Modelling of Credit Risk Parameters: 
Probability of Default (PD) and Loss given Default (LGD)

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October 6, 2010
Modelling of credit risk parameters: PD and LGD

Agenda

- Introducing credit risk
- Modelling Exposure at Default (very short)
- Modelling Probability of Default
  - Score cards
  - Calibration
  - Applications
- Modelling Loss Given Default
  - Types of models
  - Work-out LGD
  - Example: mortgage loans
Credit risk

Bank  Lends money  Loan  Borrower
Modelling of credit risk parameters: PD and LGD

Credit risk

Bank

Loan

Borrower

Pays back loan + interest
Credit risk

Bank

Loan

Borrower

Pay back loan + interest

Or fails to do so: default!
Modelling of credit risk parameters: PD and LGD

Credit risk

But how likely is that going to happen?

Bank

Loan

Borrower

Pay back loan + interest

Or fails to do so: default!
Modelling of credit risk parameters: PD and LGD

Credit risk

PD: Estimated probability of default

Bank

Loan

Borrower

Pays back loan + interest

Or fails to do so: default!
Modelling of credit risk parameters: PD and LGD

Credit risk

Bank

And what am I going to lose if it happens?

Borrower

Or fails to do so: default!

Pays back loan + interest

Or fails to do so: default!
Modelling of credit risk parameters: PD and LGD

Credit risk

Bank

LGD:
Estimated loss given default

Borrower

Pay back loan + interest

Or fails to do so: default!
Expected and Unexpected Loss

Credit defaults lead to

**Expected Loss (EL)**  
(normal case)  
covered by credit margin

**Unexpected Loss (UL)**  
(disaster scenario)  
covered by capital
Calculating Expected Loss

\[ EL = EAD \cdot PD \cdot LGD \]

- Credit risk parameters
  - \textbf{PD}: Probability of Default
  - \textbf{EAD}: Exposure at Default
  - \textbf{LGD}: Loss Given Default

- Prerequisites for definition of credit risk parameters
  - consistent definition of default event
  - consistent definition of loss amount

- From single credit to portfolio view
  - EL is additive \( \Rightarrow \) Summation over all credits
  - EL does not depend on correlations within the portfolio
Calculating Unexpected Loss

Credit Risk Loss Distribution

from credit portfolio model:

\[ f(PD_i, LGD_i, EAD_i, \rho_{ij}, \ldots) \]

Example:
1-Factor-Model (Gordy)
\[ \Rightarrow UL \text{ according to Basel II} \]
Modelling of credit risk parameters: PD and LGD

Typical data environment in credit risk estimation

- Transaction data
- Default data
- Data warehouse with historic data
- Calculation kernel
  - PD, LGD, EAD, EL, UL, ...

Samples from historic data
- Platform for model calibration and validation
- Model parameters

Integrated risk-return management
- Central bank reporting
  - Regulatory capital requirement according to Basel II
- Internal reporting
Modelling of credit risk parameters: PD and LGD

Statistical model and data collection

Calculation of EAD, PD and LGD based on historic data
Modelling of credit risk parameters: PD and LGD

Statistical Model: Exposure at Default (EAD)

- Instalment credit
  - Fixed payment schedule: exposure contains no stochastic component
  - Collaterals may be considered (statistical methods for valuation where necessary)
  - Deferrals have to be recognised

- Revolving credits (e.g. credit cards) and credit lines
  - Exposure fluctuates stochastically
  - Statistical method for EAD required:
    \[ EAD = \text{current availment (deterministic)} + \text{Add-On (stochastic)} \]

- Off-balance sheet exposures and derivatives
  - No deterministic component
  - Purely statistical estimation
Statistical Model: Probability of Default (PD) (1/2)

- Find appropriate criteria with discriminatory power:
  - Application criteria (income, domicile, etc.)
  - Corporates: information from financial statements (sales, earnings, etc.)
  - Behavioural criteria (cumulative days past due, current arrears, etc.)

