Granular Reserving

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Agenda

• Introduction
• The benefits
• The counter view
• How can these be mitigated
• Discuss…
Introduction

• Use all data available to train models that give expected claims for each claim and each policy.

• AKA
  – Individual claim loss reserving
  – Claim by claim reserving
  – Formulaic case estimation
  – Policy by policy reserving
Introduction

IBNER Model
- Response is claim movements as at time = t
- Possible rating factors are all information as at time < t
Introduction

Policy DB

Big Data

Claims DB

IBNYR and Pure IBNR Model

- Frequency average severity model.
- Frequency is a reporting delay model
- Average severity by segment driven by results of IBNER model.
Introduction

Example Models

Traditional
• The Linear Model: \( Y \sim N(X\beta, \sigma^2) \)
• The GLM: \( Y \sim F( \mu=h(X\beta), \text{Var} = \sigma^2 \text{diag}(v(\mu_i)) ) \)

Non Traditional
• Machine Learning
• Artificial Intelligence
The benefits
Impact on Reserving

Better Reserving

– Reduction in bias
– Material reduction in standard errors
– Change understanding of business
  • Identifying Trends
  • Identifying Emerging Issues
  • Portfolio mix changes automatically addressed
  • Earlier warning of differences in profitability of different segments
Impact on Reserving

Reduction in volatility

Total Hold Out Sample
MSE = 214 %

MSE = 88 %
Impact on Pricing

Importance of Pricing Model

– Clearly having a better view of the “true” technical price of any policy can significantly impact the profitability of an organisation. In competitive markets, being better able to rate than your competitors results in a gearing where you attract better risks and apparently small changes in price can result in much larger increases in profitability.
Impact on Pricing

Severity modelling

– This approach naturally allows for a statistically valid allocation of IBNER to each claim. As a result more recent data can be used, without losing the potentially significant effects of the rating factors.

Trends

– Through being able to use more recent data, recent trends in the effect of different rating factors can be more readily identified and allowed for in the parameters of the resultant pricing model.

Emerging Issues

– Being able to use more recent data can give an earlier warning and a resultant earlier quantification of the effect of emerging issues.
Impact on Pricing

Example:

Average cost per claim by policy type where the claims reserves is calculated by the VWCL and GLM.
The counter view
Background

Timeline

- 2007 – Simon’s granular reserving CAS and GIRO presentations
- 2008 – Simon’s granular reserving GIRO presentation
- 2009 – Simon’s granular reserving GIRO presentation
- 2011 – I took over a LM reserving project using granular reserving
- 2012 – I changed methodology to standard techniques for that project
- 2013 – GIRO granular reserving plenary
- 2017 – mooted GIRO granular reserving WP

Big data – big opportunity!
Stress balls

- No subjectivity
- Difficult to communicate to stakeholders
- Huge extra time to project
- Rubbish in / rubbish out
- Trends
- Good for IBNER only
- No help for key reserve issues
- Independence of reserving and pricing functions
- Just a really complex BF
- Excess/limit complexity
- Computer says no!
- Allocation more efficient to get policy level reserves
- Actuary or claims handler?
- More complexity means more errors

No subjectivity

Allocation more efficient to get policy level reserves

Actuary or claims handler?
Really stressful balls

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Actuary or claims handler?
Allocation more efficient to get policy level reserves
Just a really complex BF
No help for key reserve issues
Huge extra time to project
No IBNER only
Good for IBNER only
Light blue
- R124  G179  B225
Cyan
- R0  G156  B200
Light grey
- R220  G221  B217
Pea green
- R121  G163  B42
Forest green
- R0  G132  B82
Bottle green
- R17  G179  B162
Cyan
- R0  G156  B200
Light blue
- R124  G179  B225
Violet
- R128  G118  B207
Purple
- R143  G70  B147
Fuscia
- R233  G69  B140
Red
- R200  G30  B69
Orange
- R238  G116  29
Dark grey
- R63  G69  B72

What granular reserving could look like

Information known about policy X
- Driver
- Location
- Past claims history

Big data on policy X
- Traffic density in locality
- Friends on Facebook...
- Credit rating

Emerging data since underwriting
- Claim count and cost
- Other policy claim count and cost
- Trends in other policies

Clever maths

End product for policy X
- Closed: 0, Reported: 0, Ultimate count: 0.1
- Paid: 0, Incurred: 0, Ultimate cost: £50

Just a really complex BF
Financial data for policy X
- Closed: 0, Reported: 0
- Paid: 0, Incurred: 0

Reopened claims module
- Closed: 0
- Expected reopened: 0
- Expected ultimate: 0

IBNER claims module
- Open: 0
- Closed: 0, Reported: 0
- Paid: 0, Incurred: 0

IBNYR claims module
- Expected IBNYR count: 0.1
- Expected average cost: 500
- Expected IBNYR: 50

End product for policy X
- Closed: 0, Reported: 0, Ultimate count: 0.1
- Paid: 0, Incurred: 0, Ultimate cost: £50
IBNR flows weighted to IBNYR

Financial data for policy X
- Closed: 0, Reported: 0
- Paid: 0, Incurred: 0

Reopened claims module
- LOTS OF CLOSED CLAIMS
- BUT LITTLE IBNR

IBNER claims module
- SOME OPEN CLAIMS
- BUT LITTLE IBNER (FOR CLASSES WITH ENOUGH DATA)

IBNYR claims module
- KEY AREA TO PROJECT
- TO WHAT EXTENT DOES EMERGING CLAIMS EXPERIENCE IMPACT PRIOR EXPECTATION?

