LGD Distributions

Introduction & Overview

In any form of portfolio analysis, it is appropriate to regard some inputs as stochastic and others as deterministic. In areas where key inputs are uncertain, it may be more suitable to map such inputs to a distribution than to "guess" an average result. This however increases the modelling complexity in terms of the sampling precedence that will occur in the simulation process, and increases the processing load, with sometimes less than material benefits in terms of accuracy.

In credit risk, the initial approaches to LGD estimation were deterministic in nature, although the new commercial products (e.g. LossCalc from MoodysKMV), provide distribution statistics with other outputs. It is increasingly accepted that there is merit in treating LGD as a loss severity distribution rather than to regard each estimate as deterministic, since a number of factors play a role in the ultimate recovery, and to estimate these deterministically is difficult. A simple example is when an issuer defaults on a debt obligation; the holder of the paper is likely to suffer financial loss. The amount of the loss is uncertain, but will depend inter alia on the seniority of the debt obligation, the legal jurisdiction, the issue conditions etc.

There are two main ways of modelling loss severity. The first is to treat all recoveries as fixed values that are known with certainty. The argument for this is that this simplification is reasonable because the uncertainty of the recovery value does not contribute significantly to the risk of the facility when compared with default rate volatility. In general, the default rate estimate dominates the LGD estimate when estimating the expected loss of an exposure. CSFB's CreditRisk+ uses such a fixed loss methodology: all exposures are input into the model net of any losses in the event of default.

The second method models the recovery value as a random variable of between 0% and 100%. A beta distribution is often used to model the uncertain recovery value. This distribution is useful because it can be bound between two points and can assume a wide range of shapes. All the popular commercially available portfolio management applications use a beta distribution to model the recovery value in the event of default, although only one (KMV PortfolioManager) currently provides this option at both the exposure and portfolio level.

The beta distribution has 2 “shape” parameters, and, beyond using the default symmetrical shape, the issue arises as to how the modify these shape parameters to best reflect the LGD characteristics of a particular exposure of portfolio.

Note: The term “LGD” is used in a variety of contexts, and refers to a number of different measures. Two commonly used definitions for LGD are:

1. LGD = (1 – (Recovery Value / Face Value))
2. LGD = (1 – (Recovery Value/Present Value of Future Cash Flows))

While many credit derivative traders currently find version (2) more tractable for use in pricing models, version (1) is the definition behind much of the currently available empirical research on recovery rates. A third version, used in portfolio modelling is to based on expressing all values at the analysis horizon i.e.

3. LGD = (1 – (Recovery Value at Analysis Horizon/Value of Future Cash flows at Horizon))

1. Shaping the Beta Distribution

Alpha and Beta can be calculated as follows:

$$Alpha = \left[m_{LGD}^{2} \times \frac{(1 - m_{LGD})}{s_{LGD}^{2}} \right] - m_{LGD}$$

$$Beta = Alpha \times \left(\frac{1}{m_{LGD}} - 1 \right)$$

where:

m_{LGD} is the average of the LGD for each exposure in the portfolio; and

s_{LGD} is the standard deviation of the LGD for the portfolio

The implied LGD is calculated as follows:

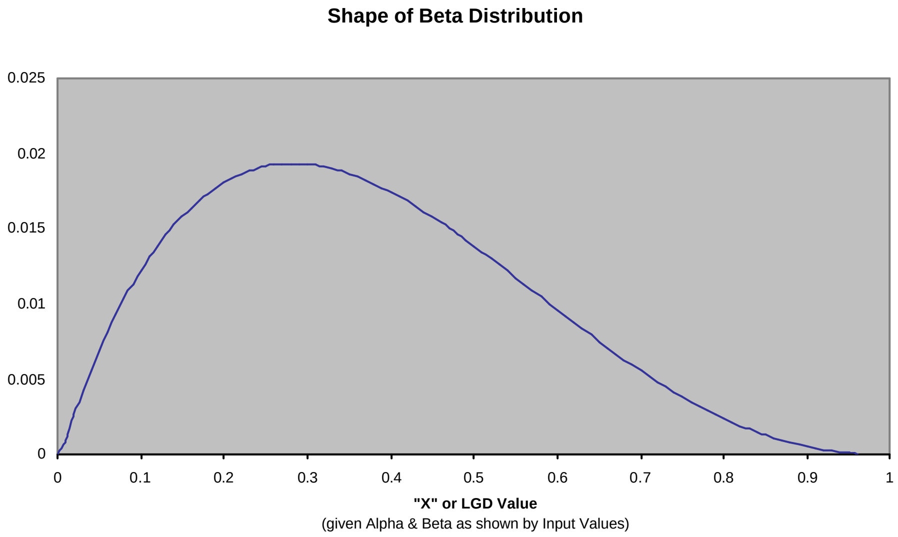
LGD = 1 – RR

LGD averages and standard deviations are impacted by the nature of each transaction and obligor, but can, as a first pass, be estimated by a historical analysis of recovery history. Another approach is to imply the LGD from available data.

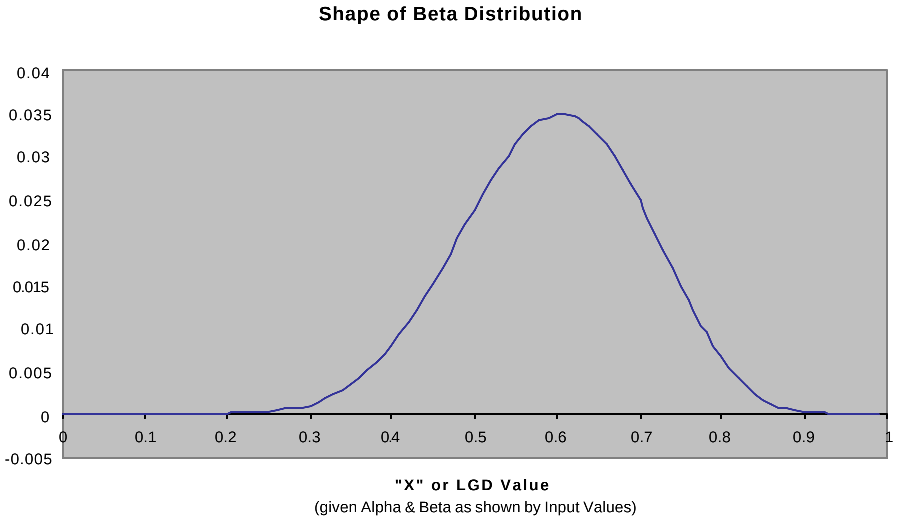
Examples

In Graph 1 the mean LGD is 36% with a standard deviation of 19%, whereas in Graph 2 the mean LGD is 59% with a standard deviation of 11%.

Graph 1:



Graph 2:



2. Conclusion

Refining the shape of the LGD distribution does not typically have a major effect on the overall capital/tail risk/maximum loss component of the distribution, but can impact the EL and UL components, with effects on any performance measures based on those measures.

3. References

Basel Committee on Banking Supervision: Credit risk modelling: current practices and applications

Merton, R, Bell Journal of Economics and Management Science, 4, 1973 pp 141-183: Theory of rational option pricing

Miller, R, Risk, August 1998 pp 97-99, Refining ratings

Wilson, T, Risk, September 1997 pp 111-117, Portfolio credit risk

Wilson, T, Risk, October 1997 pp 56-61, Portfolio credit risk

4. Glossary of Terms

- LGD: Loss Given Default (sometimes referred to as Loss in the Event of Default)
- RR: Recovery Rate, given by:
  RR = 1 – LGD