AN OVERVIEW OF CREDIT RISK MODELLING

Outline

- What is a credit risk model?
- Where do models fit in the scheme of credit risk management?
- Modelling approaches to the data inputs
- Modelling approaches to calculating Portfolio Credit Risk
- A Caveat - focus will be on the styles and methodologies rather than the vendors

A Credit Risk Model is …..

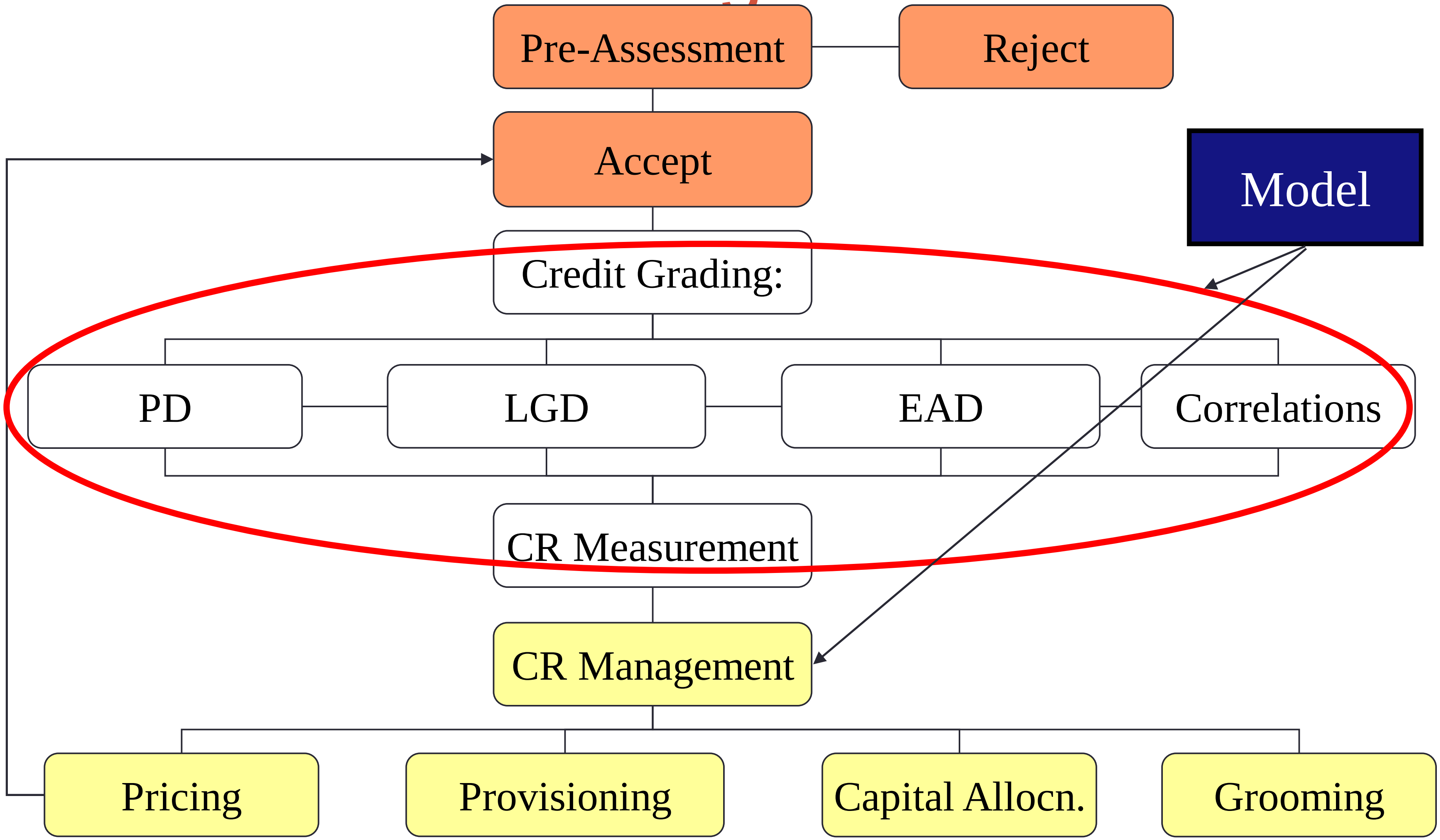
A set of procedures for:

- Measuring credit risk
- Managing credit risk

Model may be:

- Statistical or non-statistical
- Comprehensive or specialised

The Credit Management Process



Challenges for Modellers & Users

- How can we estimate/calculate PD, LGD and EAD?
- How should we estimate correlations?
- What is the appropriate time horizon?
- How should we combine the information to measure portfolio risk?
- How can we use the model to price loans?
- How can we use the model to manage risk?
- How can we use the model to manage capital?
- How can we use the model to measure performance?
- How do we know that it is a good model?
- Are there other/better models?

