CREDIT RISK MODEL

AN OVERVIEW

Lecture 2

CREDIT RISK MODEL

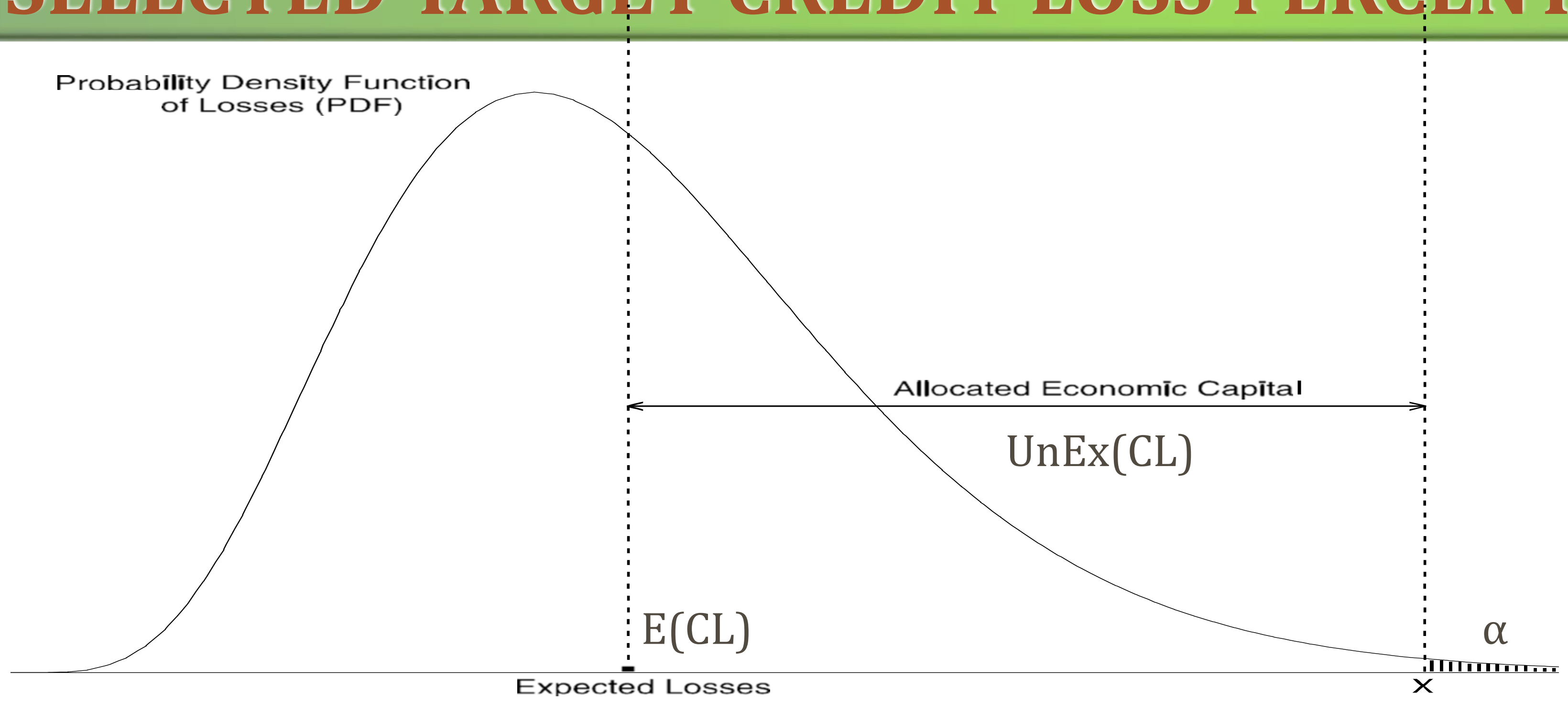
- Aim
  - To quantify the economic capital needed to support the bank activity exposed to credit risk
    - Narrow definition: risk caused only by a possible shift in the merit of credit of the borrower
    - Wide definition: risk caused also by a possible shift in the credit spread for a borrower of a given credit class

