

GENERAL INSURANCE PRICING SEMINAR

13 JUNE 2008, LONDON

Demand Modelling in Personal Lines

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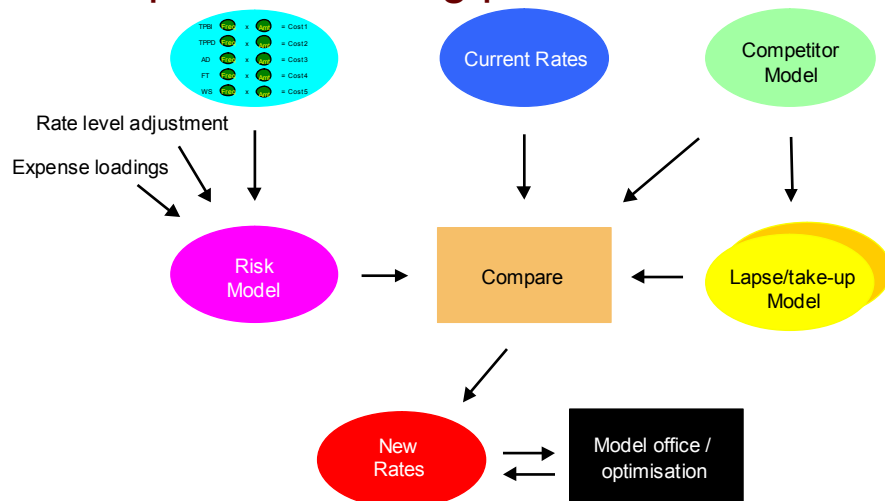
Agenda

- **Motivation**
 - What makes a demand model special?
 - Why are we interested?
- **Tools**
 - Linear and non-linear models
 - Continuous variables
- **Challenges**
 - Market price
 - Aggregators

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The premium rating process

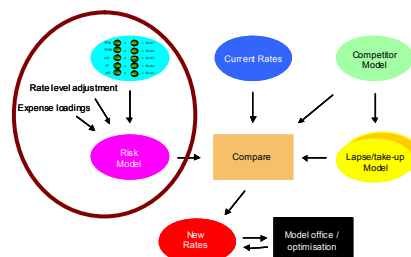


What makes demand models special?

- A demand model:
 - Looks at customer purchasing behaviour
 - Key element is market price
- Retention models are easier
 - Can get away with only old and new premiums
 - New business as proxy for market premium
- Probability of purchase may be low

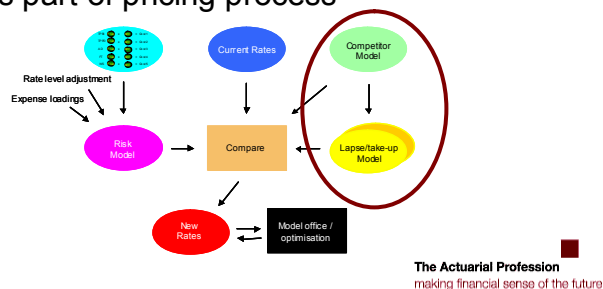
Why are we interested?

- We understand risk
 - GLM modelling over 10 years old
 - Data is clean and reliable
 - We know the interactions to look for



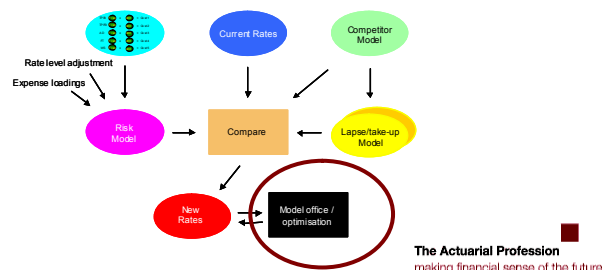
Why are we interested?

- We have a handle on retention
 - Data is collected
 - Standard models used
 - Price change understood
 - Integrated as part of pricing process



Why are we interested?