No Truly Universal Models - Yet

- Most credit modellers stake out a niche in the market
- Cost of providing everything is too high
- Many banks to prefer to build their own model - using inputs such as PD and LGD from external providers
- Some models best known for one component
- No universal provider

Focus Areas

A. Data inputs/credit grading:

- Default probabilities*
- Loss given default
- Exposure at default
- Correlations

B. Portfolio Analysis:

- Default mode Vs Mark-to-market*
- Conditional Vs unconditional

A. Data Inputs to Credit Grading

1. Loss given default
2. Exposure at default
3. Correlations
4. Default probabilities - most differences of opinion (so do it last)

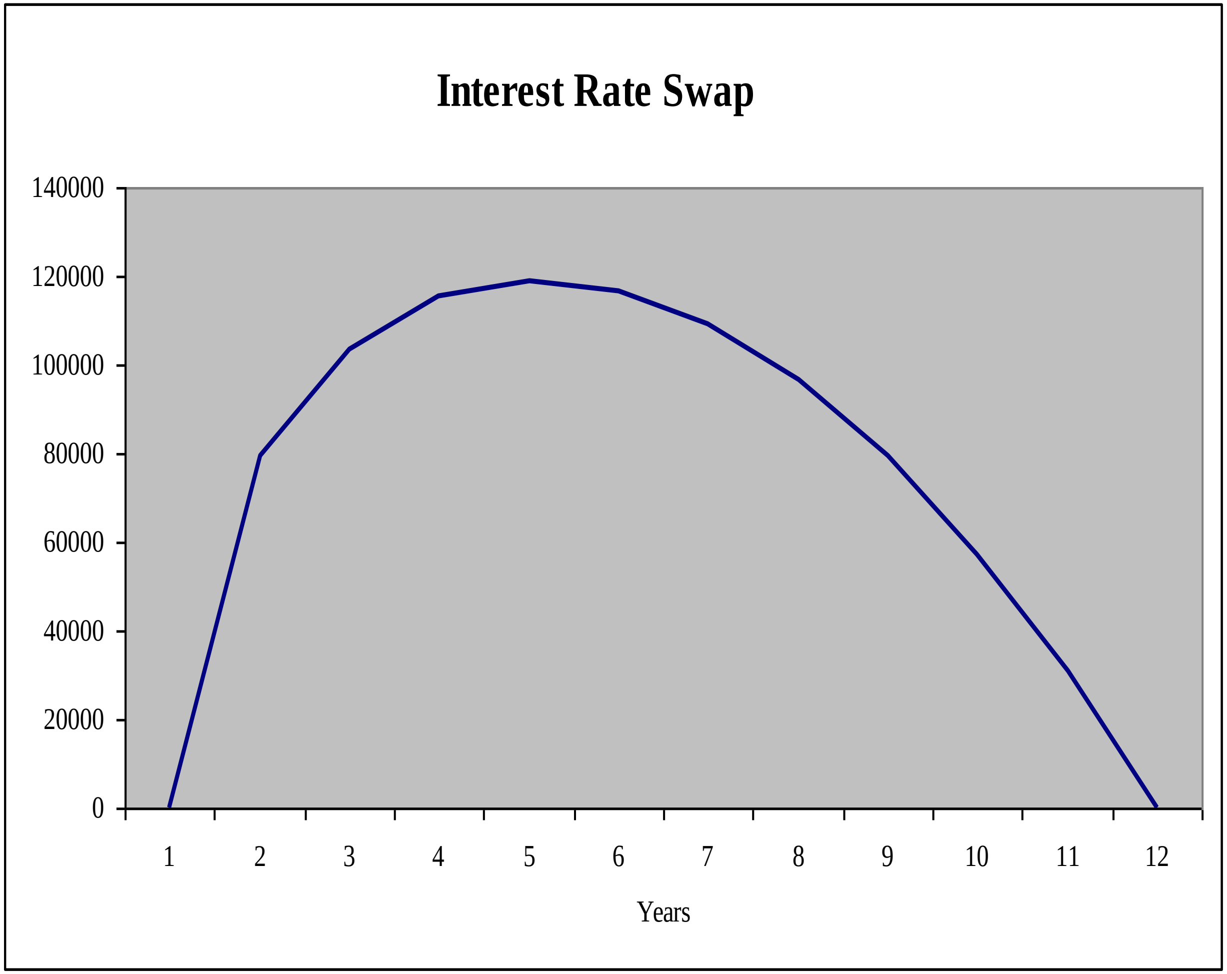
1. Loss Given Default

- LGD is largely an empirical issue
- Most models use common estimates of LGD
- Primary determinant of recoveries is seniority
- Collateral is relevant
- Data need to be country specific
- Area where banks need to develop their own data
- LGD should be stochastic