End product for policy X
- Closed: 0, Reported: 0, Ultimate count: 0.1
- Paid: 0, Incurred: 0, Ultimate cost: £50

Just a really complex BF
IBNYR module calculation

• Module seeks to adjust expected claims experience
• One option is to use reported time lag and simply reduce expected claims experience by this factor
• So expected future IBNYR = initial expected ultimate reported x (1-% expected reported)
• Bornhuetter Ferguson future IBNYR = initial expected ultimate reported x (1-% expected reported)
• So total projected IBNYR will not differ between complex and simple model.
  – Seeking to build most simple model that reflects reality
• Splitting into frequency and severity components can improve this method by allowing for different characteristics of later claims
IBNYR module and emerging claims experience

• Cannot run the GLM model on latest data given deadlines
• So prior expectation of losses is in arrears for this module
• Does the emerging evidence in the IBNER module flow through into the IBNYR module?
  – If link then model becomes much more complex and time consuming
• Could use machine learning to fix time issue but danger that model becomes a black box
• BF slows down recognition of emerging trends
  – So benefit of more complex model for spotting trends will be lost
Policy level projection

• This model will create an actuarial best estimate for each individual policy

• This leaves the actuary open to challenge in too many areas

• In my experience, stakeholders challenge where they perceive the actuary’s ultimate claims assessment is too high
  – Challenging where the actuary is too low is less common

• It is much harder to defend a claim level projection than an aggregate projection
  – You simply don’t have the detail which a claim handler does

• So results will be inherently biased or stakeholders will be dissatisfied

• Time taken to make all these manual adjustments
  – It felt like I had more adjusted ultimates than unadjusted!

Actuary or claims handler?
Complex models don’t build trust

• If senior management trusted Internal Models then we’d:
  – be buying far less reinsurance
  – be buying far more equities and
  – be expanding into uncorrelated classes of business
• If you can’t explain what you mean in a few simple sentences then you can’t build trust
• Granular reserving has to produce more accurate results to be worth the effort…
• …but do you think the following will happen?:
  – Stop writing class X as new method says it is less profitable than we thought
  – Increase/decrease total booked reserves by £millions
    • And get them signed off by the auditors
  – Change reserving team from actuaries to data scientists

Difficult to communicate to stakeholders
Ogden / PPOs / BI frequency trends by layer
- Granular reserving is of no assistance here
- But my windscreen projection will be spot on

Allocation to policy achieves all the benefits of granular reserving but is quicker and simpler, and you don’t have to justify every individual claim projection

If get pricing wrong then double whammy when prices and reserves change
- Can allow for exposure changes by using pricing risk mix index as input to standard reserving
- Governance issues when independence not respected

Reserving is an art not a science. Back of the envelope methods simple to explain and justify to stakeholders.
How these can be mitigated
IBNYR module calculation

- Results of IBNER model feeds into IBNYR model
- This along with model driven reporting delay model drives an appropriate segmentation (rather than the one we first thought of)
- We should note that a traditional BF makes an assumption that \( \% \text{ expected reported} = \frac{1}{\text{factor to ultimate}} \)
- All things being equal this gives a biased estimator (understated) due to right skewed nature of claims distribution
- Ie GR Model will give different answers!
IBNYR module and emerging claims experience

• Model can be trained on older datasets and applied to current data so as to meet deadlines

• Link to IBNER model is key, but training can be on earlier dataset.
  – Ensures trends, etc identified at an early stage

• There are ways of visualising GLM, ML, AI, AA approaches
Policy level projection

• This model will create an actuarial best estimate for each individual policy

• Actuaries should not be afraid of challenge
  – Strong challenge is already present at an aggregate level and this is often biased in nature

• It is reported large losses where challenge is most likely and where claims manager have most information. Indeed reserves on these losses are already likely to be driven by a deeper understanding of the issues on the claims.

• A granular approach actually gives you some defence against claims managers.
Complex models don’t build trust

- Effort is required to enable senior management to understand these models.
- These models are genuinely more accurate
  - This helps generate trust in these models
- Actuaries should not be surrendering this area to data scientists
  - Many companies already have teams looking to add value
  - Data scientists are relatively cheap

Difficult to communicate to stakeholders
• GR is not magic – it just maximises value from the data
  – It cannot help predict Ogden rate, legislative changes, FCA rulings, cats, etc
  – But my windscreen projection will be spot on!!!

• Allocation is usually very crude and is not based on models driven by identified rating factors

• The potential link to pricing is via IBNYR or unearned exposures. These are already linked to business plan which is already linked to pricing. Note IBNER projection may produce alternative expected loss cost results by policy. The IBNER projection in GR is independent of pricing.

• There is no excuse for not using the data to its full potential. There are aspect of judgement that still need to be applied. Eg pricing models are not devoid of judgements
Discussion

Proceed with caution?

Or full steam ahead?

We invite your views, comments and questions
Expressions of individual views by members of the Institute and Faculty of Actuaries and its staff are encouraged.

The views expressed in this presentation are those of the presenters.