- Customer demand is last ingredient
 - Some data is collected – some is missing
 - “Hot money”
 - Lifestyle changes
- Price optimisation requires model which are:
 - Accurate
 - Up to date



GIRO working party

- Chairman
 - James Tanser (Watson Wyatt)
- Members
 - John Light (RSA)
 - Owen Morris (NU)
 - Sophia Mealy (AON)

GIRO Working party

- Provide an introduction to the topic describing the terms used
- Summarise the current methodologies used in the market
- Summarise possible alternate methodologies identified by a search of available literature
- Investigate several methods using agreed methodology to determine the descriptive and predictive power of the methods when applied to actual insurance data
- Provide a brief conclusion and highlight areas for further work.

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Generalised linear models

$$E[\underline{Y}] = \underline{\mu} = g^{-1}(\underline{X}.\underline{\beta} + \underline{\xi})$$

$$\text{Var}[\underline{Y}] = \phi.V(\underline{\mu}) / \underline{\omega}$$

Typical model forms

\underline{Y}	Claim frequency	Claim number	Average claim amount	Probability (eg lapses)
$g(x)$	$\ln(x)$	$\ln(x)$	$\ln(x)$	$\ln(x/(1-x))$
Error	Poisson	Poisson	Gamma	Binomial
ϕ $V(x)$	$\frac{1}{x}$	$\frac{1}{x}$	estimate x^2	$\frac{1}{x(1-x)}$
ω	exposure	1	# claims	1
ξ	0	$\ln(\text{exposure})$	0	0

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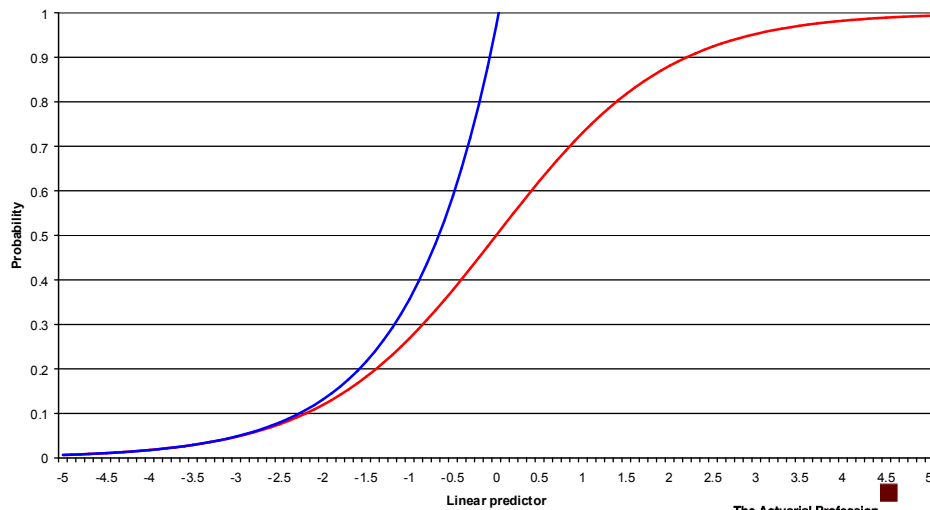
Models

- Generalised linear models cope well with most common requirements
- A logistic model is most appropriate
 - considers $\log(p / [1-p])$ with binomial error
 - maps $[0,1]$ to $[-\infty, \infty]$
 - invariant to whether you model success or failure
- If lapses are low and results not to be used directly, a Poisson multiplicative model can help
 - theoretically wrong (can predict multiple lapses), but easier to communicate

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Understanding the logit transform