2. Calculating EAD

- EAD is a computational challenge
- The model for EAD should be facility specific e.g.:
  - Fully drawn lines
  - Secured loans
  - Undrawn lines
  - Derivatives, guarantees and other off balance sheet items

e.g. EAD of an Interest Rate Swap



e.g. 10-year IRS paying floating & receiving fixed @ 5%

- Principal \$1m
- Annual i vol. is ±50 bps
- Confidence level = 97.5%
- EAD is the market value of the swap (close out value) at each date

3. Correlations

- Conceptually should be straightforward
- Problem - exposures are to obligors, while correlation data only exist in terms of industries
- Problem compounded since obligors often operate in multiple industries - and countries
- Hence there is a modelling issue to resolve

Estimating Correlations - Alternative Approaches

- Assume fixed correlations across all industries
- Use equity prices to estimate correlations
- Third approach is to use index correlations at an aggregated level and map these to the firm’s composition

4. Models that Calculate PD

- Most basic input to credit grading
- Most widely used and best known “models”
- Many banks buy PD estimates from commercial vendors
- Approaches:
    - Traditional (accounting & historical data)
    - Modern (market data):
        - Structural
        - Reduced form

Traditional Approach to PDs

- Focus on historical accounting data
- Purely empirical approach uses historical default rates of different credit gradings (e.g. Moody's and S&P's)
- The traditional modelling approach attempts to identify the characteristics of defaulting firms
- First serious attempt usually attributed to Altman (late '60s) who used Discriminant analysis (Z scores)
- Scoring models have stood up well over time and are still used - especially in low-value, high-volume lending
- Later models have used Logit, Probit and ANNs

Modern Approach to PDs

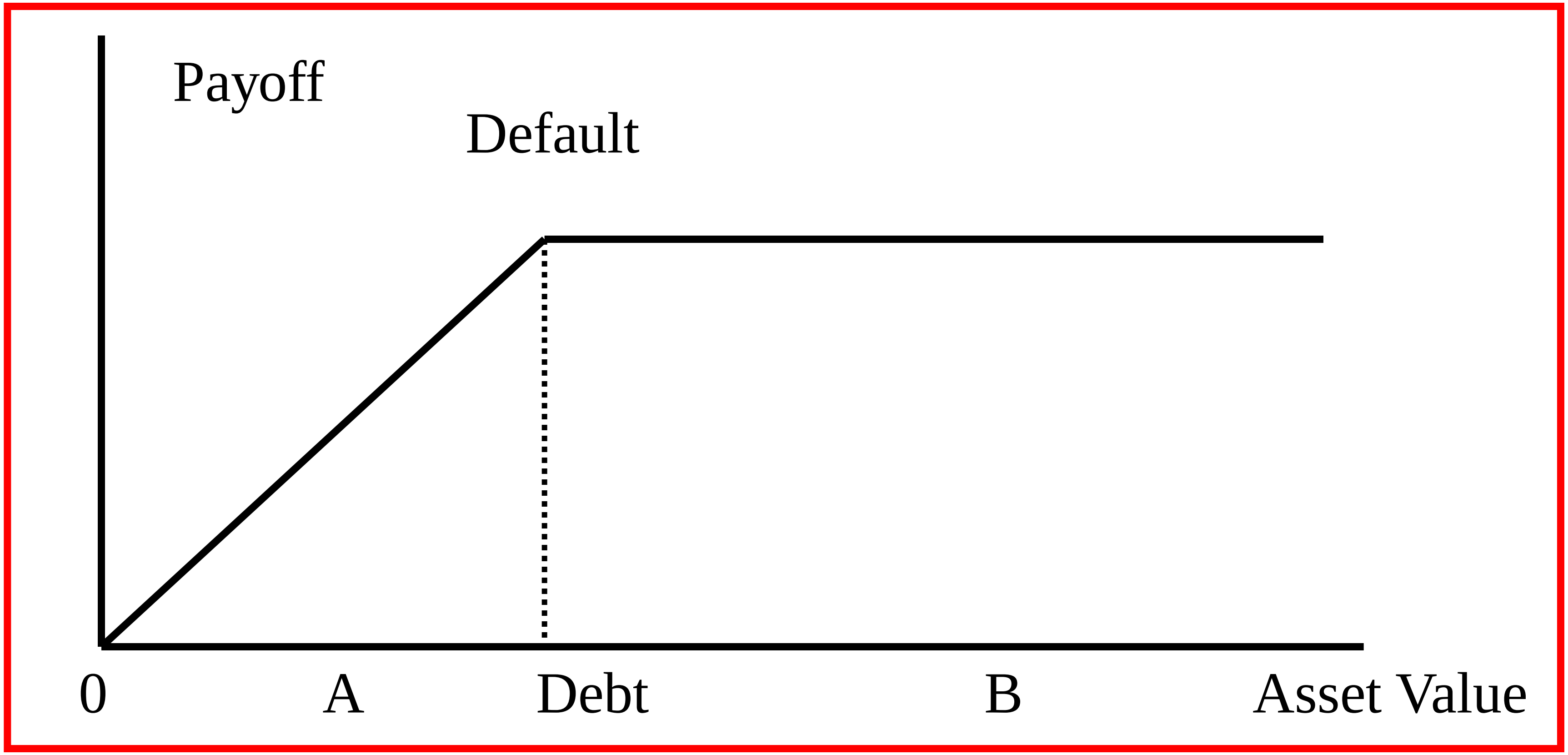
- Use current market data about debt and/or equity to “back out” a market measure of PD
- Structural Models:
  - Predict the likelihood of default occurring over a given time horizon based on market data and an economic explanation of the default process (e.g. KMV, RiskMetrics)
- Reduced Form Models:
  - Use market information about credit spreads to extract default probabilities - they measure PD but give no explanation (e.g. Kamakura, KPMG)

