Counterparty Credit Risk Simulation Analytics

Counterparty credit risk (CCR) is the risk of loss that will be incurred in the event of default by a counterparty. Counterparty credit risk is measured by credit exposure.

Monte Carlo simulation is used to predict credit exposure distributions at predefined future dates (credit node). Exposure is determined by sampling results from the exposure distributions based upon the required confidence interval.

The essence of the Monte Carlo process is the stochastic simulation of market rates. To produce the future market scenarios, one can use the form of parametric simulations that assumes the normality or log normality of future distributions of the market rates. The future values of the market rates representing financial markets snapshots are simulated according to a specified stochastic model.

The stochastic models may be specifically associated with each individual rate class, or sub class of rate classes, or simply defaulted globally to the one model which is applied to all rate classes. In other words, the user may override the default global simulation model with a specific simulation model for individual asset types or rate classes.

Currently all market rates which must be simulated, must not change state moving from one day to the next. In other words the term to maturity must be relative and not an explicit date such as would be the case for specific security or futures for example. The historical time series of data used to generate the stochastic parameters for a specific rate must also be constant in state throughout the time series.

The statistical parameters of these models (e.g. volatilities, level and speed of mean reversions, correlations, etc.) are either specified explicitly or derived from historical time series.

The statistical parameters of simulation are pre-calculated using these past prices of some historical sampling period. To produce realistic future scenarios outcomes these statistical parameters can be reviewed and adjusted for all or selected set of market rates.

The same price history can be also used for generation of meaningful correlation matrices that reflects interdependency among market rates and should be used to achieve the co-integration of simulated scenarios. It is assumed that the correlations of market rates historical price changes are stable.

Thus, the length of the historical sampling periods is important for both the generation of parametric coefficients of stochastic simulations and for building of non-degenerated correlation matrices. Ideally the number of price records of the historical time series should be at least the same as the number of simulated market rates.

However, even this condition can not guarantee positive semi-definite feature of correlation matrix when some of the price series may be very close to linear dependency. In these situations some fast methods of matrix decomposition, as, for example, Cholesky decomposition, fail to perform.

One popular IR simulation model under real-world measure is Cox-Ingersoll-Ross (CIR) model

$$dr = k(\theta - r)dt + \sigma\sqrt{r}dW$$

FX rate simulation is commonly using Black Karasinski (BK) model

$$d(\ln(r)) = k(\ln(\theta) - \ln(r))dt + \sigma dW$$

Geometric Brownian Motion (GBM) is a popular equity simulation model

$$\frac{dr}{r} = \mu dt + \sigma dw$$

You can find more details at

https://finpricing.com/lib/EqWarrant.html