IFRS 9: Probably Weighted and Biased?

Alexander Marianski | August 2017

Introductions

Alexander Marianski

Associate Director

amarianski@deloitte.co.uk

Alexandra Savelyeva

Assistant Manager

asavelyeva@deloitte.co.uk

Jean-Marié Delport

Assistant Manager

jmdelport@deloitte.co.uk

Sam Tesseris

Assistant Manager

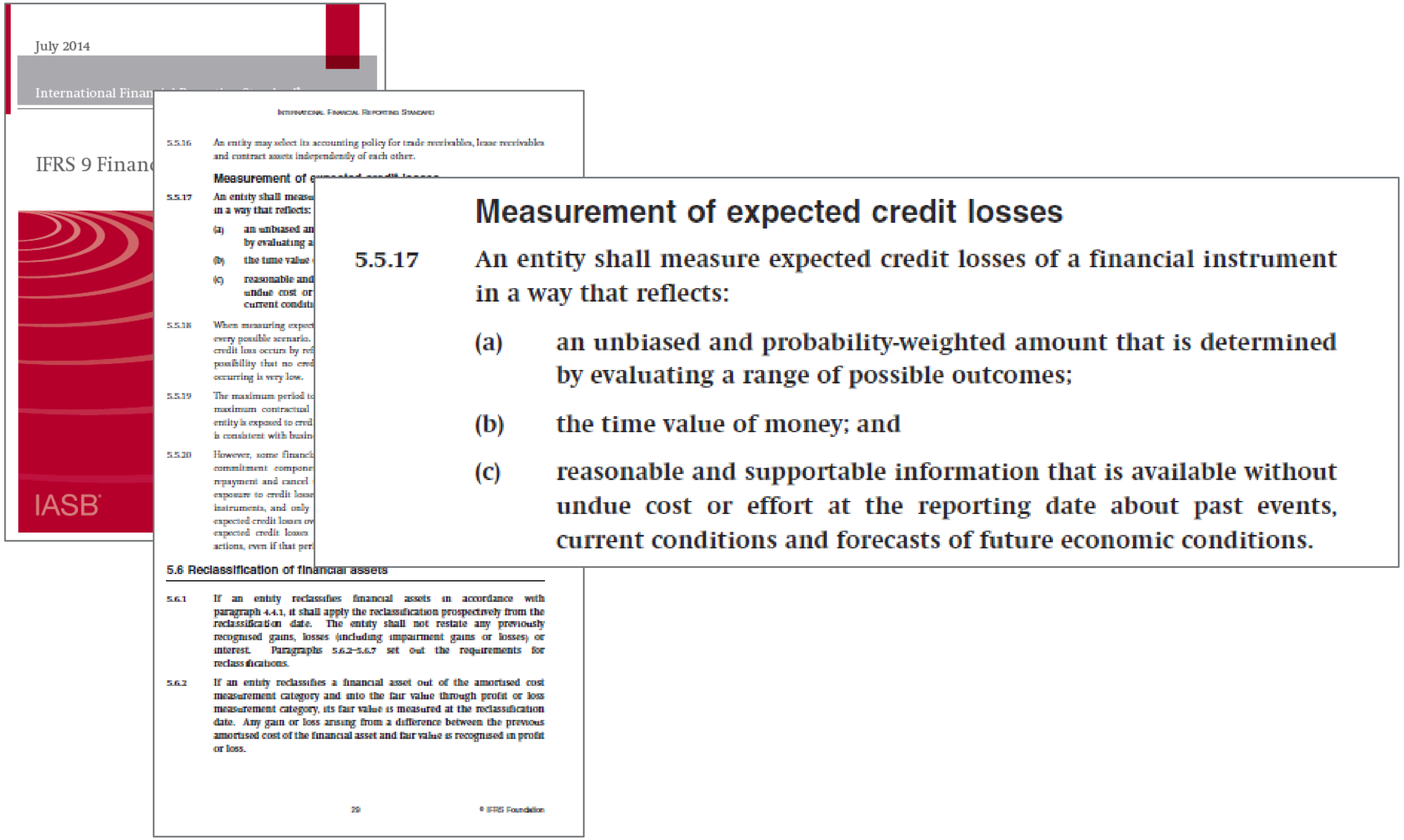
stesseris@deloitte.co.uk

Contents

Part 1

Recap of the IFRS 9 Standard

The IFRS 9 standard requires estimation of an unbiased expectation of credit losses.