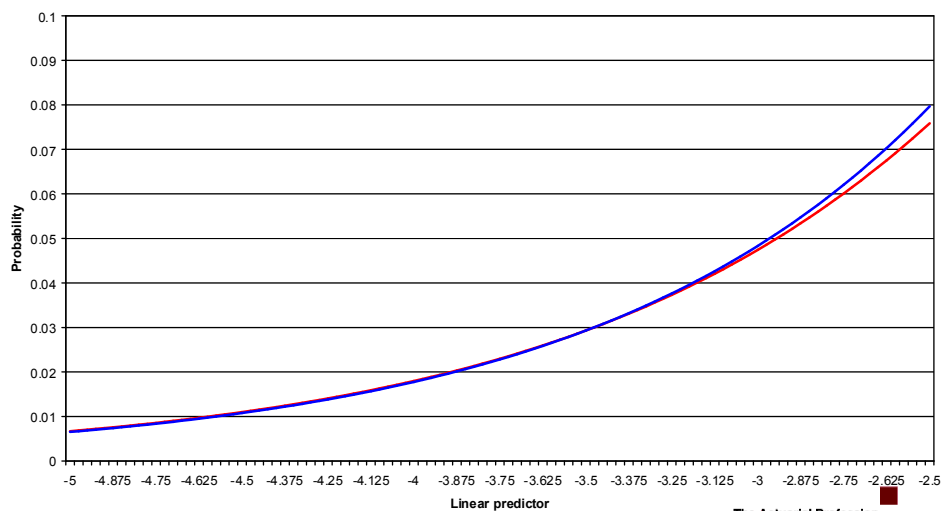
Logit link function



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Understanding the logit transform

Logit link function

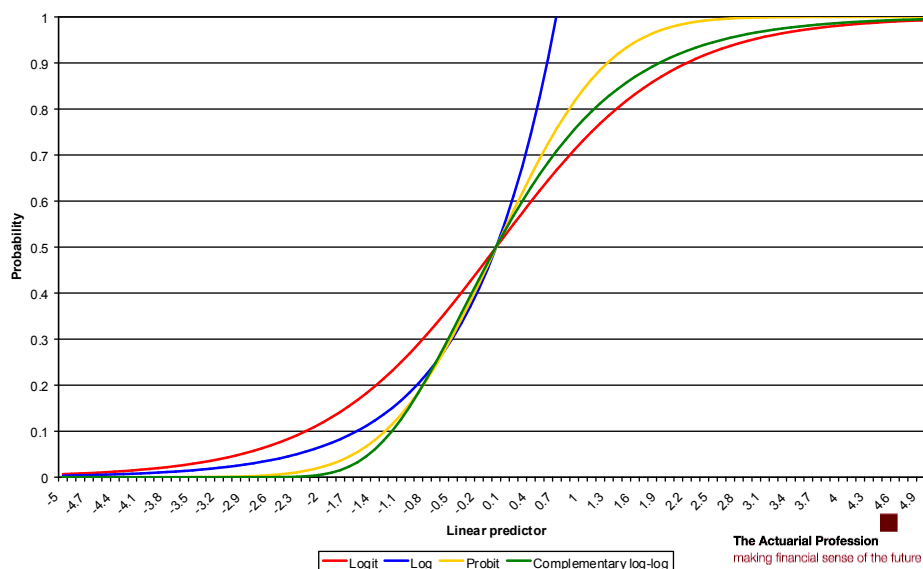


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Other models

- Could try:
 - Binomial / log link
 - Binomial / probit link
 - Binomial / complementary log-log link
- Transform the data
 - Sampling
- Working party is looking at these

Link functions



Sampling

- Take 100% of conversions and x% of others
- In theory, makes not difference to binomial/logit models
- Questions:
 - What rate should be targeted?
 - Predicative versus Descriptive
 - What about other links?

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Continuous variables

- Why continuous?
- Model form
- Continuous variables in a GLM framework

Why continuous?

- Key drivers of demand:
 - Own price
 - Market price
 - Interaction between the two
- Best modelled continuously
- Price sensitivity not necessarily the same everywhere...

Model form: Linear versus non-linear

- Varying views:
 - Simplistic
 - Complex linear
 - Non-linear
- Consider relative competitiveness as an example
 - Our price / market price

Simplistic

- Treat as variate, assume linear
$$\mu = g^{-1}(\sum X_j \beta_j + c(p/m))$$
- Assumes “same” prices sensitivity everywhere
 - Logit link => Lower probability individuals more sensitive ($\Delta p/p$ larger)
- No-one does this, but helpful to understand issues

Complex linear

- Use a continuous function of competitiveness

$$\mu = g^{-1}(\sum X_j \beta_j + c_k \cdot f_k(p/m))$$

- Function is polynomial or spline
- Can interact with other variables to achieve range of shapes
- Simple to apply with existing tools

Non-linear

- Linear in competitiveness, gradient varies by segment

$$\mu = g^{-1}(\sum X_j \beta_j + (p/m) \cdot \exp(\sum Z_j \gamma_j))$$

- Similar issues to simplistic, but locally OK
- Hard to fit due to co-linearity of parameters

What is best approach?

