PROPERTIES OF IBNR CLAIMS RESERVING

There are certain properties of IBNR claims reserves that affect the techniques that may reasonably be used to forecast them. We discuss the following properties: changing calendar year trends cannot be modelled with parameters in the other directions, but calendar year effects are often the most important; taking logarithms before modelling produces the most natural variance behaviour; the fundamental principle of insurance – the standard deviation of a sum is less than the sum of the standard deviations; overparameterised models should not be used for prediction; data should resemble a sample from the model.

1. *Changing calendar year trends cannot be modelled with parameters in the other directions.*

Claims inflation may be regarded having two components, *economic* and *social*. Economic inflation is present in the general economy, it may be measured through available indexes, and financial tools allow insurers to immunise against its effects. On top of that, claim payments may exhibit social inflation, which has a variety of causes, such as changes in legislation, or growth in litigation.

Social inflation does not correlate well with economic inflation (indeed, some components of it are counter-cyclical). Because of these factors, social inflation cannot be readily immunised against. However, it can be measured, and must be considered when projecting into the future: we cannot make informed judgments about the future if we cannot understand the past.

Unrecognised high claims inflation has led to numerous collapses in recent years. Changes to higher rates of inflation continue to go undetected because the usual actuarial models do not explicitly consider trends in the calendar year direction.

A trend in the calendar year direction is projected onto the development year and accident year directions. A *constant* percentage trend (e.g. a 10% per annum increase) in the calendar year direction will appear as an increased trend in the other two directions, and can be modelled using parameters in the development and accident year directions. However, when there are *changing* trends, the changes *cannot* be modelled using parameters in the other directions.

The appropriateness of the model should always be examined by plotting residuals against the calendar year direction, as in the plot below. These residuals come from example_1 of the IFM WebDemo v1.1, accessed at http://www.posthuma-partners.nl/index2.html.

There appears to be a change in the calendar period trend somewhere around 1996-1997: in the later calendar periods, many of the residuals lie below the zero line, indicating that the model predictions have been too high for many quarters. Fitting two trends to the residuals, we find that the quarterly calendar period trend has decreased by 7%! Projecting a model with a constant trend into the future could result in substantial errors.

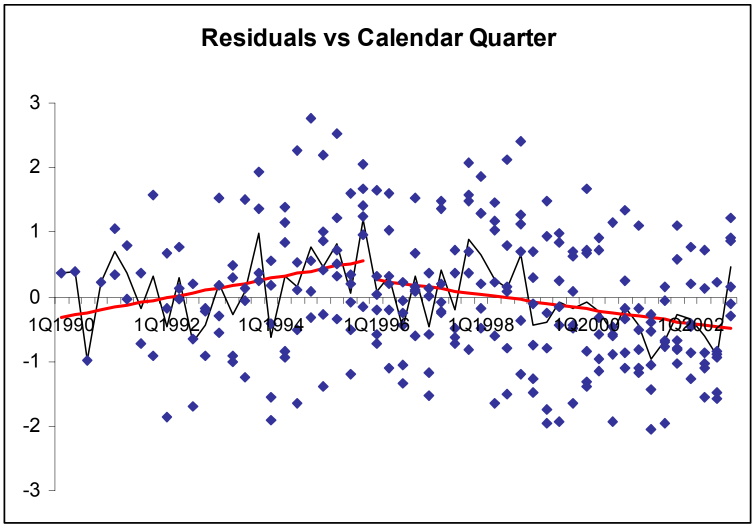

Figure 1

If a change in inflation is undetected, the resulting trends in the other directions will be equivalent to an “average” inflation from the past. For example, suppose superimposed inflation has been running at around 10% per annum when a change in a legislated scale of benefits comes in over several years, during which time the inflation is 20%. If the data is modelled at this point without measuring the change in calendar year trend, the future is effectively forecasted with a calendar year trend somewhere between 10% and 20%. This in-between value may not be a good estimate for the future.

2. *Calendar year effects require close attention*

When forecasting a triangle of data, the forecasts are often restricted to the accident and development years in the original triangle. However, the forecasts are always *outside* the range of the calendar years of the original data. Even when projecting past the last development year, the total amount paid in the additional development years is almost always a small fraction of the total.

A change in the rate of decay of the tail in the last few development years does not affect the majority of the predictions, and it is generally only changing the *smallest* predictions, over only a few years. A change in the rate of superimposed inflation in the last few calendar years affects all future payments, large and small, and its average duration of effect within the completed array can be quite large. Consequently relatively small changes in the superimposed inflation can have dramatic effects on the insurer’s liability.

Indeed, in many cases – particularly if the forecasts are for many years into the future - the assumptions about calendar year effects have the biggest impact.

It is therefore important to use the information that can be extracted from the data about calendar year effects.

3. *Taking logarithms before modelling produces the most natural variance behaviour*

Many models of the loss process assume that the *variance* of the payment process is proportional to its mean. For example, any model that reproduces the chain ladder forecasts makes that assumption.

