Credit Scoring (Biennial) Edinburgh Conference
University of Edinburgh (27-29 August, 2013)

Risk Tools & Algorithms

Agenda:

1. ***Brief overview of risk concepts***
2. ***Present some technical model details***
3. ***Then demonstrate some practical applications of a credit model (using Microsoft Excel and VBA code)***

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Data & Analytics (Institutional and Business Banking Risk)

Disclaimer: The opinions expressed in this presentation are those of the author and do not necessarily reflect the views of the Commonwealth Bank of Australia.

August 2013

Corporate failure rates are predicted to go up!

"Companies are like living creatures. They come into the world and, once they survive their teething troubles, they mature and eventually cease to exist. Sometimes, if they're not killed off by bankruptcy, they even reproduce through the medium of merger or acquisition.

Arie De Geus, a retired Shell executive, has conducted research that shows the *life expectancy of new firms in Europe or Japan to be less than **13** years* – down from 20 in the late 1970s and early 80s. Even if they grow up to be large multinationals they're likely to last only 40 to 50 years in total. And Foster and Kaplan estimate that **by 2020 the average S&P 500 firm** will stay in the index for just **ten** years – down from 65 in the 1920s, when the list first appeared.

There are, as usual, exceptions. Like giant tortoises, there are some companies that have made it to over 150 years of age. But they tend to move like giant tortoises too. All the evidence points to the conclusion that the financial performance of long-lasting firms is below the market average. As Foster and Kaplan say, "the corporate equivalent of the El Dorado, the golden company that continuously performs better than the markets, has never existed. It is a myth." Managing for survival doesn't guarantee strong performance for the entire corporate lifespan – in fact, just the opposite."

Source: Excerpt from Chapter 6: 'Lessons from Gurus' in book 'Dance with Chance' by Spyros Makridakis, Robin Hogarth and Anil Gaba, 2009

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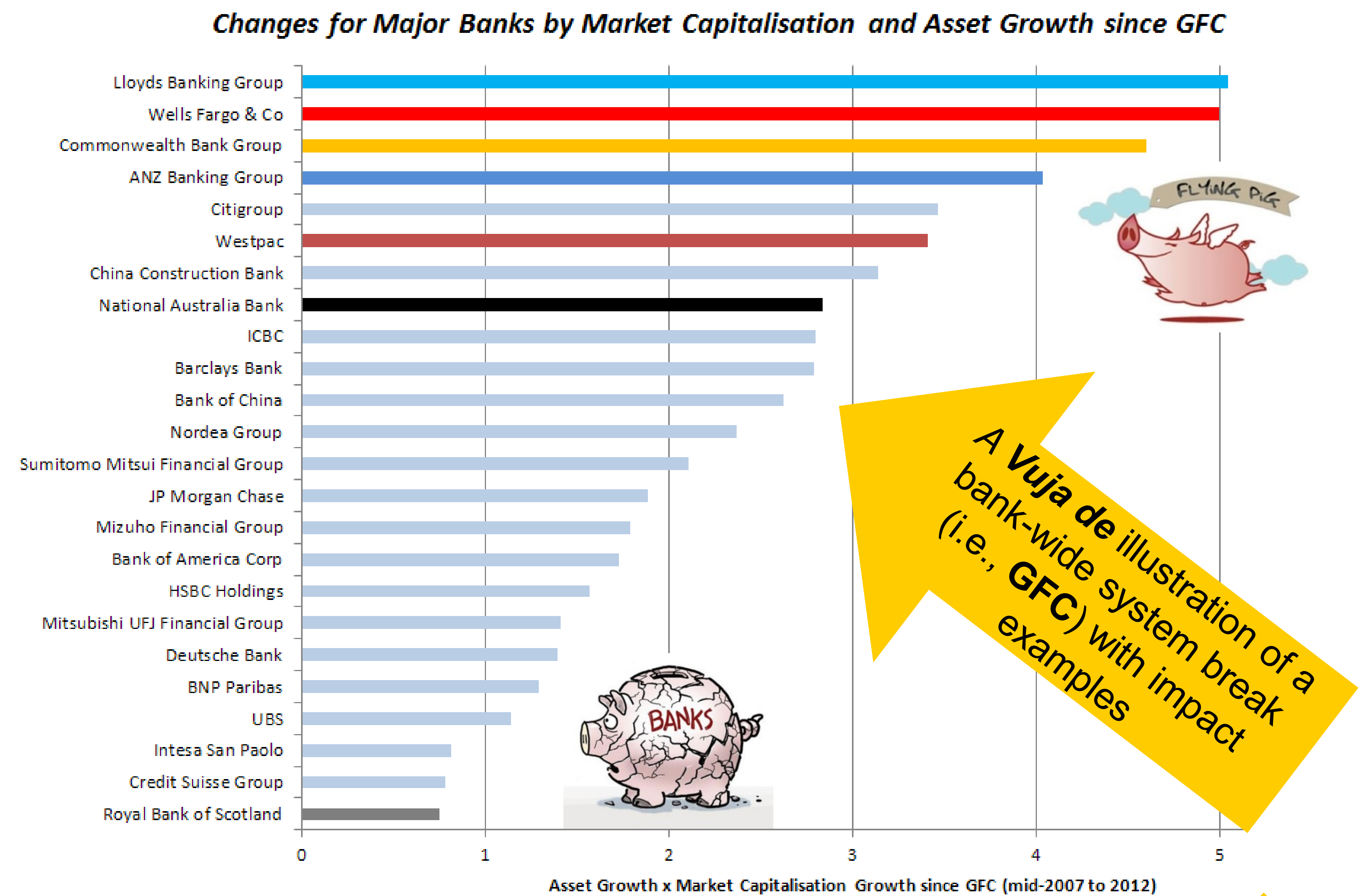
How major banks worldwide (using both Size & Value measures) have changed since Global Finance Crisis



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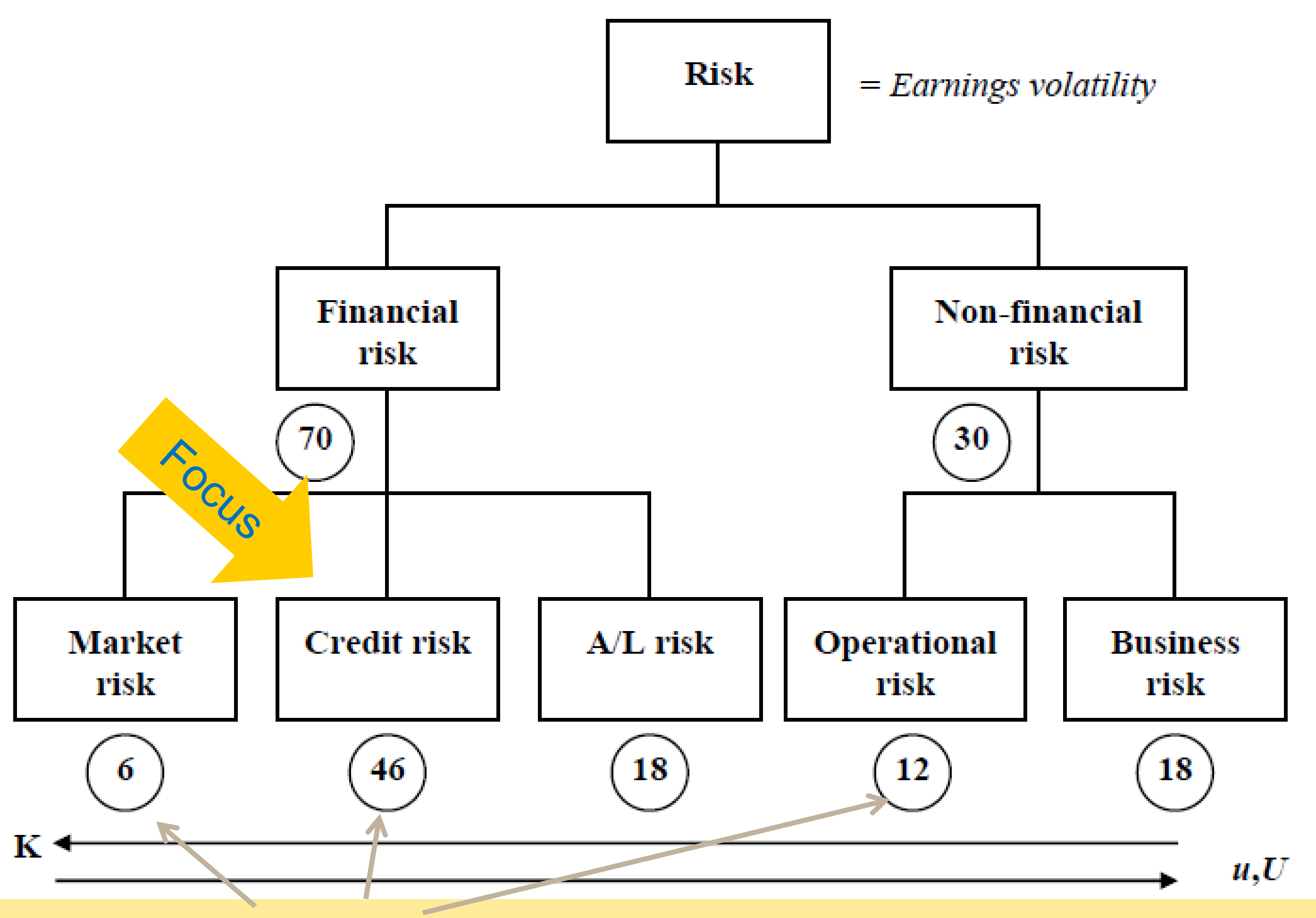
There is a useful taxonomy of bank risk types (covering both known & unknown risks)



∑=100%

BASEL II *(only accounts for approx. 2/3 of total risk exposure)*

Source: *"WHAT WE KNOW, DON'T KNOW AND CAN'T KNOW ABOUT BANK RISK: A VIEW FROM THE TRENCHES"* By Andrew Kuritzkes (MOW) and Til Schuermann (US FED) March 23, 2008

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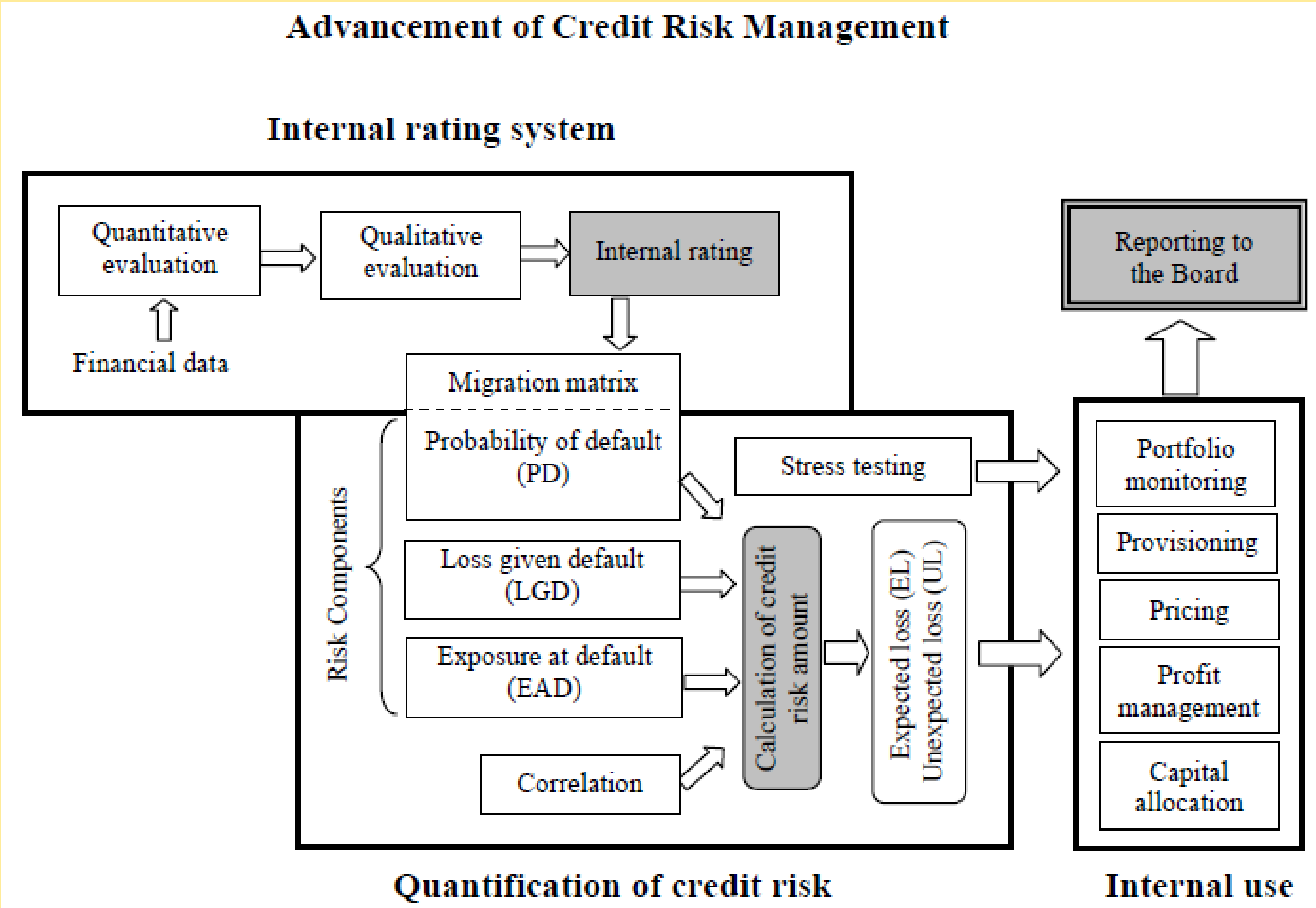
Goal is to create superior credit risk systems based on advanced risk metrics and controls…



Source: "Advancing Credit Risk Management through Internal Rating Systems – August 2005 – Bank of Japan (Oyama & Yoneyama)

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Regulators set capital requirements to control the probability of bank failures → a simple example

Assets		Liabilities	
Loan 1	100		
Loan 2	100	Equity	50
Loan 3	100	Deposits	350
Loan 4	100		
Total	400	Total	400

Scenario: Assume 1 loan is in default

=> with 50% LGD, the bank is just solvent

Scenario: Now assume that 2 loans are in default

=> with 50% LGD, the bank is now insolvent!