The Option Theoretic Approach

- The best known of the modern structural approaches to estimating PDs is the option theoretic approach (Merton 1974)
- Used by KMV, Moody's, RiskMetrics and others
- Basic concept recognises that a corporate bond is essentially a "sold" put option issued by the equity holders over the assets of the firm

Debt and Optionality

- Payoff function for a bond-holder is same as that for issuer of a put option - this links debt value and PD



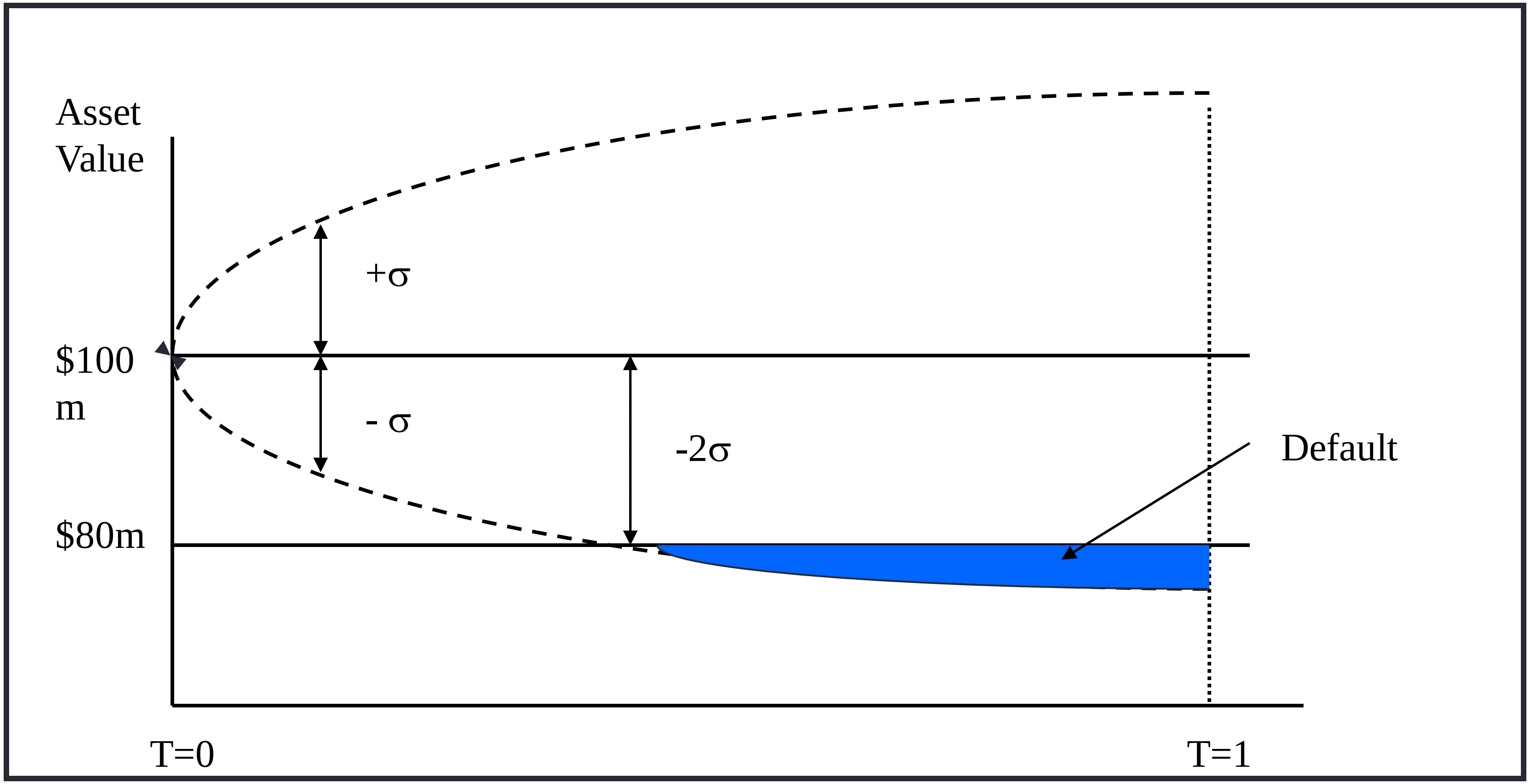
Simplified e.g. - Calculating PD

- Current asset Value A = \$100m
- Debt value in 1 year D = \$80 m (using option model)
- Asset value volatility σ_A = \$10 m (1-year)
- Calculate the "Distance to Default" (in units of Standard Deviations) as:

$$\boxed{DD = \frac{A - D}{\sigma_A} = \frac{\$100m - \$80m}{\$10m} = 2}$$

The Stochastic Process

- If asset values are normal, there is a 2.5% chance that A will fall by more than 2 SD, hence PD = 2.5%