- Determine score function:
  \[ \text{score} = \text{weight}_1 \cdot \text{value(criterion}_1) + \ldots + \text{weight}_n \cdot \text{value(criterion}_n) \]

- Calibration: find the relationship between probability of default and score
  - Data basis: observed historic defaults
  - Specify reference dataset
  - Find appropriate counting method (e.g.: how to handle re-ageing of facilities?)
Modelling of credit risk parameters: PD and LGD

Statistical Model: Probability of Default (PD) (2/2)

- With increasing „age“ of credit:
  - Application criteria partly lose their discriminatory power
  - Behavioural criteria gain importance
  - Segregate exposures into different "age classes"

- Link between credit decision and PD estimation
  - Scoring methods (solely based on application criteria) for credit decision (application score) have been established within banks for a very long time, independent of Basel II
  - Application score can be used directly within PD model
  - Similar methods are well known in other fields like sociology or medical science

- Score card
Score cards

- What is a score card?
- What kind of risk factors do we have?
- What is the discriminatory power of a score card?
  - histograms, ROC curve and CoC value
- How to determine the score function?
- How to choose the risk factors?
- How can we transform scores into PDs?
What is a score card?

- **abstractly**: mapping from the risk factor space (age of obligor, profession, amount financed ...) to the real numbers (score)

\[
\begin{pmatrix}
\text{risk factor 1} \\
\text{risk factor 2} \\
\vdots \\
\text{risk factor N}
\end{pmatrix}
\xrightarrow{\text{score function}} \text{score}
\]

- **example**: assign points to the answers of a questionnaire and interpret sum of these points as classification

- **purpose**: reduction of a multi-dimensional decision problem to a one-dimensional scale

- **goal**: ex-ante separation between ex-post defaulted and non-defaulted obligors
What kind of risk factors do we have?

- **metric risk factors**
  - values are numbers
  - there is a ranking order
  - credit related examples: credit amount, instalment, time to maturity, age of obligor ...

- **categorical risk factors**
  - values do not have to be numbers
  - typically no ranking order
  - credit related examples: marital status, gender, profession, purpose of financing, zip code …
Discriminatory power: histograms

- example: distributions of defaulted (red) and non-defaulted (green) loans are separated
Discriminatory power: ROC curve & CoC value

- ROC curve

1. Order loans according to metric risk factor (if necessary, one has to transform to metric)
2. Start at the end where most non-performer are expected (economic hypothesis)
3. Looking at the first N loans, which percentage of performers and which percentage of non-performers are captured?
4. Use these percentages as x- and y-coordinates to build up a curve

<table>
<thead>
<tr>
<th>loan</th>
<th>score</th>
<th>status</th>
<th>perform.</th>
<th>non-perf.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10,5</td>
<td>D</td>
<td>0%</td>
<td>33%</td>
</tr>
<tr>
<td>2</td>
<td>8,35</td>
<td>D</td>
<td>0%</td>
<td>66%</td>
</tr>
<tr>
<td>3</td>
<td>8,3</td>
<td>A</td>
<td>50%</td>
<td>66%</td>
</tr>
<tr>
<td>4</td>
<td>7,3</td>
<td>D</td>
<td>50%</td>
<td>100%</td>
</tr>
<tr>
<td>5</td>
<td>-2,1</td>
<td>A</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>
Discriminatory power: ROC curve & CoC value

1. Order loans according to metric risk factor (if necessary, one has to transform to metric)
2. Start at the end where most non-performer are expected (economic hypothesis)
3. Looking at the first N loans, which percentage of performers and which percentage of non-performers are captured?
4. Use these percentages as x- and y-coordinates to build up a curve

- CoC value or Accuracy Ratio (AR)
  - Ratio of the area under the ROC curve and the maximum value ( = 1)
  - Lies between 50 % and 100 %
  - In the example: CoC = 83 % ( = 5/6)
CoC value: what does it mean?

Example:

<table>
<thead>
<tr>
<th>loan</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
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<td>score</td>
<td>10,5</td>
<td>8,35</td>
<td>8,3</td>
<td>7,3</td>
<td>-2,1</td>
</tr>
<tr>
<td>status</td>
<td>D</td>
<td>D</td>
<td>A</td>
<td>D</td>
<td>A</td>
</tr>
</tbody>
</table>

- Build all pairs of defaulted and non-defaulted loans
- Is score of defaulted loan higher than score of non-defaulted loan?

