

Credit Risk Fundamentals

Sara Nowogórska
sara.nowogorska@ubs.com

Risk Analytics Specialist

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Section 1

Credit risk and its types

Default Risk

Default risk is that a counterparty does not honour their obligations.
We call the risk of a payment default **credit risk**.

- Default Risk is ubiquitous as any transaction carries a risk that one of two parties involved does not deliver.
- Examples of obligors:
 - A company has borrowed money from a bank
 - A company has issued bonds.
 - A household borrowed money from a bank, to buy a house (a mortgage).
 - A bank has entered into a bilateral financial contract (e.g an IR swap) with another bank.
- Examples of defaults:
 - A company goes bankrupt.
 - As company fails to pay a coupon for some of its issued bonds on agreed time.
 - A household fails to pay amortisation or IR on their mortgage.

Credit risk types

There are at least four aspects of the credit risk.

- **arrival risk**, the risk connected to whether or not a default will happen in a given time-period, for a obligor
- **timing risk**, the risk connected to the uncertainty of the exact time-point of the arrival risk
- **recovery risk**, the risk connected to the size of the actual loss, should a default occur.
- **dependency risk**, the risk that several obligors jointly defaults during some specific time period.

This is one of the most important risk factors that has to be considered within the credit portfolio framework.

Credit Loss

Credit loss, loss due to default of obligor = $EAD \times LGD$,

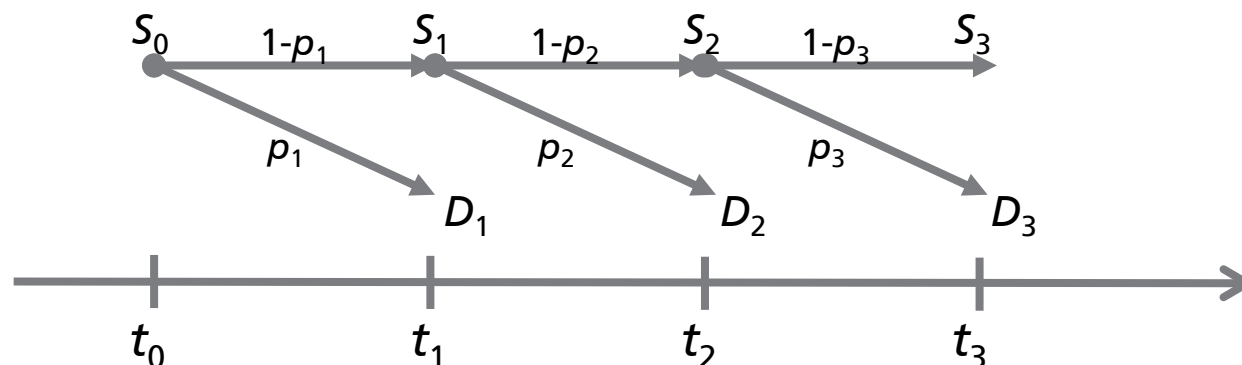
Expected credit loss ECL = $PD \times EAD \times LGD$

- The credit risk may be described by the following processes:
 - $\mathbf{1}_{\tau}(t)$, the **default indicator** process
equals to 1 if there was a default by the time t , and 0 if the obligor is still alive;
 - $\mathbf{E}(t)$, the **exposure at default** process (EAD),
the total amount of payment obligations of obligor at time t ;
 - $\mathbf{L}(t)$, the **loss given default** process,
a proportion of the exposure to be recovered in bankruptcy proceeding.
- The expected credit loss, assuming mutual independence of the above processes:
 - $ECL = PD \times EAD \times LGD$.
- Modelling PD and LGD is one of the main tasks of Credit Risk Quants

More details on default probabilities

PD is usually **time dependent**. It depends on specific features of the borrower and the loan itself, however very often it is impacted by the economical situation.