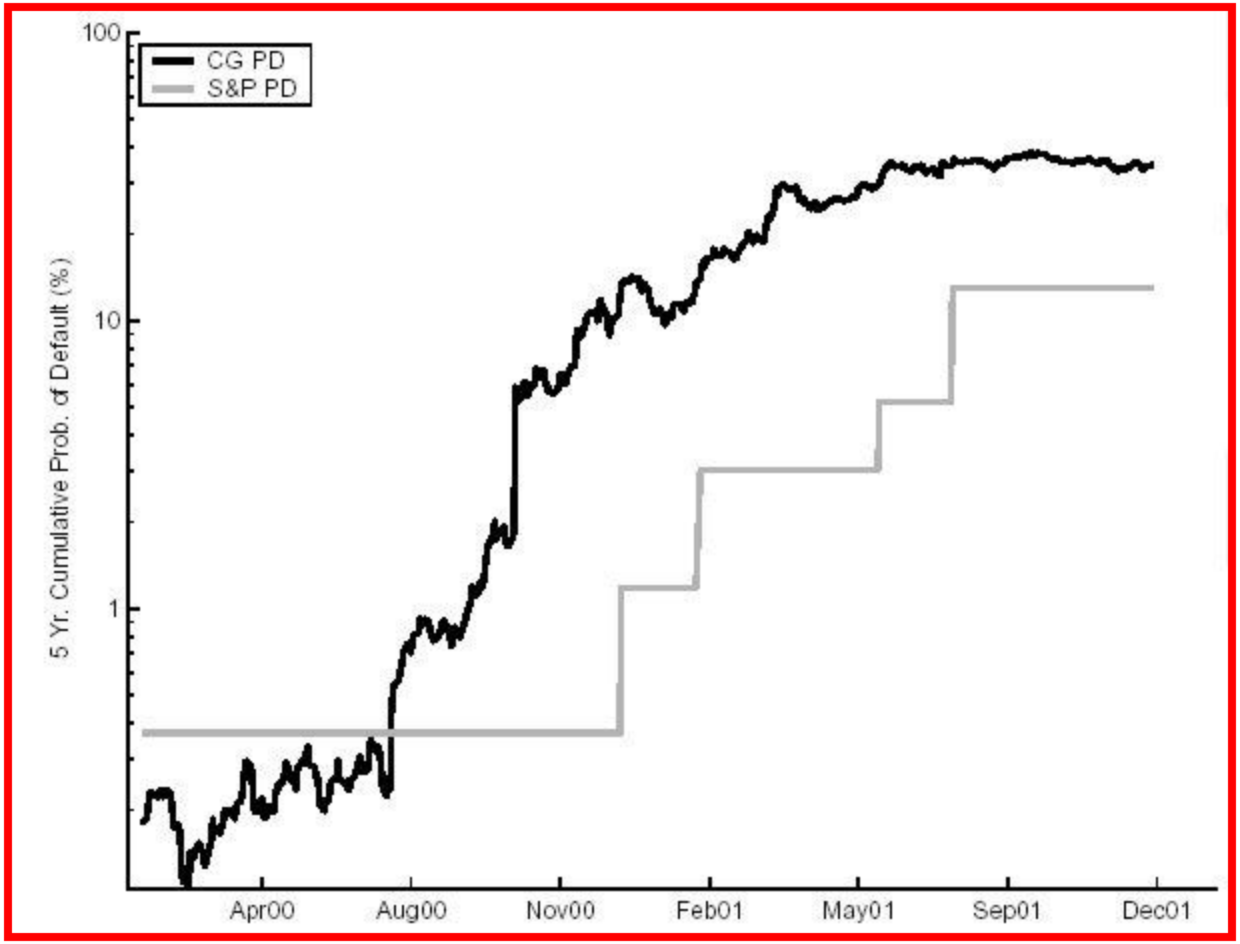
Alternative Structural Approaches

- RiskMetrics uses this approach (with some sophisticated wrinkles including stochastic default) to back-out "theoretical" PDs as RiskGrades
- KMV compare the theoretical default rates from a model like this with their proprietary database of actual defaults
- Given a theoretical PD they then look at how many firms with that same PD actually defaulted over the time horizon

Empirical Performance

- The ultimate test of these alternative approaches is how they perform empirically
- Evidence suggests they generally outperform ratings agencies such as Moody's and S&P's - not surprising given that they are amenable to continuous updates from market prices
- The following are some RiskMetrics examples

Lucent Technologies



Enron


100
10
1
CG PD
S&P PD
5 Yr. Cumulative Prob. of Default (%)
Mar99
Jun99
Oct99
Jan00
Apr00
Aug00
Nov00
Feb01
May01
Sep01
Dec01

Structural Models - Strengths and Weaknesses

- Structural models are well based in theory
- Can be updated rapidly as markets move
- But only as smart as markets
- KMV is very dependent on its proprietary database
- KMV is also a “black box”
- CreditGrades more transparent but less empirical accuracy
- In general these models don’t handle jumps well

Reduced Form Models

- Structural models use:
  - Information embedded in equity prices and/or accounting data, plus