The default probability optionality is associated with the Merton model

Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

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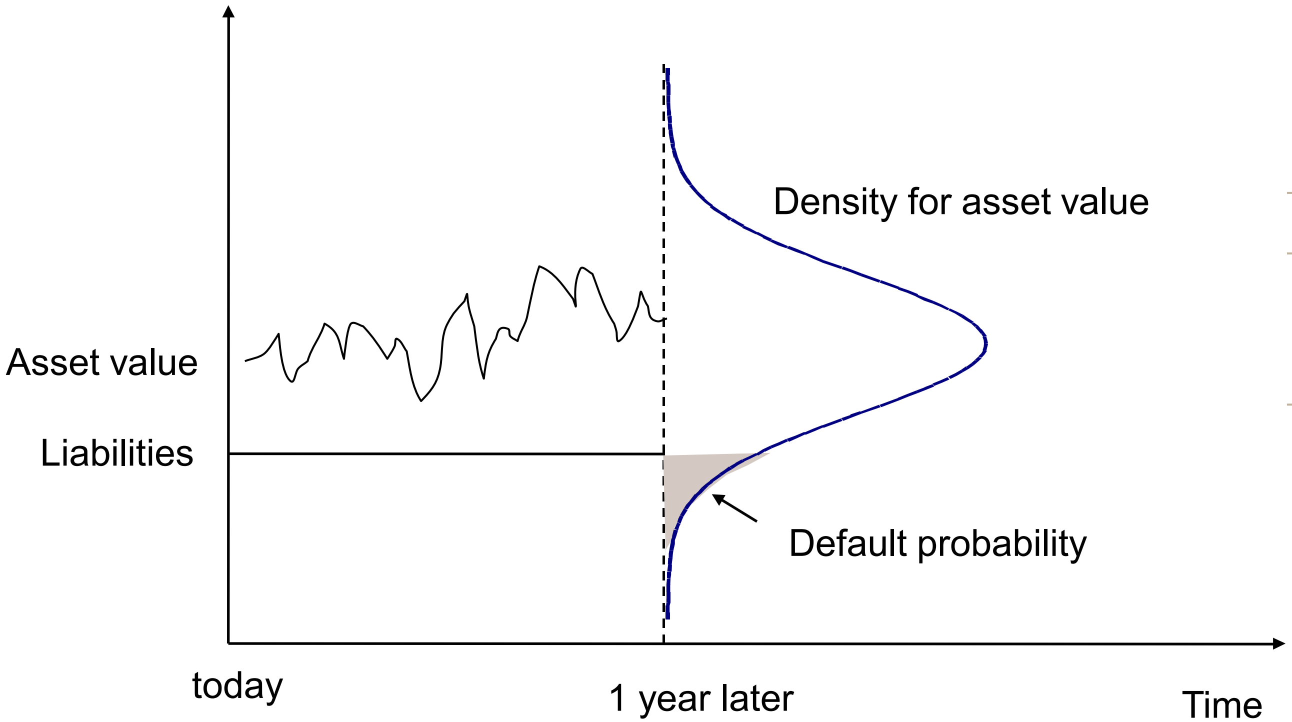
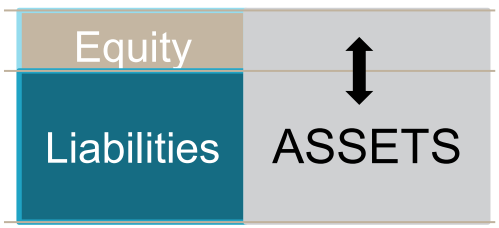
The basic idea underlying the structural approach





Default Probability with the Merton model *(<u>without</u> any option pricing)*

<u>Source</u>: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

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Reliability and Validity – two key model aspects

The two most fundamental formal properties of every model are the models:
(a) Validity (“hitting the target") and (b) its Reliability ("truthfulness").

- The **validity** relates to how well does the model describe reality or the underlying phenomena that is being investigated. Validation is the process of ensuring outcomes are valid, in the sense of explaining what needs to be predicted or evaluated (e.g., PD estimate).
- The **reliability** pertains to the "representativeness" of the result found in our specific sample for the entire population. *(In other words, it says how probable it is that a similar relation would be found if the experiment was replicated with other samples drawn from the same population i.e., population stability.)*

Neither **Valid** Nor **Reliable** Outcomes

Valid but NOT **Reliable** Outcomes*

NOT **Valid** but has **Reliable** Outcomes**

Both **Valid** and **Reliable** Outcomes

**Increasing sample size can make a model more reliable even though it is valid.*
***Re-calibration of a model can help ensure future validity for a reliable model.*

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BIS came up with the Basel Credit Risk Parameters

Estimating Basel II Credit Risk Parameters

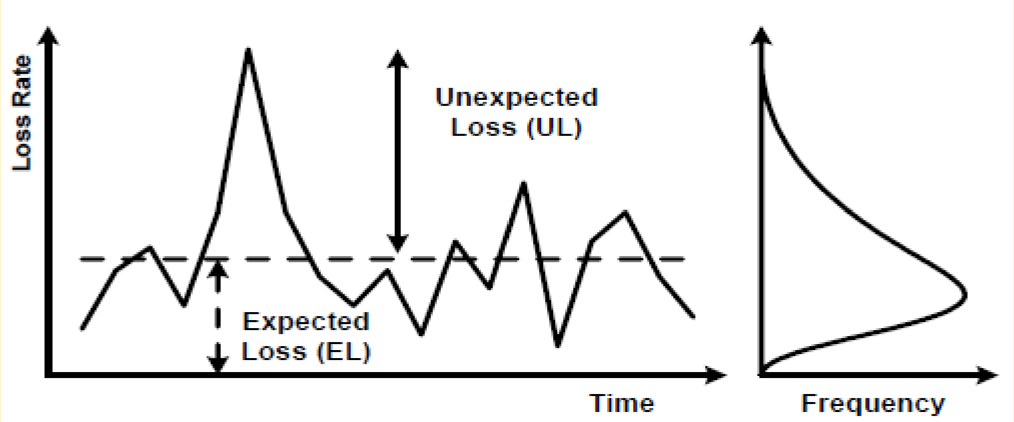
Overview of Expected Loss (EL):

- Probability of Default (PD),
- Loss Given Default (LGD),
- Exposure At Default (EAD)
- Maturity (M) {corporate only}

EL = PD x LGD x EAD

Credit Risk (or the measurement of both EL and UL (Unexpected Loss)) can be calculated by using one of three approaches:

1. Standardised Approach
2. Foundation IRB (Internal Ratings Based) Approach
3. Advanced IRB Approach



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Several methods available for estimation of PDs

- ✓ PD estimates must be a *long-run average* of one-year default rates for borrowers covering at least seven non-default grades and one default grade (8 grades in total).
- ✓ Five years is the minimum length of time for the underlying historical data observation period.

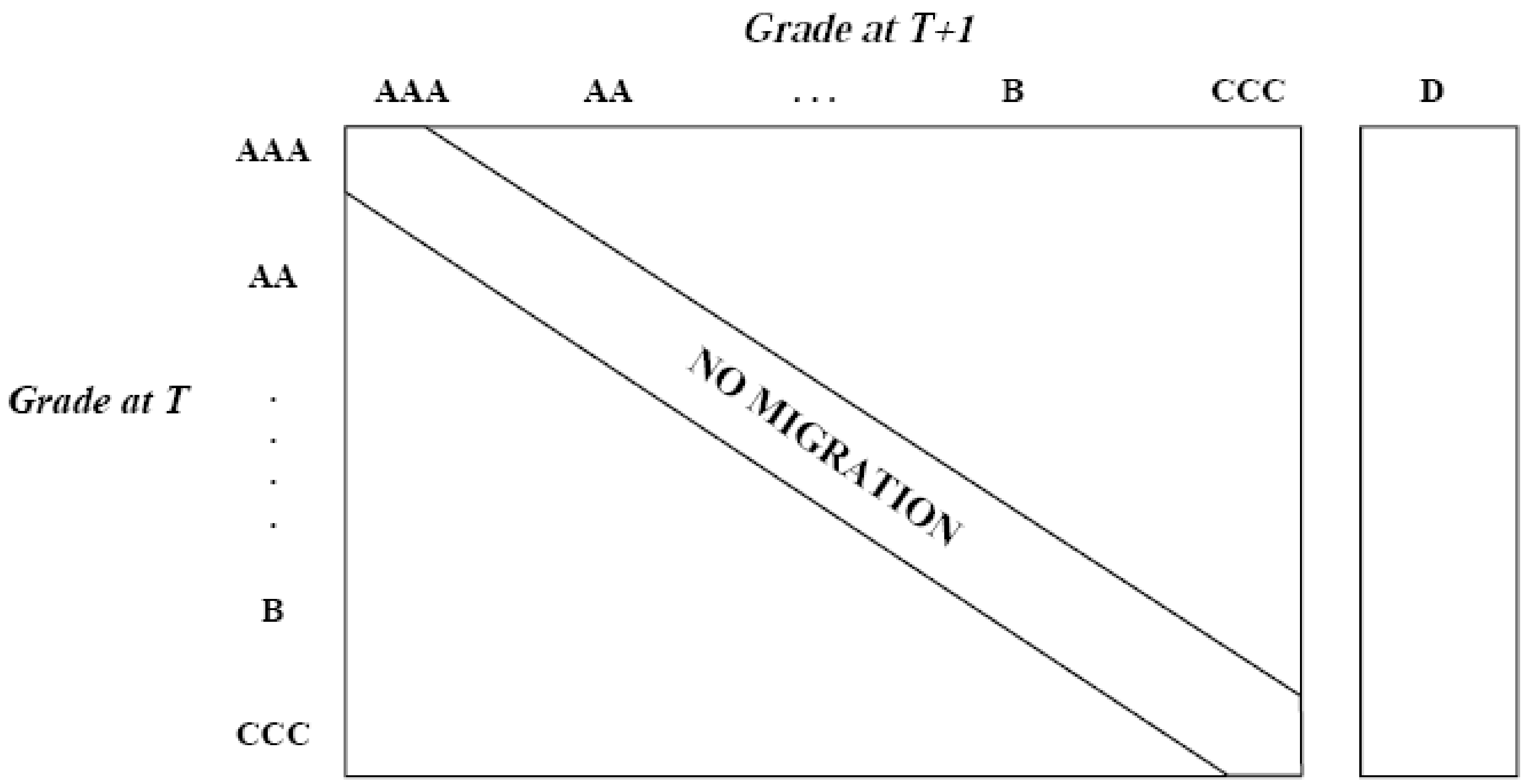
Three approaches are possible (and combinations thereof):

1. You can map bank internal grades to public rating agencies grades and use their historical default rates;
2. Apply average of default probability estimates from *statistical default prediction models* (e.g., Large corporate model mapped across to a PD Masterscale);
3. Or use default rates from internal loss experience (via for example transition probabilities combined into a PD Masterscale).

IRB = Internal Ratings Based

Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

What is credit migration analysis?

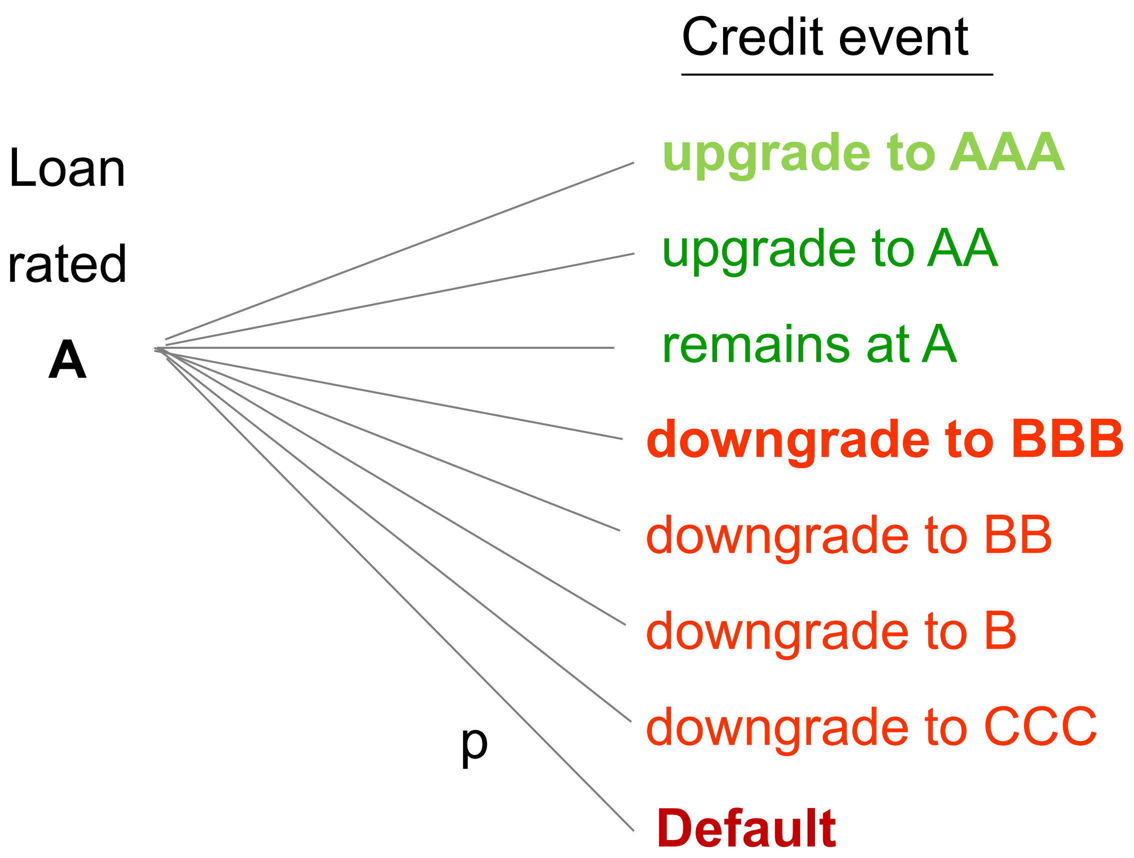


Source: **“Ratings Migration and the Business Cycle, With Applications to Credit Portfolio Stress Testing”**

