Credit Risk

MFF UK, Praha
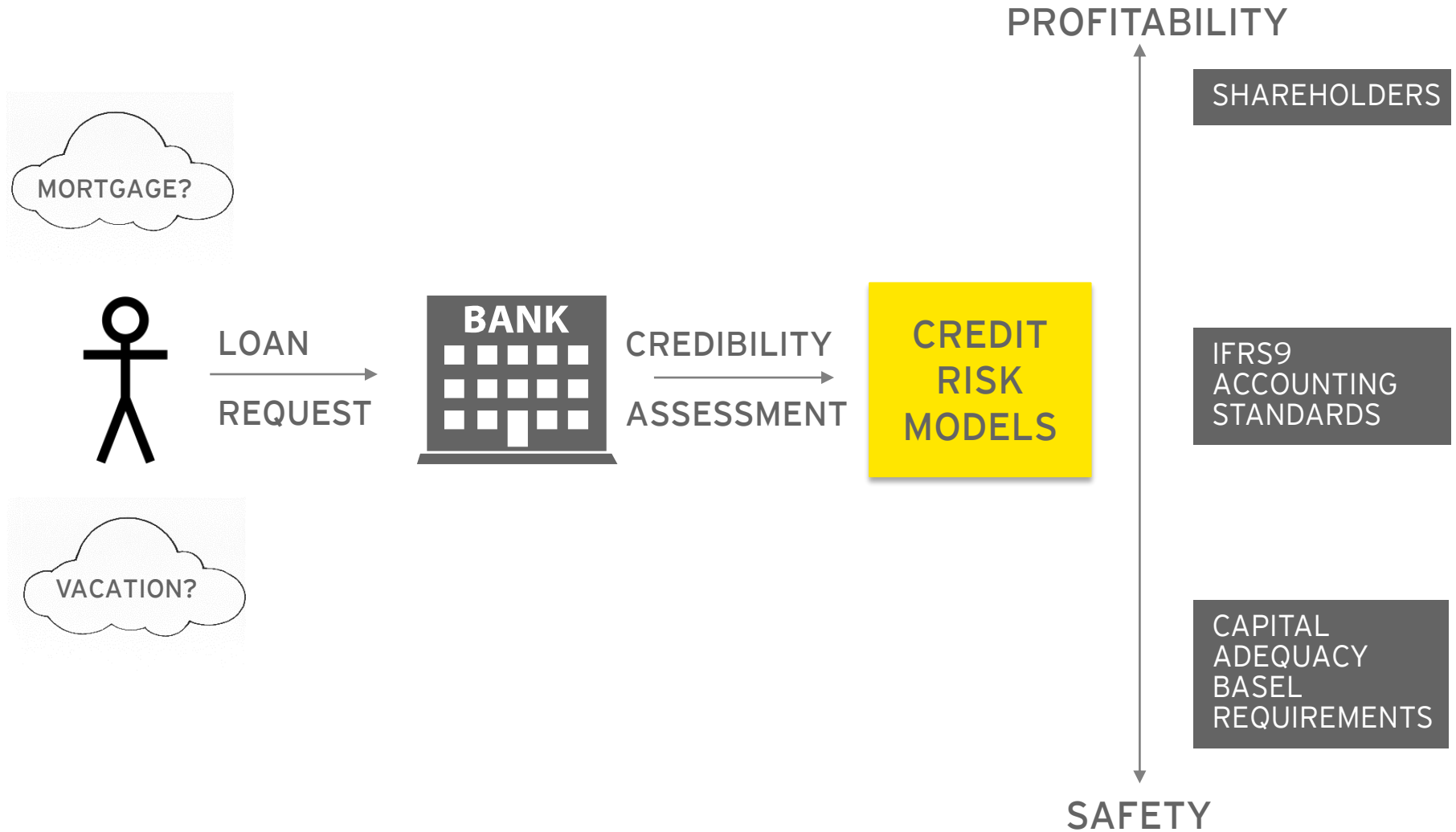
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Presented by: Jaroslav Kačmár
Email: jaroslav.kacmar@cz.ey.com

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Building a better
working world

Agenda

▶ Introduction   10 min

▶ What is credit risk   25 min

▶ Model development and validation   35 min

▶ Tools   10 min

▶ Questions   10 min

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What is credit risk?

MORTGAGE?

VACATION?

LOAN REQUEST → **BANK** → CREDIBILITY ASSESSMENT → **CREDIT RISK MODELS**

PROFITABILITY

SHAREHOLDERS

IFRS9 ACCOUNTING STANDARDS

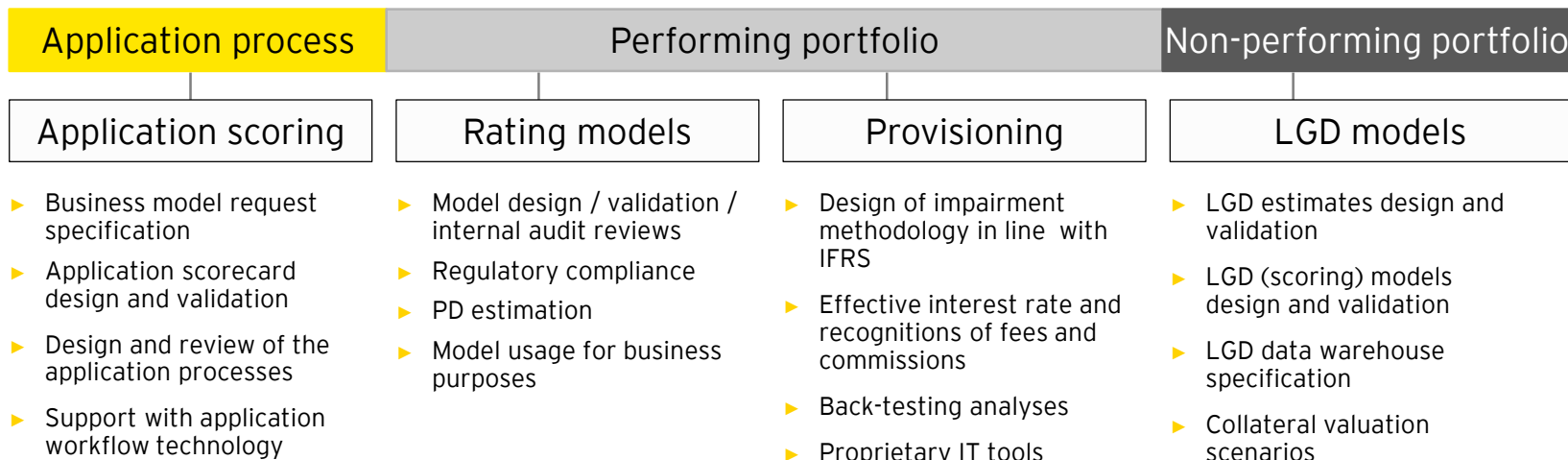CAPITAL ADEQUACY BASEL REQUIREMENTS

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Credit risk agenda

- ► Risk management function reshaping roadmap
- ► Credit risk strategy and linkage to business strategy
- ► Risk appetite framework and statements
- ► Credit risk processes and segregation of duties
- ► Model governance framework (model request, design implementation, validation)
- ► Stress testing framework

- ► Diagnostics on the effectiveness & efficiency of the collections process
- ► Development of a collections strategy, strategic and tactical (cost-benefit) analysis of available outsourcing options
- ► Design of a collections framework
- ► Support with collections technology requirements analysis, selection and implementation of an appropriate solution

Governance	Collection services

Application process	Performing portfolio	Non-performing portfolio

Application scoring	Rating models	Provisioning	LGD models

- ► Business model request specification
- ► Application scorecard design and validation
- ► Design and review of the application processes
- ► Support with application workflow technology

- ► Model design / validation / internal audit reviews
- ► Regulatory compliance
- ► PD estimation
- ► Model usage for business purposes

- ► Design of impairment methodology in line with IFRS
- ► Effective interest rate and recognitions of fees and commissions
- ► Back-testing analyses
- ► Proprietary IT tools

- ► LGD estimates design and validation
- ► LGD (scoring) models design and validation
- ► LGD data warehouse specification
- ► Collateral valuation scenarios

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Components of credit risk

PD

- **Probability of Default:** The likelihood the borrower will default on its obligation either over the life of the obligation or over some specified horizon.

LGD

- **Loss Given Default:** Loss that lender would incur in the event of borrower default. It is the exposure that cannot be recovered through bankruptcy proceedings or some other form of settlement. Usually expressed as a percentage of exposure at default.