Example:

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<thead>
<tr>
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<td>8,3</td>
<td>7,3</td>
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CoC value: probability that score of defaulted loan is higher than score of non-defaulted loan
ROC curves: limits

- Perfect discriminatory power: CoC = 100%
ROC curves: limits

• No discriminatory power: CoC = 50%
ROC curves: science

- **Origin:** signal detection theory

![Contingency table](image)

<table>
<thead>
<tr>
<th>Actual value</th>
<th>p</th>
<th>n</th>
</tr>
</thead>
<tbody>
<tr>
<td>p</td>
<td>True positive</td>
<td>False positive</td>
</tr>
<tr>
<td>n</td>
<td>False negative</td>
<td>True negative</td>
</tr>
</tbody>
</table>

**Examples:**
- Radar
- Particle detectors
- Psychophysics
- Psychology
- Medicine
- Data mining

![Diagram](image)
How to determine the score function?

Score = $\beta_1 \cdot X_1 + \beta_2 \cdot X_2$

distribution of the risk factors

discriminatory direction

distribution of the score

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How to choose the risk factors?

• **Pros**
  - Choice according to …
  - … univariate discriminatory power (CoC value)
  - … technical criteria
    - risk factors related to loan, obligor, behaviour, financed object …
  - … contribution to increase in discriminatory power of score (CoC value)

• **Cons**
  - No substantial increase in discriminatory power of score
  - Mutually dependent risk factors (having high correlation)
How can we transform scores into PDs?

- **Calibration**
  - Look at historic transaction data
  - Calculate score for each transaction
  - Determine whether or not transaction defaulted
  - Assign probability of default to score

- **Problem**
  - Default information is binary, PD is continuous
PD calibration

- Kernel density estimation

\[ PD(score) = \sum_{defaults \ i} Kernel(score - score_i) \]
Why would a bank want to estimate the PD?

**Portfolio management**
- Do we want to make (or keep) the deal? (Limits)
- What should we charge for the risk of default? (Pricing, standard risk costs)

**Risk management**
- How much do we expect to lose? (Expected loss)
- How much should we set aside for expected losses? (Provisioning)

**Stress testing**
- How much could we lose under adverse conditions?
- How would the PD change?

**Capital requirements**
- How much capital do we need to cover unexpected losses? (Economic capital, regulatory capital (Basel II))
How to define the probability of default?

The PD depends on a reference date and a time horizon:

\[
PD = \text{Probability to default between the reference date and the time horizon}
\]

Dependence on time horizon and reference date:
How to estimate the probability of default?

Answer: Look at history and count defaults!

\[ PD = \frac{N_D}{N_A} \]

Eg. PD = 2/5
Calibration: Point-in-time vs. Through-the-cycle

Long default history available:

Reference date

Time horizon

2003 2004 2005 2006 2010 2010
Calibration: Point-in-time vs. Through-the-cycle

Long default history available:

Point-in-time (PIT) calibration
Calibration: Point-in-time vs. Through-the-cycle

Long default history available:

Through-the-cycle (TTC) calibration
Example: Automobile bank retail portfolio

Observed Default Rate

- Point-in-time 2003: PD = 3.8%
- Through-the-cycle 2003-2010: PD = 3.0%
- Point-in-time 2010: PD = 2.3%

Time

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Economic interpretation of different calibrations

Through-the-cycle calibration
(average macroeconomic conditions)

Idiosyncratic Risk influences PD influence Macroeconomic Conditions

Point-in-time calibration
(current macroeconomic conditions)
Why would a bank want to estimate the PD?

**Portfolio management**
- Do we want to make (or keep) the deal? (Limits)
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What PD?
What PD to use for portfolio management?

Deal initiation:

- PD can be used for risk adjusted pricing: risk over the life of the loan = standard risk costs
- PD can be used to limit risks (expected loss, unexpected loss)

PIT: adjusted to current risk, but pro-cyclical, decreases volume of business

TTC: less cyclical, but underestimates risk in bad times

Answer for portfolio management:

Point-in-time PD, time horizon = maturity of loan
What PD to use for risk management?

Collective risk provisioning / impairment:

- Risk provisioning should compensate expected losses in the near future
- Time horizon = 1 year
- Losses are cyclical $\Rightarrow$ risk provisioning should be cyclical
- Pro-cyclical risk provisioning adds strain during economic downturn
What PD to use for risk management?

Losses and provisions over time:

Overestimated losses in good times compensating underestimated losses in bad times

Realised losses, PIT provisions

TTC provisions

Answer for risk management:

Point-in-time/Through-the-cycle PD, one year time horizon
What PD to use for capital requirements?