- PD language:
 - Cumulative PD : $F(t) = P(\tau \leq t) = E(\mathbf{1}_\tau(t))$
 - Marginal PD: $F(t_i, t_{i+1}) = P(t_i < \tau \leq t_{i+1}) = F(t_{i+1}) - F(t_i)$
 - Forward PD, point in time: $p(t_i, t_{i+1}) = P(t_i < \tau \leq t_{i+1} \mid t_i < \tau)$
- Multi-step default tree, $p_i = p(t_{i-1}, t_i)$:



- $F(t_i) = 1 - (1-p_1)(1-p_2)\dots(1-p_i) = 1 - s_1 s_2 \dots s_i$, where survival probability (pit) $s_i = 1-p_i$

Section 2

Estimation of PD

Credit Ratings – Historical DRs

Credit Rating is the assessment of the credit risk of the obligor. Agency rating it is one of the tools to assess likelihood that an obligor defaults based on historical default rates.

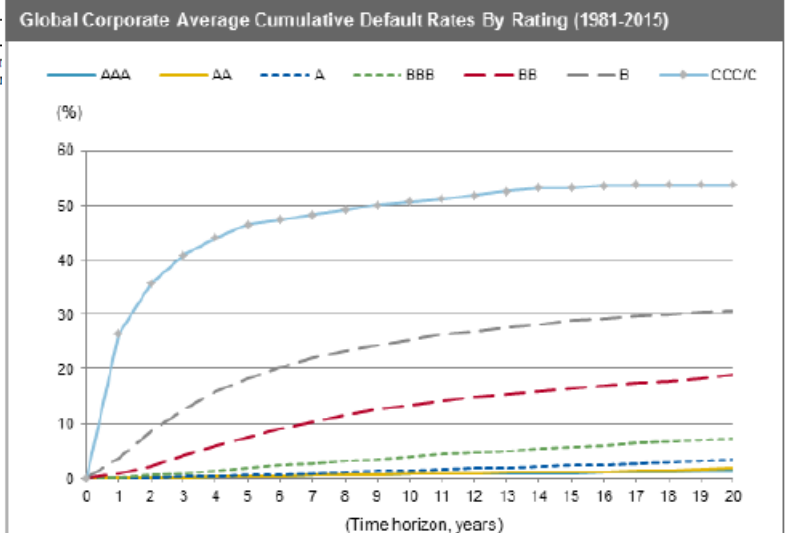


Table 33

Average Multiyear Global Corporate Transition Matrix (1981-2015) (%)

From/to	--One-year transition rates--								
	AAA	AA	A	BBB	BB	B	CCC/C	D	NR
AAA	87.08 (7.14)	9.00 (7.16)	0.53 (0.83)	0.05 (0.25)	0.08 (0.25)	0.03 (0.17)	0.05 (0.35)	0.00 (0.00)	3.18 (2.44)
AA	0.53 (0.52)	86.69 (5.32)	8.06 (4.28)	0.53 (0.69)	0.06 (0.20)	0.07 (0.21)	0.02 (0.07)	0.02 (0.08)	4.02 (1.94)
A	0.03 (0.09)	1.81 (1.02)	87.65 (3.55)	5.39 (2.14)	0.33 (0.39)	0.13 (0.27)	0.02 (0.07)	0.06 (0.11)	4.58 (1.81)
BBB	0.01 (0.04)	0.11 (0.16)	3.55 (1.68)	85.43 (3.80)	3.82 (1.56)	0.52 (0.72)	0.12 (0.23)	0.19 (0.26)	6.24 (1.63)
BB	0.01 (0.06)	0.03 (0.09)	0.13 (0.27)	5.08 (1.89)	76.78 (4.47)	6.96 (3.21)	0.64 (0.77)	0.73 (0.87)	9.63 (2.46)
B	0.00 (0.00)	0.03 (0.09)	0.09 (0.22)	0.21 (0.22)	5.25 (2.07)	74.27 (4.37)	4.39 (2.25)	3.77 (3.37)	11.99 (2.25)
CCC/C									