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- **Exposure at Default:** The exposure that the borrower would have at default. Takes into account both on-balance sheet (capital) and off-balance sheet (unused lines, derivatives or repo transactions) exposures.

Expected Loss (EL) = PD x LGD x EAD

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IRB approach
Risk weight in detail

Capital > Capital requirement = Capital ratio * RWA

$$\text{Capital ratio} = \frac{\text{Capital}}{\text{Risk Weighted Assets}} > 8\%$$

$$RW = 12.5 * 1.06 * \left[LGD * N\left[\frac{N^{-1}(PD) + \sqrt{R} * N^{-1}(0.999)}{\sqrt{1-R}} \right] - PD * LGD \right]$$

Conservatism factor

Value at Risk (VaR)

Expected loss (EL)

Unexpected loss (UL) = VaR - EL

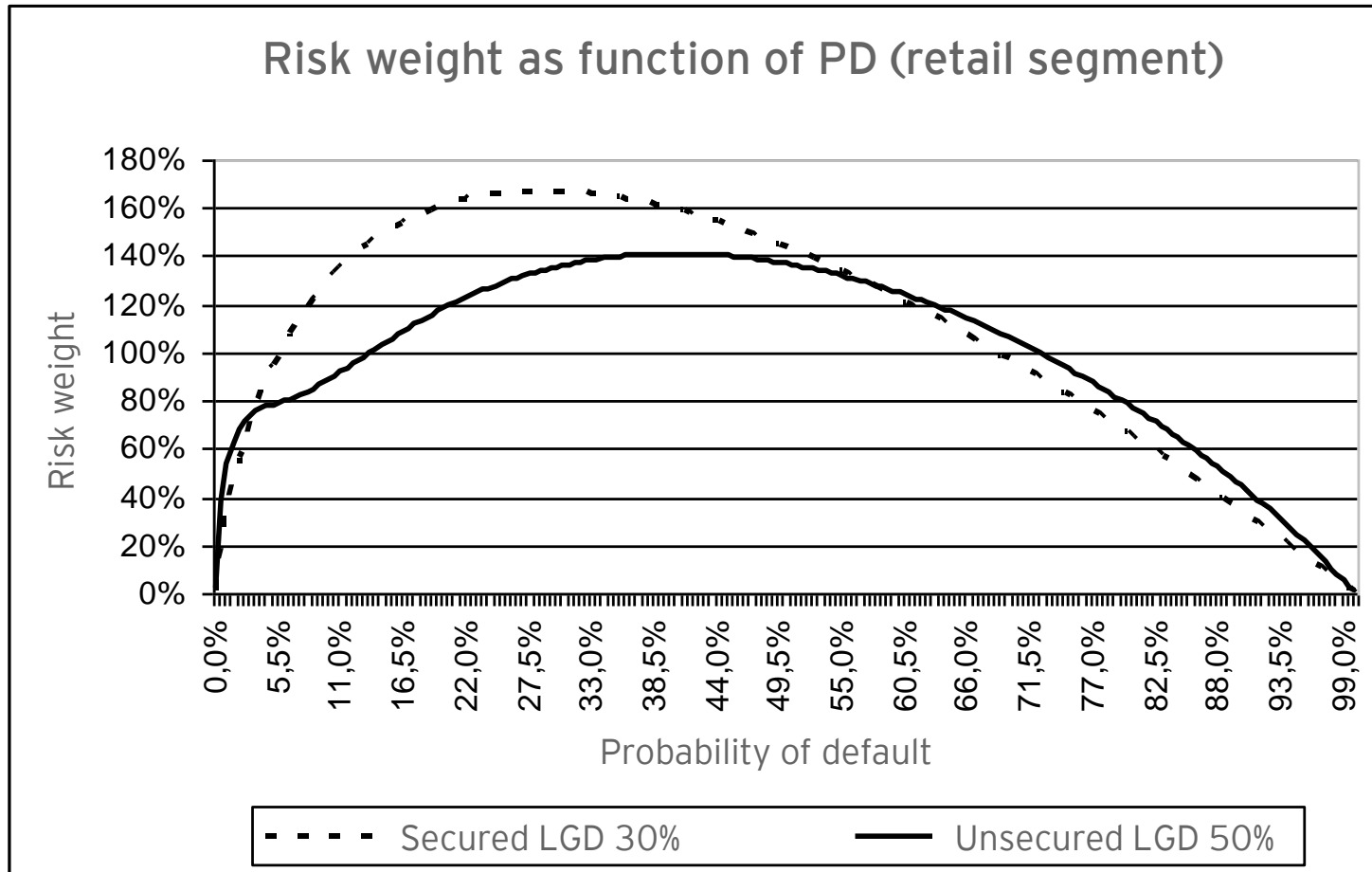Fudge factor - Introduced to get STA and RWA to the same basis.
The RW formula (without 12.5 multiplication) gives us exactly what we need, i.e. the money (when multiplied by EAD) that bank needs to hold as the capital requirement.
However, because the overall capital adequacy is calculated as 8% or RWA, we need to multiply it by 12.5 to cancel the 8%.
Remember that the constant is still 12.5, even when the requirement is more or less than 8%.
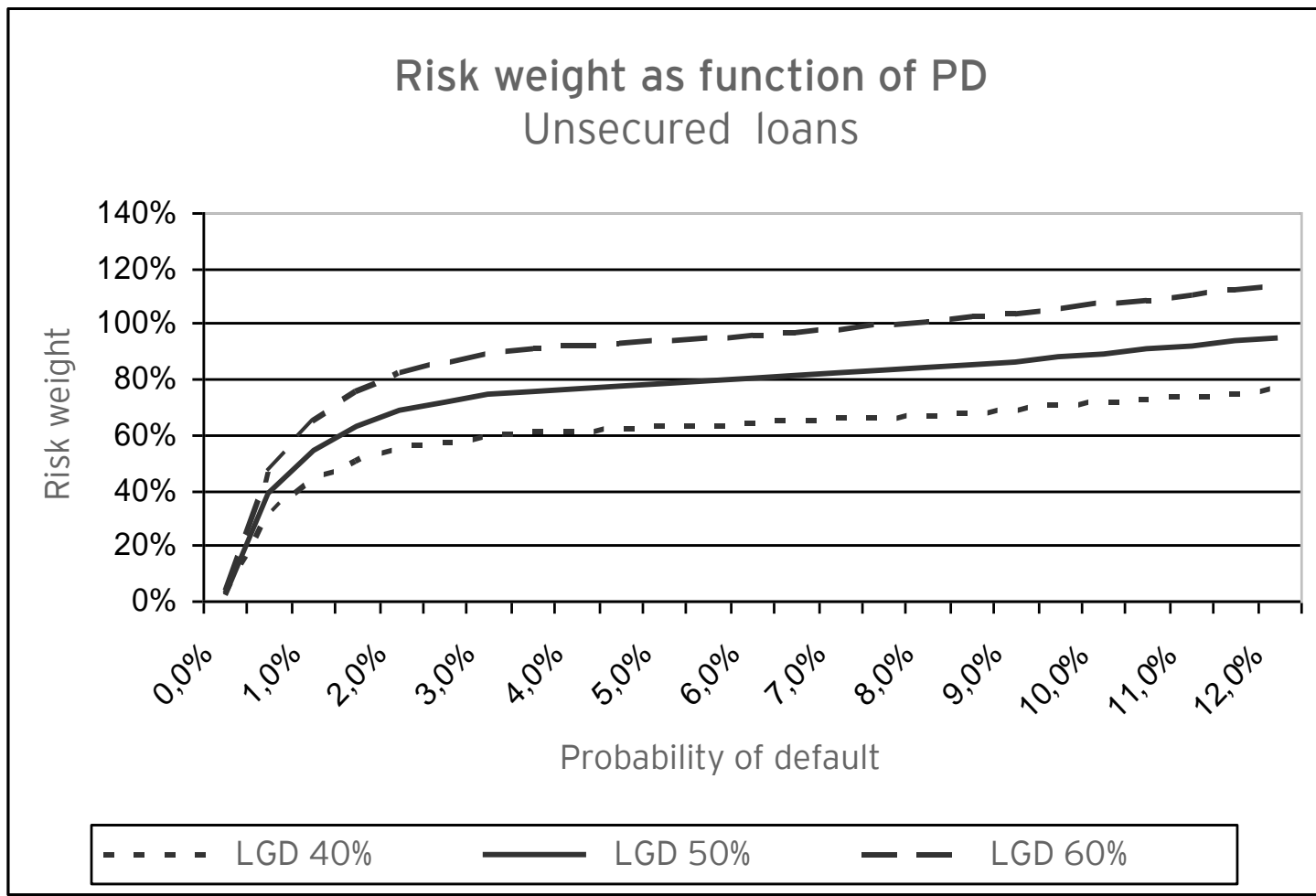Note that Capital charges for Market risk and operational risk are multiplied for the same reason.