July 2014

International Financial Reporting Standard

IFRS 9 Financ

IASB

INTERNATIONAL FINANCIAL REPORTING STANDARD

5.5.16 An entity may select its accounting policy for trade receivables, lease receivables and contract assets independently of each other.

Measurement of expected credit losses

5.5.17 An entity shall measure expected credit losses of a financial instrument in a way that reflects:

(a) an unbiased and probability-weighted amount that is determined by evaluating a range of possible outcomes;

(b) the time value of money; and

(c) reasonable and supportable information that is available without undue cost or effort at the reporting date about past events, current conditions and forecasts of future economic conditions.

5.6 Reclassification of financial assets

5.6.1 If an entity reclassifies financial assets in accordance with paragraph 4.4.1, it shall apply the reclassification prospectively from the reclassification date. The entity shall not restate any previously recognised gains, losses (including impairment gains or losses) or interest. Paragraphs 5.6.2–5.6.7 set out the requirements for reclassifications.

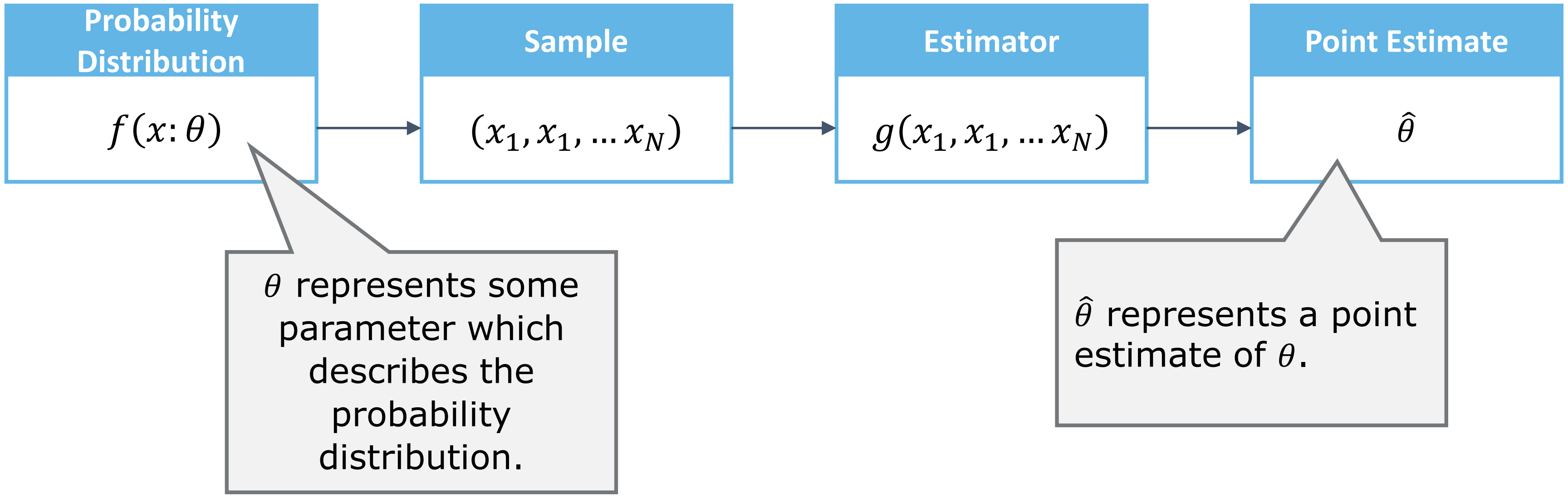
5.6.2 If an entity reclassifies a financial asset out of the amortised cost measurement category and into the fair value through profit or loss measurement category, its fair value is measured at the reclassification date. Any gain or loss arising from a difference between the previous amortised cost of the financial asset and fair value is recognised in profit or loss.

29 © IFRS Foundation

Credit Losses can be represented as a random variable (with some unknown distribution). The challenge is to estimate the expectation.

