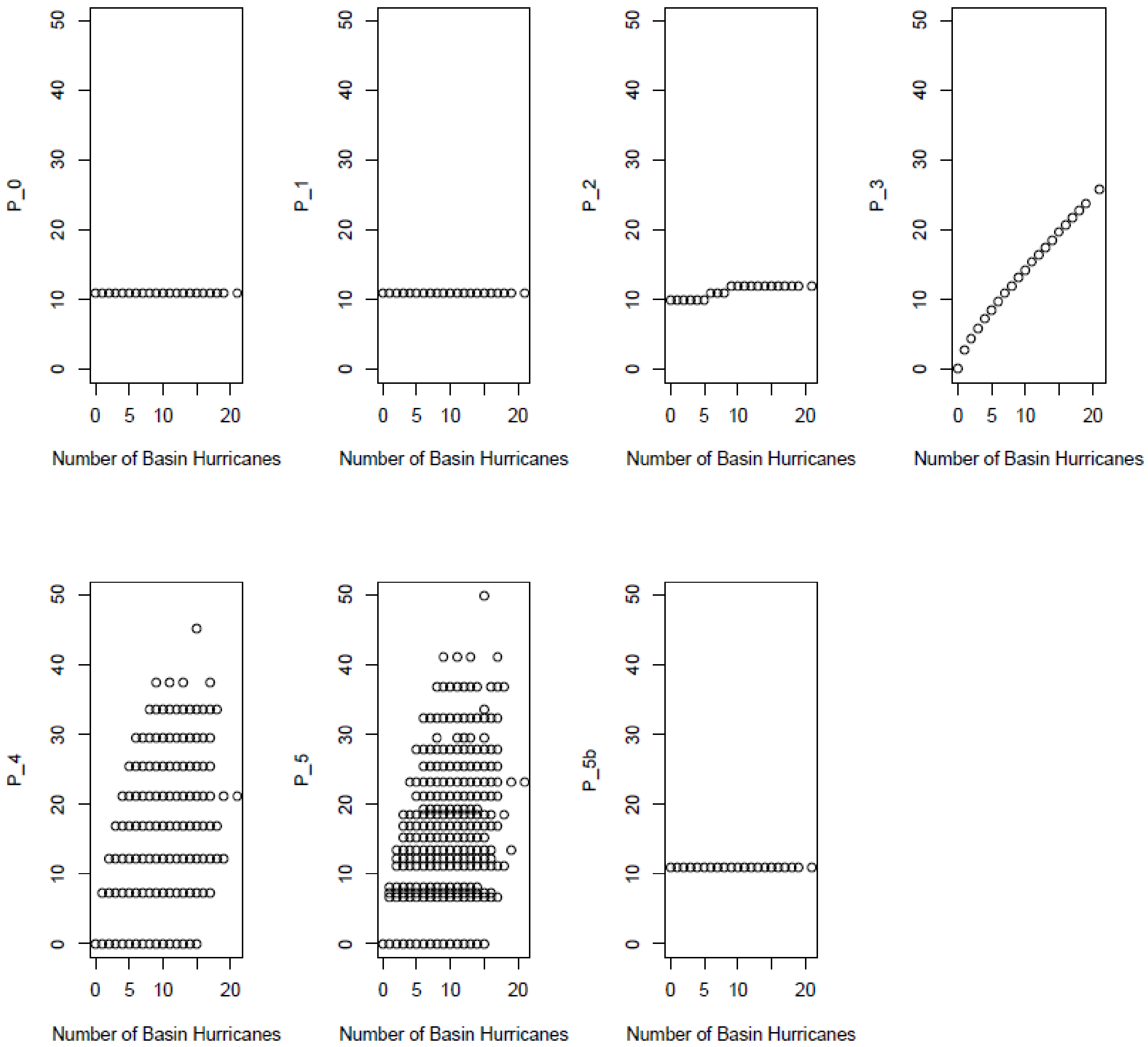


Figure 6: Premium rates against number of Atlantic Basin hurricanes

Variant 3 lower triangle blank
– if a given number of landfalling hurricanes has occurred at least that number of basin storms must have occurred (giving a lower bound on the premium)