Anil Bangia1, Francis X. Diebold, André Kronimus, Christian Schagen, Til Schuermann, (2001)

Figure 4.1: Structure of the transition matrix

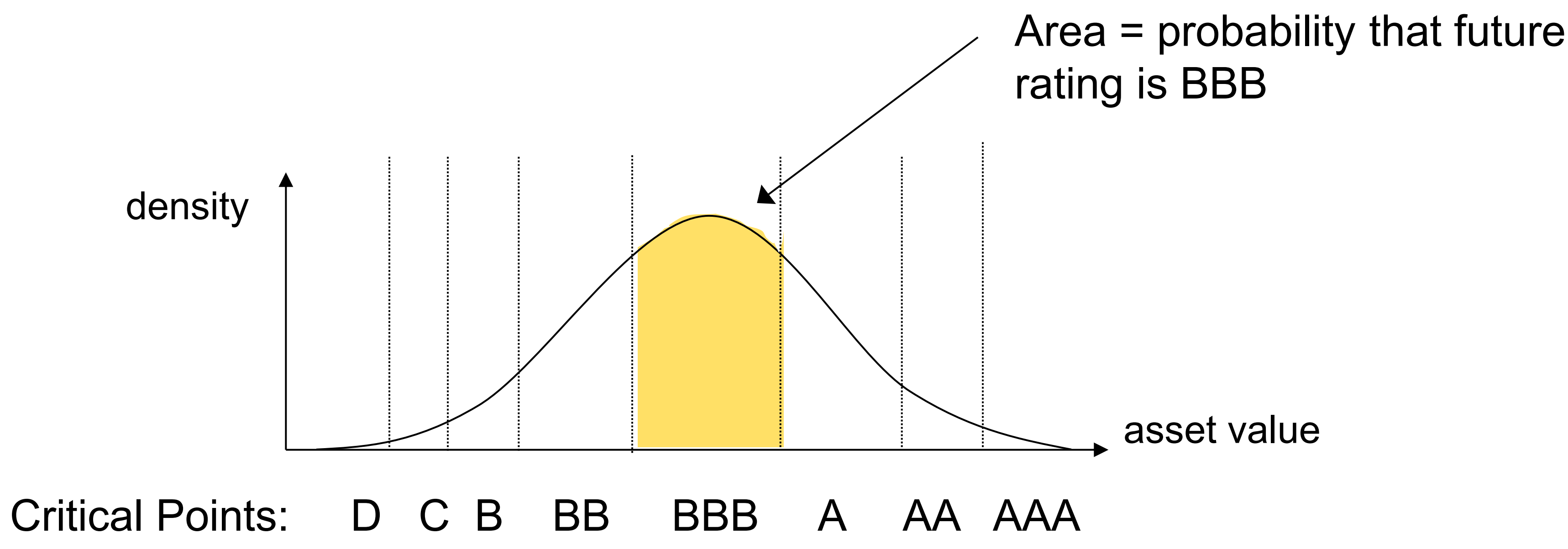
Risk of migration can be incorporated by modelling transitions to other rating classes



Source: Loffler & Posch, “Credit Risk Modeling using Excel and VBA” , 2nd Ed. – Wiley Finance - 2011

As with default correlations, correlations of rating migrations can be modeled via asset correlations

- For the default/no default case, we needed only one critical default point for the asset value distribution
- Now we need critical points for each rating category



Source: Loffler & Posch, “Credit Risk Modeling using Excel and VBA” , 2nd Ed. – Wiley Finance - 2011

On the quality of agency (or external) ratings

Rating agencies are often accused of being slow to adjust to new information

Alternative rating information (e.g. EDFs)

- predicts rating changes
- has better default prediction power

But: rating agencies do not aspire to be "high-frequency sources of information"

- ♦ through-the-cycle approach
- ♦ avoidance of frequent rating reversals
- ♦ good long-term predictive power of ratings is consistent with this claim

Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

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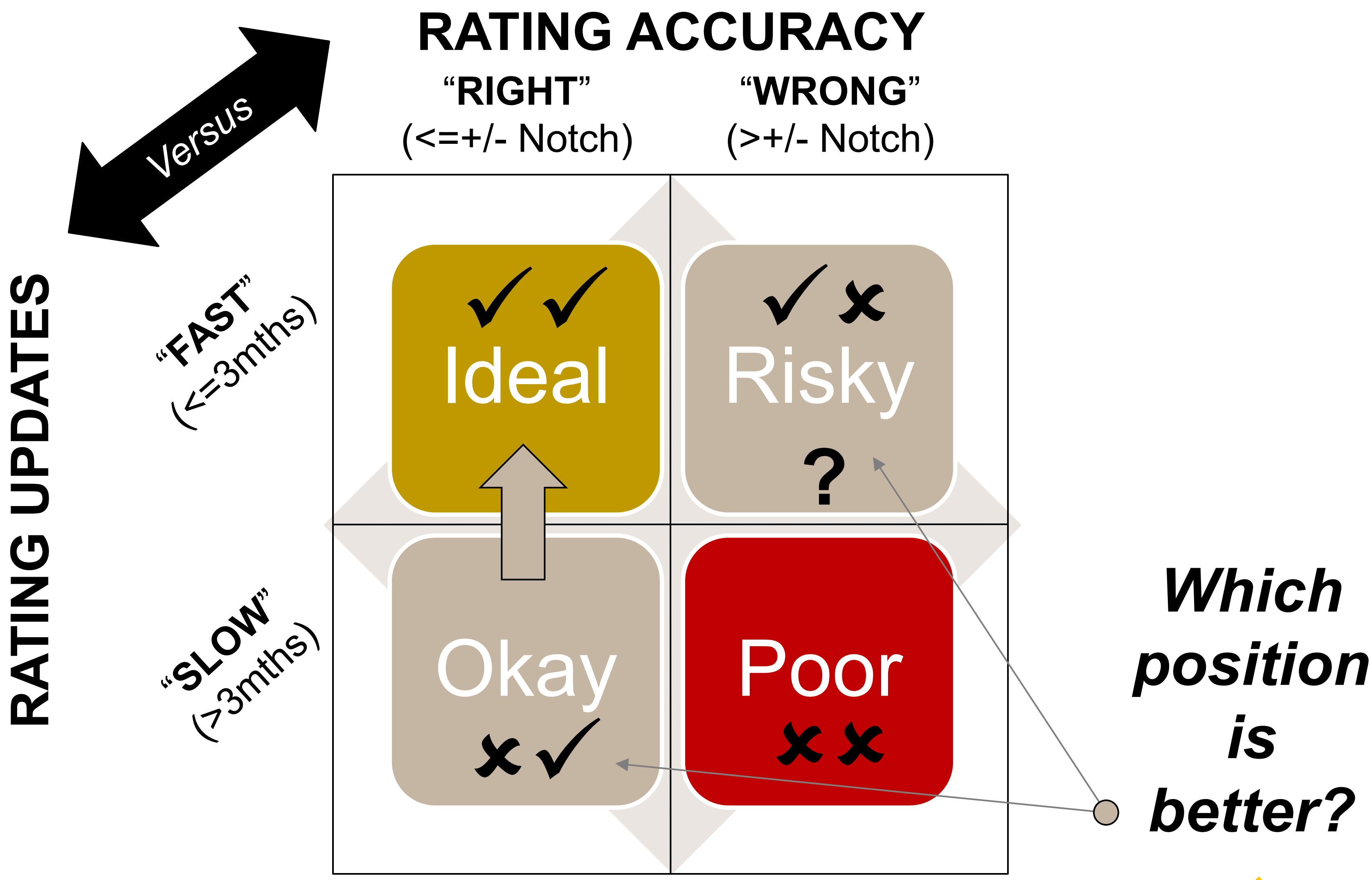
The basic dilemma facing rating agencies is…



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Probabilities for rating migrations can be estimated with historical data as per the matrix

S&P transition matrix (1981-2008)

	Rating at year end (%)								
Initial Rating	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**CCC**	**D**	**N.R.**
AAA	88.39	7.63	0.53	0.06	0.08	0.03	0.06	0	3.23
AA	0.58	87.02	7.79	0.54	0.06	0.09	0.03	0.03	3.86
A	0.04	2.04	87.19	5.35	0.4	0.16	0.03	0.08	4.72
BBB	0.01	0.15	3.87	84.28	4	0.69	0.16	0.24	6.6
BB	0.02	0.05	0.19	5.3	75.74	7.22	0.8	0.99	9.68
B	0	0.05	0.15	0.26	5.68	73.02	4.34	4.51	12.00
CCC	0	0	0.23	0.34	0.97	11.84	46.96	25.67	14.00

* Source: Vazza, Aurora, Kraemer (2009): Default, Transition, and Recovery: 2008 Annual Global Corporate Default Study And Rating Transitions, Standard and Poor's.

Comparison of rating Agencies across time

RAM Malaysian Corporate Average One-Year Transition Rates, 1993 to 2012 (%) [Cohort Method]

From/To	*Grades*	AAA	AA	A	BBB	BB	B	C	D	NR
Grades	Numbers	1	2	3	4	5	6	7	8	NR
AAA	1	95.67%	1.44%	-	-	-	-	-	-	2.88%
AA	2	1.40%	90.42%	1.64%	1.17%	0.12%	-	0.23%	-	5.02%
A	3	0.11%	3.68%	81.19%	6.16%	0.22%	0.22%	-	0.86%	7.57%
BBB	4	0.17%	0.69%	4.99%	69.36%	8.95%	1.20%	0.86%	1.20%	12.56%
BB	5	-	-	0.40%	5.93%	57.31%	6.72%	2.77%	7.91%	18.97%
B	6	-	-	-	-	6.06%	74.24%	3.79%	3.03%	12.88%
C	7	-	-	2.38%	-	2.38%	-	47.62%	26.19%	21.43%
D	8	-	-	-	-	-	-	-	100.0%	-

S&P Global Corporate Average One-Year Transition Rates, 1981 to 2012 (%) [Cohort Method]

From/To	*Grades*	AAA	AA	A	BBB	BB	B	CCC/C	D	NR
AAA	1	87.17%	8.69%	0.54%	0.05%	0.08%	0.03%	0.05%	-	3.38%
AA	2	0.54%	86.29%	8.36%	0.57%	0.06%	0.08%	0.02%	0.02%	4.05%
A	3	0.03%	1.86%	87.26%	5.53%	0.36%	0.15%	0.02%	0.07%	4.71%
BBB	4	0.01%	0.12%	3.54%	85.09%	3.88%	0.61%	0.14%	0.22%	6.39%
BB	5	0.02%	0.04%	0.15%	5.18%	76.12%	7.20%	0.72%	0.86%	9.71%
B	6	-	0.03%	0.11%	0.23%	5.42%	73.84%	4.40%	4.28%	11.68%
CCC/C	7	-	-	0.16%	0.24%	0.73%	13.69%	43.89%	26.85%	14.43%
D	8	-	-	-	-	-	-	-	100.0%	-

Sources: a) RAM Ratings published report: "Default Study: 2012 CORPORATE DEFAULT AND RATING TRANSITION STUDY" MARCH 2013
(Exhibit 31: Cumulative WA Rating Transitions by Rating Category, 1992-2012)
b) Standard & Poor's Rating Services: Ratings Direct - "Default, Transition, and Recovery: 2012
Annual Global Corporate Default Study and Rating Transitions" March 18, 2013 (WWW.STANDARDANDPOORS.COM/RATINGSDIRECT)) - Table 33

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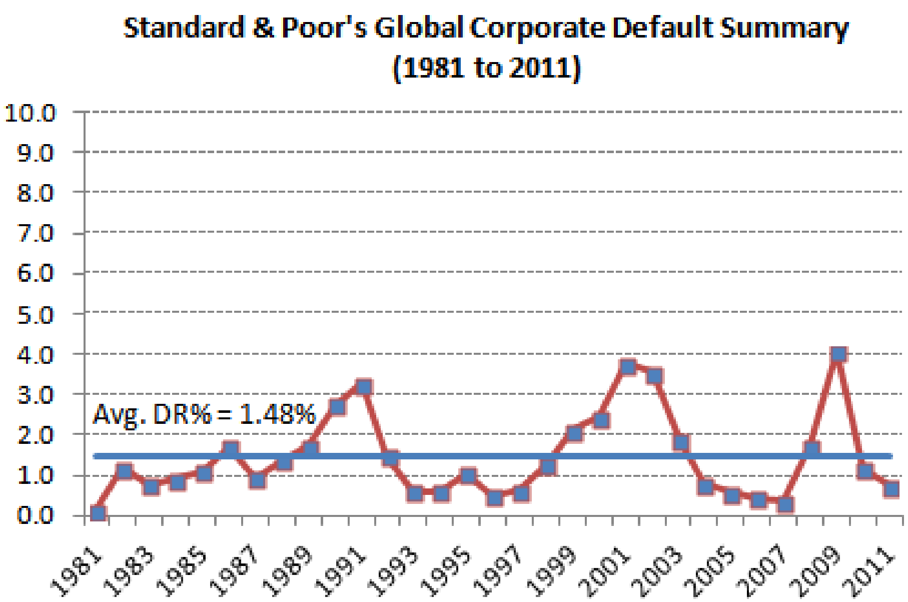
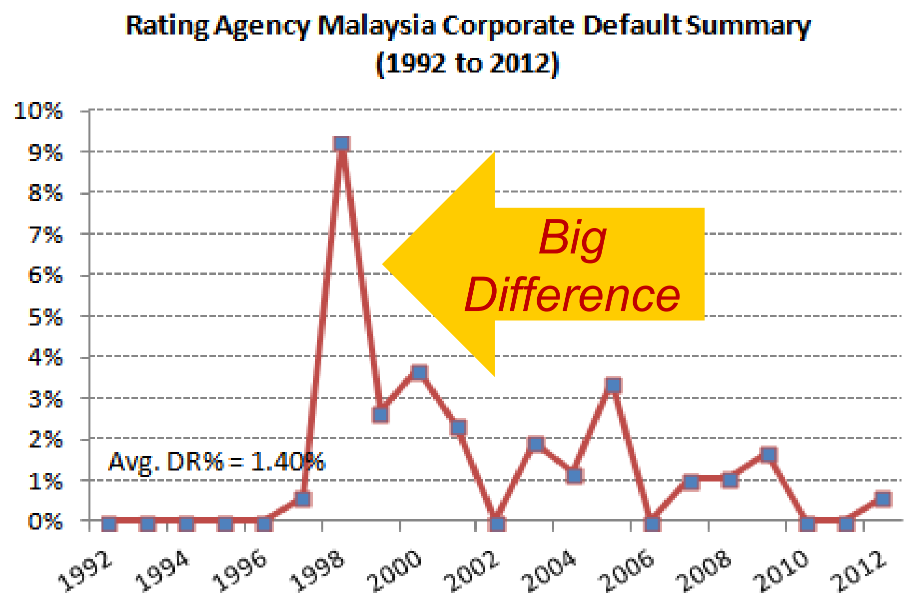
Comparison of rating Agencies across time





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Agencies estimate average default and transition rates using the cohort (frequentist) approach

A cohort comprises the issuers with a given rating at a given point in time

For grade i and period t, the empirical frequency of transitions to grade j is determined by relating the number of issuers that migrated from grade i to j within period t ($=N_{ij,t}$) to the number of issuers that were rated i at the start of period t ($=N_{i,t}$) :

$$\hat{p}_{ij,t} = \frac{N_{ij,t}}{N_{i,t}}$$

The published statistics are a weighted average of these single period statistics, where the weighting is done grade by grade based on the number of issuers included in the cohorts:

$$\hat{p}_{ij} = \sum_t N_{i,t}\hat{p}_{ij,t} \Big/ \sum_t N_{i,t}$$

This can also be computed through N_{ij} / N_i where N_{ij} is the overall number of migrations from i to j and N_i is the overall number of obligors rated i at the start of the considered periods.