Estimation Theory

IFRS 9 requires us to go back to first principles if we are to be sure of achieving a minimum-variance unbiased estimate of expected loss.



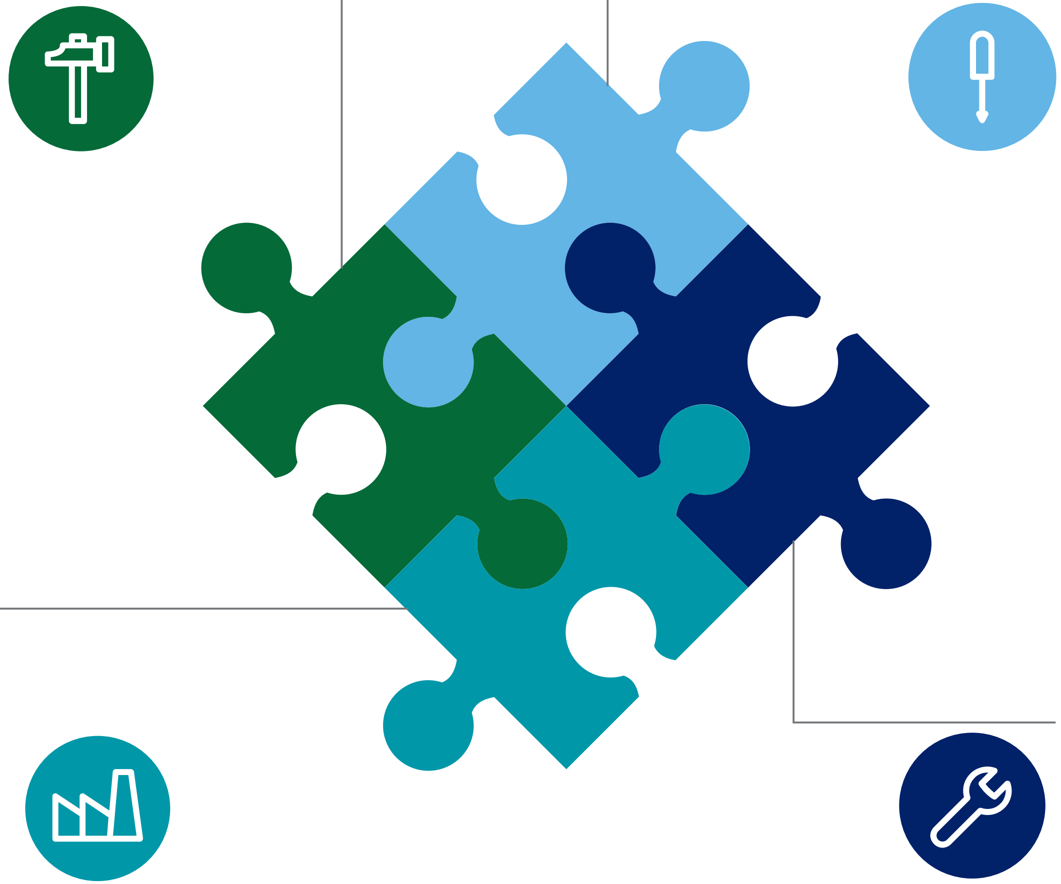
Features of a "good" estimator for θ which returns estimate $\hat{\theta}$

Unless the estimator is unbiased, consistent, sufficient and efficient, then mis-statement of expected loss is likely to occur.

Unbiased
The estimate converges on the true value:
$E[\hat{\theta}] = \theta$

Consistency
Bias and variance both tend towards zero:
$MSE(\hat{\theta}) = Var(\hat{\theta}) + [Bias(\hat{\theta})]^2$

$Var \to 0 \text{ and } Bias \to 0 \text{ as } n \to \infty$



Sufficiency
Observations x_i contain all information about the parameter – typically a sum or sum of squares of data points.

Efficient
The Efficient Estimator has the lowest possible variance:

$$var(\hat{\theta}) = \frac{1}{I(\theta)}$$

The Science of Inference meets the Art of Credit Modelling

Without a large, precise and random sample, model selection requires the application of significant judgement.