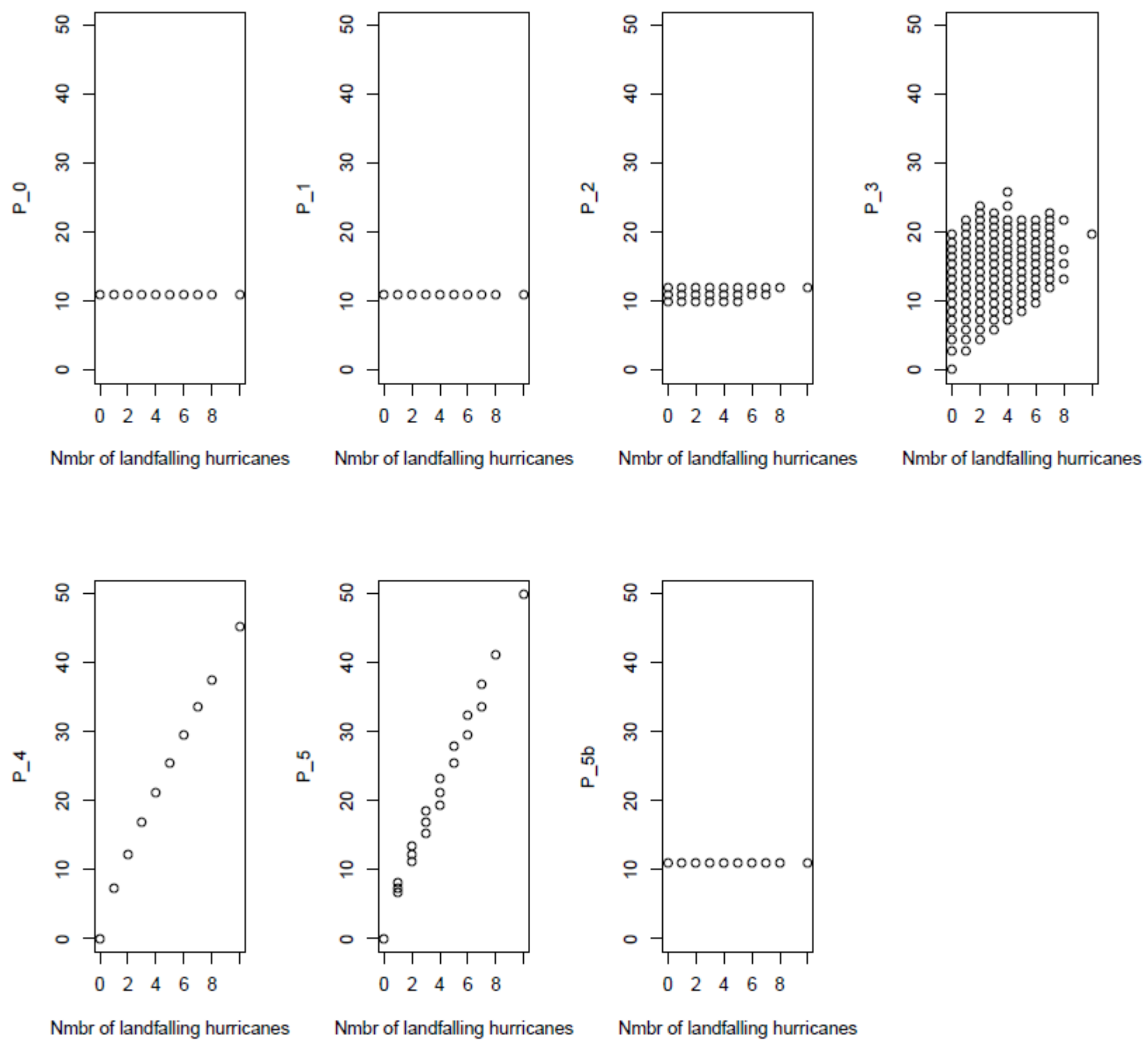


Figure 7: Premium rates against number of landfalling hurricanes

Key point: even the most sophisticated methods give wide spread of premium rates – sometimes lower than the control.