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Risk weight
Retail segment

Risk weight as function of PD (retail segment)

Legend: Secured LGD 30% (dashed), Unsecured LGD 50% (solid)

Risk weight
Retail - Unsecured loans

Risk weight as function of PD
Unsecured loans

Risk weight (y-axis): 0% to 140%

Probability of default (x-axis): 0,0% to 12,0%

Legend:
- LGD 40% (dotted line)
- LGD 50% (solid line)
- LGD 60% (dashed line)

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Models

► The purpose of the **scorecard/rating/PD model** is to determine the creditworthiness of the clients (either new or existing) and to assign expected probability of default (PD) value. Typically like this:

  ► Scorecard (using client's characteristics) is used to determine the score

  ► The score range is split into several rating grades

  ► Each rating grade is assigned expected PD value

► The purpose of the **LGD model** is to determine the loss the bank will incur in case that the account defaults. Typically like this:

  ► Clients are categorized into homogeneous segments (e.g. by LTV)

  ► Each segment is assigned LGD value

► The purpose of **CCF model** is to determine the part of the off-balance exposure that will be drawn by client before the default

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Scoring/rating and PD models
Introduction

► **Scoring/Rating**

  ► **Order** of the clients

  ► Good clients are the clients with high **creditworthiness**

  ► Expressed in rating grades (A-, 4+)

► **Probability of default (PD)**

  ► **Measure** of creditworthiness

  ► **Probability** that the client will **not be able to pay the debt**

  ► Assigned to each rating grade (0.03, 3%)

► **Areas of applications**

  ► Approval process, loan regular reviews

  ► Risk management – impairment losses, capital adequacy

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Scoring/rating and PD models
Types

- ▶ **Retail**
  - ▶ **Application rating**
    - ▶ New clients
    - ▶ Demographic data, loan characteristics, data from registers

  - ▶ **Behavioral** rating
    - ▶ Clients **with history** (6M)
    - ▶ Data about transactions behavior

- ▶ **Corporate**
  - ▶ **Financial** rating
    - ▶ Financial statements data
  - ▶ Qualitative rating - questionnaires
  - ▶ Behavioral rating

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PD models
Methods

▶ Target variable – probability of default

   ▶ **"Default"**: Yes (**1**) / No (**0**)

▶ **Default definition** is regulatory requirement

   ▶ 90 DPD

   ▶ Any other reason indicating higher probability of inability to pay the commitments (insolvency proceeding, bankruptcy, restructuring,..)

▶ How to model 0-1 variable? -> **Logistic regression**

$$Y = \alpha + \sum \beta_i X_i$$

$$\downarrow$$

$$Y = \frac{1}{1 + e^{-\left(\alpha + \sum \beta_i X_i\right)}}$$

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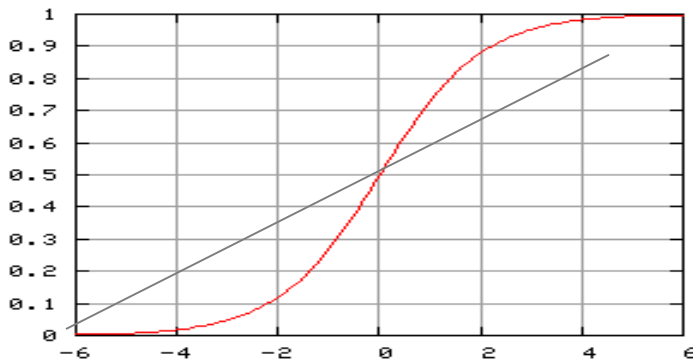
PD models
Scorecards

Example:

Variable	Coefficient*
Constant (α)	2.0
Age < 25	0
Age 25-50	0.5
Age > 50	-0.2
Education – Elementary	0
Education – High school	0.25
Education – University	0.8
Sex – Male	0
Sex – Female	0.4
Income < AUD 100 000	0
Income > AUD 100 000	0.9
Region = Prague, Brno	0
Region = Plzen	-0.4
Region = Rest	-1.0

* Higher score is better

$$Score = \alpha + \sum \beta_i \cdot X_i$$

▶ Each relevant characteristic has several possible values with different assigned score

▶ Continues characteristics are typically transformed to several intervals

▶ Clients from Prague and Brno will always have better score than the exactly same clients (regarding the other factors) from other regions

▶ Output: order of the clients

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PD models
Calibration

► Calibration **at rating level**

Rating grade	Expected default rate
A+	1.5 %
A	2.5 %
A-	3.5 %
B+	4.5 %
B	6.0 %
B-	8.5 %
C	15.0 %
D	100 %
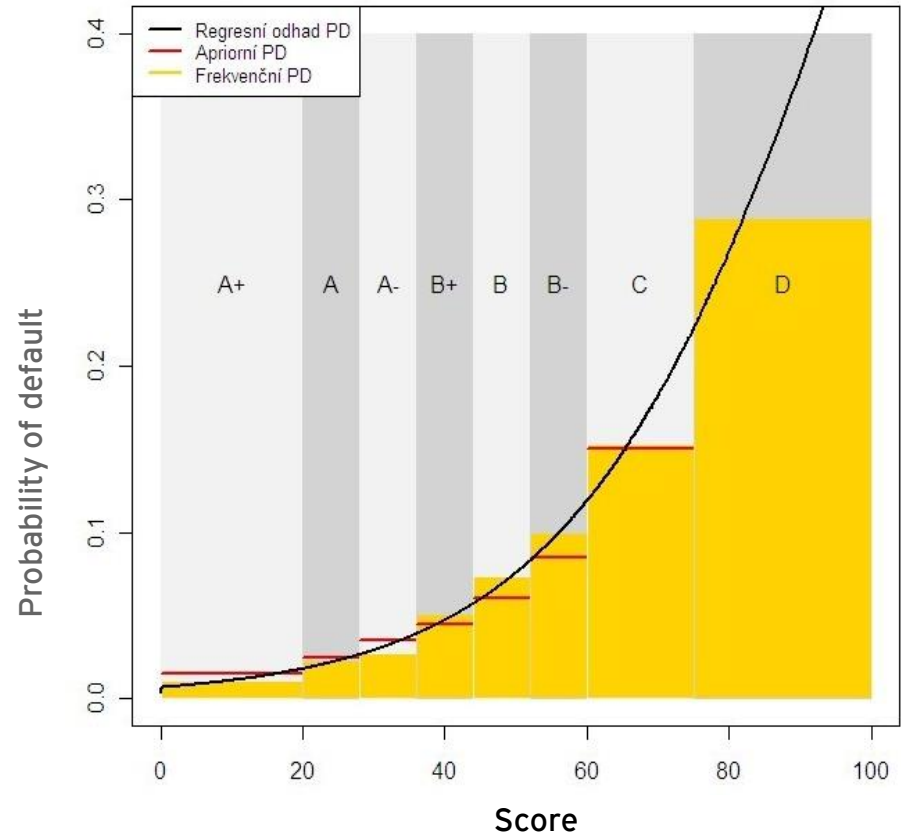
► Calibration **at portfolio level**

► $PD = PD_i \cdot CT / avgPD$, where CT is average default rate at portfolio

Parameters
LGD and EAD

► LGD:

- ► Single LGD for performing portfolio and LGD curve for non-performing portfolio should be built

- ► Must not be downturn

- ► Should be forward looking:

  - ► Uses forecasted values of any collateral and best estimate of haircuts

  - ► Current and future modelled value of the house collateral (HPI evolution)

  - ► Costs of repossession and sale

► EAD:

- ► EAD estimates for off-balance sheet exposures

- ► EAD model for prediction of exposure run till maturity of the loan

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LGD models
Introduction

► The probability of default is not the only information about risk related to the client:

Client A

Higher PD
Consumer loan 1M
Unsecured

Client B

Lower PD
Mortgage loan 1M
Real estate collateral 2M

Whom would you give the loan?