Source: Loffler & Posch, “Credit Risk Modeling using Excel and VBA” , 2nd Ed. – Wiley Finance - 2011

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Multiyear default and transition rates can also be estimated with the cohort approach

Assume the following

One-year matrix with two grades A, B:

	A	B	D
A	95%	5%	0%
B	15%	65%	20%
D	0%	0%	100%

Possible events for Grade A today is grade B in two years

(i) issuer is downgraded to B this year and stays there next year

Prob(i) = 0.05×0.65

(ii) issuer remains A this year but is downgraded to B next year

Prob(ii) = 0.95×0.05

=>This gives the overall probability of 0.08

In general: a T-year transition matrix P_T can be obtained from the one-year matrix P_1 by matrix multiplication

$P_T = P_1^T = P_1 \, P_1 .... P_1$ (i.e. multiply P_1 T times with itself)

Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

Comparison of methods for default estimation

US Research Comparison Data Table

	US S&P PD Estimates		
Ratings	Cohort Method	Duration Method	Cohort / Duration
AAA	0.0000%	0.0002%	0.0%
AA+	0.0000%	0.0005%	0.0%
AA	0.0000%	0.0093%	0.0%
AA-	0.0384%	0.0044%	872.7%
A+	0.0520%	0.0046%	1130.4%
A	0.0699%	0.0084%	832.1%
A-	0.0599%	0.0100%	599.0%
BBB+	0.3137%	0.0467%	671.7%
BBB	0.3623%	0.1165%	311.0%
BBB-	0.4012%	0.1453%	276.1%
BB+	0.5501%	0.3301%	166.6%
BB	1.1633%	0.4564%	254.9%
BB-	2.0718%	0.8851%	234.1%
B+	3.4980%	1.7541%	199.4%
B	9.8201%	7.5833%	129.5%
B-	14.3016%	13.4330%	106.5%
CCC	28.5354%	42.4904%	67.2%

Source: Confidence Intervals for Probabilities of Default By Hanson, S. & Til Schuermann (2005) US Fed. Reserve

- This table opposite shows the potentially large disparity from usage of cohort versus duration approaches for PD estimates.
- A cohort approach uses all companies at the start of the year as the base reference and ignores any changes in between.
- However, the more accurate duration based method treats each month (for example) as a separate rating and the base becomes all monthly ratings across one year.
- This approach picks up mid-year rating changes and also any Not Rated outcomes occurring before year end.
- Given its finer measurement periods, the duration method yields a smoother and more accurate set of PD estimates (especially at both ends of the risk spectrum) across the rating span compared with the cohort approach.

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The BIS IRB formula for corporates, banks and sovereigns:

271. The derivation of risk-weighted assets is dependent on estimates of the **PD, LGD, EAD** and, in some cases, effective maturity (M), for a given exposure. Paragraphs 318 to 324 discuss the circumstances in which the maturity adjustment applies.

272. Throughout this section, PD and LGD are measured as decimals, and EAD is measured as currency (e.g. euros), except where explicitly noted otherwise. For exposures not in default, the formula for calculating risk-weighted assets is:[70, 71]

Correlation (R) = 0.12 × (1 – EXP(-50 × PD)) / (1 – EXP(-50)) +
0.24 × [1 – (1 – EXP(-50 × PD)) / (1 – EXP(-50))]

Maturity adjustment (b) = (0.11852 – 0.05478 × ln(PD))^2

Capital requirement (K) = [LGD × N[(1 – R)^-0.5 × G(PD) + (R / (1 – R))^0.5 × G(0.999)]
– PD x LGD] x (1 – 1.5 x b)^-1 × (1 + (M – 2.5) × b)

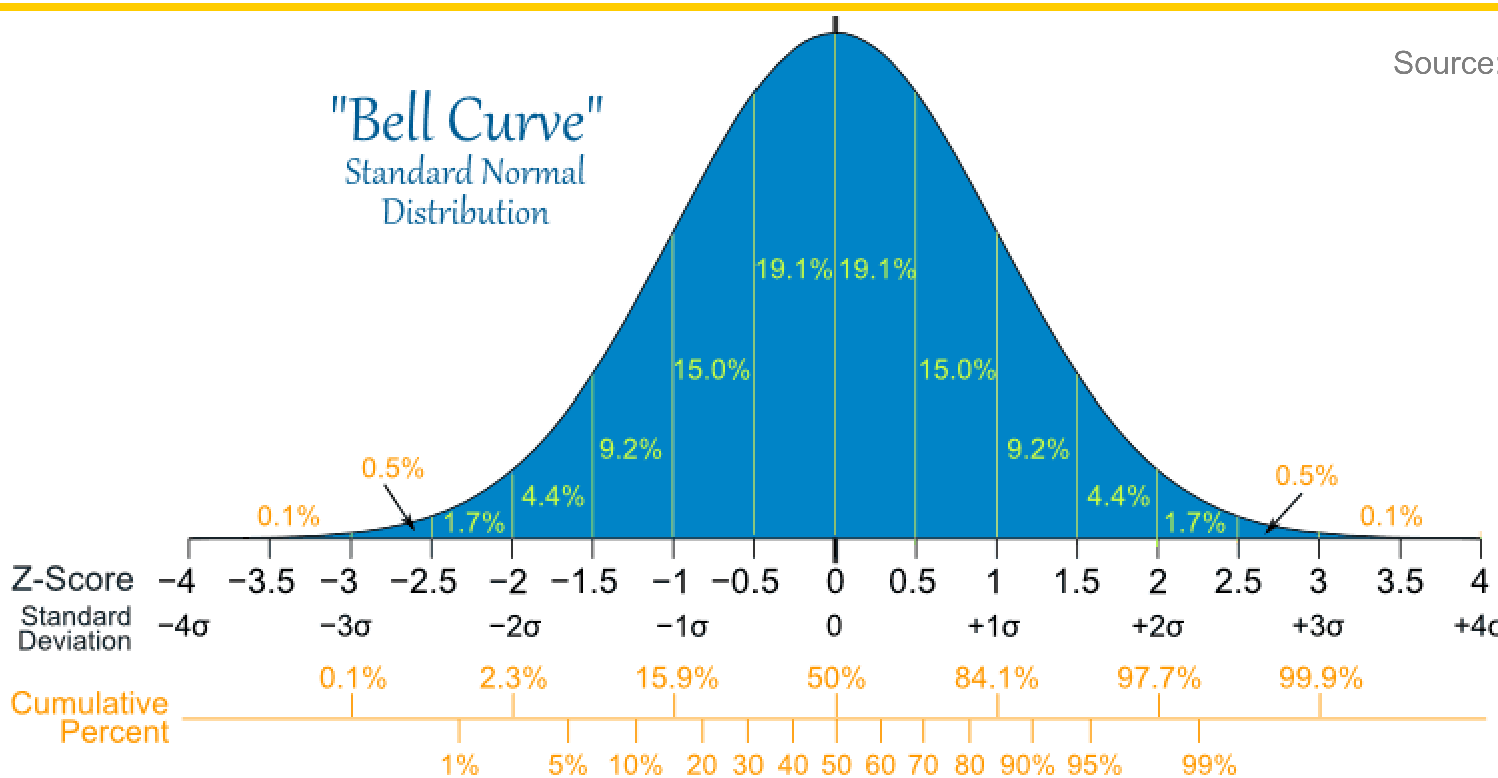
70 Ln denotes the natural logarithm.

71 N(x) denotes the cumulative distribution function for a standard normal random variable (i.e. the probability that a normal random variable with mean zero and variance of one is less than or equal to x). G(z) denotes the inverse cumulative distribution function for a standard normal random variable (i.e. the value of x such that N(x) = z). The normal cumulative distribution function and the inverse of the normal cumulative distribution function are, for example, available in Excel as the functions NORMSDIST and NORMSINV.

Source: http://www.bis.org/publ/bcbs128b.pdf

Main statistical distribution → Normal distribution

Source: Google Images



- The Normal distribution represents one of the empirically verified elementary "truths about the general nature of reality," and its status can be compared to the one of fundamental laws of natural sciences. The exact shape of the normal distribution (the characteristic "bell curve") is defined by a function which has only two parameters: mean μ and standard deviation σ.
- *Note, however the exponentially declining tails that represent very low probabilities or extreme risk events–is this really likely in an interactive system?*

Basel estimate a general form of unexpected loss formula for banks to calculate the capital.

Factors in Basel2

Basel estimates
A General formula
For banks

Factor	Description
•PD	*1 Year PD is considered, instead of cumulative PD*
•LGD	*Based on historical data*
•EAD	*Current status of EAD*
•Tenor	B = $\left[0.11852 - 0.05478 \times \ln(PD)\right]^2$
•Correlation	$0.12 \times \left[\frac{1-e^{(-50\times PD)}}{1-e^{(-50)}}\right] + 0.24\left[1-\left(\frac{1-e^{(-50\times PD)}}{1-e^{-50}}\right)\right]$

K =

$$\left[LGD\times N\left[(1-R)^{-0.5}\times G(PD)+\left(\frac{R}{1-R}\right)^{0.5}\times G(0.999)\right]-PD\times LGD\right]$$

$$\times(1-1.5\times b)^{-1}\times\left[1+(M-2.5)\times b\right]$$

↓

RWA = K * 12.50 * EAD

↓

Capital = RWA * BIS Ratio

Source: Eric Kuo - "Sound Credit Risk Experience Sharing" – Vietnam FSA Presentation 2007

Banks can estimate the capital requirement based on the general formula→ basic example:

INPUTS

Factors in Basel2

•PD	1.35%
•LGD	45%
•EAD	100 Million
•Tenor	2.5 Years
•Correlation	0.1811

OUTPUTS

*EL = PD * LGD * EAD*

*= 1.35% * 45% * 100 Mn*

= 0.61 Million

AIRB K = 0.082

*RWA = K * 12.50 * EAD*

*= 0.082 * 12.5* 100 Mn*

= 102 Million

*Capital = RWA * BIS Ratio*

*=102 Mn * 10% =10.2 Million*

Source: Eric Kuo - "Sound Credit Risk Experience Sharing" – Vietnam FSA Presentation 2007

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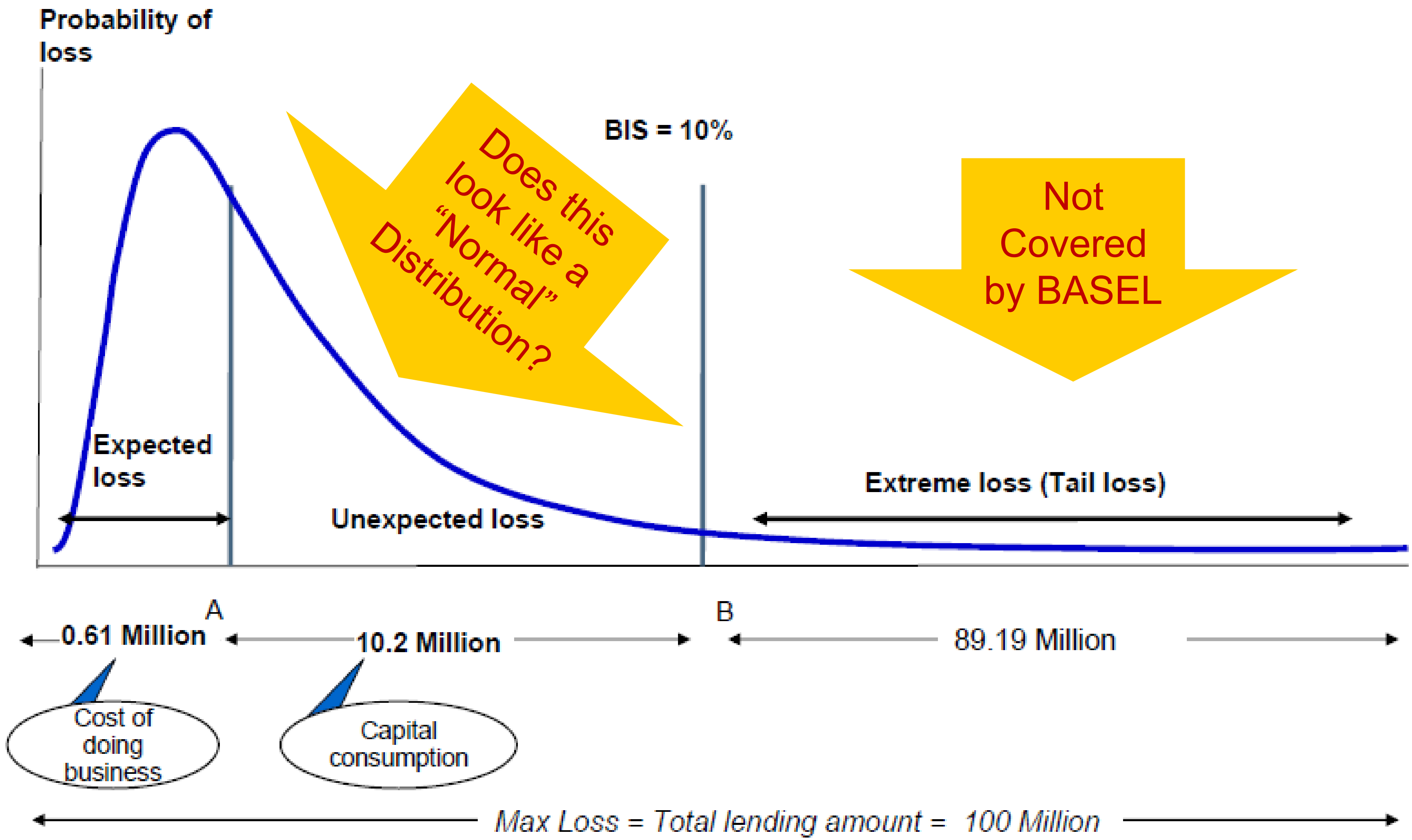
Note that the long tail risk is 8.7 times the capital charge as per the case illustrated below….