  - Economic theory of default and firm's value

  To solve for default probabilities
- Reduced form models offer no economic causality
- They simply recognize that risk premia should be evident in market prices and solve backwards for implied default probabilities

Risk-Neutral Pricing

- Underlying assumption of reduced form PD models is risk-neutral pricing
- Essence of risk-neutral pricing is that: risky investments should offer same ***expected*** return as risk-free investment
- Essentially the same “trick” used by Black and Scholes in solving the “unsolvable” option pricing problem 30+ years ago

Role of Risk Neutral Pricing

- Risk neutral pricing basically asserts that the value of a risky loan today (its face value discounted at its risk-adjusted discount rate) is equal to its expected value in the future discounted at the risk-free rate
- E.g. for a $100 face value in 1 year:

$$V_t = \frac{100}{1+r} = \frac{E[V_{t+1}]}{1+f}$$

$$where$$

$$E[V_{t+1}] = 100(1-PD) + 100.PD(1-LGD)$$

Thus Prices Imply PDs

- From this simple relationship we can derive:

$$\boxed{PD = \frac{1 - \dfrac{1+f}{1+r}}{LGD}}$$

- Thus observed risky rates, *r*, and risk-free rates, *f*, imply PDs
- Even better, observing the term structures of *f* and *r* provides estimates of future PDs for different periods
- The catch is that PD is not uniquely determined unless we also know LGD – this is where models differ – constant LGD, stochastic PD etc

