Sensitivity Testing of Dependency and Parameter Uncertainty

Dependency

Sensitivity testing of dependency could be with reference to a benchmark model or as tests build up with reference to the history of models tested.

There are basically two directions for sensitivity testing of dependency. One is to eliminate the dependencies assumed in the model, which would show how different, if at all, the model is from assuming everything is independent. The other direction is to test model outputs to see how much dependency actually exists at the end of the day.

Eliminating dependencies is straightforward if correlations are used in the model to generate the dependencies. The correlations could just be set to zero. It is not much different if copulas are used. There is an independence copula that could be substituted for the actual copulas in the model.

Testing correlations across risk classes, lines, business units, assets, etc is also straightforward if the same classes etc. exist in all the scenarios. Besides the linear correlation, rank correlation and Kendall's tau correlation can be measured. However the tail correlation is also important to measure, because it is the simultaneous occurrence of large losses in different areas that creates extreme scenarios for the firm as a whole. For instance if focus is on the 99^{th} percentile, the tail correlation of X and Y is the probability that X is greater than its 99^{th} percentile given that Y is greater than its 99^{th} percentile. In the normal copula the limit of the tail correlation is zero as the probability level approaches 100%. This is a problem as it eliminates the extreme scenarios that are most capital intensive. The tail correlation can be measured for several probability levels approaching 100%, as it gets noisy at the very end. This is not just a problem in underwriting. Credit risks can be quite correlated, as can be asset risks.

Parameter Uncertainty

Since parameter uncertainty is a large component of property-liability insurer risk, it should be included in the modeling in an explicit way and how it is done needs to be explained and its effects quantified. In the beginning of the review process, the methods used to reflect parameter uncertainty should be explained. A basic method for quantifying its effect would be to re-run the model without parameter uncertainty. The effects can again be benchmarked to reference models and the history of models reviewed. The main importance of parameter uncertainty is that it is a systematic risk that does not reduce by adding volume the way diversifiable risks do. Thus it will be a significant component of risk for large, diversified companies and ignoring it for those companies can significantly understate the overall risk. However it is present in all risk modeling and should be reviewed in all of them, even though it may be most critical in underwriting risk.

When simulating scenarios in the collective risk model, parameters are used that generate either equally-likely or probability-weighted scenarios. But those parameters are estimated from some process, always with associated uncertainty. Modelers often reflect this uncertainty by a two-stage simulation: first draw the parameters from a distribution of parameters, then simulate the events from the simulated parameters. The distribution of parameters is a by-product of parameter estimation methods, like regression and MLE. When parameter uncertainty is reflected in this manner, the first stage simulation can be altered to just produce the best-estimate parameters in every case. This would remove parameter uncertainty from the simulation.

In cat modeling this is more problematic as most companies will be relying on cat models from commercial vendors, and these have parameter uncertainty built in to various degrees. Just weighting together the results from different models is a form of parameter uncertainty. Other methods that can be used include rerunning the cat models with different assumptions, like long-term frequency vs. a shift to higher frequency, etc. Companies with internal cat models have more flexibility in this direction. The sometimes large differences among vendor models shows that there is still a high degree of uncertainty associated with cat model output, and it would understate the risk to take them at face value.

The situation is similar for marine and aviation models that have many assumptions about the world risk situation. Sensitivity testing of those models could be similar to that for cat models. Also some stress testing along the line of assuming the model understates total losses by 20% would be another way to get at parameter risk for such models. An assumption like that could have a large impact on excess losses. Something similar could be done for cat models.

Reserve risk models generally include exlicit terms for parameter uncertainty. This is in the Mack and bootstrap models, for example. Projection uncertainty due to unexpected inflation is a systematic risk for reserves, and may not be in some models. This can come out in the initial discussions, and its lack could suggest an understatement of reserve risk.

Models of asset risk and market risk all have parameters, usually fit to historical data or calibrated to current option prices. The parameter distributions can be estimated like they are for frequency and severity distributions. If the modeler is not doing this, the asset risk is probably understated. Again the models can be run in a two-stage process of simulating parameters then asset values, and the first stage can be skipped to see what effect the parameter uncertainty is having.

For credit risk, the Merton-type models have a fair degree of parameter uncertainty. Things like the value of the default put option and the future earnings have to be estimated, and these are subject to large potential errors. There have been studies of the predictive accuracy of these models, and that is probably the place to start in reflecting parameter uncertainty. If no attempt is made to estimate this, the model is most likely underestimating credit risk.

Operational risk modeling is difficult and most people recognize that the models are more suggestive than quantitative. Probably a range of distributions could be used. However the parameter uncertainty problem is not as intense here as it is in insurance losses, as it is usually done for the firm as a whole, so does not artificially disappear with business volume the way insurance risk does when parameter risk is not considered.