► **Loss Given Default (LGD)**

  ► The loss amount expected in the case that the client comes to default.

$$LGD = 1 - RR$$

$$RR_i = \frac{\sum_{j=1}^{t} PV(CF_{ij})}{EAD_i}$$

  ► RR is a recovery rate = recoveries after default related to exposure at default

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LGD models
Structure

▶ **Types of recover**

  ▶ Repayments from clients

  ▶ Realization of collaterals

  ▶ Costs – direct/indirect

▶ **Recovery horizon:** The last day when a recovery is expected

▶ **Haircut (h):** Adjustment for collaterals real value

$$CF = Coll \cdot h$$

▶ **Interest rate used for discounting**

  ▶ Choice is up to bank for Basel purposes (market rate is usually used)

  ▶ Original effective interest rate (EIR) is used for IAS 39/IFRS purposes

▶ **Cases**

  ▶ **Closed:** Recoveries finished till the end of development time window

  ▶ **Open:** Future recoveries remain unknown, must be estimated

  ▶ Typically, open cases from minimal lasting time threshold included (24M)

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LGD models
Distribution

▶ **"U-shape"**

▶ It does not make sense to use average LGD = 45% for these clients

▶ Real LGD is lower then 10% for the best 1/3 of the clients and higher then 90% for the worst 1/4 of the clients
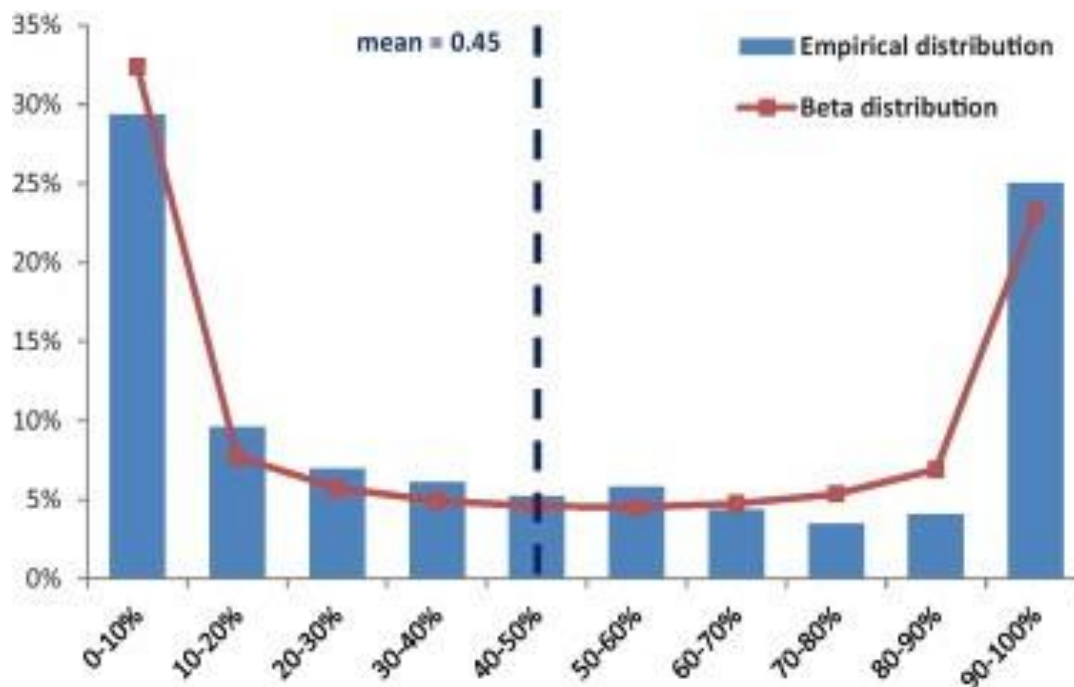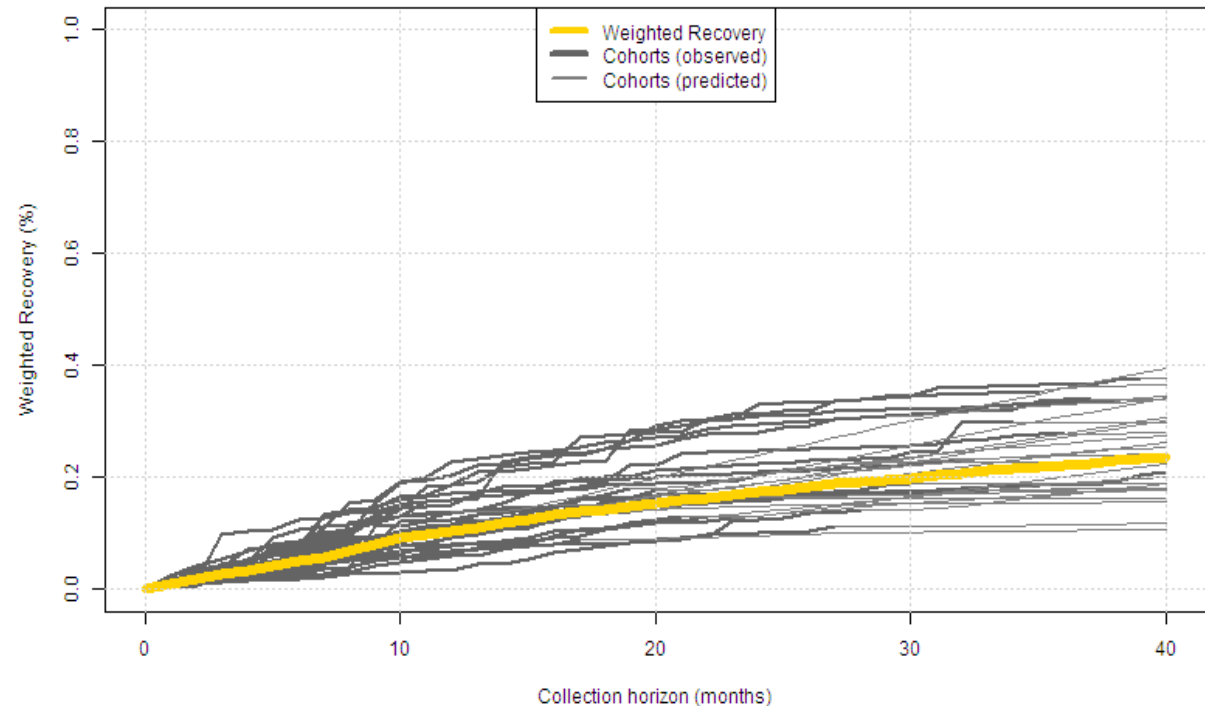
LGD models
Methods – decision trees

► **Loss class** -> a class of exposures with a similar level of loss given default