Source: Eric Kuo - "Sound Credit Risk Experience Sharing" – Vietnam FSA Presentation 2007

Commercial credit risk models differ in several dimensions...

- Which dimensions of credit risk are modeled?
  - default risk
  - migration risk
  - recovery risk
  - exposure risk

- How are the driving forces of credit risk modeled / estimated
  - default probabilities
  - default correlations

- Modeling details
  - distributional assumptions
  - computational approximations

Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

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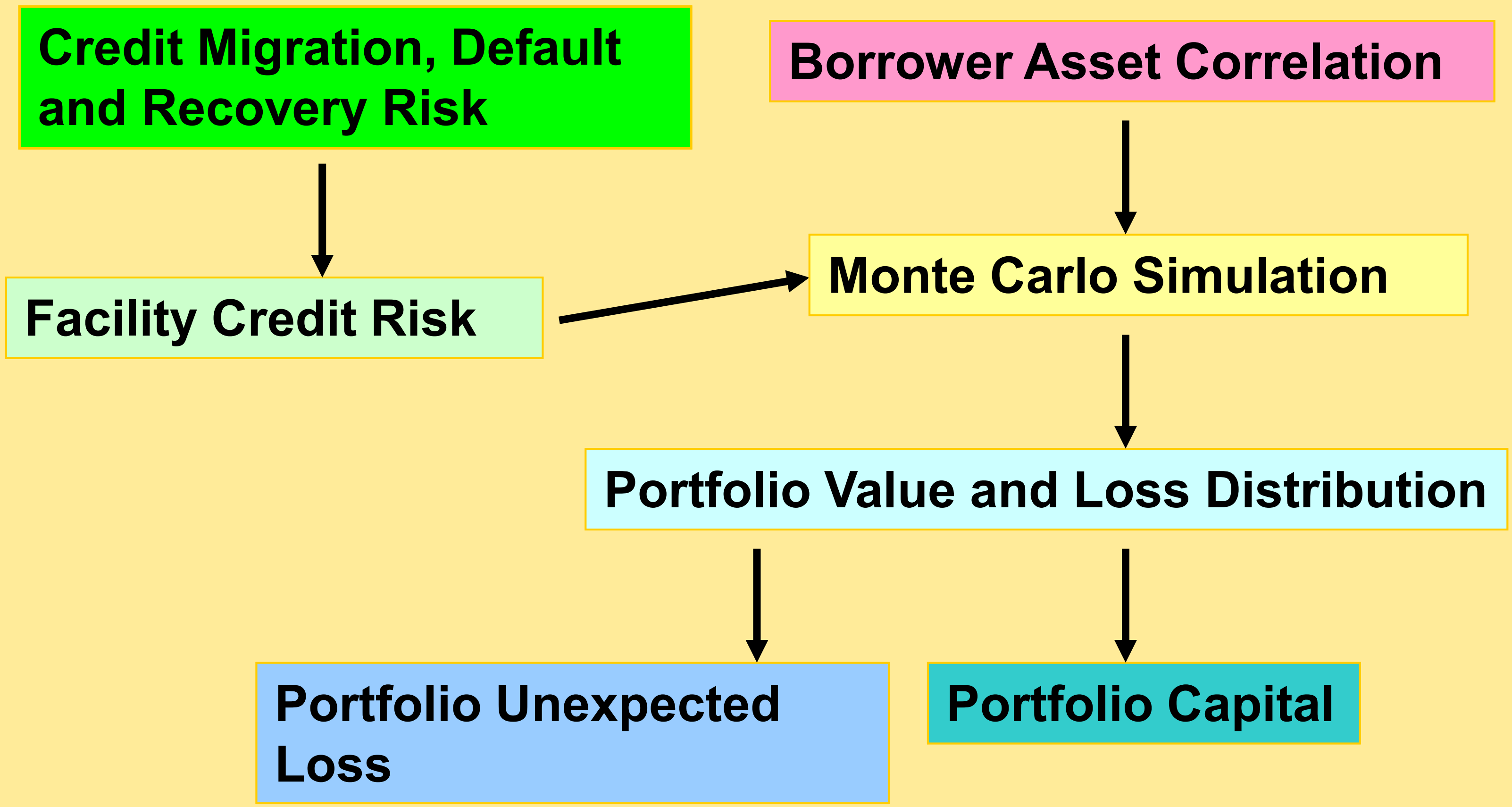
The MKMV capital modelling framework



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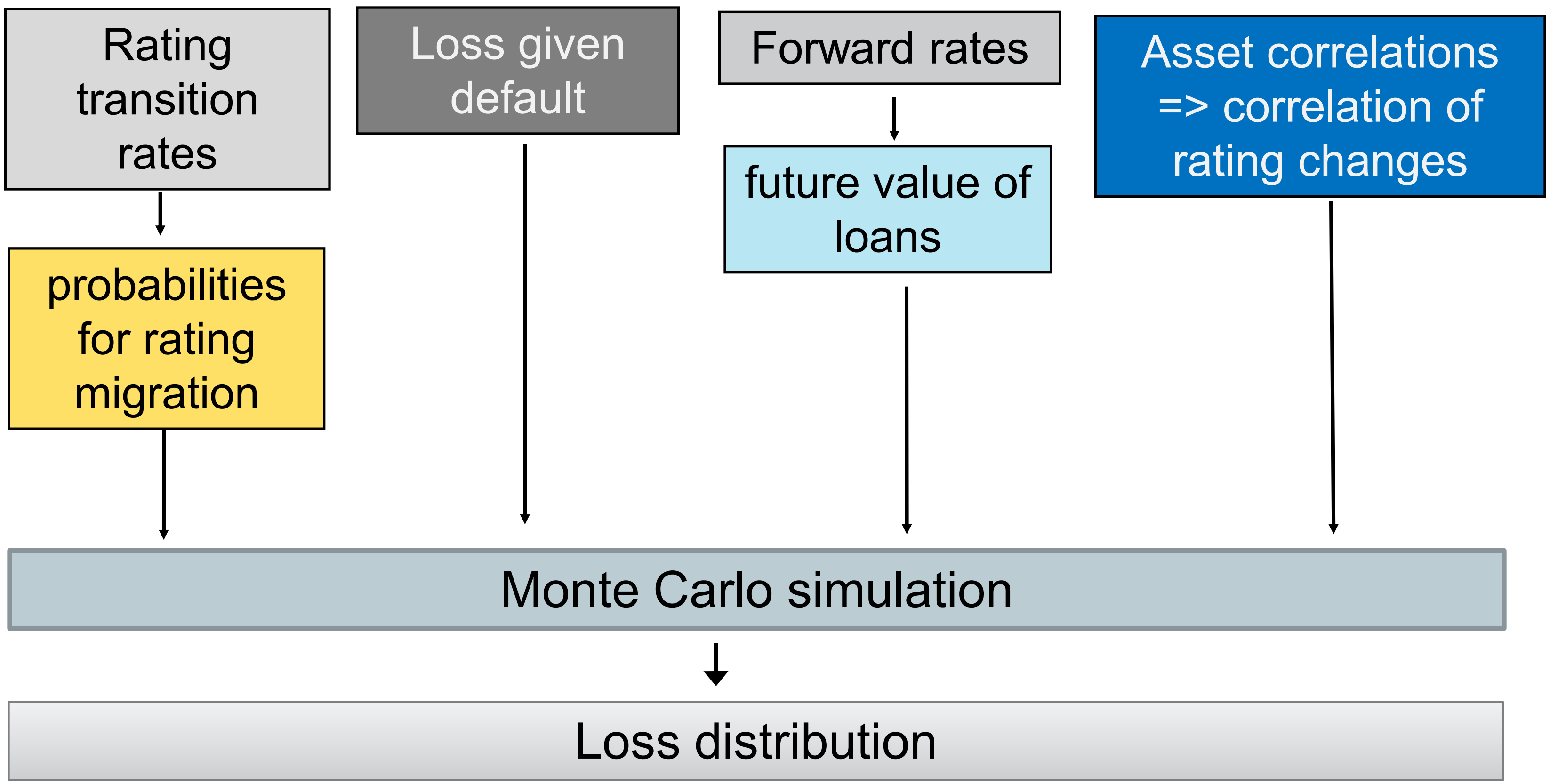
The Credit Metrics model ("standard" version)



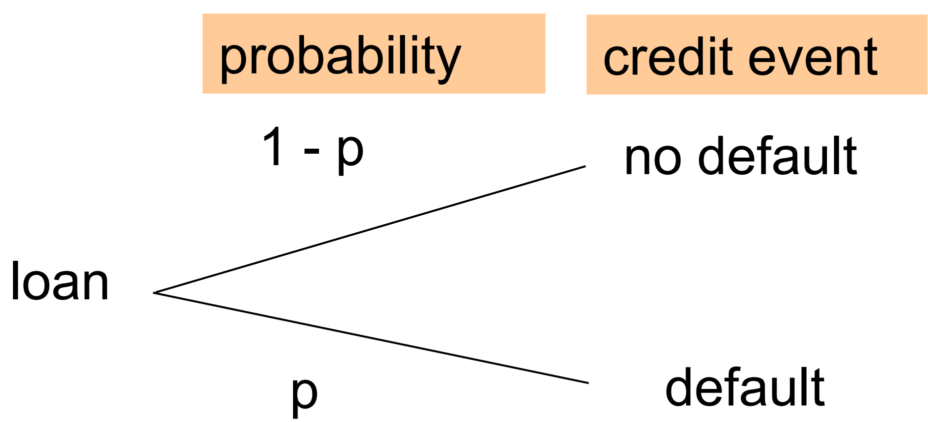
Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

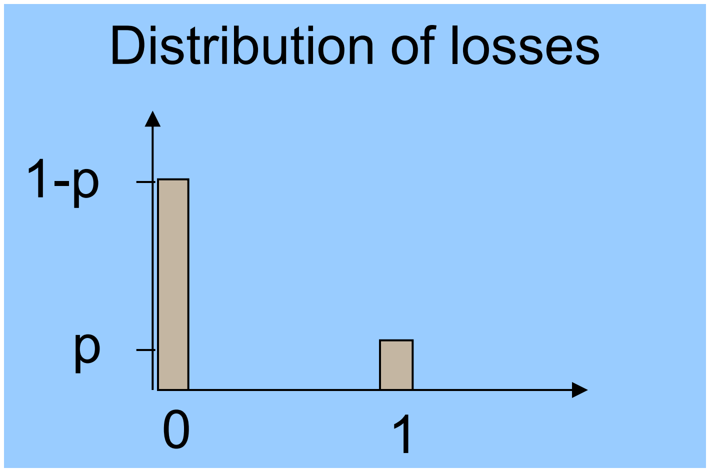
The logic behind portfolio credit risk models can best be understood by looking at simple portfolios

To keep matters simple:

- we neglect uncertainty about exposure at default
- we set the loss given default to 1
- there are only two possible states: default / no default
- we know the probabilities of default (p)

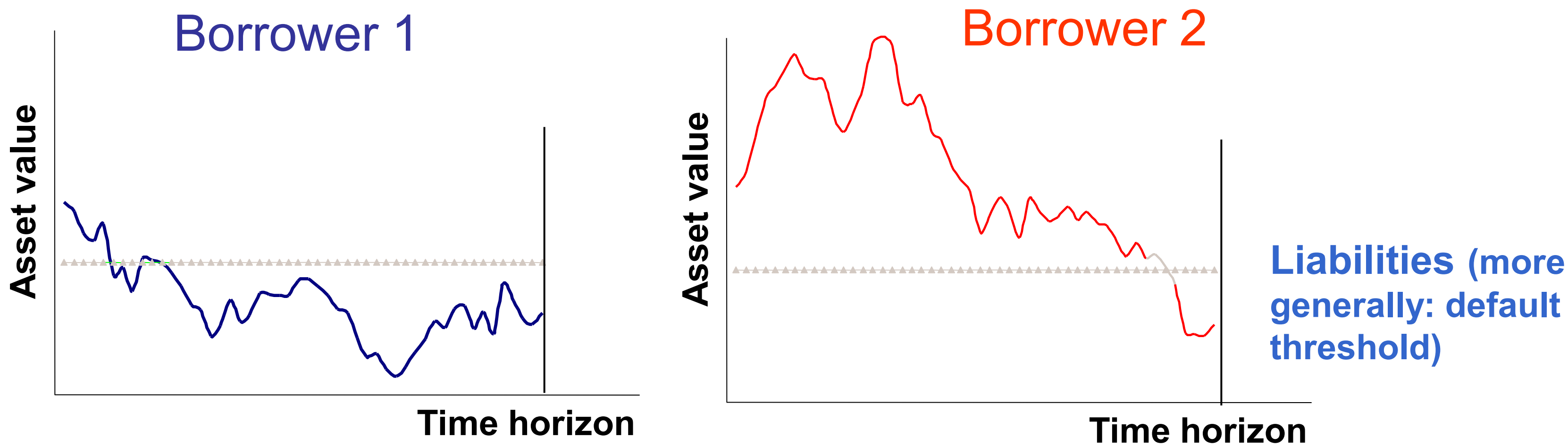
We start with a portfolio containing only one loan