- More research needed
- Working party looking at variations to test predictive power
- In our survey, 4 times as many people (12) used complex linear than non-linear (3)

Continuous variables in a GLM framework

- Variates allow each unique data value to have a different effect on the linear predictor, but force some smoothness
- Even detailed discrete treatment can produce odd results
- In practice implemented via:
 - Polynomialsor
 - Splines

Polynomials

- Include powers of the variate in the model
 - One parameter for each power
 - Can scale variates to avoid large (small) values
 - Can defined orthogonal polynomials to reduce correlation
- Extrapolated values may not be sensible

Design matrix Polynomial

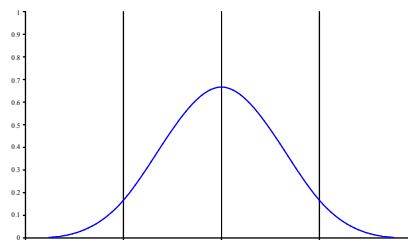
18	M	1	18	324	5832	104976	...	1
20	F	1	20	400	8000	160000	...	0
22	F	1	22	484	10648	234256	...	0
24	M	1	24	576	13824	331776	...	1
26	M	1	26	676	17576	456976	...	1
28	M	1	28	784	21952	614656	...	1
30	F	1	30	900	27000	810000	...	0
32	F	1	32	1024	32768	1048576	...	0
34	M	1	34	1156	39304	1336336	...	1
36	F	1	36	1296	46656	1679616	...	0

Regression splines

- Include a number of spline basis function in the model
 - Number of parameters depends of type of spline and number of knots
 - Sensible choice of basis function (eg B-splines) ensures values in $[0,1]$
- Can specify type
 - Order of spline
 - Type of extrapolation

B-Splines

- Set of basis functions usually covering four segments (defined by five knots)
- Each function is itself a cubic spline
- Each basis function has the same shape, except for the three basis functions at each extreme which occupy fewer than four segments



Spline formula

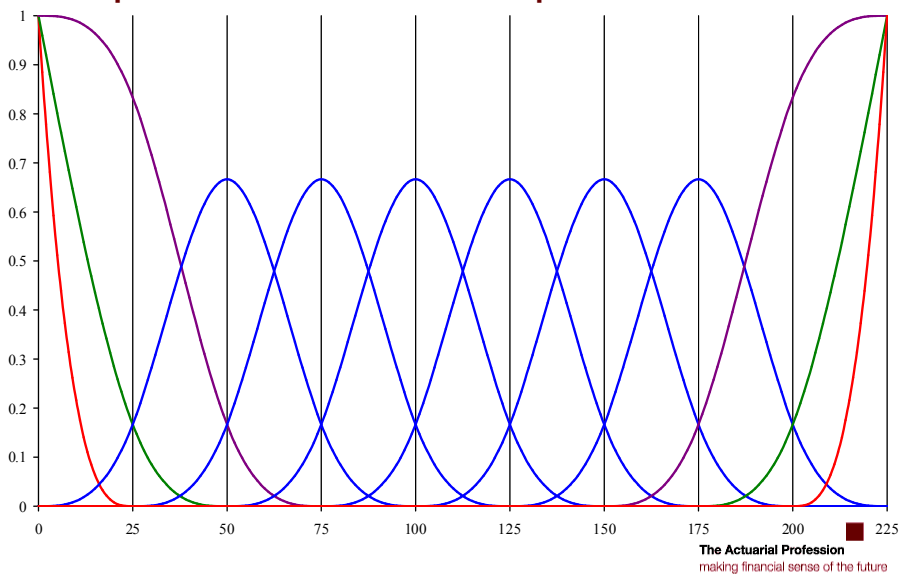
$$\frac{(x - t_i)^3}{(t_{i+1} - t_i)(t_{i+2} - t_i)(t_{i+3} - t_i)}$$