Inference Step	Mathematical Representation	Credit Risk Examples
What set of models is available?	M_i describes each possible model	• Targeted roll rate • Credit cycle indices • Hazard functions • Structural LGD
What adjustments to data points are required in order to make them representative of how today's portfolio?	Data points D can themselves be modelled as random variables.	• Establishing a segmentation by asset class, product and collateral • Assuming a probability of "apartment" if older data points say "house".
For the available models, which parameters are useful (i.e. they are not "nuisance" parameters), and what values should be assigned?	Bayes theorem allows us to articulate the probability of the parameter values w as a function of the observed data D and model M_i $p(w\|D, M_i) = \frac{p(D\|w, M_i)p(w\|M_i)}{p(D\|M_i)}$	• Estimation of collateral haircuts for houses and flats • Regression of default rate against macro indices • Decomposition of credit cycle indices into their principal components.
Which model and input parameters is the most plausible?	The evidence can be expressed as the probability of data observations D occurring, for each model. In theory the optimal model maximises the likelihood ratio $p(D\|M_i)$	• Implementation constraints (e.g. Working-day calendar and materiality) • Employ methodologies management understand and can explain.
What is the appropriate choice of distributional assumption for random inputs?	Maximise the Entropy, defined as: $H(X) = -\int_{-\infty}^{\infty} p(x)log(x)dx$ Apply constraints to observable quantities such as mean, variance, median, etc. Solve using Lagrange multipliers.	• In practice, sufficient information may not be observable and assumptions are often required. • The Normal distribution fits constraints of μ and σ but assumes zero kurtosis. • Leptokurtic processes greatly increase the probability of large values occurring, relative to a Normal distribution – the textbook example is FX options.

Sum of discounted marginal losses framework

This approach has near-universal acceptance for expected loss modelling.

Lifetime Credit Losses

$$LCL|M,d,m = \sum_{t=1}^{T} \frac{\left(SR_{t-1}^{FiT}|M,d,m\right) \cdot \left(PD_{t}^{FiT}|M,d,m\right) \cdot \left(LGD_{t}^{FiT}|M,d,m\right) \cdot \left(EAD_{t}^{FiT}|M,d,m\right)}{(1+r)^{t}}$$

Note that this approach assumes zero correlation between the individual components.

Model **M**
Data **d**
Macroeconomic scenario **m**

Lifetime *Expected* Credit Losses

Let $x = (LCL|M,d,m)$

$$(LECL|M,d) = \mathrm{E}[x] = \int x\, p(x)\, dx$$

For convenience, **M** and **d** are generally assumed fixed and (along with other nuisance variables) omitted from notation

Part 2

Sum of discounted marginal losses framework

Many options for model selection and parameter estimation remain, including:

Time Step

- Should the model use daily, monthly, quarterly, semi-annual or annual samples?

Parameter Selection and Estimation

- Should cyclicality in ratings be modelled?
- Should idiosyncratic migrations be modelled?
- Can we use OLS to parameterise independent expectations of inputs?

Number of macroeconomic scenarios and their design

- How should future macro paths be selected?
- What cumulative likelihood should be assigned to the resulting loss severity?

Approach to integration to recover the expectation of the loss distribution

- How can information about the unsampled portions of the distribution be incorporated?

What time-step (sample interval) should IFRS 9 models use?

Our analysis suggest that the choice of annual or monthly time-step has a minimal impact on PD. However, if amortisation, credit cycle and discounting are also considered then immateriality of ECL impact should not be assumed.

Approach

The following key assumptions were made within our estimation process:

- Smoothed ODR based PD calibration;
- Smoothed (Laplace) based transition risk;
- PIT=TTC ratings and transitions;
- No credit cycle adjustment; and
- Annual transition matrix raised to the power of (1/12) to derive the monthly matrix.

