“Individual” modeling – what, when and a little bit of how

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Agenda

• What
  – Some definitions
  – Aggregate vs individual
  – Simple vs complex

• When
  – Model purposes
  – Illustrative example

• How
  – Structural issues
  – Model evaluation
What
Definitions (imprecise)

• An aggregate model gives cash flow or liability predictions for a “large” group of claims only, recognising that there are many different types of claims in the group.
• An individual model gives a “genuine” prediction for each claim, using the actual characteristics of the claim.
Spectrum

- In fact, models are not often one or the other but somewhere in between
  - Payment chain ladder models are “aggregate”
  - PPCF and PPCI models are thought of as aggregate but can be expressed “per claim” (if we remove IBNR)
    - The claim characteristics are development at the valuation date (or accident year)
    - They make the assumption that all claims with common characteristics are the same
Spectrum

- In fact, models are not often one or the other but somewhere in between
  - Transition models can be expressed “per claim”, again if we remove IBNR
    - Claim characteristics are development year, accident year, state and maybe others
    - Assume that all claims with common characteristics are the same
      - This includes path independence!
• Should we replace “aggregate” with “simple” and “individual” with “complex”?
When
How do we choose?

• Purpose is important
  – Reserving; minimise error in aggregate prediction
  – Driver analysis; establish causality
  – Pricing; maximise predicted range of claim size relativity
  – Operational monitoring; benchmark operationally distinct groups;
• It is asking a lot of one model to do all these!
Complex models and reserving

• Illustrative example
  • Assume a large population of claims where the claim size is a function of several time independent claim characteristics plus an error term
  • Take a sample of $n$ claims, drawn independently and fit two models
    – A "simple" model which is just the mean of realised claim sizes
    – A "complex" model which has the same structure as the population but with the parameters fitted from the sample
Complex models and reserving

• Now take another sample of m claims and use each model to give an expected liability for the sample
Complex models and reserving

• When n and m are large then both models will likely give a good result
  – The complex model will fit better but both have low prediction errors

• Let’s reduce m
  – The probability of the characteristic profile being different than that of the population becomes more significant
  – The complex model gives an increasingly better prediction since it takes account of this
  – Note that if we know in advance what the drivers are then we know when this situation is occurring
Complex models and reserving

• Let’s make \( m \) large again and reduce \( n \)
  – The performance of both models will degrade as parameter error increases
  – As \( n \) gets small, the profile of the sample again may be different than the population and again the complex model will perform better
  – How does the number of parameters affect this? Is there a penalty for having many parameters?
Illustrative example – tentative conclusions

- For large stable portfolios, complex models are better but by how much? How much does “random” error matter compared to systemic risks?

- Complex models are most useful for small subgroups of claims or when they incorporate the dependence of a claim characteristic in respect of which the portfolio make-up is changing over time.
Complex models and reserving

• Complex models are more likely to be correctly specified (?)

• BUT
  • In practice it can be very difficult to fit complex structures, including interactions, without introducing bias
  • Other risks from model complexity
    – Operational changes/variations in predictors
    – Modeler error
    – Coding/translation error
# Purposes revisited

<table>
<thead>
<tr>
<th>Purpose</th>
<th>Aggregate or Individual?</th>
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<tbody>
<tr>
<td>Reserving</td>
<td>Evaluate risks and implications for capital then decide between simple and complex</td>
</tr>
<tr>
<td>Driver analysis</td>
<td>Potentially complex with external rationale</td>
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<tr>
<td>Pricing</td>
<td>Sufficiently complex to take account the differences in claim characteristics between pricing segments</td>
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<tr>
<td></td>
<td>Maybe very complex if redefining pricing segments</td>
</tr>
<tr>
<td>Operational monitoring</td>
<td>Sufficiently complex to take account the differences in claim characteristics between operational groups</td>
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Structural issues

Dynamic and static predictors
Complex models – static and dynamic predictors

• Static predictors
  – Accident quarter, age

• Dynamic predictors
  – Injury severity, medical payments to date, case estimates, date of finalisation

• One of the most important decisions in any complex model is how to handle dynamic predictors
Dynamic predictors – chaining

• “Normal” actuarial process uses “chaining” to get a “lifetime value”
Dynamic predictors – chaining

– Need to predict the value of the dynamic predictor at each chaining point
  – Not so easy if there are several correlated dynamic predictors
  – Considerable danger in using the predicted mean for chaining
    » Small biases can become very large
    » Non-linearity of model causes distributional problems
Dynamic predictors – chaining

– Distributional distortion
Dynamic predictors – chaining

• Problem is that the distribution of forecast predictor is different from the distribution of actual predictors used to fit the model

• To overcome can
  • Parameterise the distribution of actual predictors and simulate
  • Band the predictor and predict proportions in each band. This often ends up as a transition model
    – Potentially many states and parameters
    – Assumption of path independence
Dynamic predictors – not chaining

- PPCF models can be thought of as transition models
  - Choose long chaining period and minimise chaining iterations (maybe zero!)
    - E.g. build complex model to predict claim payments over three years and then just extrapolate
    - Will likely get the relativity between claims correct
    - The extrapolation procedure is suspect but of lesser importance if the initial modeling period is long enough
Dynamic predictors – not chaining

3 yr prediction for pattern node = $25,000
3 yr individual prediction = $28,500

Pattern prediction = 14% or $3,500 (qtr 1)
Pattern prediction = 3.8% or $950 (qtr 12)

Tail hazard prediction = 8.3% (per quarter).
Total tail = $13,050,
Consisting of $1,083 per quarter, decreasing at 8.3%

Total SCE for individual claim is $41,050
Dynamic predictors - prediction

• If we do use dynamic predictors it is vital to understand the uncertainty associated with their prediction
  • Finalisation rates for PPCF
  • Compare with finalisation rates for PPCF in operational time
  – Consider possibility of specification error as well as random error, e.g. operational delays
Model evaluation
How to evaluate individual models

- Use statistical tests if fitting statistical model
  - Typically only useful for “component” models
  - Not always applicable if fitting data-mining type models
- Don’t use $R^2$
- Use learn/test/validation framework
  - On component models
  - On incurred cost for combined model
Actual vs expected for component model
Actual vs expected – interaction bias

Actual versus Expected by Predicted Band

![Graph showing actual vs expected gains by predicted band](image)
Incurred cost development – for claim subgroups
Automated validation

• Individual models can be very complex and evaluation is often “avoided”
• Validation tests comparing actual versus expected over past time periods, using current parameters should be standard, frequent practice
• Consider making part of “model code”
Overall conclusions

• Don’t build/use a complex model just because you can!
• If you do
  • Keep a clear idea of purpose
  • Think hard about the model structure and dynamic predictors
  • Assess the error from using dynamic predictors
  • In addition to statistical tests on component models
    – Learn/test/validation discipline
    – Incurred cost test on overall model