- Output
  - Probability density function (PDF) of credit losses (CL) over a chosen (stated) time horizon
    - single name vs. credit portfolio
    - PDF has a relatively long and fat tail (Expected credit loss > Median credit losses)

  - Expected Credit Loss
    - To be addressed with provisions and pricing, being a cost of doing business, not a risk

  - Unexpected Credit Loss = actual loss – expected loss
    - An exact measurement is possible only ex post
    - An ex ante measurement of the risk of such unexpected loss is provided by:
      - the standard deviation of the PDF (CL) or other statistics of dispersion
      - The difference between a selected target credit loss percentile and the expected loss

SELECTED TARGET CREDIT LOSS PERCENTILE (α)



α is the confidence level

(1- α) is the significance level

- Given the credit losses PDF, the **target loss percentile «α»** defines the economic capital for credit risk so that the estimated probability of unexpected credit loss exhausting such capital is less than some target insolvency rate (1- α)
- The **economic capital** is the capital in excess of the provisions necessary to cover the expected credit loss that is required to achieve the target insolvency rate desired for the bank
  - E(CL) – Accounting Provision = Shortfall
- The **target insolvency rate** is chosen to be consistent with the bank desired credit rating (the board's risk appetite)
  - if AA is desired (rating whose historical 1y default rate is 3 bps), then (1- α) = ….

CREDIT RISK MODELS: DEFINITION AND USE

- Credit Risk Model (CRM)
  - bank's policies, procedures, practices used to estimate the PDF of the CL of its exposures
  - All CRMs aim to quantify a portfolio's credit risk via the concept of a PDF of credit losses over a given horizon
- CRM Use Test
  - agree on a target insolvency rate (i.e. on a desired credit rating) for the bank
  - quantify the economic capital needed to make the probability of unexpected losses exceeding it lower than such rate
  - make sure that the bank's own funds exceed such economic capital at all time (raise capital and/or modify exposures)
- Key Methodological Issues in measuring credit risk
  - Time horizon: liquidation period vs. common horizon
  - Loss calculation paradigm: default mode vs. "market/model" mode
    - *if market/model mode: discounted contractual cash flow valuation vs. risk neutral valuation*
  - Variable definition: state of default, loss given default
  - Time perspective: conditional model vs. unconditional model
  - Portfolio Aggregation: top down approach vs. bottom up approach
  - Credit events correlation

CREDIT LOSS: DEFINITION AND TIME HORIZON

- Portfolio's credit loss = [portfolio current value - its future value at the end of an agreed time horizon]
- The calculation of such value (& of all the CRM operational details) depends on the concept of credit loss adopted
  - default mode vs. Market/model mode
- Two most common approaches in terms of time horizon
  - "liquidation period" - each loan facility per customer is associated with a unique interval, namely the instrument's maturity or the time needed for its orderly liquidation
    - choice of a "hold to maturity" approach motivated by:
      - exposures are intended to be held to collect till maturity;
      - there are limited markets in which the credits can be traded.
  - "common time horizon across some (asset specific horizons) or all asset classes", mostly one year
    - interval must reflect the time during which:
      - new capital could be raised or loss mitigating action could be taken to eliminate future risk from the portfolio;
      - new obligor information could be revealed or new default rate data may be published;
      - credits are normally reviewed for renewal.
      - internal budgeting, capital planning and accounting statements are prepared;

LOSS CALCULATION PARADIGM: DEFAULT MODE

- Dicothomic outcome
  - credit loss arises only if a borrower defaults within the planning horizon

- **Credit Loss** = [bank's credit exposure at default (EAD) – PV (expected future recoveries, net of workout costs)]

- **EAD** = [current value + (further withdrawals from the credit line - principal payments over the period if any)]