Note: Numbers in parentheses are from Research and Standard

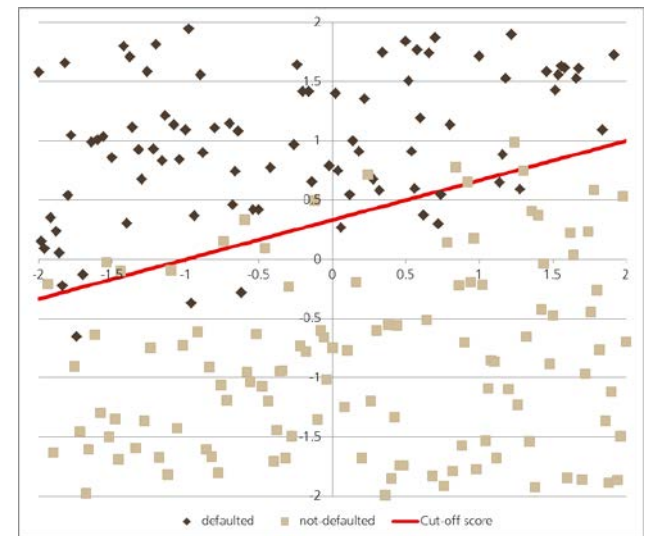


Credit Scoring

The ratings from agencies are published only for relatively large corporates. Therefore banks need to prepare internal ratings based (IRB) approach for determining PDs for small and medium enterprises as well as individual clients.

- Altman's Z-Score
 - the first credit scoring models; relies on accounting ratios:
 - $A = \text{Working Capital} / \text{Total Assets}$
 - $B = \text{Retained Earnings} / \text{Total Assets}$
 - $C = \text{Earnings before Interest and Taxes} / \text{Total Assets}$
 - $D = \text{Market Capitalisation} / \text{Debt}$
 - $E = \text{Sales} / \text{Total Assets}$.
 - $Z = 1.2A + 1.4B + 3.3C + 0.6D + E$.
- Credit score is used also to rank obligors: **higher** score implies **better** credit quality.
- Accounting ratios are used to measure: indebtedness, cash flow available for debt service, profitability.

Market capitalisation refers to the total market value of company's outstanding shares. Commonly referred to as "market cap"; calculated by multiplying company's shares outstanding by the current market price of one share.



Zones of discrimination:

$Z > 2.99$ – "Safe" Zone
 $1.81 < Z < 2.99$ – "Grey" Zone
 $Z < 1.81$ – "Distress" Zone

If $Z < 1.81$ the obligor is likely to default and a loan should be refused.

Estimation of PD

Another way of measuring credit risk is estimation of the direct default probability via an assumed functional relationship: $p = f(\beta_0 + \beta_1 x_1 + \dots + \beta_n x_n)$

- Probit model:

- $f(x) = \Phi(x)$,
i.e., cdf of the standard normal distribution.

- Logit model:

- $f(x) = 1 / (1 + \exp x)$

In general, one can use $f(x)$ as a mapping from something like Z-score into the default probability space.

- Let ε be a standard normally distributed noise component. Then we define the credit index:

$$- (\beta_0 + \beta_1 X_1 + \dots + \beta_n X_n) + \varepsilon.$$

Fact. Assuming that the obligor defaults when his **credit index drops below zero**, the default probability of the obligor is exactly equal to the p given by the probit model.

Can you prove it?