Source: Loffler & Posch, “Credit Risk Modeling using Excel and VBA” , 2nd Ed. – Wiley Finance - 2011

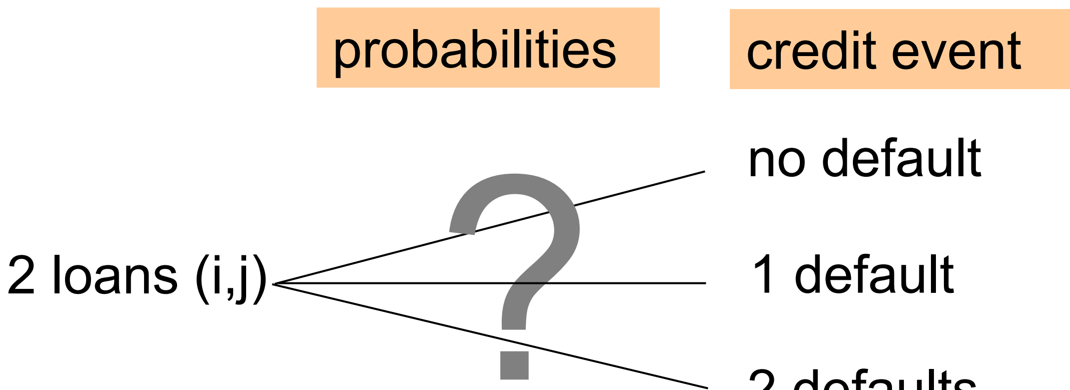
The Merton model provides a basis for modelling correlation of credit events

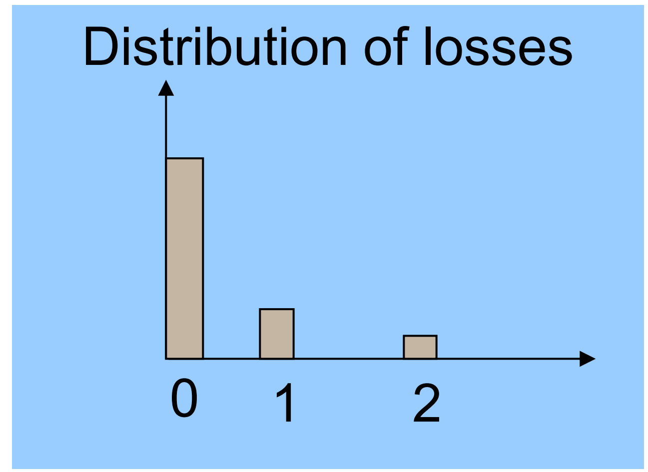


- Probability that both loans default = probability that asset values of both borrowers drop below the respective liabilities
- Within the Merton model, asset correlations directly translate into default correlations

Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

Already with a two-loan portfolio, we need to know more than individual default probabilities



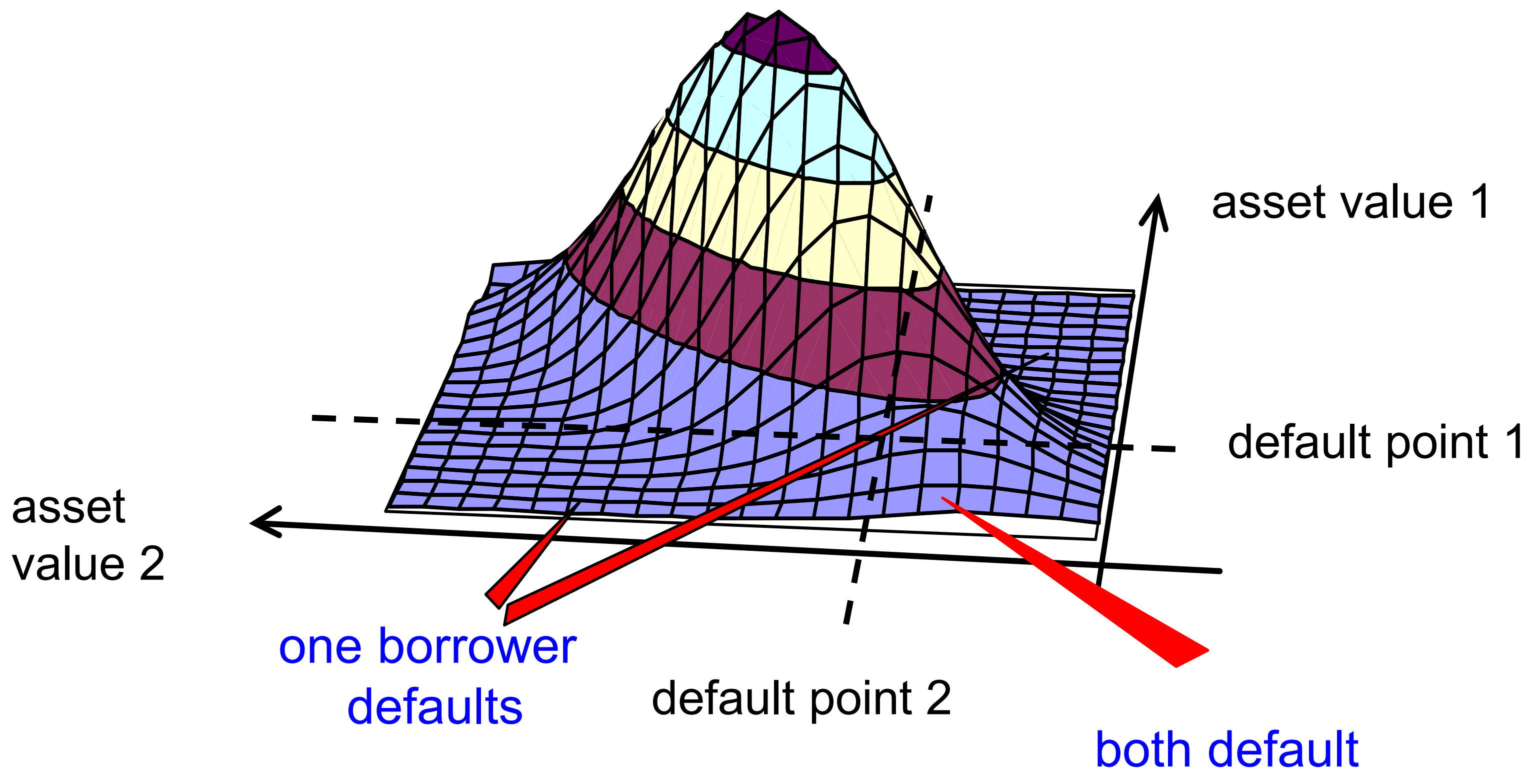


- The individual probabilities p_i and p_j are not sufficient to obtain the distribution of portfolio losses
- We need the probability that both loans default simultaneously *(easy only if defaults are independent: $p_{ij} = p_i p_j$)*

Source: Loffler & Posch, “Credit Risk Modeling using Excel and VBA” , 2nd Ed. – Wiley Finance - 2011

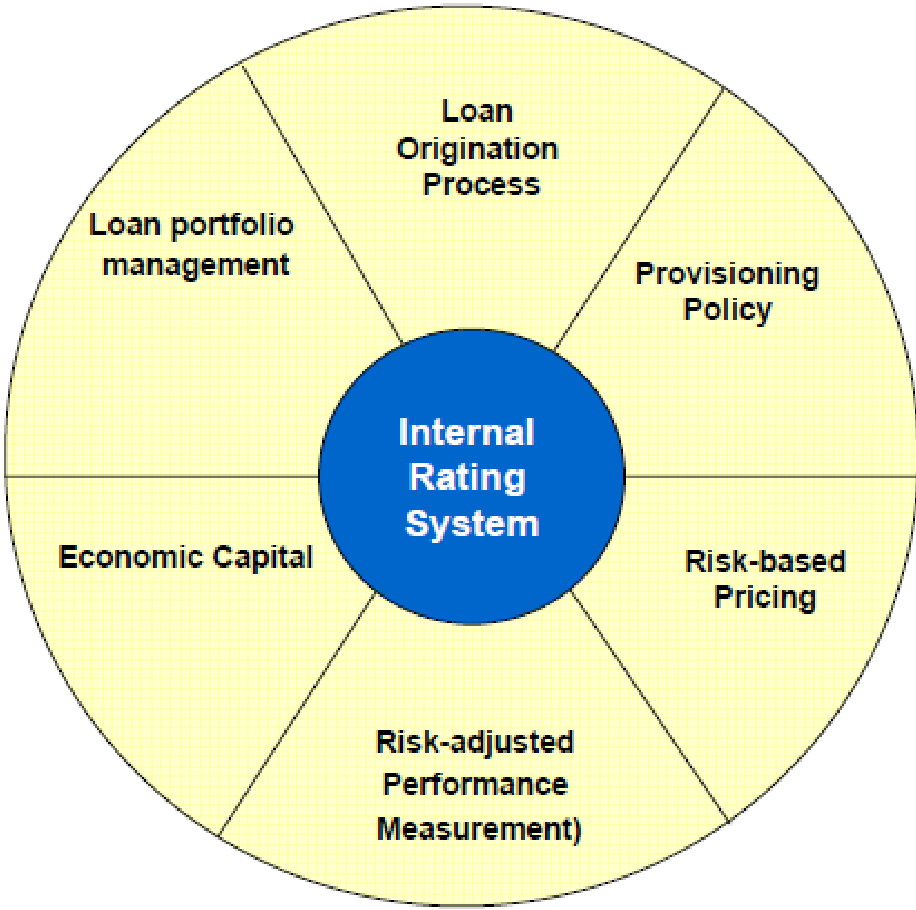
So we need to resort to joint default probabilities

Joint probability distribution of asset values of two borrowers



Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

Credit risk measurement & monitoring process with core Internal Rating Based (IRB) system



1. Internal rating	▪: PD ,LGD ,EAD Estimation
2. Loan origination	▪ Process of lending
3.EL based provision	▪ Reserve provision for the bad debt
4. Risk based pricing	▪ What factors should bank need to consider for the price of a loan
5. Risk adjusted performance measurement	Measuring the credit performance based on EP, RAROC
6. Economic capital	▪ **How to calculate the IRB Capital and economic capital**
7. Credit portfolio management	▪ Diversification and manage loan in a portfolio level

Source: Eric Kuo - "Sound Credit Risk Experience Sharing" – Vietnam FSA Presentation 2007

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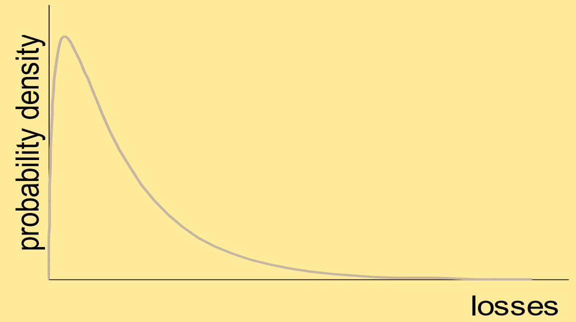
Portfolio credit risk models: Summary overview

- Portfolio credit risk is driven by:
  - probabilities of credit events
  - value effects of credit events
  - credit event correlations

- The output of a credit portfolio risk analysis is
  - a probability distribution for portfolio losses



Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

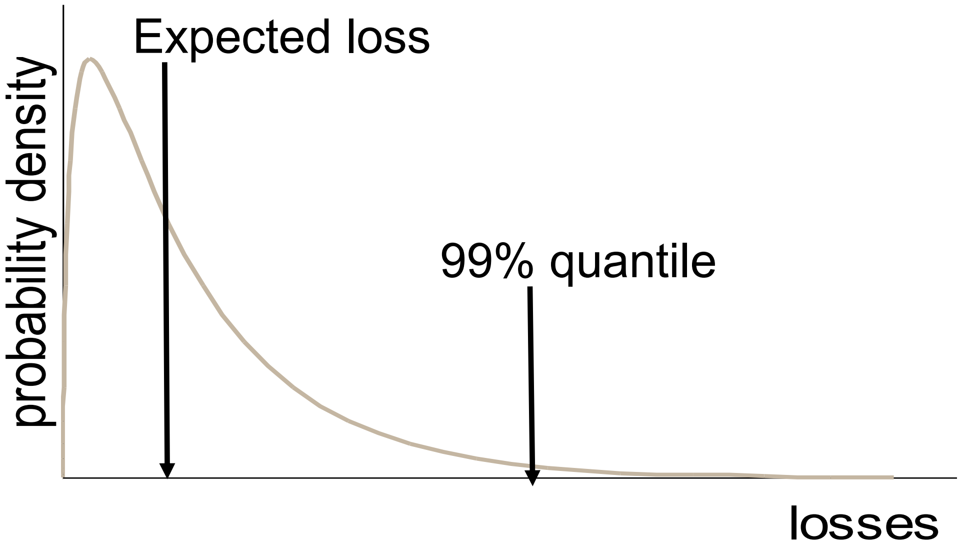
In modelling of asset correlations, the loss distribution is derived via Monte Carlo simulation

Simulation steps

1. Draw (correlated) random future asset value for each obligor
2. Check whether it falls below obligor-specific default point
3. Compute portfolio losses in scenario
4. Repeat steps 1. to 3. sufficiently often to derive loss distribution
5. Analyze loss distribution

Source: Loffler & Posch, “Credit Risk Modeling using Excel and VBA” , 2nd Ed. – Wiley Finance - 2011

The output of portfolio credit risk models is a distribution of portfolio losses



(time horizon: usually 1 year)

The portfolio distribution is usually described through

- expected loss
- α-quantiles: loss which exceeds α of all possible losses

  also called Value at Risk (VaR), economic capital, unexpected loss

Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

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How many scenarios?

The more extreme the quantiles we study, the more scenarios we need

Quick check of robustness after having conducted M scenarios

Compute statistics using only the first *m* scenarios

Check whether results are stable when approaching m=M

Today, 100,000+ scenarios are standard

Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

DEMO Deriving Credit Portfolio Risk Model

We can demonstrate the **Asset Value Approach** for measuring Credit Risk for a portfolio of loans (in this example just 100 loans). We need to simulate the Asset Values (using a normal distribution and uniform random number range) to derive estimated losses per loan, which can then in turn be summed across the portfolio and this is repeated many times, which help us derive percentile extreme values.