- **Assuming no withdrawals/payments, then EAD = current value**
  - If, no default, at all times: Future Value = Current Value → CL = 0
  - If default, at its recognition: Future Value = PV (net expected recoveries) = EAD * (1- Recovery Rate)

    since Recovery Rate (RR) = (1 – Loss Given Default Rate) → CL = current value * LGDR

- The PDF of the a bank 's credit losses is driven by the joint probability distribution of the:
  - <u>credit exposure at default (EAD)</u>
  - <u>probability of the default/solvency states</u>
  - <u>loss given default rate</u>

- Different PDFs can be derived for <u>separate credit facilities</u> / <u>separate customer groups</u>
  - different joint probability distribution of the variables above (counterparty vs. commitment vs. loan)

EXAMPLE: MEAN/STANDARD DEVIATION APPROACH

- Pick a distribution to fit the empirical PDF of credit losses (e.g. the beta distribution)
- A mean/standard deviation (μ/σ) approach quantify both the expected and unexpected credit losses for each credit facility /customer group «i» under a set of assumptions as follows:
- **μ = E(CL) = Σ $LEEAD_i$ * EDF_i * $LGDR_i$**
  - **LEEAD** = loan equivalent exposure at default; **EDF** = expected default frequency; **LGDR** = loss given default rate
- $\sigma = \Sigma \, \sigma_i \, \rho_I$ where ρ_i = correlation between the CL on facility /customer group «i» and those on the overall portfolio
- Under the further assumptions that
  - each facility's exposure (EDF_i) is known with certainty,
  - customer defaults and LGDs are independent of one another,
  - LGDs are independent across borrowers,

➢ the SD of credit losses for the *i* facility → **σ_i** = $LEEAD_i$ * $\sqrt{EDF_i * (1 - EDF_i) * \overline{LGD_i}^2 + EDF_i * \sigma_{LGD_i}^2}$

- The economic capital might then conveniently be set at some multiple of the estimated standard deviation of the portfolio credit losses [EC = K * σ]

CLASSIFICATION OF CUSTOMERS/FACILITIES BY EDF (PD)

- Rating Process
  - Grouping of different exposure with similar expected default frequency
  - Ratings are usually believed associated with borrowers, but, in practice, they should be associated with each specific facility belonging to any given borrower.
- Implementing a rating process
  - <u>Spreading the Numbers</u>
    - financial and other characteristics of the customer (e.g. country and business sector code) are incorporated into a relatively subjective approach to determining grades
  - <u>Scoring Models</u>
    - a formal model, independently from how it was built, is used to aggregate financial and other characteristics of the customer into a score from which the grade assignment is derived (<u>Internal models</u> vs. <u>External vendors' models</u>)
- Rating scale
  - Different rating scales for different facilities / customers
  - Concordance schedule between internal rating scales and rating agencies scales is usually
- Rating transition Matrix
  - It shows the likelihood of a customer migrating from its current rating to any other rating within the time horizon

RATING TRANSITION MATRIX

		AAA	AA	A	BBB	BB	B	CCC	Default
Current credit rating	AAA	87.74	10.93	0.45	0.63	0.12	0.10	0.02	0.02
	AA	0.84	88.23	7.47	2.16	1.11	0.13	0.05	0.02
	A	0.27	1.59	89.05	7.40	1.48	0.13	0.06	0.03
	BBB	1.84	1.89	5.00	84.21	6.51	0.32	0.16	0.07
	BB	0.08	2.91	3.29	5.53	74.68	8.05	4.14	1.32
	B	0.21	0.36	9.25	8.29	2.31	63.89	10.13	5.58
	CCC	0.06	0.25	1.85	2.06	12.34	24.86	39.97	18.60

Since under the DM paradigm only rating migrations into the default state lead to changes in the values of loans, only the last column of this matrix would be relevant.

What about all other pieces of information contained in the matrix?