But never lower than when the number greater than 2

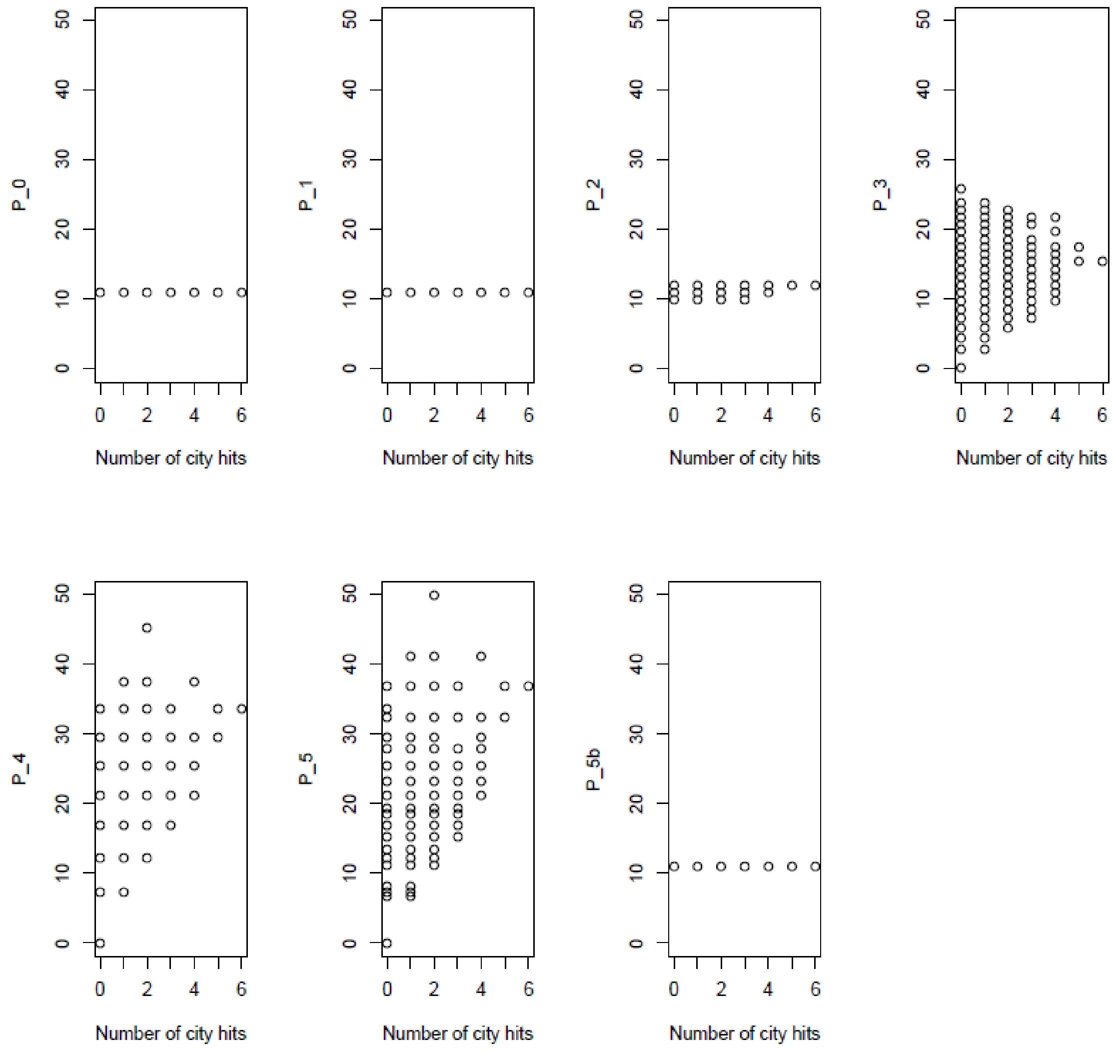
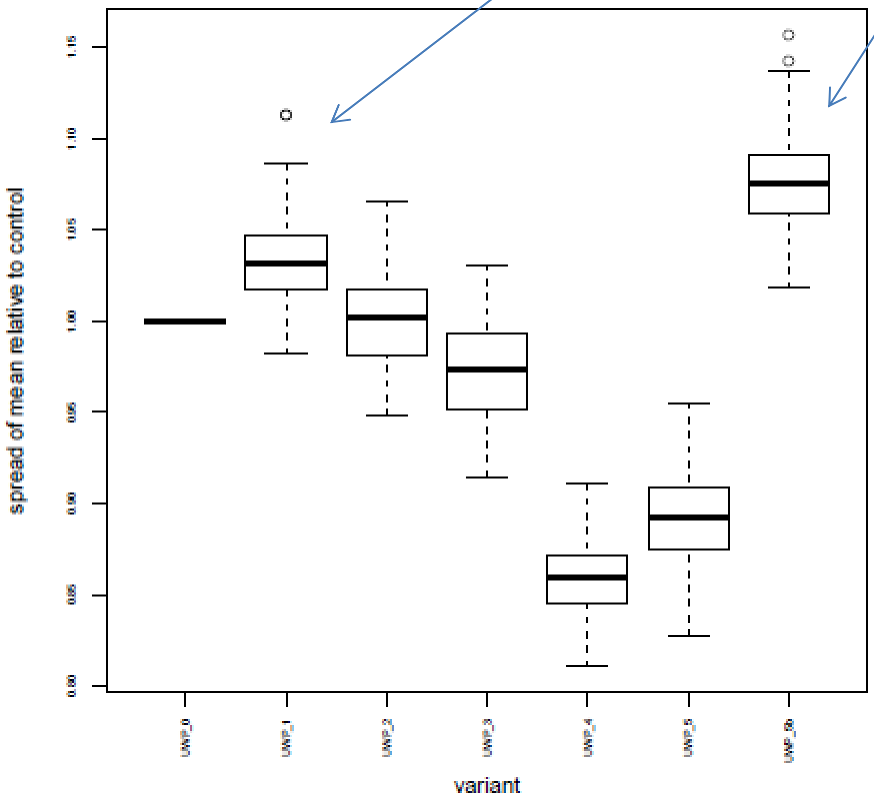