The assumption that the variance is proportional to the mean has some unexpected consequences. For example, if the amount of noise in percentage terms in the data were relatively constant for data without inflation, then when the data were inflated by an index, the values that were inflated the most *would become more accurate in percentage terms*. In other words, the coefficient of variation (the standard deviation divided by the mean) would decrease for some values. (This problem is not unique to use of an index – any scaling causes related problems. The problem is that if standard deviation is not proportional to the mean, the model is not scale invariant. A mere change of currency may may your forecast uncertainties larger or smaller in percentage terms!)

In reality, if you take paid loss data and inflate it by an index, values that are inflated most don't become more precise. In fact, the inflated numbers *don't change their variability in percentage terms*. This makes sense – multiplying a random variable by a constant increases its mean and standard deviation by that same constant ratio, so that the coefficient of variation is unaffected.

If adding a trend (such as economic inflation) is not to affect the variability in percentage terms, the *standard deviation* (square root of the variance) must be proportional to the mean. Not many distributions have this property. Two that do are the lognormal and the gamma. However, while the lognormal distribution always has this property, the gamma only has it if restrictions are placed on its parameters (the shape parameter, usually denoted by alpha, must not vary with time).

The proportionality of standard deviation to mean for incremental payments is an algebraic identity. That is not to say it is the only thing that impacts variability (so we do not claim that on a log scale the data must be homoskedastic), but that on top of any other factors influencing variance, the effect necessarily holds. This effect does not apply to other quantities than payments, such as claim numbers, however.

4. *The fundamental principle of insurance*

Insurance and reinsurance companies are primarily poolers of risk. They exist because the standard deviation of a pool of risks is smaller than the sum of the standard deviations of the individual risks. If this were not so, diversification benefits would not exist, and insurers would not be able to provide a service that was worth purchasing.

Consequently, forecasts that make assumptions which ignore the fundamental principle of insurance cannot be correct. One such assumption is that the standard deviation of the sum is equal to the sum of the standard deviations, for which there is no diversification benefit whatever. A more common assumption (often made implicitly) is that risks are independent. This is generally untrue. For example, even apparently unrelated risks may have common economic and social environments. It is better to try to identify the extent to which payments are related than to work on the basis they are either completely independent or completely dependent.

Modelling the trends in the development, accident and calendar year directions will usually capture the majority of the dependence between payments. Forecasts from such a model will (if they are done in the proper manner) produce appropriately correlated forecasts for the different accident year totals and calendar year totals. In some cases, there may be some degree of correlation in the residuals even after capturing common trends. If the correlation is strong enough, it should be incorporated into the model. However, care must be taken not to overparameterise the model with a plethora of correlation parameters (see below).

5. *The problem of overparameterisation*

Many models used for prediction of outstanding claims contain a parameter for the mean of each development year (except possibly delay zero), and often a parameter for the variance as well. Further, most have a parameter for each accident year, though in some cases the presence of this parameter is not explicitly acknowledged. More complicated models introduce other parameters, such as correlation parameters. The number of parameters may be a substantial fraction of the data points.

The effects of overparameterisation are that the model:
- is fitting noise rather than signal
- has high parameter uncertainty
- will produce unstable forecasts: a small change in the data may produce a large change in the predictions because an overparameterised model projects and amplifies noise into the future (as an extreme example, consider fitting a model with 7 parameters to 7 data points – the data is fitted very well, but forecasts outside the range of the data will be highly sensitive to a small change in any of the observations – and parameter uncertainties are infinite!)

A model should be able to produce the data it purports to summarise. The data should not look out of place beside random triangles generated from the model: the trends in the development, accident and calendar directions and the amount of variability around those trends should be similar in the data and the generated triangles.

In our experience, many models in common use do not generate triangles that look like the data they are used on. Either there must be features in the data not present in the model, or features in the model not present in the data. Often both of these are true!

We challenge you to this test of your favourite stochastic modelling technique – choose a real dataset, create a model for that data using your technique, and simulate five triangles from that model. Calculate residuals for the real and simulated data and plot them against development, accident and calendar periods. Then see if you can spot the real data.

Conclusions

We wish to emphasize that the data should drive the choice of a model. At a minimum, a model must not "fail" basic tests that indicate it fits the data adequately and that it is not overparametrised. Such tests are occasionally mentioned in the literature, but they are much less often seen to be applied in examples.

At a minimum, tests should include:

1. Are there trends in the model residuals when they are plotted against accident, development and calendar periods?
2. Does the variance of the residuals match the assumptions of the model? In particular, do the standardised residuals have constant variance when they are plotted against accident, development and calendar periods, and against fitted values?
3. Are all of the parameters, and parameter differences, statistically significant?

The application of these and other tests to several models is described in "Best Estimates for Reserves" by Glen Barnett and Ben Zehnwirth (Proceedings of the Casualty Actuarial Society, Vol 87, Nov 2000, 245-321).

The information about the data incorporated in the chosen model should then be used, together with relevant business information, to determine the choice of forecast assumptions.

For a basic illustration of why link ratios methods fail. Click here.