LOSS CALCULATION PARADIGM: MARK-TO-MARKET/MODEL (MTM)

- MTM Rationale
  - a change in an asset's creditworthiness, and thus, a credit loss may arise in response to any sort of events, even those that are way short of a default
  - the credit portfolio must thus be marked to market/model at the beginning and end of the planning horizon
  - the credit loss is the difference between these valuations
- MTM Models' Content
  - in addition to the EDFs, MTM models incorporate the probabilities of credit rating migrations across non-default states (the entire rating transition matrix)
  - for a given rating transition matrix associated with each customer, Monte Carlo methods are used to simulate migration paths for each credit position in the portfolio.
  - for each position, the simulated migration (and the risk premium associated with the instrument's end of-period rating grade) is used to mark the position to market as of the end of the time horizon
- MTM Model's Valuation Approaches
  - discounted contractual cash flow (DCCF) approach
  - risk-neutral valuation (RNV) approach

MTM PARADIGM: *DCCF APPROACH*

- **DCCF methodology** is commonly associated with J.P. Morgan's CreditMetrics
- **Value of a non defaulted loan = discounted value of its future contractual cash flows**
  - for a loan with a given internal risk rating (e.g., comparable to BBB), the credit spreads used in discounting contractual cash flows equal the market-determined term structure of credit spreads associated with comparable grade corporate bonds
- **Current Loan Value**: market price or straightforward market-to-model valuation
  - known rating - known spot credit spreads for that rating
- **Future Loan Value** $= f$ [loan's uncertain end-of-period rating; term structure of spreads for each rating]
- **The loan value can change over time because of:**
  - a migration of the borrower to a different rating grade (migration risk)
  - a change in the market-determined term structure of credit spreads (spread risk)
- **What about the implication of a migration to default?**
  - value of a defaulted loan cannot be obtained by discounting contractual cash flows
  - as in DM-type models, in the event of a default the future value of a loan is given by its recovery value

MTM PARADIGM: RNV *APPROACH*

- DCCF approach not consistent with finance theory (value of assets depends on return correlation with the market)
  - same discount rate for loans to 2 identically rated firms even if not equally sensitive to business cycle/systematic factors

- RNV approach avoids this, leveraging on Merton's structural model of firm value/bankruptcy (assets < debt service)
  - the payment to the lender is the contractual amount only if the firm has not defaulted; else it is (1-LGDR) * the face value
  - being the loan a set of derivative contracts on the borrower's assets, its value = Σ (present values of these derivatives)

- The discount rate applied to the contracts' contingent cash flows is determined using a risk-neutral pricing measure, i.e. the risk free term structure of interest rates
  - risk-neutral pricing measures can be thought of as adjustments to the borrower default probabilities at each horizon, incorporating the market risk premium associated with the borrower's default risk.
  - the size of the adjustment depends on the expected return and volatility of the borrower's asset value.

- If asset return is modelled consistent with the Capital Asset Pricing Model (CAPM), the expected return are function of the *market* expected return and the firm's correlation with the market.
  - consistent with standard finance theory, the pricing of loans under RNV adjusts not only for the EDF and the LGDR of the borrower but also for the correlation between the borrower's risk and the systematic risk.

OPEN ISSUES: DEFINITION OF DEFAULT

- In CRMs, a loan is deemed to be in default once it migrates to a pre-defined "worst state".
- The definition of the "worst state" is not precise and may vary across countries, banks and specific situations
  - a common definition of "default" is one of the key target of EBA in building the Single RuleBook
- Such differences may affect the measures of default, credit loss and the estimation of the PDF of credit losses
  - LGD vs. PD
- Several interpretation are possible for the concept of "default status"
  - loan still performing, but worrying sign of the probability of default worsening ("substandard")
  - concession granted to the borrower ("forborne")
  - payments are materially past due ("past due") ,
  - workouts expected / initiated / loan placed on non-accrual status ("unlikely to pay")
  - recovery proceedings initiated («bad loans»)
- The definition of default used in credit risk models is not equivalent to that used for legal / accounting purposes
  - "<u>defaulted loans</u>" vs. "<u>impaired loans</u> " "non performance loans"
- The comparability of credit loss estimates between banks is also affected by the choice of adjustments that banks may incorporate in the measurement of credit loss (workout expenses; carrying costs; time to recovery)

OPEN ISSUE 2: TIME HORIZON (T.H.)