► **Regression trees** -> explanatory variables

► Thresholds for split

► Additionally **pruned** or **trimmed** to abandon spurious dependencies without economical interpretation and over-fitting
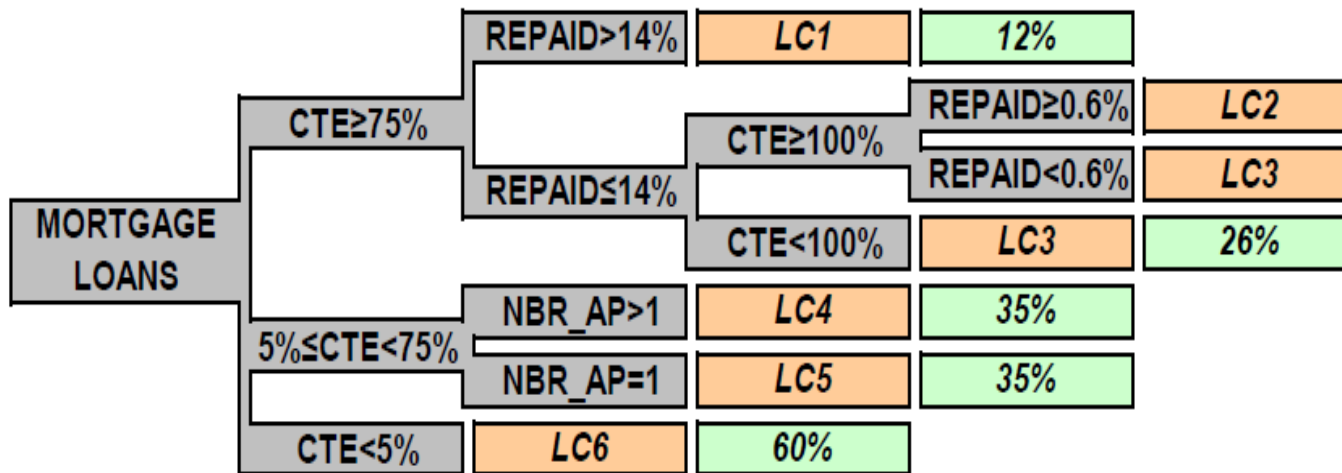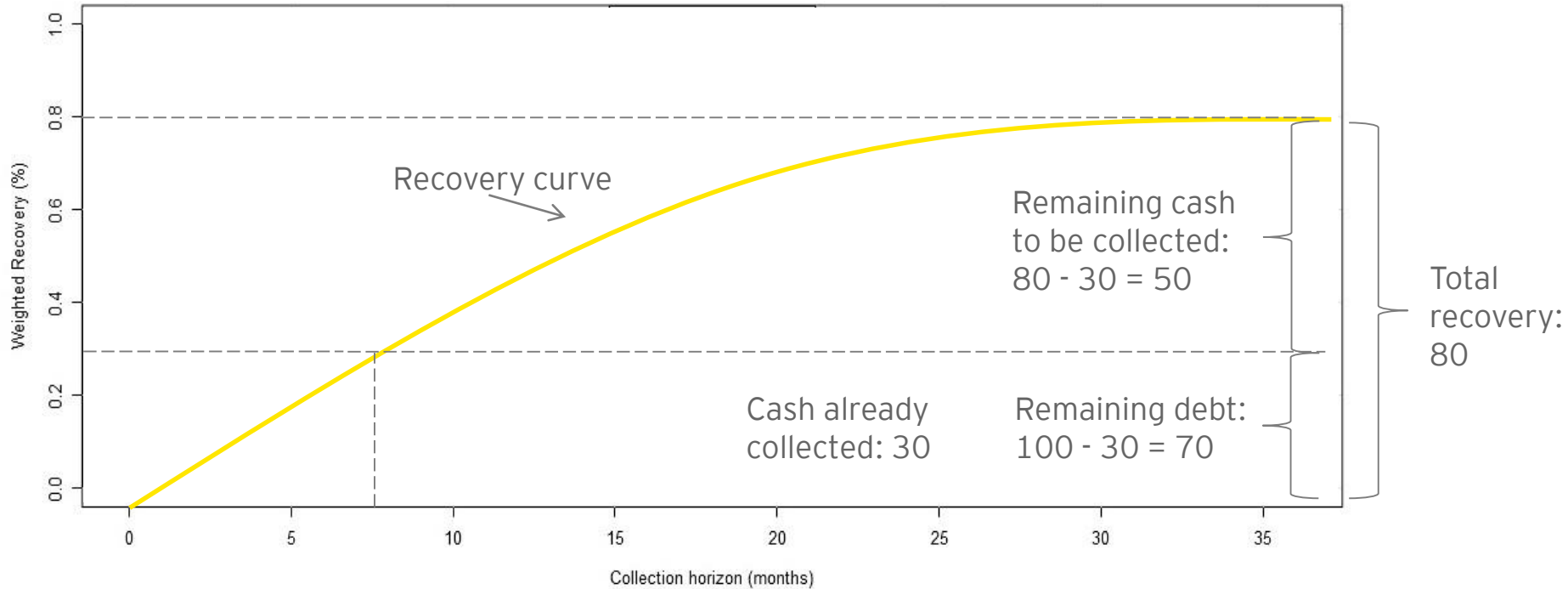
LGD models
Recovery curves

► Recovery rate can be calculated for different time t -> **Recovery curve**

► **Regression by time *t*** can be used to "smooth" the curve

  ► E.g. for all cases or by individual cohorts (for individual segments)

► Graphical analysis allows better expert view about recovery horizon setting, segmentation, etc.

LGD models
Residual LGD curve


Residual recovery rate:
(80-30)/70 = 71.4%

→ **Residual LGD:**
100% - 71.4% = 28.6%

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Model development

- ► Historical data storage setting
- ► Data preparation and quality assessment
- ► Data transformations
- ► Univariate analysis of individual data characteristics
- ► Choice of method
- ► Model versions development
- ► Battery of tests
- ► Expert assessment of interpretation and data form
- ► Calibration
- ► Documentation of model and development results
- ► Management approval
- ► Implementation
- ► Data storage, reporting

Model validation

► Validation of the model should cover both qualitative (process) and quantitative (model performance) aspects of the model

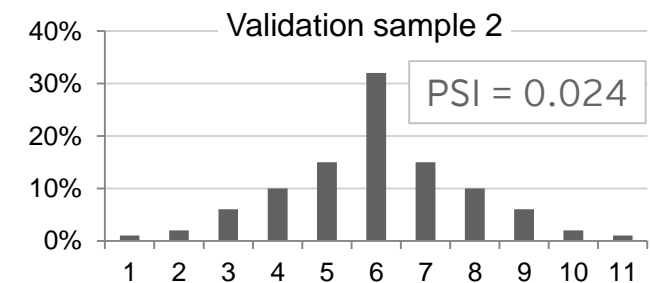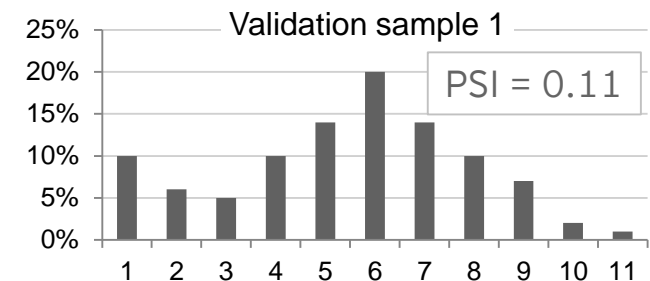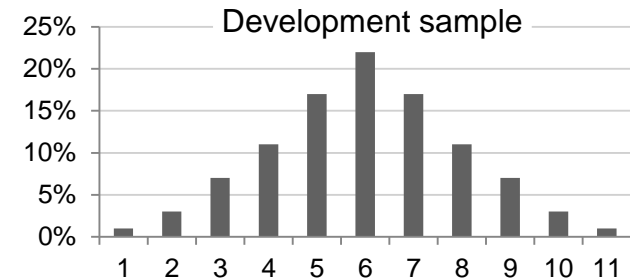► Typical model validation should cover the following areas:

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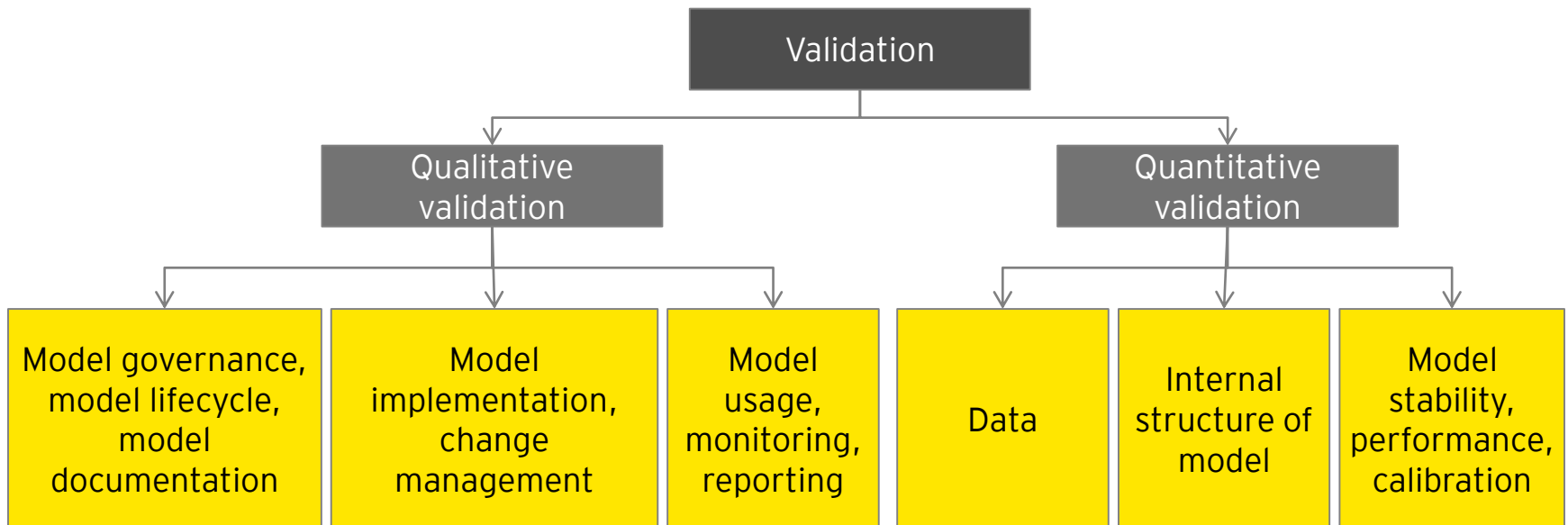
Model validation
Stability - Population stability index (PSI)

▶ The aim of the stability analysis is to assess whether there is significant shift in the underlying data since development