$$\begin{aligned} & \frac{(x - t_i)(t_{i+3} - x)^2}{(t_{i+3} - t_i)(t_{i+3} - t_{i+2})(t_{i+3} - t_{i+1})} \\ & + \frac{(x - t_{i+1})(t_{i+3} - x)(t_{i+4} - x)}{(t_{i+3} - t_{i+2})(t_{i+3} - t_{i+1})(t_{i+4} - t_{i+1})} \\ & + \frac{(x - t_{i+2})(t_{i+4} - x)^2}{(t_{i+3} - t_{i+2})(t_{i+4} - t_{i+2})(t_{i+4} - t_{i+1})} \end{aligned}$$

$$\begin{aligned} & \frac{(x - t_i)^2(t_{i+2} - x)}{(t_{i+2} - t_i)(t_{i+2} - t_{i+1})(t_{i+3} - t_i)} \\ & + \frac{(x - t_i)(x - t_{i+1})(t_{i+3} - x)}{(t_{i+3} - t_i)(t_{i+2} - t_{i+1})(t_{i+3} - t_{i+1})} \\ & + \frac{(x - t_{i+1})^2(t_{i+4} - x)}{(t_{i+2} - t_{i+1})(t_{i+3} - t_{i+1})(t_{i+4} - t_{i+1})} \\ & \frac{(t_{i+4} - x)^3}{(t_{i+4} - t_{i+3})(t_{i+4} - t_{i+2})(t_{i+4} - t_{i+1})} \end{aligned}$$

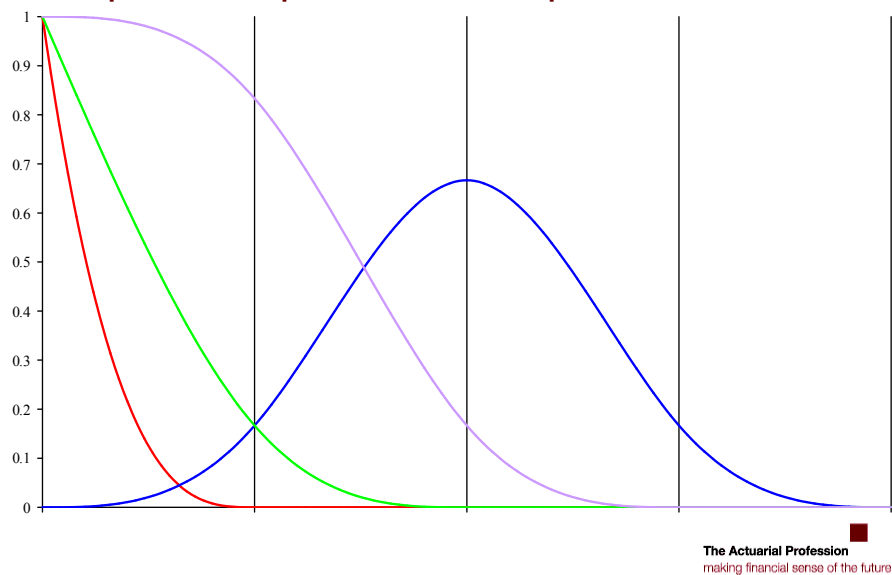
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B-Splines – cubic example