- **T.H. choice is a major decision** in assessing the CRM capacity to meet risk management & capital allocation needs

- The ability of a default mode (DM) model to capture the effects of credit events is particularly sensitive to the length of the time horizon due to its "two states" nature.
  - Preference for a 1yr horizon **(12 Month Expected Losses)** due to computational convenience rather than model optimization
  - It is often not even tested the sensitivity of DM model output to the chosen holding period

- The reasonableness of the decision to opt for 1y horizon rests on whether this is period over which:
  - fresh capital can be raised to fully offset portfolio credit losses beyond that horizon,
  - risk-mitigating actions (loan sales, purchase of credit protection) can be implemented against the risk of further losses

- Not clear if a DM-type model with a 1y T.H. can accurately represent the riskiness of a multi-year loans portfolio

- To raise the sensitivity of the DM approach to maturity differences among loans, banks apply *ad hoc* adjustments such as measuring an instrument's EDF over its maturity (e.g. 1y EDF for a 1y loan, a 2y EDF for a 2y loan,…)
  - such adjustments may lead to internal inconsistencies within the modelling framework, as multi-year EDFs may be used in combination with loss correlations calculated on the basis of a fixed (often 1 year) time horizon
  - such approach is now compulsory for substandard (Stage 2) performing loans **(Lifetime Expected Losses)**

OPEN ISSUE 3: METHODOLOGIES COMPARISON

- The superiority between DM and MTM paradigms depends on the fit between the model's output vs. application
  - Banks using CRMs for performance/risk measurement goals associated with a buy-and-hold portfolio may opt for a DM model
  - Banks trading/pricing more liquid loans require a loss measurement definition that includes shifts in credit spreads / ratings
- The dichotomy between the DCCF and the RNV as *valuation approaches is* sharper in theory than in practice
  - both methodologies value a loan in terms of the discounted present value of its future cash flows
  - they differ mainly in how the discount factors are calculated
    - DCCF takes a nonparametric approach in estimating these discount factors, as borrowers are grouped into rating categories and their credit spreads are averaged within each "bucket".
    - RNV method is highly structural, imposing a model that prices each loan simultaneously in a single unified framework. In practice, the calibration of the market risk premium in the model makes use of the credit spreads from the debt market.
  - Econometric theory shows that:
    - structural estimators make efficient use of available data but are vulnerable to model misspecification,
    - nonparametric estimators make minimal use of modelling assumptions but perform poorly where data are scant or noisy
- The two approaches assign different values to any given loan, but if debt markets are fairly efficient and RNV model assumptions approximately valid, they should produce similar aggregate values for well diversified portfolios

PDF OF CREDIT LOSSES

- Some vendor models provide the PDF (CreditRisk+, PortfolioManager, CreditPortfolioView, CreditMetrics – MC based)
  - statistics (mean, SD, a chosen target credit loss percentile) are then easy to calculate
- Other proprietary and vendor models generate the PDF's first two moments only, leaving the PDF implicit
  - choice of models like CreditMetrics (analytical version) and the mean/SD approach made either from the outset for ease in modelling-computating (no PDF functional form assumed) or because the full PDF is available only for some sub-portfolios
- Differently from market risk, a consensus about a "standard" shape of the PDF has yet to emerge
  - historical portfolio credit loss distributions are non-normal, skewed towards large losses and leptokurtic, which makes the probability of large losses greater than in the case of a normal distribution
  - no clear "industry standard" portfolio credit loss PDF since it is more difficult to model credit losses than market risk
    - wide range of simplifying assumptions needed (are losses binary or follow one of the several possible continuous distributions?)
  - portfolio PDFs obtained aggregating single exposure losses = f (both these assumptions and those on credit correlations)
- **The precision in estimating high quantiles of distributions used in credit risk models is a key consideration**
  - **target loss quantiles** for <u>credit risk in the 99-99.99% range</u> ; for <u>market risk models in the 95-99% range</u>
  - **reasons:** <u>size of the estimation error</u> + <u>thick distributional tails</u> + <u>sensitivity of the PDF tail to modelling assumptions</u>
  - these reasons may imply large differences in very high quantiles estimates of credit losses