    ▶ Shift in rating distribution

    ▶ Shift in distribution of each model variable

▶ Not crucial aspect of the model but instability might make the model assumptions incorrect

▶ Standard measure is Population Stability Index (PSI)

$$PSI = \sum_{i=1}^{n} \left[(p_{i0} - p_{i1}) \log \left(\frac{p_{i0}}{p_{i1}} \right) \right]$$

PSI	Result
< 0.1	Stable
0.1 – 0.25	Warning
> 0.25	Not stable

Development sample

Validation sample 1 — PSI = 0.11

Validation sample 2 — PSI = 0.024

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Model validation
Stability – Transition matrices

► PSI provides us with aggregate view of stability

► Transition matrix provides us with client/loan level dynamics

► Unless there is significant change on client's quality scorecard/rating model should be stable (i.e. assigning similar rating in consecutive periods)

		T=1				
		A	B	C	D	E
T=0	A	67%	33%	0%	0%	0%
	B	20%	40%	20%	0%	20%
	C	0%	0%	50%	0%	50%
	D	0%	0%	0%	0%	100%
	E	0%	0%	0%	0%	100%

Rating grade	No change	<= +/- 1	<= +/- 2	> +/- 2
A	67%	100%	100%	0%
B	40%	80%	80%	20%
C	50%	50%	100%	0%
D	0%	100%	100%	0%
E	100%	0%	100%	0%
Total	50%	83.33%	91.66%	8.33%

Transition matrices evaluation criteria (indicative)[#]	
Condition	Performance
Each eligible* rating grade has at least 75% of transitions on the main diagonal	Strong
Each eligible* rating grade has at least 60% of transitions on the main diagonal AND Each eligible rating grade has at least 80% of transitions in +/-1 transitions range	Acceptable
At least one eligible* rating grade has less than 60% of transitions on the main diagonal	Unsatisfactory

\# More complex assessment of transition matrix is described in the Model validation methodology, chapter 4.1.5 Complex stability test

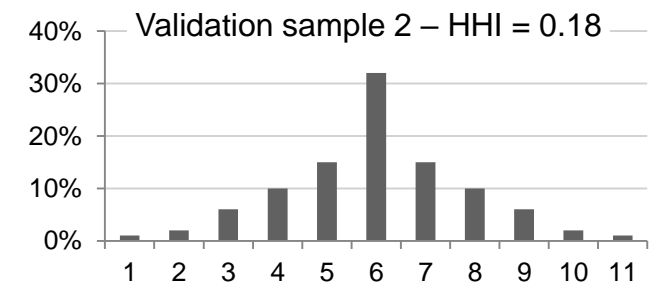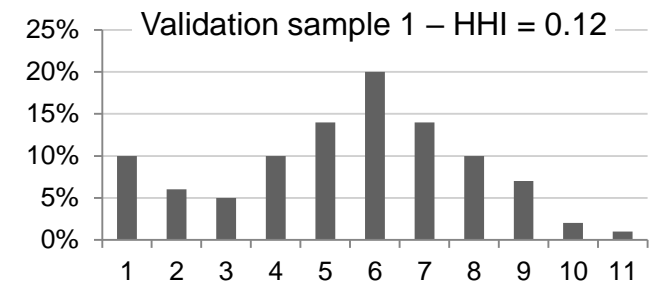* Rating grade has to contain at least 100 observations to be eligible
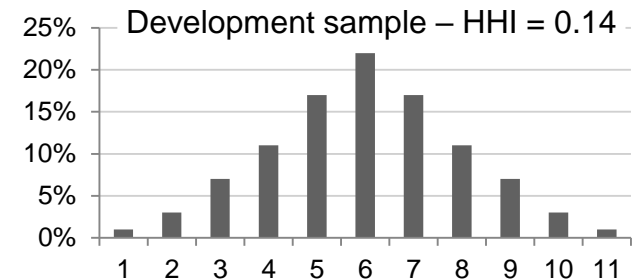
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Model validation
Concentration - Herfindahl – Hirschman Index (HHI)

▶ The aim of the analysis of concentration is to assess whether there is undue concentration in the underlying data

- ▶ Concentration on rating level
- ▶ Concentration on variable level

▶ Not crucial aspect of the model but it can indicate model deficiency

▶ Standard measure is Herfindahl-Hirschman Index (HHI)

$$HHI = \sum_{i=1}^{n} \left(\frac{N_i}{N} \right)^2$$

HHI	Result
< 0.1	Not concentrated
0.1 – 0.25	Warning
> 0.25	Too concentrated

Development sample – HHI = 0.14

Validation sample 1 – HHI = 0.12

Validation sample 2 – HHI = 0.18

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Model validation
Discriminatory power

► The crucial aspect of a rating model is its ability to distinguish between groups of "bad" (defaulted) and "good" (non-defaulted) clients

► Weak discriminatory power should always lead to re-development

► Standardized measures

   ► Gini

   ► AUC (Gini = 2 * AUC - 1)

   ► Kolmogorov-Smirnov

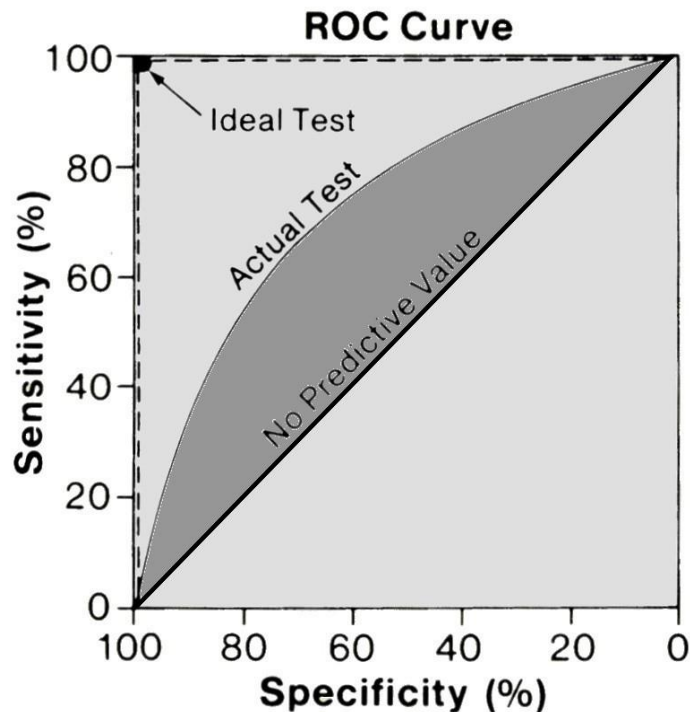| Gini	AUC	Result
>= 0.5	>= 0.75	Strong
0.3 - 0.5	0.65 - 0.75	Acceptable
< 0.3	< 0.65	Weak