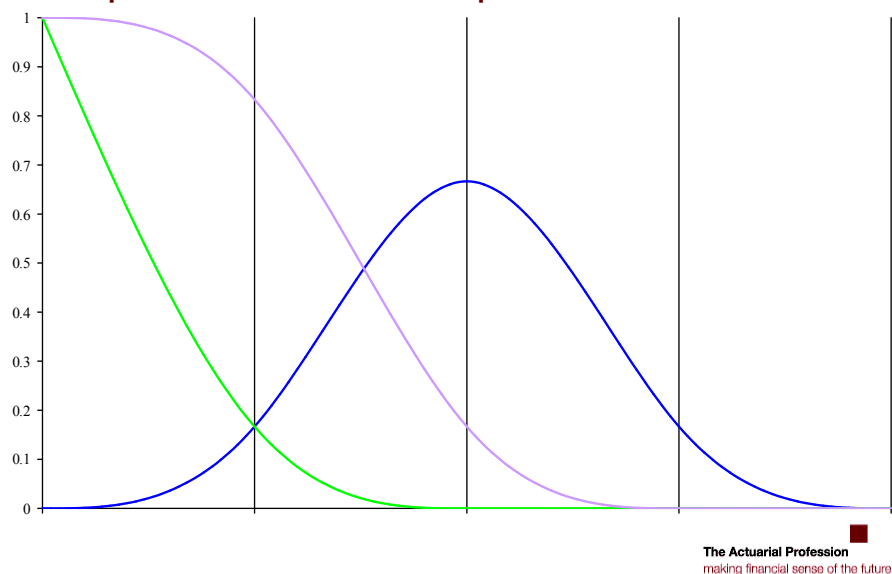


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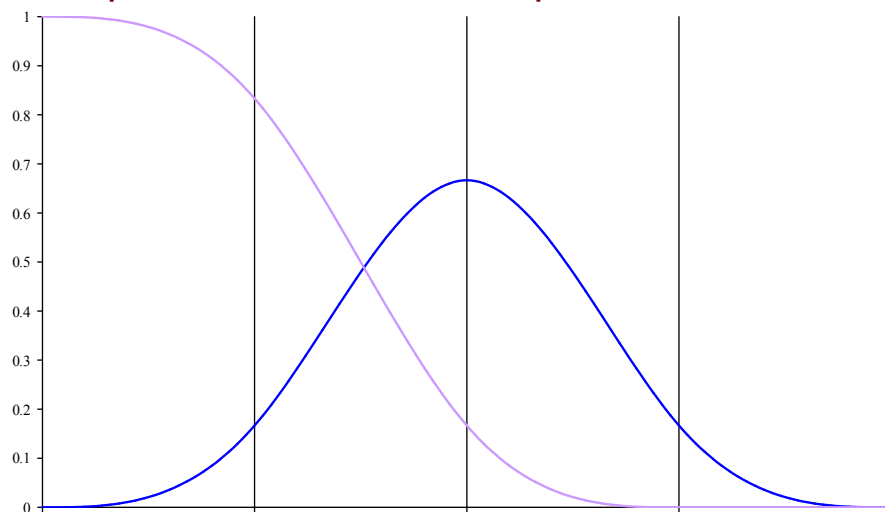
B-Splines – quadratic extrapolation



B-Splines – linear extrapolation



B-Splines – constant extrapolation



Design matrix Spline

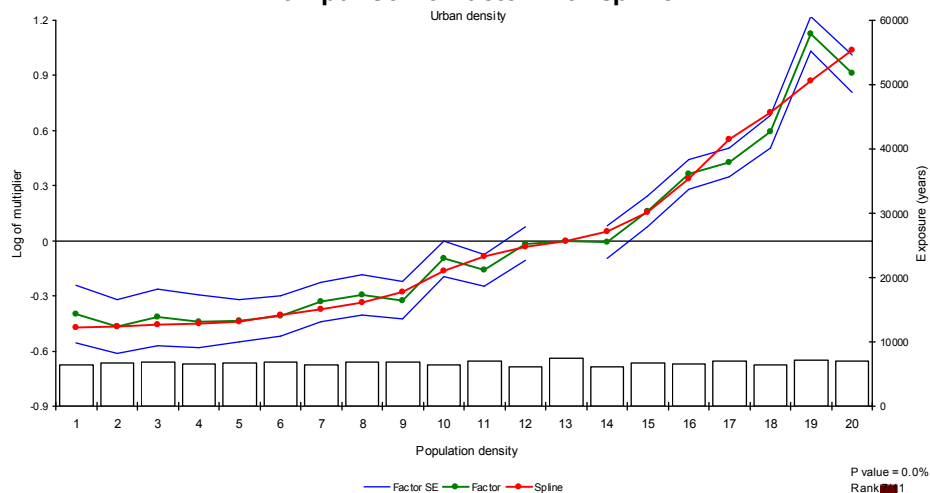
18	M	1	1	1	0	0	...	1
20	F	1	0.52	0.98	0.02	0	...	0
22	F	1	0.17	0.83	0.17	0	...	0
24	M	1	0.02	0.5	0.48	0.02	...	1
26	M	1	0	0.17	0.67	0.17	...	1
28	M	1	0	0.02	0.48	0.48	...	1
30	F	1	0	0	0.17	0.67	...	0
32	F	1	0	0	0.02	0.48	...	0
34	M	1	0	0	0	0.17	...	1
36	F	1	0	0	0	0.02	...	0

