GENERAL INSURANCE PRICING SEMINAR

13 JUNE 2008, LONDON

Demand Modelling in Personal Lines
James Tanser
Watson Wyatt Limited

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

- Rate level adjustment
- Expense loadings
- Risk Model
- Current Rates
- Competitor Model
- Compare
- Lapse/take-up Model
- New Rates
- Model office / optimisation
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

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

\[
Var[Y] = \phi \cdot V(\mu) / \omega
\]
## Typical model forms

<table>
<thead>
<tr>
<th>Y</th>
<th>Claim frequency</th>
<th>Claim number</th>
<th>Average claim amount</th>
<th>Probability (eg lapses)</th>
</tr>
</thead>
<tbody>
<tr>
<td>g(x)</td>
<td>ln(x)</td>
<td>ln(x)</td>
<td>ln(x)</td>
<td>ln(x/(1-x))</td>
</tr>
<tr>
<td>Error</td>
<td>Poisson</td>
<td>Poisson</td>
<td>Gamma</td>
<td>Binomial</td>
</tr>
<tr>
<td>V(x)</td>
<td>1</td>
<td>1</td>
<td>estimate x^2</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>x</td>
<td>x</td>
<td></td>
<td>x(1-x)</td>
</tr>
<tr>
<td>ω</td>
<td>exposure</td>
<td>1</td>
<td># claims</td>
<td>1</td>
</tr>
<tr>
<td>ξ</td>
<td>0</td>
<td>ln(exposure)</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

## 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 [-∞, ∞]
  - 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
Understanding the logit transform

Logit link function

Probability

Linear predictor

The Actuarial Profession
making financial sense of the future
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
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
  \[ \mu = g^{-1}(\sum X_i \beta_j + c(p/m)) \]
- 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
  \[ \mu = g^{-1}(\sum X_j \beta_j + c_k f_k(p/m)) \]
- 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
  \[ \mu = g^{-1}(\sum X_j \beta_j + (p/m) \exp(\sum Z_j \gamma_j)) \]
- 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:
  - Polynomials
  - 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

<table>
<thead>
<tr>
<th>Design matrix</th>
<th>Polynomial</th>
</tr>
</thead>
<tbody>
<tr>
<td>18 M</td>
<td>1 18 324 5832 104976 ... 1</td>
</tr>
<tr>
<td>20 F</td>
<td>1 20 400 8000 160000 ... 0</td>
</tr>
<tr>
<td>22 F</td>
<td>1 22 484 10648 234256 ... 0</td>
</tr>
<tr>
<td>24 M</td>
<td>1 24 576 13824 331776 ... 1</td>
</tr>
<tr>
<td>26 M</td>
<td>1 26 676 17576 456976 ... 1</td>
</tr>
<tr>
<td>28 M</td>
<td>1 28 784 21952 614656 ... 1</td>
</tr>
<tr>
<td>30 F</td>
<td>1 30 900 27000 810000 ... 0</td>
</tr>
<tr>
<td>32 F</td>
<td>1 32 1024 32768 1048576 ... 0</td>
</tr>
<tr>
<td>34 M</td>
<td>1 34 1156 39304 1336336 ... 1</td>
</tr>
<tr>
<td>36 F</td>
<td>1 36 1296 46656 1679616 ... 0</td>
</tr>
</tbody>
</table>
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

\[
\frac{(x-t_i)^3}{(t_{i+3}-t_i)(t_{i+2}-t_i)(t_{i+1}-t_i)} + \frac{(x-t_i)(t_{i+2}-x)^2}{(t_{i+3}-t_i)(t_{i+2}-t_i)(t_{i+1}-t_i)} + \frac{(x-t_i)(t_{i+2}-x)(t_{i+4}-x)}{(t_{i+3}-t_i)(t_{i+2}-t_i)(t_{i+4}-t_i)} + \frac{(x-t_i)(t_{i+4}-x)^2}{(t_{i+3}-t_i)(t_{i+4}-t_i)(t_{i+5}-t_i)}
\]

B-Splines – cubic example
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

Urban density

Population density

Log of multiplier

Exposure (years)

Factor SE  Factor  Spline

P value = 0.0%  Rank 7/11
Example retention elasticity curve

Retention analysis
Run 4 Model 2 - Interactions - Retention model

Change in premium vs. Tenure

Log of multiplier of \( \frac{p}{1-p} \)

Exposure (years)

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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

Batch quotations systems (e.g. Whatif) | Own conversion experience | Mystery Shopping | Customer "lowest quote"

Sources of information

Competitor Data Sources - By Channel

Affinity | Broker | Direct Aggregator | Direct Phone | Direct Web | Lloyds | Other (Please specify)

Legend:
- Don’t use
- Own conversion experience
- Batch quotations systems (e.g. Whatif)
- Mystery Shopping
- Customer "lowest quote"
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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%?)
Aggregators

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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
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!

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