Good discriminatory power - Gini = 56%

Low discriminatory power - Gini = 30%

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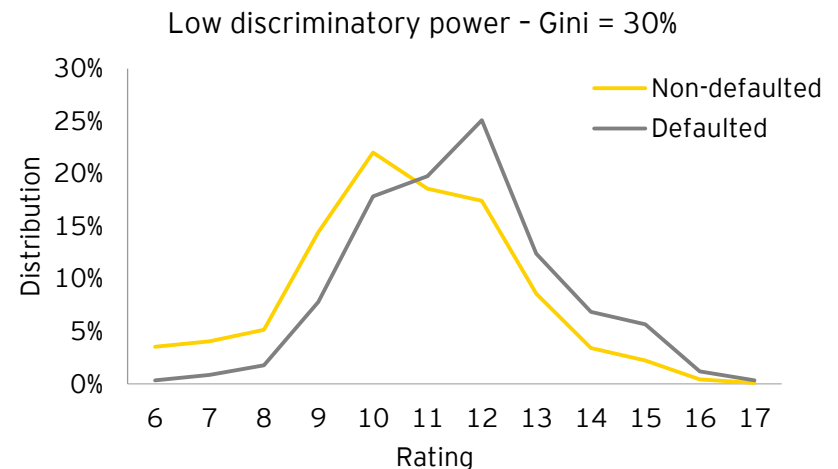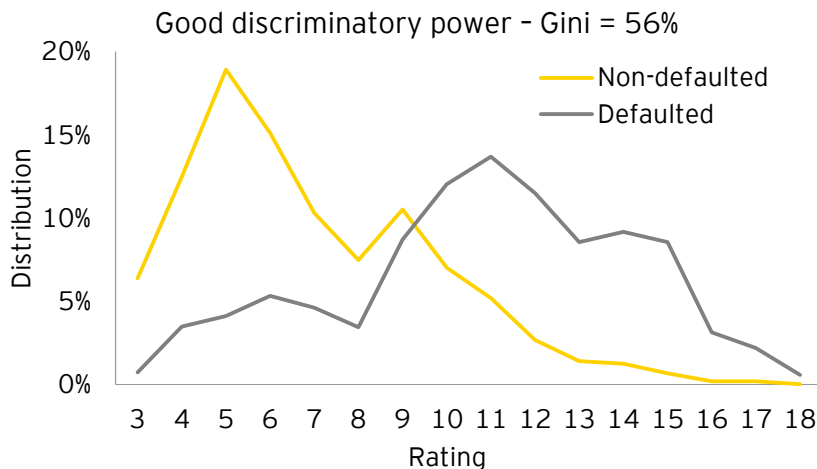
Model validation
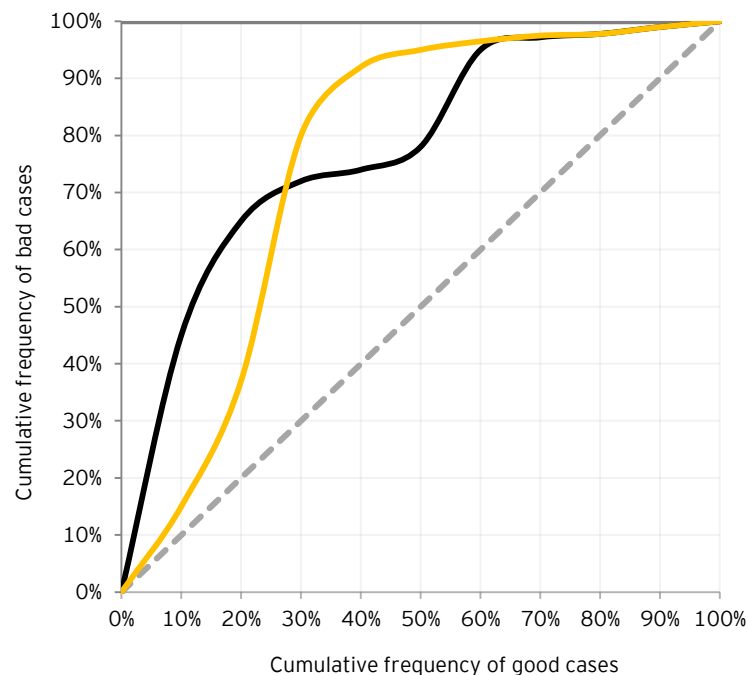## Discriminatory power – Gini/AUC

► Coefficient Gini = 2*AUC-1

► **Sensitivit**y = true positive observations

► **Specificity** = true negative observations

► Gini from **0% (No predictive)** to **100% (Ideal)**

► If **Gini < 0%**, it's better to throw a dice at client approval process.

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Model validation
Discriminatory power - ROC

► While Gini is important measure of discriminatory power, it is important to analyze the ROC curve itself

► Analysis of the shape of the curve can point out specific deficiencies not observable from the Gini index

► Both of the ROC curves shown on the right have the same Gini value but each point to deficiency in different part of the rating scale

   ► Yellow line indicates that the model has high share of good clients who are assigned the lowest score

   ► Black line indicates (in particular its "flat" segment in the middle) that there is a part of the score band, with very limited number of bad clients

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Model validation
Discriminatory power – Information value

► Gini/AUC measure can be used for variables as well

► However, Information Value (IV) measure is more widely used

$$IV_v = \sum_{i=1}^{n} \left\{ \left(\frac{G_i}{G} - \frac{B_i}{B} \right) \times ln \left(\frac{G_i}{B_i} \times \frac{B}{G} \right) \right\}$$

Information value evaluation criteria	
Information value	Performance
>= 0.25	Strong
[0.10,0.25)	Acceptable
[0,0.10)	Unsatisfactory

► where

  ► G is the total number of good observations

  ► G_i is the number of good observations in given category

  ► B is the total number of bad observations

  ► B_i is the number of bad observations in given category

► Limitations

  ► Does not work if there are no bad (or no good) observations at all or even in one category

  ► It's zero if the Good/Bad ratio is the same for each category of variable

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Model validation
Discriminatory power – Kolmogorov-Smirnov (KS) test (1/2)

► Non-parametric test for the equality of two continuously valued distributions

► Testing the equivalence of two distributions

  ► distribution of score of good clients

  ► distribution of score of bad clients

  ► This statistic is defined as the maximum difference between the cumulative percentage of goods and the cumulative percentage of the bads:

$$KS = max|F_0 - F_1|$$

► Evaluation criteria

$$KS_{max} = c(\alpha)\sqrt{\frac{n_1+n_0}{n_1 n_0}}$$

α	0.1	0.05	0.01	0.001
c(α)	1.22	1.36	1.63	1.95

Kolmogorov-Smirnov test evaluation criteria	
Condition	Result
KS > KSmax	Good – Reject H0 of equivalence of good and bad distributions
KS < KSmax	Bad – Do not reject H0 of equivalence of good and bad distributions

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Model validation
Discriminatory power – Kolmogorov-Smirnov (KS) test (2/2)

Kolmogorov-Smirnov test - Example

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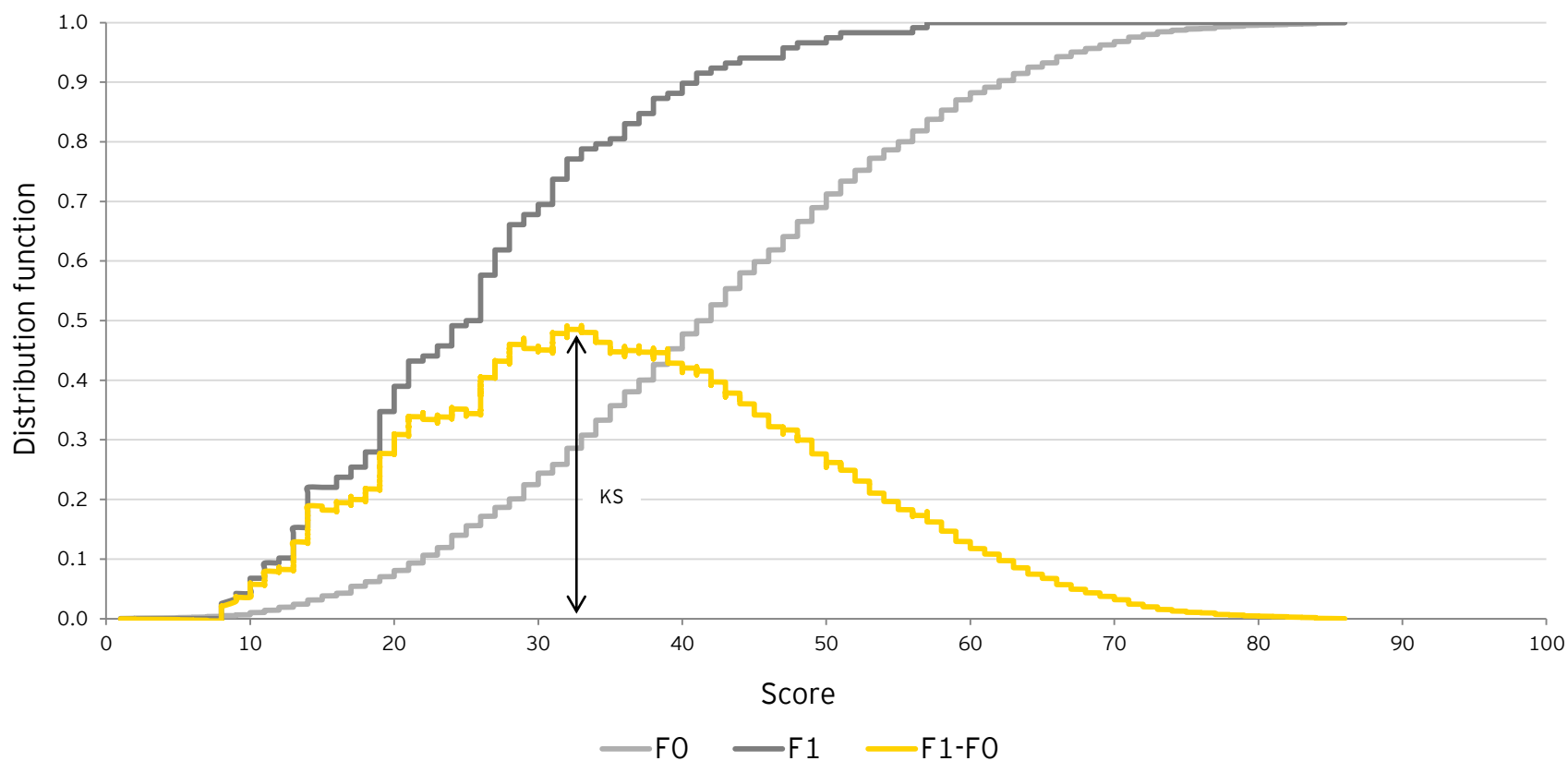
Model validation
Calibration