1y PD

	Annual	Monthly
AAA	0.00%	0.00%
AA+	0.00%	0.00%
AA	0.01%	0.01%
AA-	0.01%	0.02%
A+	0.02%	0.03%
A	0.05%	0.06%
A-	0.09%	0.10%
BBB+	0.17%	0.19%
BBB	0.30%	0.33%
BBB-	0.53%	0.58%
BB+	0.89%	0.97%
BB	1.45%	1.55%
BB-	2.29%	2.42%
B+	3.52%	3.68%
B	5.23%	5.41%
B-	7.56%	7.59%
CCC	10.60%	10.17%

20y PD

	Annual	Monthly
AAA	1.67%	2.01%
AA+	1.75%	2.11%
AA	2.52%	2.93%
AA-	2.86%	3.30%
A+	3.86%	4.31%
A	5.31%	5.78%
A-	7.19%	7.73%
BBB+	10.43%	11.02%
BBB	14.17%	14.79%
BBB-	20.36%	20.95%
BB+	27.71%	28.28%
BB	35.95%	36.46%
BB-	45.71%	46.11%
B+	55.70%	55.91%
B	63.90%	63.78%
B-	69.09%	68.67%
CCC	72.46%	71.61%

What is the impact of including and calibrating a rating cyclicality parameters?

Our analysis suggest that the inclusion of rating cyclicality has minimal impact on PD. However, the result cannot be assumed to hold at different points in the economic cycle, and/or under different credit cycle forecasts.

Approach

The following key assumptions were made within our estimation process:

- Quarterly time-step.
- Long Run PDs of (0.01% ,0.6%, 20%, 30%).
- 15% annual prepayment rate
- Merton-Vasicek credit cycle adjustment aligned to peak 1990s default rate.
- Rating cyclicality parameter α sensitised as (0,0.2, 0.5).

1y PD

LRPD	0% PIT	20% PIT	50% PIT
0.01%	0.01%	0.01%	0.01%
0.6%	0.52%	0.53%	0.54%
20%	18.03%	18.19%	18.42%
30%	27.23%	27.43%	27.72%

20y PD

LRPD	0% PIT	20% PIT	50% PIT
0.01%	0.08%	0.07%	0.07%
0.6%	4.07%	3.94%	3.77%
20%	59.63%	59.23%	58.63%
30%	69.43%	69.18%	68.81%

What is the impact of assuming that obligors' rating never migrates idiosyncratically?

Our analysis suggest that ignoring idiosyncratic migrations is unlikely to impact ECL in cohorts which contribute materially toward the overall estimate; but the *relative* error in lower-risk cohorts can be profound, with significant impacts on applications such as pricing.

Approach

The following key assumptions were made within our estimation process:

- One year time step
- Smoothed ODR based PD calibration;
- PIT=TTC ratings and transitions;
- No credit cycle adjustment; and
- Transition risk sensitised between Identity Matrix and Laplace Interpolation.

1y PD

Rating	Identity	Laplace
AAA	0.00%	0.00%
AA+	0.00%	0.00%
AA	0.01%	0.01%
AA-	0.01%	0.01%
A+	0.02%	0.02%
A	0.05%	0.05%
A-	0.09%	0.09%
BBB+	0.17%	0.17%
BBB	0.30%	0.30%
BBB-	0.53%	0.53%
BB+	0.89%	0.89%
BB	1.45%	1.45%
BB-	2.29%	2.29%
B+	3.52%	3.52%
B	5.23%	5.23%
B-	7.56%	7.56%
CCC	10.60%	10.60%

20y PD

Rating	Identity	Laplace
AAA	0.02%	1.67%
AA+	0.05%	1.75%
AA	0.11%	2.52%
AA-	0.23%	2.86%
A+	0.47%	3.86%
A	0.94%	5.31%
A-	1.79%	7.19%
BBB+	3.30%	10.43%
BBB	5.86%	14.17%
BBB-	10.00%	20.36%
BB+	16.30%	27.71%
BB	25.29%	35.95%
BB-	37.09%	45.71%
B+	51.12%	55.70%
B	65.87%	63.90%
B-	79.24%	69.09%
CCC	89.36%	72.46%

What is the impact of only running a base case, versus full Monte Carlo model?

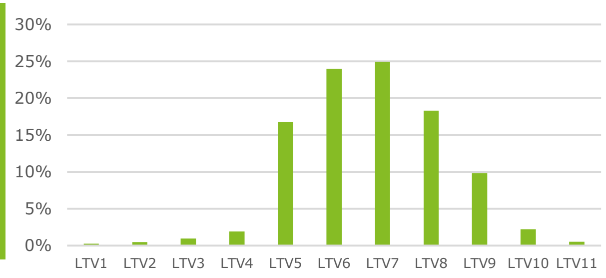
Our analysis suggests that, at the current point in the cycle, multiple scenarios add no discernible additional accuracy to ECL estimates. However, this cannot be guaranteed in sub-segments of the portfolio or at different points in the economic cycle.