Logit and probit models

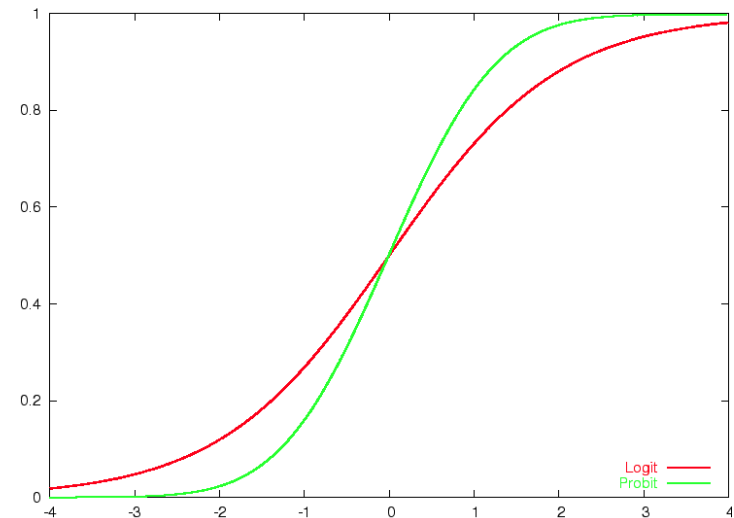
The logit and probit models regress a function of the probability that a case falls into a certain category of the dependant variable

- In the logit model it is assumed that

$$P(Y = 1 | x_1, \dots, x_k) = 1 / (1 + \exp(b_0 + b_1x_1 + \dots + b_nx_n)).$$

Binary logistic regression major assumptions:

- The dependent variable should be dichotomous (e.g., presence vs. absent, default vs. alive).
- There *should be no outliers* in the data.
This can be assessed by converting the continuous predictors to standardised scores, and removing values below -3.29 or greater than 3.29 [why 3.29?].
- There should be no *high* correlations (*multicollinearity*) among the predictors.
This can be assessed by a correlation matrix among the predictors. It is suggested that as long correlation coefficients among variables are **less than 0.90** the assumption is met.



Logit and probit models

The logit and probit models regress a function of the probability that a case falls into a certain category of the dependant variable

- In the probit model it is assumed that
 - $P(Y = 1 \mid x_1, \dots, x_k) = \Phi(b_0 + b_1x_1 + \dots + b_nx_n)$,
the cdf of the standard normal distribution.
- The regression coefficients of the probit model are effects on Φ of the probabilities that $Y = 1$, that is, that the obligor defaults.
- Logistic curve has *slightly* flatter tails. *i.e.*, probit curve approaches the axes more quickly than the curve.
- Is logit better than probit, or *vice versa*?

Both methods will yield similar (though not identical) inferences. Logit seems to be more popular partly because coefficients can be interpreted in terms of odds ratios. Probit models can be generalised to account for non-constant error variances in more advanced econometric settings (*heteroskedastic probit models*).

If these more advanced applications are not of relevance, than it **does not really matter** which method you choose to go with.

Receiver operating characteristic (ROC)

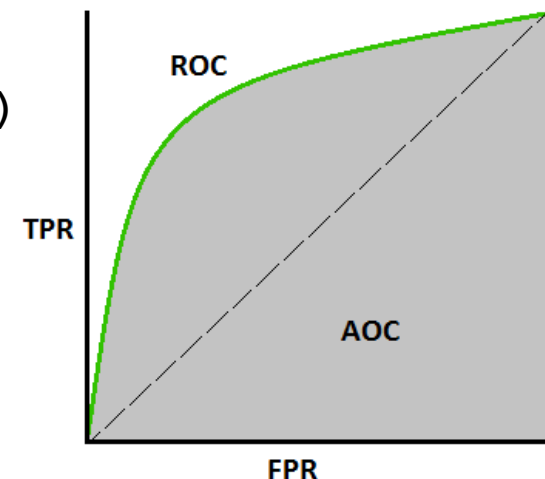
A graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied

- The ROC curve says *how much the model is capable of distinguishing* between classes. Higher the AUC (**area under the curve = integral**), better the model is at predicting 0s as 0s and 1s as 1s.

By example: higher the AUC, better the model is at distinguishing between clients who'd default from those who will survive.