100 *loans Example*

Simulation specifications

\# trials: **1000**

Portfolio loss *(Single case only)*

$ 250

Run simsheet

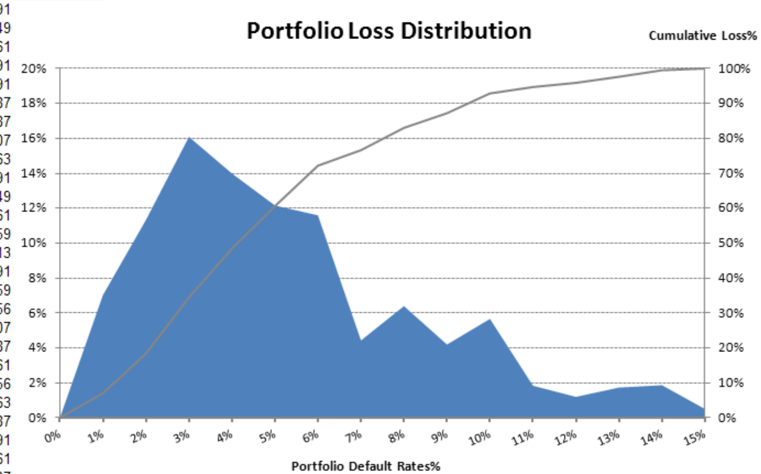
Simulated Loss Distribution Outputs

Confidence level	*Losses*	*Portfolio DR*
90.0%	$ 300.0	9.4%
95.0%	$ 400.0	11.2%
99.0%	$ 600.0	13.7%
99.9%	$ 700.0	14.9%

1000 iterations took 0 minutes and 3 seconds.

Portfolio Details / **Monte Carlo Simulation Inputs**

Loan ID	PD	LGD	EAD	w	d = NORMSINV(PD)	A = w * Z + (1 - w^2)^0.5 * NORMSINV(RAND())	Loss = IF(A < d, LGD * EAD, 0)	Factor Z = NORMSINV(RAND())	Scenarios	Number of Defaults	Default Rate	Normsinv (DR)	w (or rho) = VARP (DRt) / (1 + VARP(DRt))
1	1.0%	50.0%	$ 100	0.3	-2.33	0.68	$ -	-0.8833	$ 50.00	1	1.0%	-2.32634787	31.47%
2	1.0%	50.0%	$ 100	0.3	-2.33	0.50	$ -		$ 100.00	2	2.0%	-2.05374891	
3	1.0%	50.0%	$ 100	0.3	-2.33	-0.26	$ -		$ -	0	0.0%	-3.71901649	
4	1.0%	50.0%	$ 100	0.3	-2.33	0.11	$ -		$ 150.00	3	3.0%	-1.88079361	
5	1.0%	50.0%	$ 100	0.3	-2.33	-1.73	$ -		$ 100.00	2	2.0%	-2.05374891	
6	1.0%	50.0%	$ 100	0.3	-2.33	1.36	$ -		$ 100.00	2	2.0%	-2.05374891	
7	1.0%	50.0%	$ 100	0.3	-2.33	-0.41	$ -		$ 50.00	1	1.0%	-2.32634787	
8	1.0%	50.0%	$ 100	0.3	-2.33	0.62	$ -		$ 50.00	1	1.0%	-2.32634787	
9	1.0%	50.0%	$ 100	0.3	-2.33	-1.55	$ -		$ 200.00	4	4.0%	-1.75068607	
10	1.0%	50.0%	$ 100	0.3	-2.33	-1.02	$ -		$ 250.00	5	5.0%	-1.64485363	
11	1.0%	50.0%	$ 100	0.3	-2.33	-0.87	$ -		$ 100.00	2	2.0%	-2.05374891	
12	1.0%	50.0%	$ 100	0.3	-2.33	-0.64	$ -		$ -	0	0.0%	-3.71901649	
13	1.0%	50.0%	$ 100	0.3	-2.33	-0.40	$ -		$ 150.00	3	3.0%	-1.88079361	
14	1.0%	50.0%	$ 100	0.3	-2.33	-0.88	$ -		$ 300.00	6	6.0%	-1.55477359	
15	1.0%	50.0%	$ 100	0.3	-2.33	-0.39	$ -		$ 650.00	13	13.0%	-1.12639113	
16	1.0%	50.0%	$ 100	0.3	-2.33	-1.41	$ -		$ 100.00	2	2.0%	-2.05374891	
17	1.0%	50.0%	$ 100	0.3	-2.33	-0.17	$ -		$ 300.00	6	6.0%	-1.55477359	
18	1.0%	50.0%	$ 100	0.3	-2.33	0.48	$ -		$ 400.00	8	8.0%	-1.40507156	
19	1.0%	50.0%	$ 100	0.3	-2.33	0.48	$ -		$ 200.00	4	4.0%	-1.75068607	
20	1.0%	50.0%	$ 100	0.3	-2.33	-1.03	$ -		$ 50.00	1	1.0%	-2.32634787	
21	1.0%	50.0%	$ 100	0.3	-2.33	-1.00	$ -		$ 150.00	3	3.0%	-1.88079361	
22	1.0%	50.0%	$ 100	0.3	-2.33	1.67	$ -		$ 400.00	8	8.0%	-1.40507156	
23	1.0%	50.0%	$ 100	0.3	-2.33	0.26	$ -		$ 250.00	5	5.0%	-1.64485363	
24	1.0%	50.0%	$ 100	0.3	-2.33	0.81	$ -		$ 50.00	1	1.0%	-2.32634787	
25	1.0%	50.0%	$ 100	0.3	-2.33	-0.35	$ -		$ 100.00	2	2.0%	-2.05374891	
26	1.0%	50.0%	$ 100	0.3	-2.33	-1.23	$ -		$ 150.00	3	3.0%	-1.88079361	
27	1.0%	50.0%	$ 100	0.3	-2.33	0.52	$ -		$ 200.00	4	4.0%	-1.75068607	
28	1.0%	50.0%	$ 100	0.3	-2.33	1.36	$ -		$ 350.00	7	7.0%	-1.47579103	
29	1.0%	50.0%	$ 100	0.3	-2.33	0.89	$ -		$ 150.00	3	3.0%	-1.88079361	
30	1.0%	50.0%	$ 100	0.3	-2.33	-1.07	$ -		$ 100.00	2	2.0%	-2.05374891	
31	1.0%	50.0%	$ 100	0.3	-2.33	-1.20	$ -		$ 50.00	1	1.0%	-2.32634787	



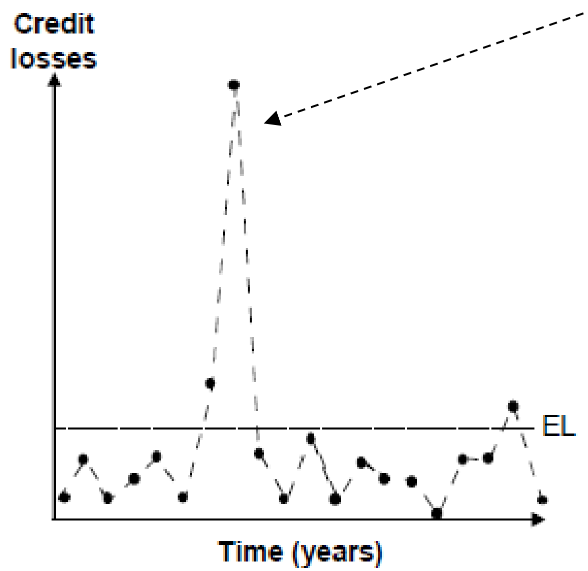
Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

Typical Applications of a Credit Model

- Provisioning
- RAROC
- Pricing-for-risk
- Low Default Probability Estimation

Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

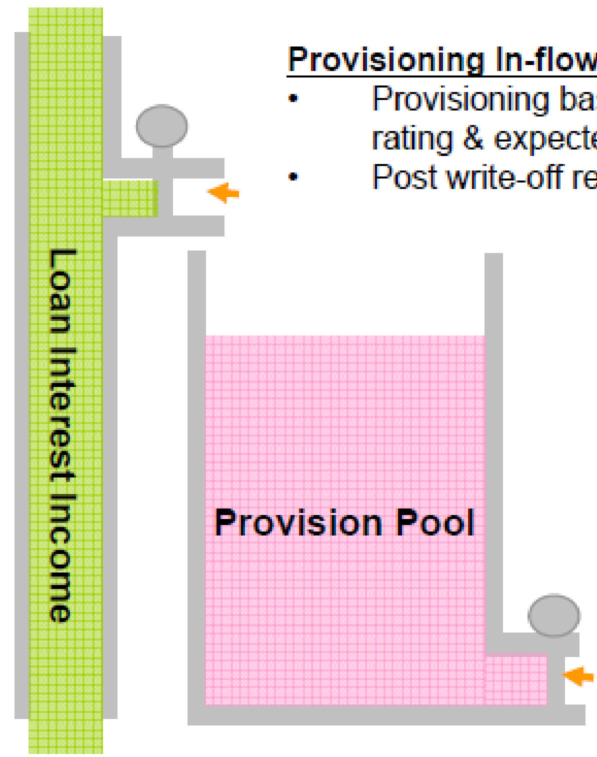
EL estimates can provide an average loss requirement over time that covers most loss situations (...but not the unexpected losses)



Expected Loss (EL)

- Anticipated average annual loss rate
- Foreseeable 'cost' of doing business
- Equal to the mean (average) of losses over an economic cycle
- Anti- economic cycle
- Avoid the dilemma over heavily increase provisioning in bad years
- Reduce the volatility of income statement

Risk-based Provisioning – EL Approach



Provisioning In-flow

- Provisioning based on risk rating & expected loss
- Post write-off recovery

Provisioning Out-flow

Bad loan write-off

Source: Eric Kuo - "Sound Credit Risk Experience Sharing" – Vietnam FSA Presentation 2007

Risk Based Provisioning Framework

Risk-based Provision Ratio – Corporate Banking

		LGD											
		0	1A	1B	2	3	4	5	6	7	8	9	10
	PD	**0.00%**	**2.50%**	**7.50%**	**15%**	**25%**	**35%**	**45%**	**55%**	**65%**	**75%**	**85%**	**95%**
1	0.03%	0.00%	0.00%	0.00%	0.00%	0.01%	0.01%	0.01%	0.02%	0.02%	0.02%	0.03%	0.03%
2	0.10%	0.00%	0.00%	0.01%	0.02%	0.03%	0.04%	0.05%	0.06%	0.07%	0.08%	0.09%	0.10%
3	0.16%	0.00%	0.00%	0.01%	0.02%	0.04%	0.06%	0.07%	0.09%	0.10%	0.12%	0.14%	0.15%
4	0.26%	0.00%	0.01%	0.02%	0.04%	0.07%	0.09%	0.12%	0.14%	0.17%	0.20%	0.22%	0.25%
5	0.42%	0.00%	0.01%	0.03%	0.06%	0.11%	0.15%	0.19%	0.23%	0.27%	0.32%	0.36%	0.40%
6	0.61%	0.00%	0.02%	0.05%	0.09%	0.15%	0.21%	0.27%	0.34%	0.40%	0.46%	0.52%	0.58%
7	0.90%	0.00%	0.02%	0.07%	0.14%	0.23%	0.32%	0.41%	0.50%	0.59%	0.68%	0.77%	0.86%
8	1.35%	0.00%	0.03%	0.10%	0.20%	0.34%	0.47%	0.61%	0.74%	0.88%	1.01%	1.15%	1.28%
9	2.04%	0.00%	0.05%	0.15%	0.31%	0.51%	0.71%	0.92%	1.12%	1.33%	1.53%	1.73%	1.94%
10	3.15%	0.00%	0.08%	0.24%	0.47%	0.79%	1.10%	1.42%	1.73%	2.05%	2.36%	2.68%	2.99%
11	4.93%	0.00%	0.12%	0.37%	0.74%	1.23%	1.73%	2.22%	2.71%	3.20%	3.70%	4.19%	4.68%
12	7.82%	0.00%	0.20%	0.59%	1.17%	1.96%	2.74%	3.52%	4.30%	5.08%	5.87%	6.65%	7.43%
13	12.61%	0.00%	0.32%	0.95%	1.89%	3.15%	4.41%	5.67%	6.94%	8.20%	9.46%	10.72%	11.98%

Source: Eric Kuo - "Sound Credit Risk Experience Sharing" – Vietnam FSA Presentation 2007