Approach

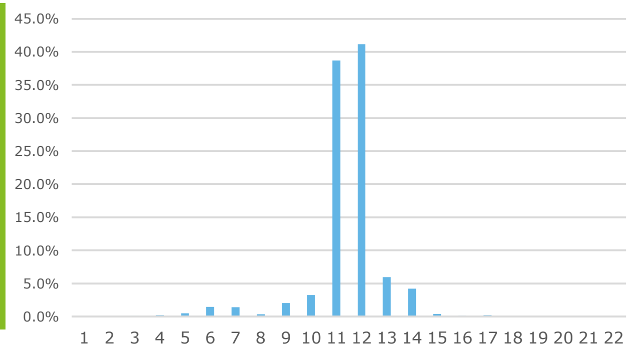
The following key assumptions were made within our estimation process:

- S-VAR model using 2 lags
- Macro series observed since 1990
- Idiosyncratic migrations modelled using Laplace (double exponential) distribution
- Portfolio attributes align to a recent UK mortgages Pillar 3.

LTV distribution

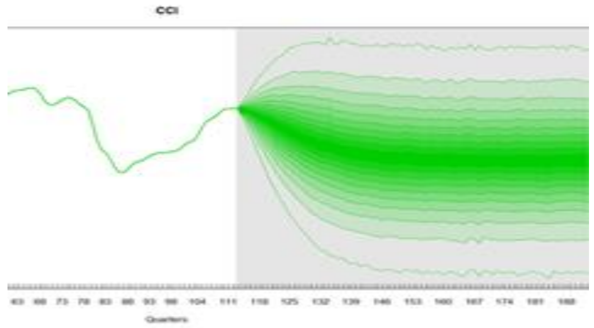


Rating distribution

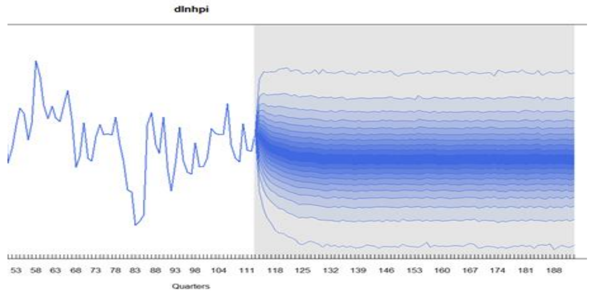


Fan Charts

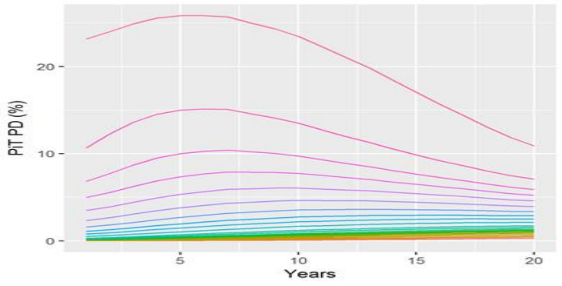
CCI



dlnHPI



PD



ECL% estimates

	MC Result	Central Case
EL	0.03%	0.03%
LEL	0.23%	0.22%

Although we observe close alignment to the base case, this cannot be guaranteed, in general, to hold:

- In individual sub-cohorts
- At different points in the cycle.

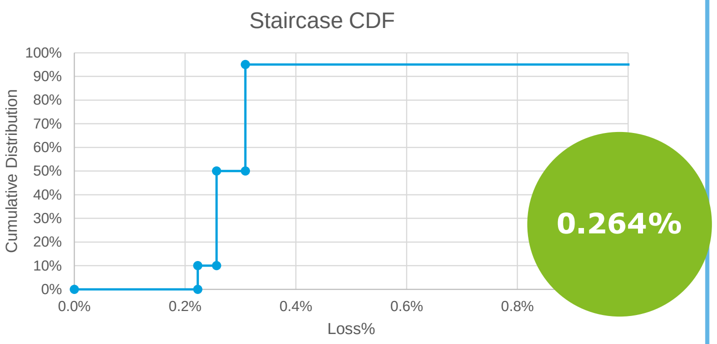
In addition, stage 2 migrations under a stress scenario are likely to result in a significant step-up as a significant proportion (if not all prior years' originations) move from 12 month to lifetime expected loss.