MODEL'S INFORMATION CONTENT: UNCONDITIONAL MODELS

- **Unconditional models are based only on borrower/facility specific information**
  - EDF; correlation between historical defaults & borrower information
  - CreditMetrics, CreditRisk+ are part of this category of models
- **They provide estimations "through the cycle"**
  - estimation covers indistinctly many business/credit cycles
  - actuarial-based unconditional estimates of EDFs, rating transitions and correlations are long-run averages estimates
- Whatever the point in the cycle, they estimate similar values for losses statistics arising from similarly rated loans
- Since both EDFs & correlations vary systematically over the course of a cycle, at any given point in time the estimated EDFs fail to reflect important variables affecting the loan performance
- These models are not appropriate **"point in time" estimates**
  - They misrepresent the short-term outlook, being it highly dependent on the state of the economy
- **They do not capture business cycle effects**, i.e. the tendency of rating evaluation to improve (fall) during cyclical upturns (downturns)

MODEL'S INFORMATION CONTENT: CONDITIONAL MODELS

- **Conditional models** incorporate the possibility that the loan may be on the book during a period of high rather than low expected default due to the then current business cycle phase

- **Their EDFs / rating transition matrices / LGD are functionally related to the state of the economy**
  - they are modified to provide an increased (decreased) likelihood of a downgrade (upgrade), and possibly of a worse LGD, during a credit/business cycle downswing

- **Different approaches are possible to achieve this conditionality**
  - McKinsey & Co. CreditPortfolioView incorporates information on state of the economy
    - level/trend in domestic/international employment, inflation, stock prices, rates, sectors' financial health
  - KMV Portfolio Manager estimates asset values and volatility based on current equity prices (inherently forward-looking)

- **Estimates of transition matrices / EDF / LGD can be improved by conditioning on the stage of the business cycle**

- **Drawbacks of these models**
- they underestimate (overestimate) losses as the credit cycle enters a downturn (upturn), exasperating the pro-cyclality
- a full reflection of business cycle effects is a difficult process, making the parameter estimates subject to high uncertainty

TOP-DOWN AND BOTTOM-UP APPROACHES

- Most CRMs use the same conceptual framework in modelling individual-level credit risk for different product lines
  - their differences arise primarily in the ways underlying parameters are estimated
- *"Bottom-up" approach - c*redit risk measured at the individual asset level for corporate / capital market instruments
  - each position is associated with a risk rating, treated as a proxy for its EDF / probability of rating migration (and its LGDR)
  - The data is then aggregated to the portfolio level taking into account diversification effects.
- *Top-down" approach -* aggregate data is used for quantifying risk in consumer, credit card or other retail portfolios
  - loans with similar risk profiles (credit scores, age and geographical location,…) are aggregated into buckets
    - all loans within each bucket treated as statistically identical.
  - Credit risk is quantified at the level of these buckets
    - the aim is to model both the (annual) aggregate default rate and the LGD rate by using historical time-series data for a risk bucket taken as a whole, rather than by arriving at this average jointly considering default and migration risk factors for each loan in the pool.
- **Differences are less clear-cut in practice, as it is crucial to distinguish meaningfully between borrower classes**
  - "bottom-up" models using borrower-specific information to slot loans into buckets, have underlying parameters calibrated using aggregate data (rely on aggregate data to estimate individual borrower parameters)
  - the **accuracy of aggregate data** is of key importance, as well as **its comparability to a bank's actual portfolio** since if these two standards are not met, the use of aggregate data can disguise loan-specific effects to which a bank is exposed