- Expected losses correspond to rare events
- 99.9% one-year-quantile ≅ “once in a thousand years”
- Long term risk buffer: should not depend on economic cycle
- Point-in-time calibration would be pro-cyclical:
  - High capital requirements in bad times
  - Low capital requirements in good times
- Bank regulators (Basel II) demand through-the-cycle calibration
- Time horizon: typically one year (Basel II)

Answer for capital requirements:

Through-the-cycle PD, one year time horizon
What PD to use for stress testing?

- Stress testing analyses the effects of stressed economic conditions on the risk position of a bank.
- Baseline for stress testing is the long-time average.
- Example:
  - “mild recession” scenario might correspond to an increase of the PD by 50% relative to long-time averages.
  - Scenario loses meaning if applied to PIT-PDs in worst recession in decades.

Answer for capital requirements:

Through-the-cycle PD, one year time horizon.
Summary

- There is not one correct way to calibrate the PD, there are many!
- Which one to use depends on what you want to use the PD for!
- Two important parameters to consider:
  - Desired level of cyclicalilty
  - Time horizon of PD estimation
Types of LGD models

**Workout LGD**

- Required Data:
  - Account data
  - Losses
  - Collateral values

- Examples:
  - Retail
  - SME
  - Large-sized corporates

**Cash flow model of LGD**

- Required Data:
  - Object data (e.g. area, postal code)
  - Market data (e.g. rental rate)

- Examples:
  - CRE
  - Project and Object financing

**Market LGD**

- Required Data:
  - Market data (e.g. bond quotes, stock quotes)

- Examples:
  - Large-sized corporates
  - Sovereigns banks

**Implied market LGD**

- Required Data:
  - Market data (e.g. bond quotes, stock quotes)

- Examples:
  - Large-sized corporates
  - Sovereigns banks

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Solutions for key challenges

Complexity
- scenarios
- recovery rates
- collateral attributes
- direct and indirect costs
- pooling criteria
- statistical uncertainties
- yield curves for discounting

Amount of data
- source systems
- interfaces
- input screens
- new data fields
- processes
- retroactive changes
- documentation

⇒ Increased cost efficiency by interleaved development processes
Statistical Model: Loss Given Default (LGD) (2/4)

Workout-LGD for single exposure

\[
\text{LGD} = \frac{\text{Economic Loss}}{\text{EAD}}
\]
Project example: LGD for mortgage loans

- The client
- Mortgage loans
- Loss given default
- Scenario model
- Recovery rate
- Transition matrix model
- Settlement rate
- Summary
The client

- German real estate bank
- Assets: 85.7 bn €
- Real estate lending: 23.5 bn €
- Residential real estate lending: 16.1 bn €
Mortgage loans

• Financing of commercial/retail real estate

- Bank
- Money
- Customer
- Collateral
- Real estate
- Buy

• Important concepts:
  - Value of mortgage ("Grundschuld"): maximum value of collateral the bank is entitled to
  - Collateral value ("Beleihungswert"): conservative estimate of value of collateral
Loss given default

- LGD = econ. loss / EAD = (EAD – discounted recoveries) / EAD

- Mortgage loans: one big recovery cash flow
Scenario model

- Alternative scenario to settlement of non-performing loan: customer reperforms
- Two scenarios: “settlement” / “curing”

\[ \text{LGD} = \text{SR} \cdot \text{LGD}_S + (1 - \text{SR}) \cdot \text{LGD}_C \]

- Risk drivers:
  - Settlement rate SR
  - Loss given settlement \( \text{LGD}_S \)
LGD model

- Recovery on mortgage depends on
  - collateral value ("Beleihungswert") CV
  - recovery rate RR
- but is not more than mortgage value ("Grundschuld") MV

\[ LGD_S = \max(EAD - \min(RR \cdot CV; MV) \cdot DF \cdot DTF; 0) / EAD \]

- for simplicity’s sake, direct and indirect costs are missing from expression
LGD pooling

• Recovery rates determined from foreclosure history (1863 foreclosures since 2004)

• Historic foreclosures pooled by
  □ object type (single-family house, others)
  □ usage (owner-occupied, rented out, mixed)
  □ region (strong, average, below average economic strength)

• Aggregated to 10 distinct pools, e.g.
  □ single-family house, owner-occupied, average region
  □ other type, rented out, below average region
  □ owner-occupied, strong region