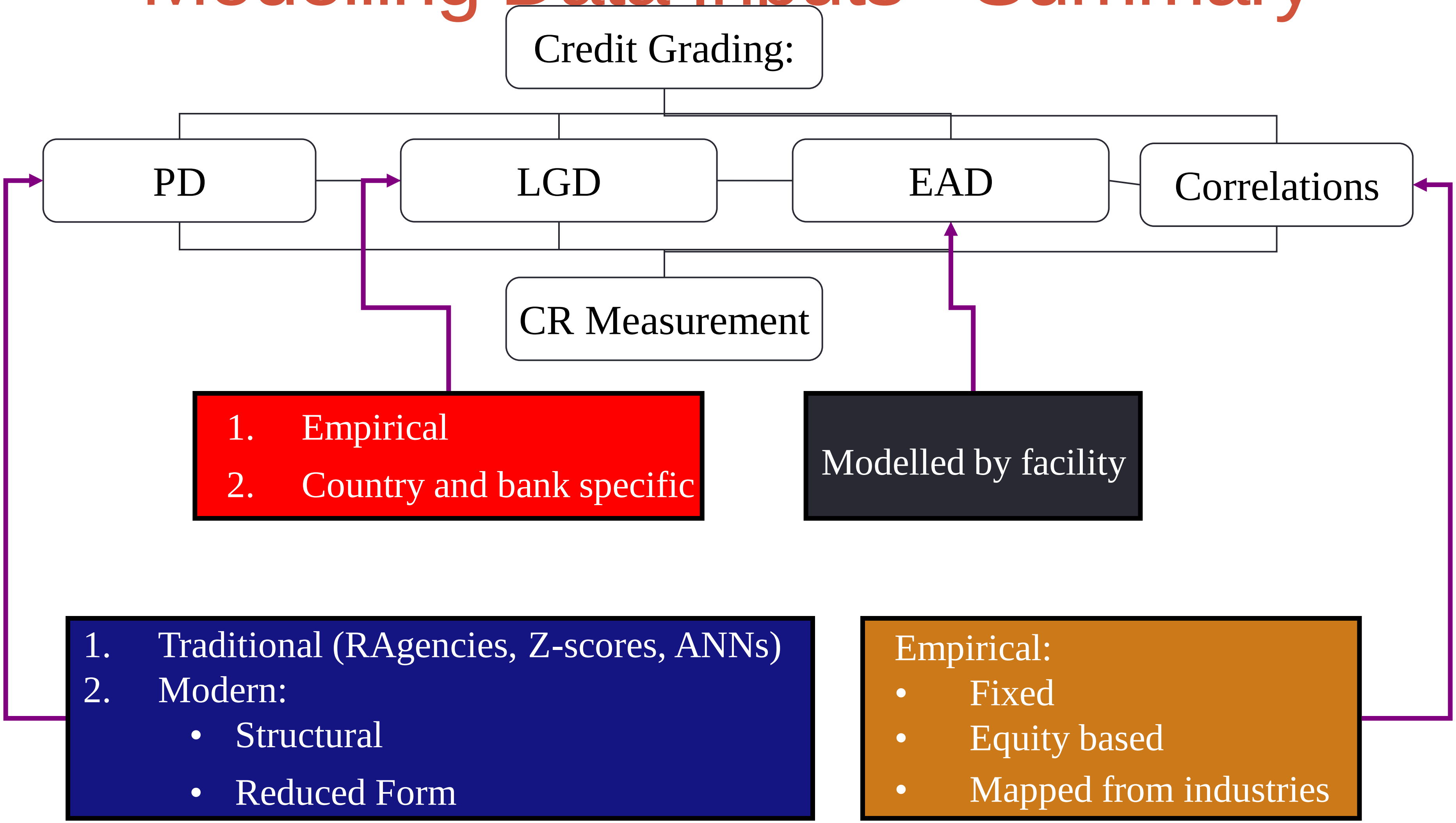
Other Determinants of Credit Spreads

- Even ignoring the identification problem, the reliance on credit spread data to imply PD and/or LGD requires that they are the dominant determinants of spreads
- In practice, bond spreads also influenced by:
  - The OTC nature of most trading
  - Unreliable data
  - Liquidity premia
  - Embedded options
  - Carrying costs, tax etc

Reduced Form - Strengths and Weaknesses

- The main strength is that they are entirely data driven and generally produce better results for credit risk pricing than structural models
- They are, however, unable to satisfactorily decompose PD and LGD

Modelling Data Inputs - Summary



B. Portfolio Modelling

- While the term “credit risk model” is applied loosely to cover all forms of statistical analysis, including the estimation of PDs, credit risk modelling in the true sense of the term involves the portfolio assessment of credit risks and the use of the model as the framework for managing credit risk within the bank
- There are essentially two fundamentally different portfolio modelling paradigms:

1. **Default mode modelling, and**
2. **Mark-to-market modelling**

Why the Portfolio Focus Matters

- Traditionally, portfolio managers have relied on their intuitive “feel” for concentration;
- This ignores basic rationale for being in the finance business – relationship between risk and return;
- Portfolio approach allows portfolio manager to re-cast credit lines in terms of contribution to “Marginal Portfolio Volatility”