▶ The main aim of the analysis of the calibration of the model is to assess whether the observed default rate is in line with expected PD values

▶ Calibration is the second most important aspect of the model

▶ Incorrect calibration of the model leads to incorrect level of capital requirement and requires recalibration of the model

▶ Various statistical tests are used:

  ▶ Hosmer Lemeshow Chi-square test

  ▶ Binomial test

Rating class	Expected PD	Observed default rate (#1)	Observed default rate (#2)
3	0.13%	0.15%	0.11%
4	0.20%	0.22%	0.22%
5	0.32%	0.37%	0.35%
6	0.49%	0.52%	0.45%
7	0.68%	0.70%	0.66%
8	0.89%	0.82%	0.82%
9	1.20%	1.12%	0.93%
10	1.82%	1.87%	1.40%
11	2.59%	2.17%	2.08%
12	3.44%	3.22%	2.74%
13	4.40%	4.61%	3.71%
14	5.44%	4.51%	4.48%
15	6.77%	6.27%	7.52%
16	8.86%	8.47%	6.16%
17	11.81%	8.26%	5.98%
18	17.81%	12.68%	3.77%
Chi square test result		🟩	🟥
Binomial test result		🟩	🟩

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Model validation
Calibration – Hosmer-Lemeshow Chi-square test

► **Hosmer-Lemeshow Chi-square test**

$$\chi^2 = \sum_{k=1}^{K} \frac{(O_k - N_k ePD_k)^2}{N_k ePD_k (1 - ePD_k)}$$

► K – number of rating grades

► O_k – number of defaults in rating *k*

► N_k – number of accounts in rating *k*

► ePD_k – expected PD for rating *k*

► **Advantage**

► Standardized test

► Easy to perform with limited number of information

► **Main disadvantage**

► Result only on the portfolio level

► It will trigger red even when overestimation (PD > DR) is present (i.e. the model is conservative), which is not such a big issue in Basel world

Hosmer-Lemeshow test evaluation criteria	
Condition	Performance
Calculated chi-square statistic is less than the critical value	Strong
Calculated chi-square statistic is more than the critical value	Unsatisfactory

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Model validation
Override analysis

► In case that scorecard/rating model is used for application purposes, often override is allowed by credit officer (i.e. he can shift the rating by several notches)

► In such cases, it is important that analysis of this process is done

► In case that significant share of cases is overridden, it indicates that the model might not be reflecting some important aspects of client's behaviour

► Individual analysis of the significant overrides should be performed as well

Override analysis evaluation criteria (indicative)	
Condition	Performance
Override rate < 10%	Strong
10% < Override rate < 25%	Warning
Override rate > 25%	Unsatisfactory

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Model validation
LGD model

► Validation of LGD models is very specific to the model structure, which can vary significantly from bank to bank

► However, typical structure of the LGD model looks like this:

$$LGD = PC * LGC + (1-PC) * LGWO$$

► where

  ► PC – Probability of cure

  ► LGC – Loss given cure – typically around 1-2%

  ► LGWO – Loss given write-off – based on recoveries and written-off amount

► Within the validation, assessment/validation of each element is done employing various suitable tests

► In case that scorecard is involved in any of the elements, standard tests that are used for scorecards are used

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Model validation
LGD model – test examples

► Segmentation – assessing whether segment have different LGD values

► Calibration - testing Average observed LGD vs. Average expected LGD

► Outliers - analysis using Box-plots

► Population stability - using Population Stability Index

► Discriminatory power (if scorecard used for segmentation) – Gini/AUC

► Concentration - Herfindahl-Hirschman Index

► Qualitative assessment of model development process

► Independent recalculation

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Model validation
LGD model – analysis example

► Analysis whether data used to determine the outcome is based on time period with sufficient number of closed cases

Distribution of defaulted accounts by outcome

Legend: Closed no loss | Cured | Default | Write-off
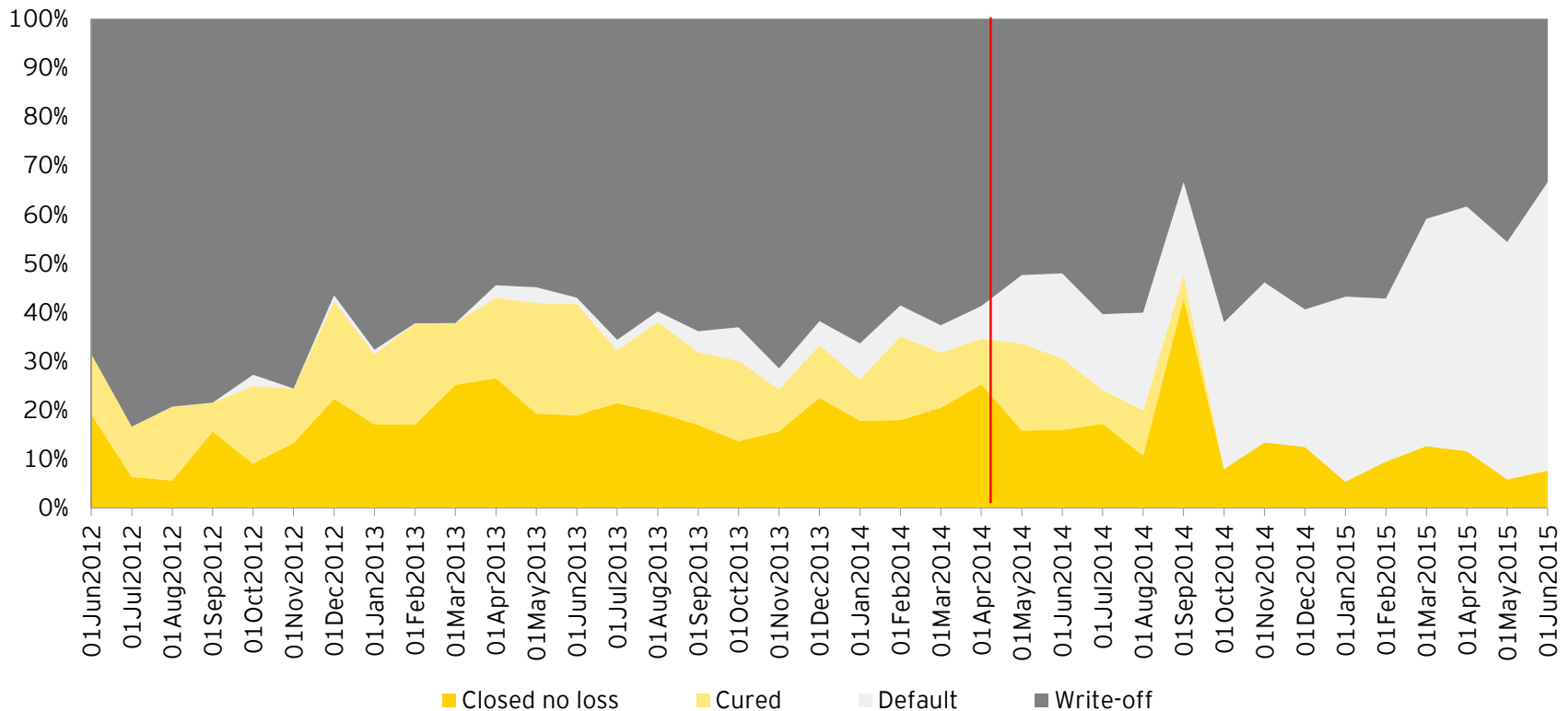
Model validation
Overall assessment

► Final step in validation of any model is to conclude on its overall assessment

► This process might be numeric/quantitative. For each assessment/analysis (e.g. PSI, HHI, Gini, Binomial, …) we must determine the following:

  ► weight of each assessment/analysis

  ► score of each assessment/analysis

► Final score of the model is weighed sum of the partial scores

► However, selection of weights and scores might be difficult to justify

► Expert assessment is then needed

► For scorecards/rating models, indicative priority/weight of the areas is as follows:

  ► Discriminatory power   ~ 50%

  ► Calibration   ~ 40%

  ► Stability and concentration   ~ 10%

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