Figure 8: Premium rates against number of city hits

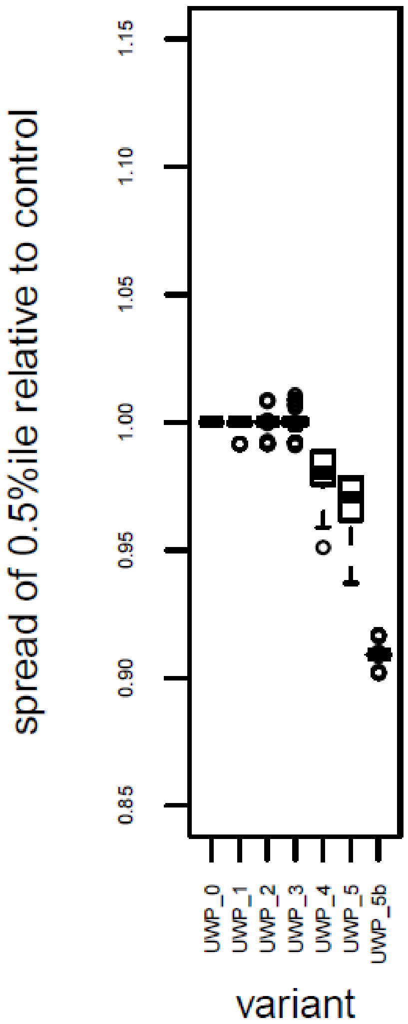
Profitability (relative to control)

Not everyone can scale line size!