Splines

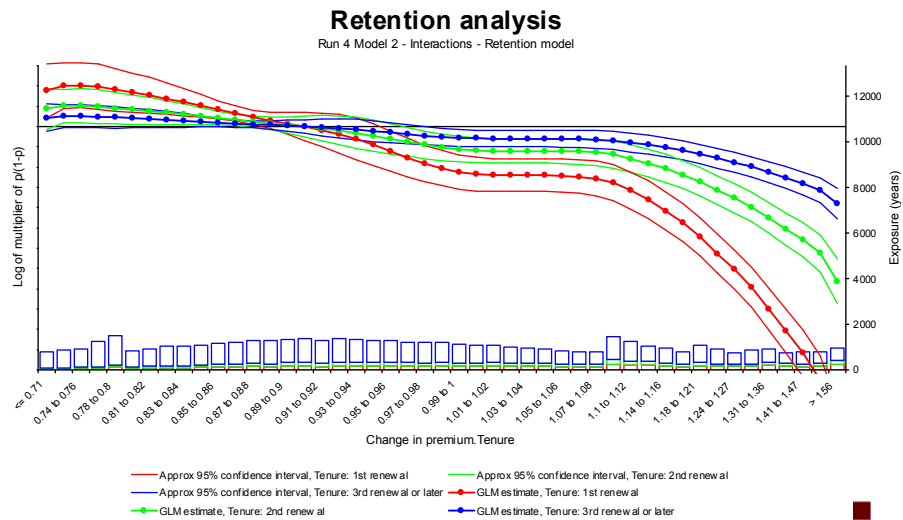
- Practical way of modelling continuous variables
- Often better than polynomials
- Increases complexity, therefore best used
 - when it is important that rates vary continuously with a variable
 - when modeling elasticity to be used in price optimisation analyses

Example

Comparison of factor with spline



Example retention elasticity curve



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Market price

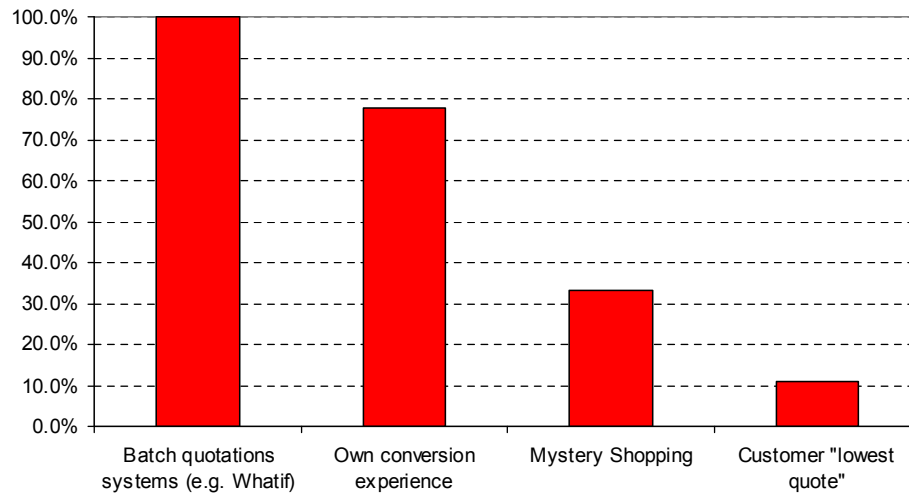
- Key to getting good model
- Hard to get hold of
 - Rates are not published
 - Rates change – daily!