Scenario based approaches – is numerical integration required?

Firms that judgementally assign weights to scenarios could introduce a significant bias to the overall estimate. Therefore numerical integration is required. Our analysis suggests that the choice of numerical integration approach has little impact on estimation of ECL.

No interpolation

With no interpolation, we assume that the loss distribution is completely described by the sampled loss data points. This leads to a "staircase" CDF:

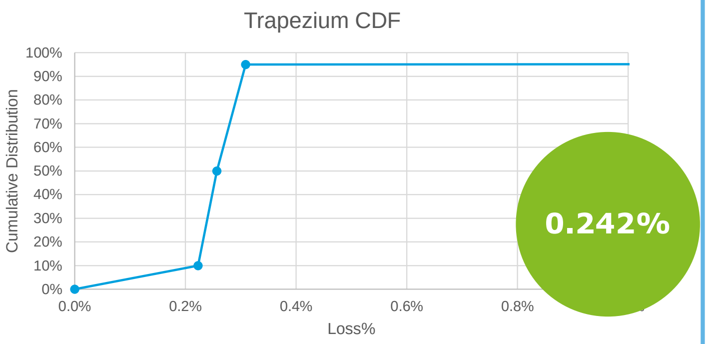


Differentiating to obtain the PDF, and then integrating to obtain the expectation from $E[L] = \int L\, f(L)\, dL$ leads to the following expression for the recovered expectation:

$$E[L] \approx p_1 L_1 + (p_2 - p_1)L_2 + (p_3 - p_2)L_3$$

Straight Line Interpolation

With straight-line interpolation, we assume that the loss distribution is completely described by flat lines the sampled loss data points. This leads to a "Trapezium" CDF:

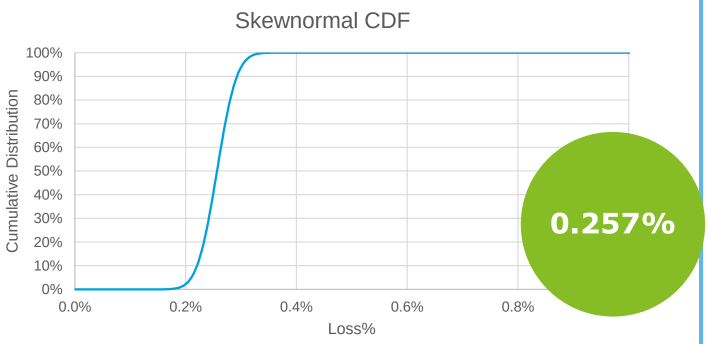


Differentiating to obtain the PDF, and then integrating to obtain the expectation from $E[L] = \int L\, f(L)\, dL$ leads to the following expression for the recovered expectation:

$$E[L] \approx \frac{p_2 L_1}{2} + \frac{(p_3 - p_1)L_2}{2} + \frac{(1 - p_2)L_3}{2}$$

Skew Normal Intrpolation

With a distributional assumption, we assume that higher moments of the true distribution are non-zero and impose a suitable functional form such as the Skew Normal distribution.



Fitting the Skew Normal parameters using Maximum Likelihood leads to the following expression for the recovered expectation:

$$E[L] \approx \xi + \omega \frac{\alpha}{\sqrt{1 + \alpha^2}} \sqrt{\frac{2}{\pi}}$$

It is important to recognise that the equivalence seen below may not hold at different points in the economic cycle.

Part 3

Conclusions and Q&A

Conclusions

- Neglecting the first principles of estimation theory can lead to non-minimum variance and material bias in estimates.
- Simplified approaches to modelling and estimation can nevertheless deliver compliant and accurate IFRS 9 estimates.
- IFRS 9 models should be critically validated before use in applications with a different materiality level, such as pricing.

Questions?