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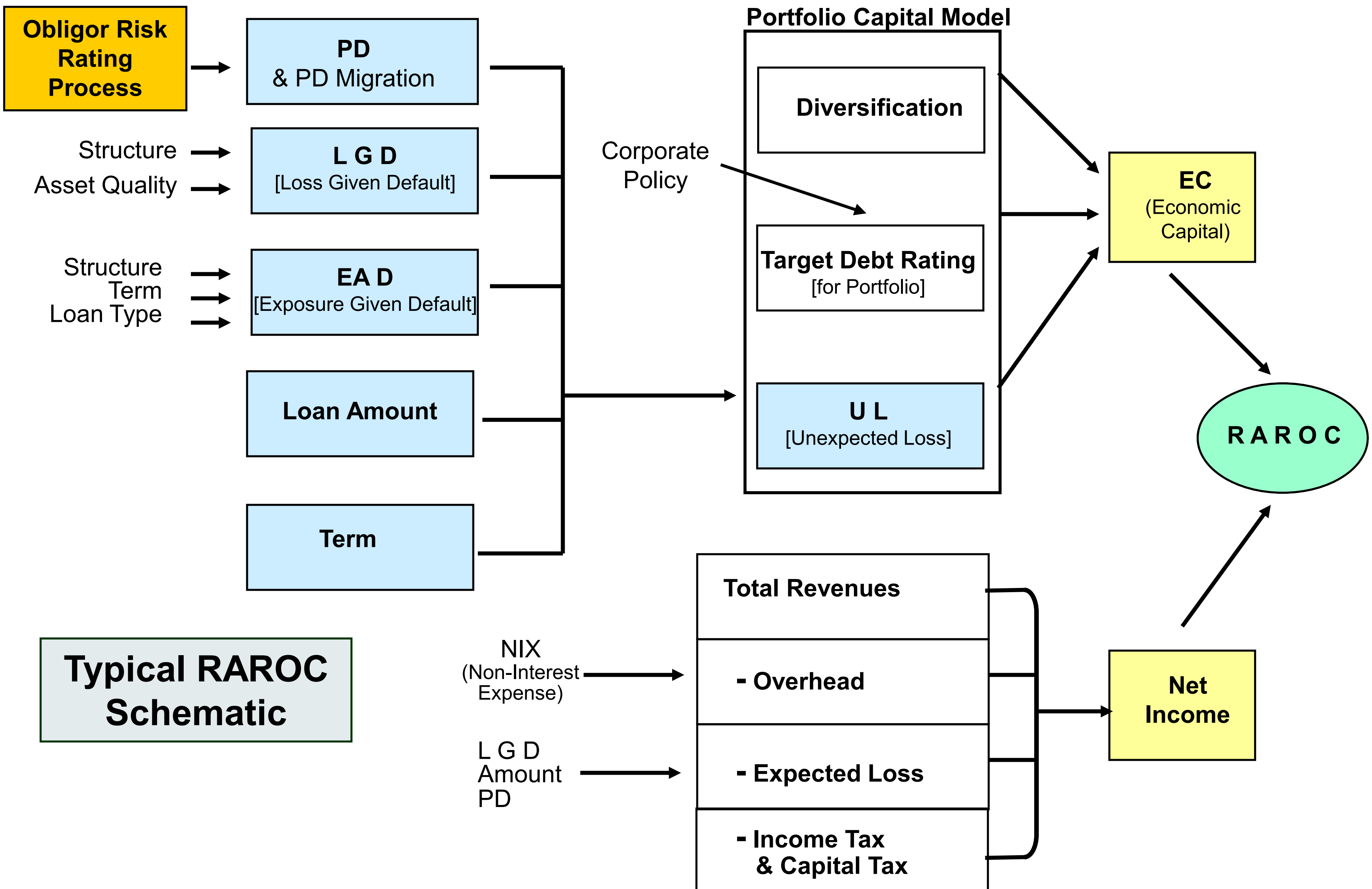
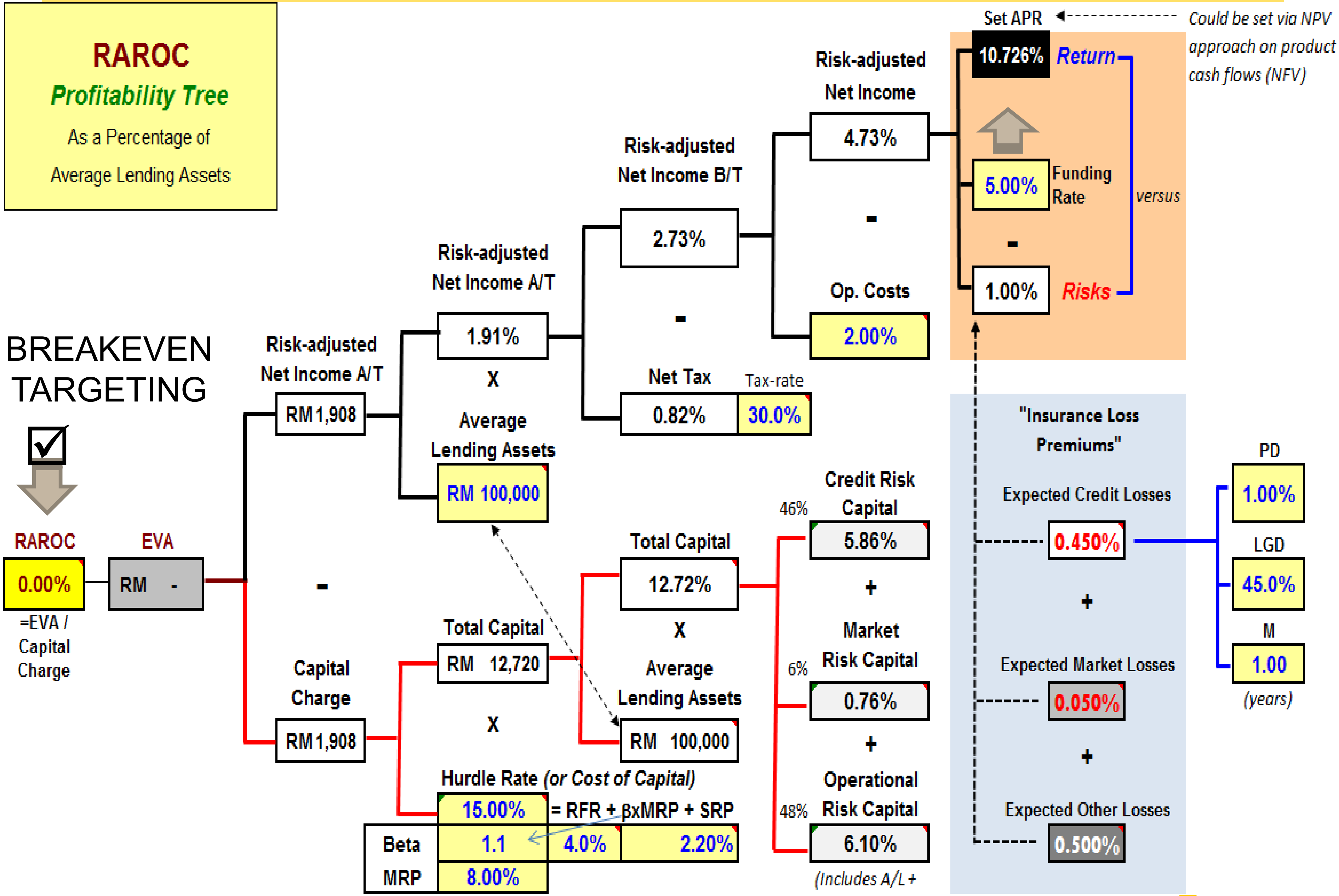
Overview of Typical RAROC Model



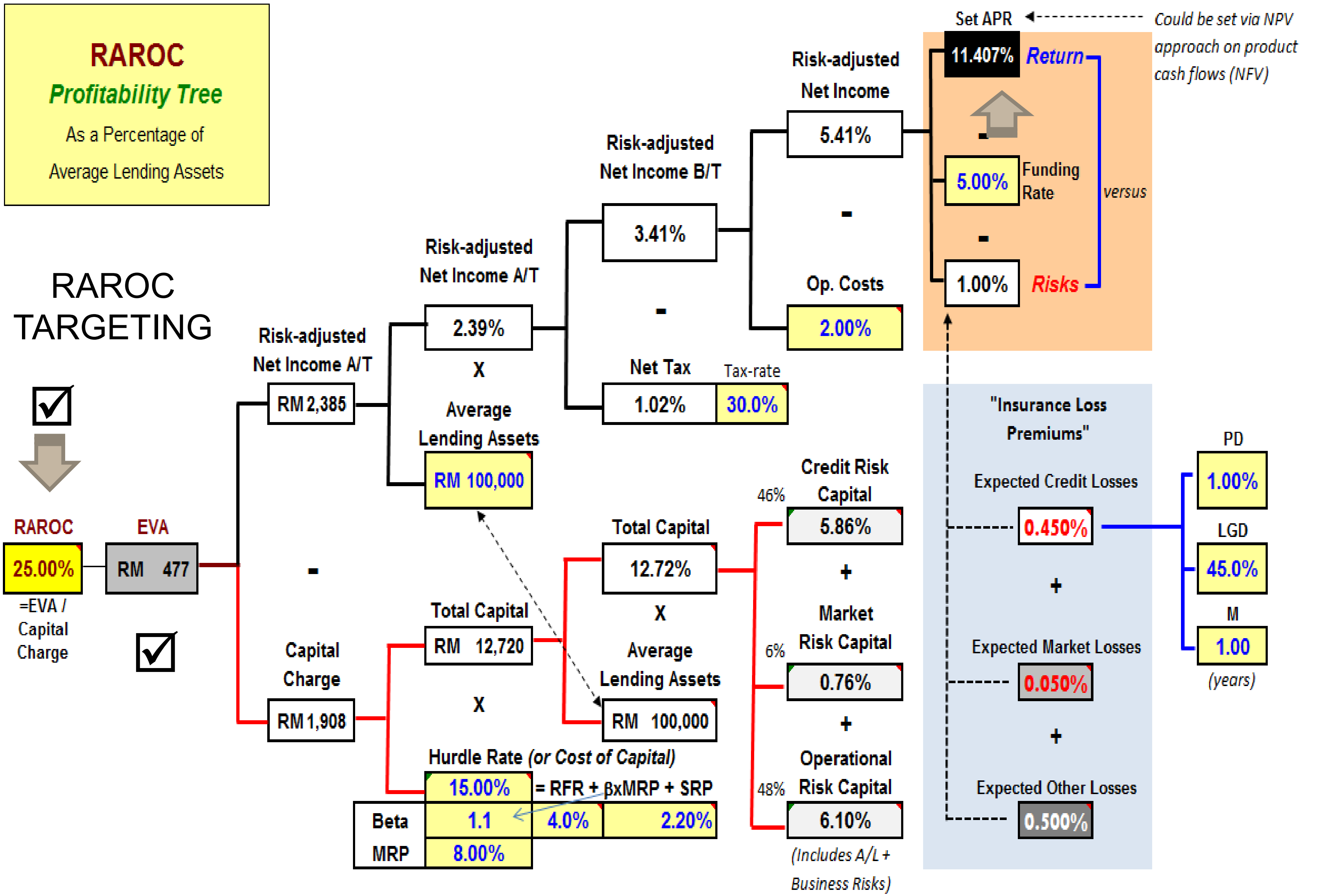
Source: Loffler & Posch, "Credit Risk Modeling using Excel and VBA" , 2nd Ed. – Wiley Finance - 2011

The RAROC 'Tree' melds many concepts together…



Created by Author

The RAROC Tree' melds many concepts together…



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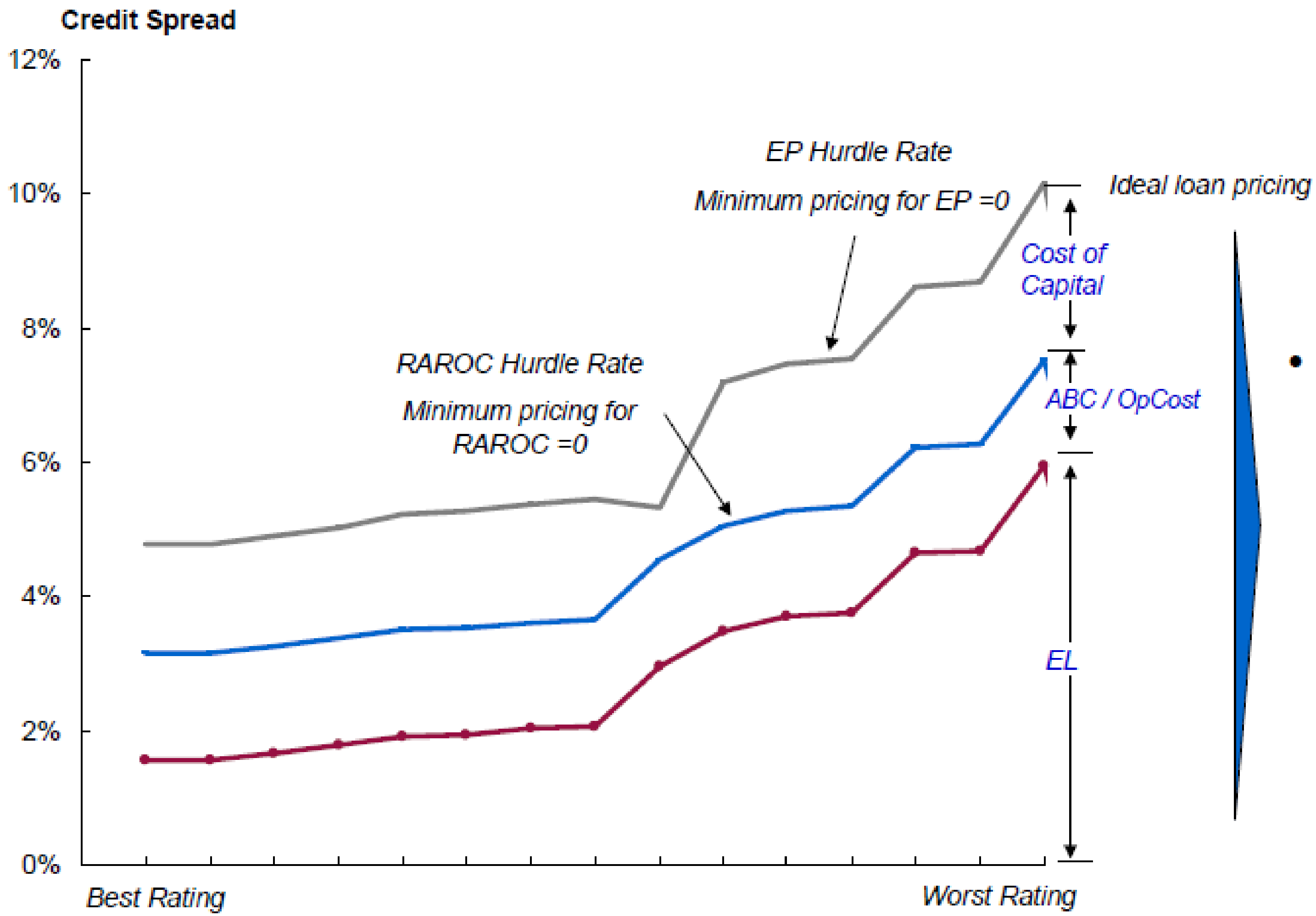
Minimum loan pricing needs to entail at least the cost of capital, operating costs and expected loss 'premium' across risk grades thus generating a spread of potential prices



Source: Eric Kuo - "Sound Credit Risk Experience Sharing" – Vietnam FSA Presentation 2007

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THANK YOU

For further information or discussion on this topic then please contact Dr Maurice Joseph (MauriceJoseph@hotmail.com)

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