• Objects of foreclosure history assigned to the 10 LGD pools
LGD pooling: average recovery rates per pool

Recovery rate

Pool

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LGD estimate for active loan

- Assign loan to one of the 10 LGD pools based on object properties
- Calculate $\text{LGD}_{S,i}$ using position data (EAD, CV, MV) of loan and recovery rate of each object in historic LGD pool

$$\text{LGD}_{S,i} = \max(\text{EAD} - \min(\text{RR}_i \cdot \text{CV}; \text{MV}) \cdot \text{DF} \cdot \text{DTF}; 0) / \text{EAD}$$

- Average $\text{LGD}_{S,i}$ over LGD pool
Settlement rate

• Can in principle be determined from loan history:

• Problem: don’t have data for long time!
• Solution: analyze short time, extrapolate to long time!
Transition matrix model

- 6-state model: each contract is in one of 6 states
  - Active (A)
  - Defaulted, but not in settlement (D1)
  - Defaulted, in settlement, but no foreclosure sale, yet (D2)
  - Defaulted, after foreclosure sale, but not written-off (D3)
  - Written-off (F)
  - Settled, no economic loss (E)

- Assign a state to each contract each month
- Calculate monthly transition rates between states
- Extrapolate monthly transition matrix to reach long time!
Transition matrix based on exposure

- Recoveries reduce exposure: base transition matrix on exposure, i.e. "Where is 1€ of exposure next month?"

- Transition of object from state X to state Y generates "flow" from state X to state E
Modelling of credit risk parameters: PD and LGD

Monthly transition rates

![Graph showing monthly transition rates between different credit ratings over time.](image-url)
Modelling of credit risk parameters: PD and LGD

Average and asymptotic transition matrices

- **Average monthly transition matrix**

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>D1</th>
<th>D2</th>
<th>D3</th>
<th>E</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>90.65%</td>
<td>7.21%</td>
<td>1.39%</td>
<td>0.00%</td>
<td>0.75%</td>
<td>0.00%</td>
</tr>
<tr>
<td>D1</td>
<td>15.29%</td>
<td>77.92%</td>
<td>5.59%</td>
<td>0.01%</td>
<td>1.19%</td>
<td>0.01%</td>
</tr>
<tr>
<td>D2</td>
<td>1.07%</td>
<td>0.17%</td>
<td>96.75%</td>
<td>0.96%</td>
<td>1.05%</td>
<td>0.00%</td>
</tr>
<tr>
<td>D3</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>65.81%</td>
<td>1.21%</td>
<td>32.98%</td>
</tr>
<tr>
<td>E</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>100.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>F</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
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</table>

- **Extrapolate behavior for long time!: asymptotic matrix**

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<tbody>
<tr>
<td>A</td>
<td>0.01%</td>
<td>0.00%</td>
<td>0.02%</td>
<td>0.00%</td>
<td>70.30%</td>
<td>29.66%</td>
</tr>
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<td>30.74%</td>
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<td>0.02%</td>
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<td>59.98%</td>
<td>39.99%</td>
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<td>100.00%</td>
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</tr>
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<td>0.00%</td>
<td>0.00%</td>
<td>100.00%</td>
</tr>
</tbody>
</table>
Settlement rate I

- Settlement in terms of 6-state model: entering state D3
- But D3 is only transient state: no asymptotic rate D1→D3
- Solution: adjust transition matrix (“make D3 absorbing”)

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<tr>
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- 31.7% of each Euro in D1 eventually pass through D3!
Settlement rate II

- But the settlement rate is the relative amount that **enters** into settlement, not the residual claim after receiving the sales amount!

- Compensate:

  \[
  SR = P_A(D_1 \rightarrow D_3) \cdot \frac{P(D_2 \rightarrow D_3) + P(D_2 \rightarrow E)}{P(D_2 \rightarrow D_3)}
  \]

- Settlement rate **SR = 66%**
Summary

• Major risk drivers:
  □ settlement rate: how much of the defaulted exposure ends up in settlement?
  □ recovery rate: how much of the collateral value is recovered in settlement?

• Scenario model with scenarios “settlement” vs. “curing”

• Recovery rate: based on history of settled contracts

• Settlement rate: direct determination based on history not feasible (long time!)

• Transition matrix model
  □ average monthly transition rates between default classes
  □ asymptotic transition rates for long times!
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