1. Default Mode Modelling

- MTM models focus on the probabilities of being in either of two states at the relevant time horizon - default or non-default
- Key to the default mode model is the separate use of PD and LGD in the calculation of ***Expected Loss*** **EL** and ***Unexpected Loss*** **UL**
- This is the level of complexity envisaged by the Basel II reforms

Losses in Default Mode

At the heart of the default mode models is the calculation of expected loss and the volatility of expected loss:

$$EL = EAD \times PD \times LGD$$

$$UL = \sqrt{EL(EAD \times LGD - EL)}$$

WHY??

Where:
EL is expected loss;
UL is unexpected loss;

Portfolio Credit Risk

- Practice is to group risks by facility type
- Then calculate correlation (ρ_i for facility i) between the default rates of each facility group and that of the portfolio as a whole
- Then calculate for the portfolio:

$$\boxed{\begin{aligned} EL_P &= \sum_i EL_i \\ UL_P &= \sum_i UL_i \rho_i \end{aligned}}$$

Example

- A bank has the following 3-facility portfolio, - PDs, EADs and LGDs are as shown
- Calculate the expected loss and risk characteristics of the portfolio

Type of Facility	Nominal principal	Risk Grade	EAD	PD	LGD	Correlation with Portfolio
2-yr Loan	$2,777,778	A3	$3,000,000	.09%	60%	.1
10-yr IRS	$5,000,000	AA	$397,283	.03%	40%	.2
15-yr Mortgages	$4,000,000	B	$300,772	13.00%	70%	.15

Calculating Individual Risks

- Given the figures in the example, we can calculate:

EL(1)	3m x .09% x .6	$	1,620
EL(2)	397,283 x .03% x .4	$	48
EL(3)	300,772 x 13% x .7	$	27,370
EL(p)	sum(ELi)	$	29,038

UL(1)	$	53,976
UL(2)	$	2,752
UL(3)	$	70,805

Calculating Portfolio Risk

- Portfolio unexpected loss is the weighted sum of the individual unexpected losses:

Contribution (1)	UL(1) x Corr 1	$	5,398
Contribution (2)	UL(2) x Corr 2	$	550
Contribution (3)	UL(3) x Corr 3	$	10,621
UL(p)		$	16,569

- Portfolio risk is a multiple of this depending on the shape of the compound distribution and risk tolerance

A Note on Credit Diversification

- Unlike market risk, default correlations tend to be very low in credit risk
- E.g. in a typical stock market portfolio, 15 - 20 shares is sufficient to gain most of the benefits of diversification
- In comparison, in a credit portfolio the empirical evidence suggests that there almost always gains from further diversification

2. Mark-to-Market Modelling

- MTM models define ***credit events*** to encompass not only default, but migration to any credit rating other than the current one
- By valuing every credit in every possible state and then probability weighting them, the MTM model effectively simulates the price at which any credit could be sold - hence the MTM label

e.g. Credit Migrations from BBB

Range of possible credit ratings at the end of the year - each has an associated probability of occurring:

Year-end Rating	Probability (%)
AAA	0.02
AA	0.33
A	5.95
BBB	86.93
BB	5.30
B	1.17
CCC	0.12
Default	0.18

Note:
In the default mode all we needed was the PD = .18

Measuring Risk in MTM Models

- MTM models value each individual credit exposure in each possible migratory state
- Risk is then measured by considering the entire distribution of possible outcomes of value across all credits, taking into account their joint probabilities
- This involves a massive computational exercise to construct a distribution covering all possible outcomes
- For example, with 8 credit grades (including default) even 2 credits involve 64 possible outcomes – each with a separate probability

MTM Models - Strengths and Weaknesses

- Strengths:
  - Account for all changes of credit rating (not just default)
  - Better replicate reality
- Weakness - ahead of their time:
  - The models demand data that are not yet widely available
  - They require knowledge about obligors that is often not readily available
  - Where information or data are not available they require heroic assumptions
  - They simulate market values where markets typically don’t exist
- They are nevertheless the way of the future

A Final Note on Conditional and Unconditional Models

- Regulatory concern - credit failures tend to be concentrated when the economy slows down
- Most credit models were initially unconditioned for cycles
- Two main ways of incorporating cyclical experience:
  - Calculate PDs and LGDs for strong and weak periods
  - Modelling/simulating the drivers of economic cycles
- Both have been used (with varying success)

Thank You