CORRELATIONS BETWEEN CREDIT EVENTS

- Factors affecting the creditworthiness of obligors tend to behave in a related manner
  - for firms in the same industry/country, financial conditions may reflect similar factors and move in a correlated fashion
  - their LGDs, as well as EAD, due to credit lines drawdowns, may tend to increase/decrease relative to long-run averages with the ebb and trough of the economic/industry cycles

- Measures of the dispersion of credit risk (i.e. its standard deviation, the full PDF) are function of the dependencies between the factors determining credit losses, i.e. the correlations (both for the same borrower and for different borrowers) among :
  - Defaults / Rating Migrations, LGDs Exposures
  - (instead the *expected loss* for a portfolio is simply equal to the sum of the expected losses for the separate obligors)

- CRMs do not usually attempt to explicitly model correlations between these risk factors due to limitations in the data and in the ability to model such correlations

- Within MTM-type models, correlations among credit spread term structures, and among credit spreads – LGD – EAD - defaults / rating migrations would also be relevant.
  - Yet, the applications of MTM models treat the term structure of credit spreads as fixed/known, abstracting from correlations
  - Moreover, correlations between defaults/rating migrations and LGDs, between defaults/rating migrations and exposures and between LGDs and exposures are typically assumed to equal zero.

- The only correlation effects usually considered are the correlations between defaults/rating migrations of different customers

DEFAULT/RATING MIGRATION CORRELATIONS: STRUCTURAL MODELS

- Structural models assume **a specific microeconomic process** to generate customers' defaults and rating migrations
  - a customer is assumed to default if the value of its assets falls below some threshold (its level of liabilities)
- Within the MTM framework, the change in the value of customer's assets in relation to various thresholds often determines the change in the risk rating over the planning horizon.
  - given a customer's current risk rating (say, equivalent to BBB), an extremely large positive change to its net worth might correspond to an upgrade to AA, while an extremely large negative realization might generate a downgrade to default
- The random variables determining the change in customers' risk rating, including default, are called ***migration risk factors***.
- Structural models specify (estimated/assumed) the correlations between migration risk factors across borrowers
- In turn, these correlations implicitly determine , the correlations among borrowers' defaults or rating migrations.
- CreditMetrics and PortfolioManager are structural models

HANDLING CORRELATIONS: REDUCED FORM MODELS

- Reduced form models assume a **particular functional relationship** between customers' expected default rate/migration matrix (or a sub-portfolio's expected default rate) and the so-called ***background factors,*** such as:
  - observable indicators of macroeconomic activity
  - unobservable random risk factors
- The dependence of the financial condition of individual customers on common or correlated background factors originates the correlations among customers' default rates or rating migrations.
- CreditRisk+ and CreditPortfolioView are reduced form models
- It is an empirical issue whether structural/reduced form models perform better or worse in specific circumstances
- Assumptions/approximations in estimating default correlations highlight conceptual and empirical questions
  - does the choice of risk factor distribution functions, e.g. normality or gamma, makes a material difference to model output?
  - do the technical approximations introduced produce a material impact?
  - whether default correlations generated by the models <u>are within the same range</u>, <u>result in a correct correlation structure</u> and <u>are stable over the TH</u>.

CREDIT EVENTS

- **Four types of credit events** may contribute to the level of credit losses in credit risk models:
  - (1) a change in LGD;
  - (2) a change in creditworthiness (in a credit rating migration / EDF / PD) over the planning horizon;
  - (3) a change in the applicable credit spread for MTM models;
  - (4) a change in a bank's exposure with respect to a particular credit facility.
- CRMs tend to be modular, involving separate sub-models for each of these credit events.
- Correlations *between obligors* due to credit events are introduced in various ways
- Most models assume zero correlation *between credit events* of different types in spite of the fact that such correlations may in fact be significant
  - for example, defaults are assumed to be uncorrelated with LGDs, changes in spreads and exposures.
- Given this assumption, the sub-models for each credit event generally do not interact with one another.