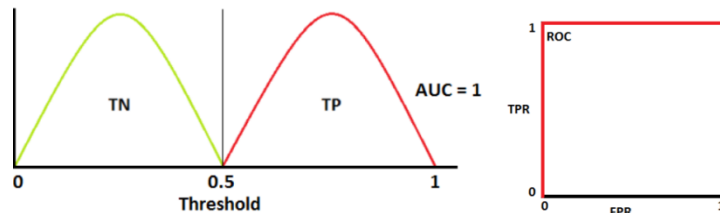
- The ROC curve is plotted with TPR against the FPR where TPR is on y-axis and FPR is on the x-axis.

- **TPR (True Positive Rate, sensitivity)** = $TP / (TP + FN)$
- **Specificity** = $TN / (TN + FP)$
- **FPR** = $1 - \text{Specificity} = FP / (TN + FP)$

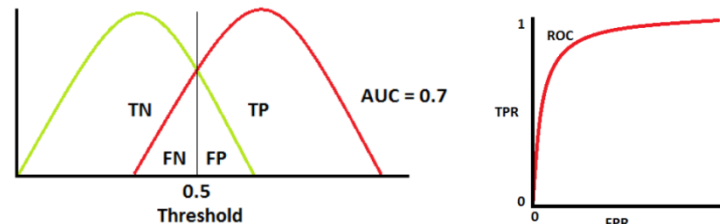


Receiver operating characteristic (ROC)

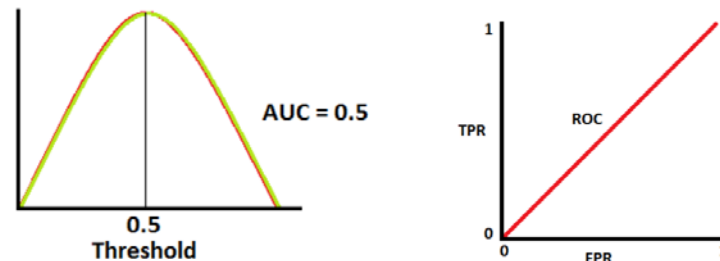
The higher AUC the better



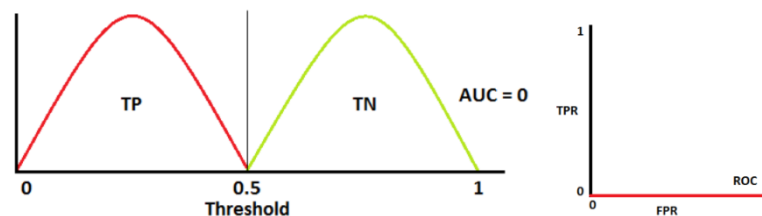
An ideal situation. When two curves do not overlap at all means model has an ideal measure of separability. It is perfectly distinguishes between 1s and 0s.



When two distributions overlap, we introduce type 1 and type 2 error. Depending upon the threshold, we can minimise or maximise them. AUC = 0.7 means there is a 70% chance that model will be able to distinguish between 1s and 0s.



This is the worst situation. When AUC is approximately 0.5, model has no discrimination capacity to distinguish between 1s and 0s.



What does AUC = 0 mean?

Section 3

Summary

Summary

Credit Quant role in the bank is to help credit officers decide if a loan should be granted. Then, after positive decision, credit quants prepares a methodology for risk monitoring and estimation of credit losses, what is needed for capital requirements forecasting

- One of the essential tasks for credit quants is to prepare a methodology for estimation of the probability of a default.
- The latter is used for credit losses estimation via formula:
 - $ECL = PD \times EAD \times LGD$.
- PD can be estimated using external ratings or via internal models.
- In general, internal models aim at finding the best set of parameters (loan and economical situation related) that fit the historical observations.
- The job itself is fun!

Contact information

Sara Nowogórska
Credit Risk Methodology
sara.nowogorska@ubs.com

UBS Poland Service Centre
UBS Service Centre (Poland) Sp. z o.o.
Krakow Business Park 800
Ul. Krakowska 280
32-080 Zabierzów k/Krakowa
Tel. +48-12-399 7000

www.ubs.com

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