Sources of information

- WhatIf?
- Direct questioning of callers
- Mystery shopping
- Conversion rates (market temperature)
- Ranking from aggregator sites

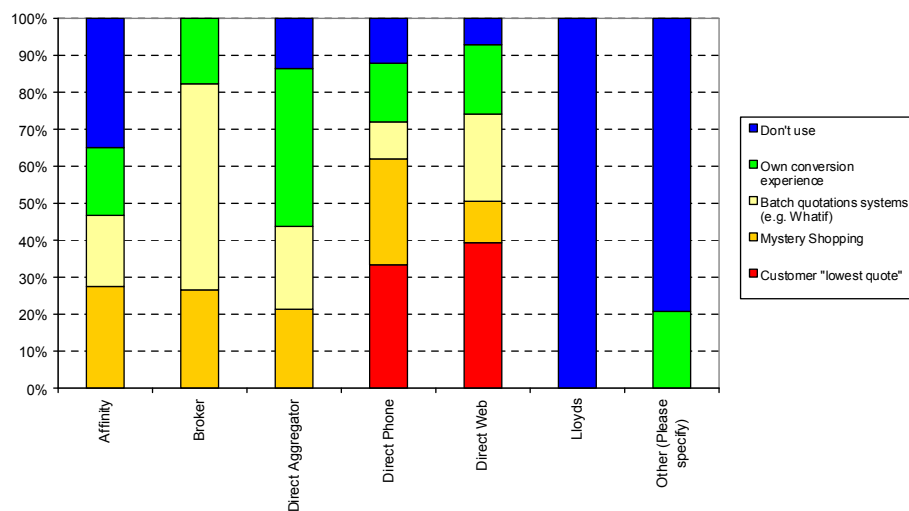
Sources of information

Competitor Data Sources - Overall Use



Sources of information

Competitor Data Sources - By Channel



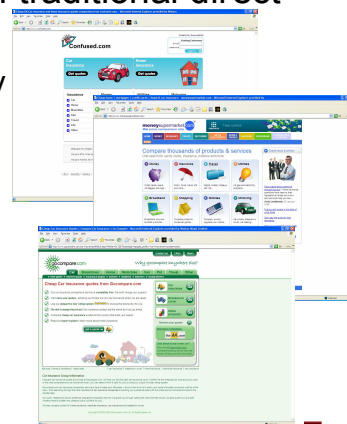
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Aggregators

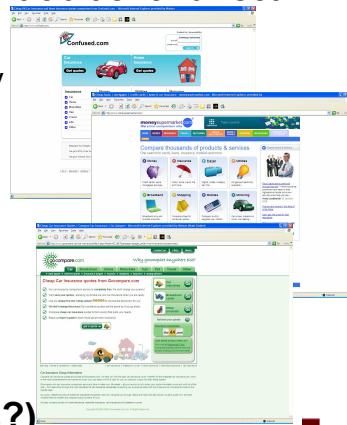
- Drives cart and horse through traditional direct model
 - Fixed cost per converted policy
 - Looks like brokerage?
 - Two sets of commission
- Data issues:
 - Limited information
 - Time constrained
 - Cannibalisation
 - Low conversion rate (1%?)



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Aggregators

- Drives cart and horse through traditional direct model
 - Fixed cost per converted policy
 - Looks like brokerage?
 - Two sets of commission
- Data issues:
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 - Cannibalisation
 - **Low conversion rate (1%?)**



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Aggregators

- Low probability models present special challenges
 - Selection of model
 - Data volumes
- Working party is looking at these issues
- Ranking is of paramount importance...
- ... but so is brand

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Conclusion

- Interesting area with many challenges
- If you get it right, it can give a significant competitive advantage
- Come and see the GIRO workshop on Demand Modelling!

Contact details

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