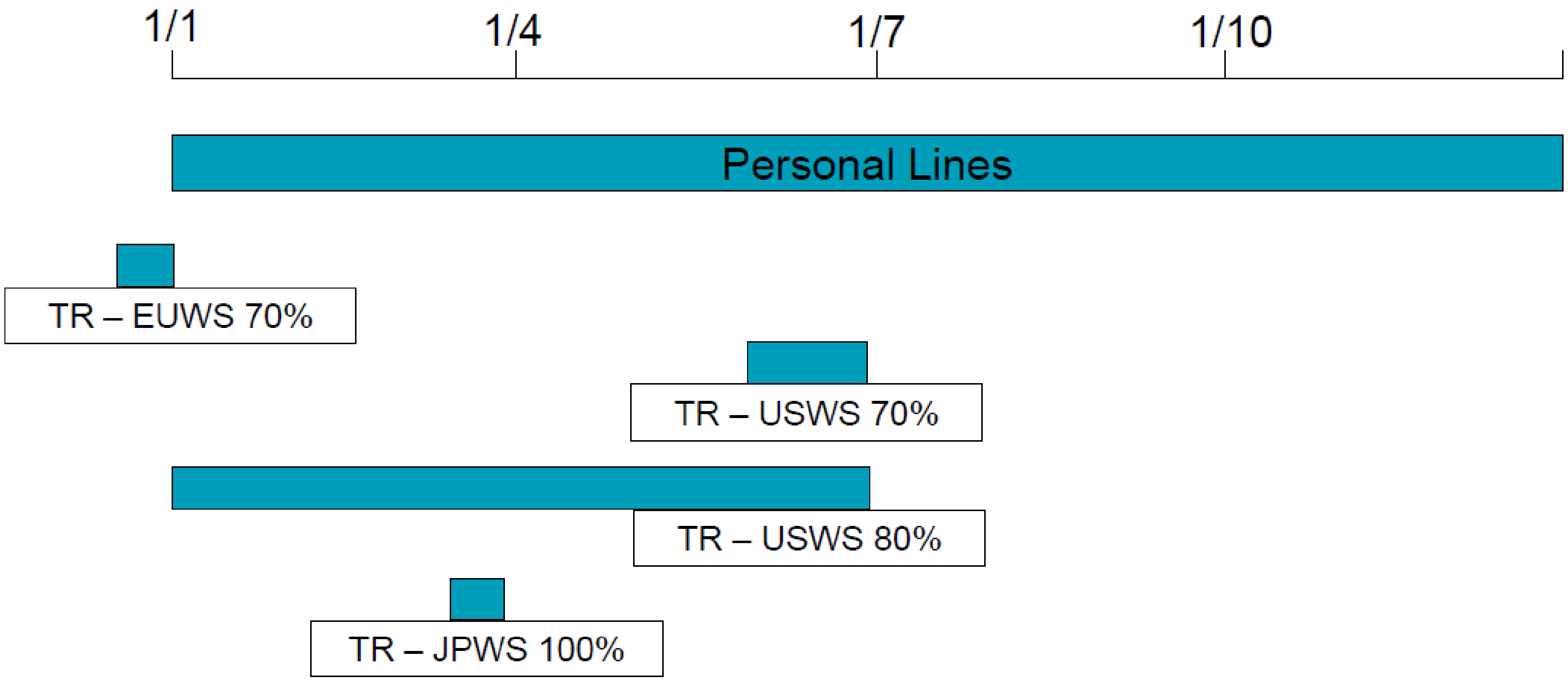


Premiums are on average lower

Capital requirements



Renewals timeline



Multi-year considerations

- These remarks in context….
  …. typical strategy 3 years
- Pre-purchase materials? Resilience vs Optimal
- Inform building codes/ design standards
- Pre-decade preparation
- Tele-connections – changes in dependency in year
- Value of Climate Change Adaptation
- Social issues – impact of climate and man made issues (political unrest etc)

Social and other issues

- There is a lack of symmetry between positive and negative outcomes.
  - Can't expose capital too far
  - Simple modelling suggests differential pricing could be *less* profitable; but may need less capital?
- Is more volatile pricing desirable?
- Formulaic use of forecasts – leads to systemic risk?
- Danger of too-accurate forecasts?

Questions?