Credit Risk Fundamentals

March 21, 2023

Section 1

Introduction

Brainstorming

What do you know about credit risk?

PD

EAD

ECL

LGD

DEFAULT

RWA

What do you think these words mean?

Let’s have a look into them …

Regulatory Framework

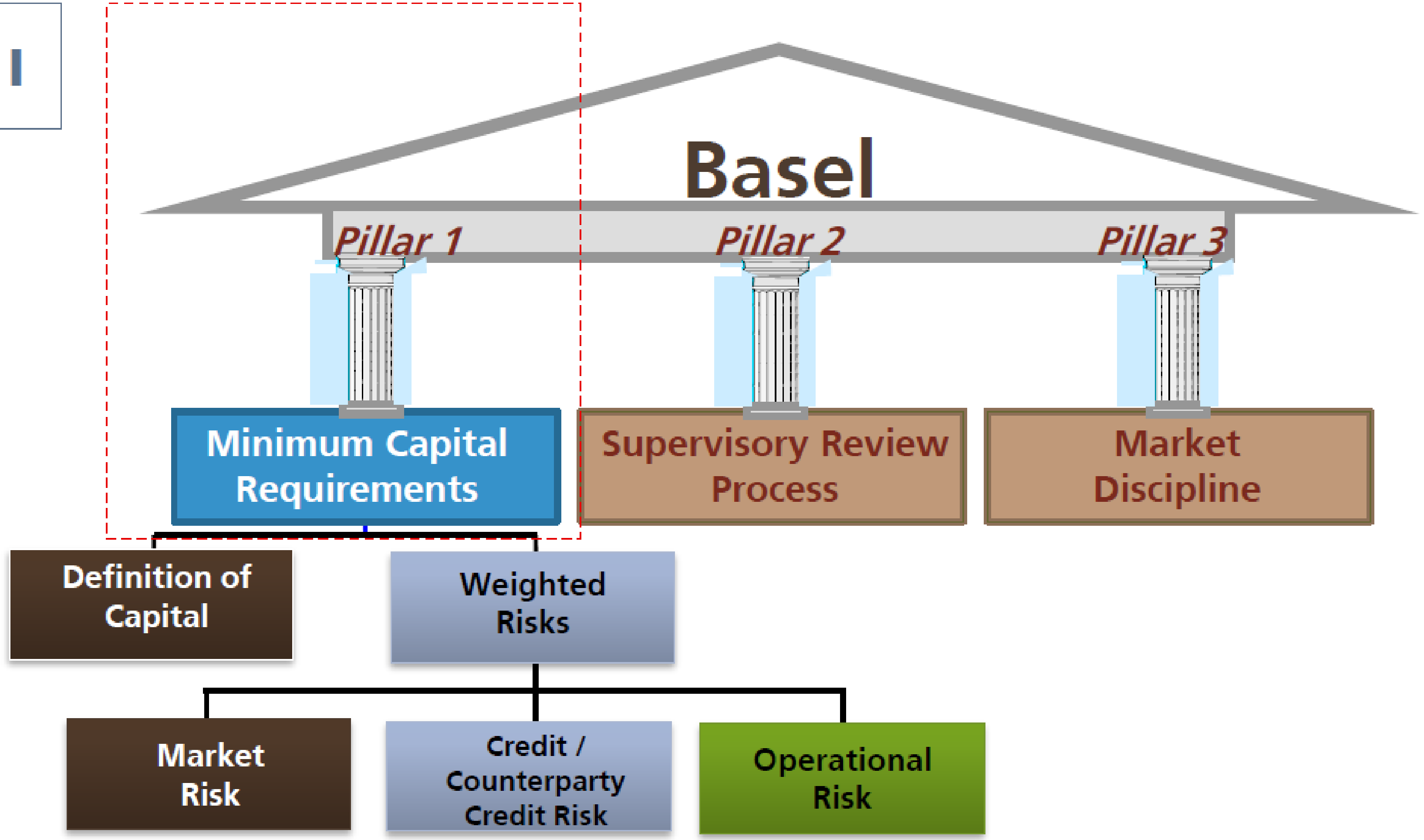
- **Why are global capital requirments set?**
  - To strengthen stability of international banking system
  - To provide a level playing field in capital requirements across the globe
- 1998: Basel I introduced global minimum ratio of Capital / RWA of 8%
- 2004: Basel II introduced the three Pillars system
- 2009-2025: Basel II – Basel III
  - Response to 2007-2009 Global Financial Crisis
    - Basel 2.5: Higher Market Risk charge (stressed VaR, default risk in the trading book)
    - Higher Counterparty Credit Risk charge for derivatives (stressed EPE, CVA charge)
    - RWA for CCPs and higher RWA for securitisations
    - Additional requirements on liquidity and funding

The Three Pillars of Basel III (1)

- **Pillar 1: Minimum Capital Requirements**
  - MCR that banks have to meet to cover risks.
    - Credit Risk is among one of the most important risk in banks’ balance sheets: typical source of income is *money lending*.
- **Pillar 2: Supervisory Review Process (SREP)**
  - Banks regularly run self-assessments on their risk profiles and risk management practices.
- **Pillar 3: Market Discipline**
  - Banks are required to disclose information so to enable market participants to make informed investment decisions.

The Three Pillars of Basel III (2)

Focus on Pillar I



Section 2

Regulatory Capital and RWA

Capital Adequacy (1)

- Basel III sets a target for the relationship between risk and capital, which forms the basis of the capital adequacy framework (Pillar 1).
- Indeed, banks have to set aside capital to cover unexpected losees (UL) from their day-to-day operations. The amount of capital is proportional to the amount of risk banks bear in their balance sheet.
- How is risk quantified?
    - Risk-Weighted Assets (RWA) take into account
        - Credit Risk: Lending activities, Counterparty default
        - Market Risk: Trading activities
        - Operational Risk: Human errors, System failures and external causes

Capital Adequacy (2)

- Why do Basel agreements put so much stress on Capital Requirments?

- Bank capital helps alleviate the three market failures:
    - Absorbs unexpected losses and reduces the risk of contagion within the financial system
    - Protects depositors and stakeholders
    - Reduces exposure to excessive risk by bank shareholders and managers

Definitions of Capital

- **Common Equity Tier 1 (CET1) Capital**
  - Common shares
  - Earning reserves, valuation reserves and other
  - Share premium from issuing instruments included in the CET1 Capital
  - Ordinary shares issued by consolidated subsidiaries of the bank
  - accumulated Other Comprehensive Income (OCI) and other disclosed reserves
- **Additional Tier 1 (AT1) Capital**
  - Financial instruments that can be converted into equity in a crisis event
- **Tier 2 Capital**
  - Financial instruments that represent *supplementary capital* such as perpetual/preferred stocks

Capital Ratios

Three main capital ratios with a minimum regulatory requirment

Common Equity Tier 1 (CET1) Ratio	Tier 1 Ratio	Total Capital Ratio
$\frac{\text{CET 1}}{\text{Risk Weighted Assets}}$	$\frac{\text{CET1 + AT 1}}{\text{Risk Weighted Assets}}$	$\frac{\text{Tier 1 + Tier 2}}{\text{Risk Weighted Assets}}$

The Minimum Capital Requirments are the following

	CET1 Ratio	Tier 1 Ratio	Total Capital Ratio
Minimum requirement	4.5%	6%	8%

Additional Capital Requirements (1)

- On top of the Minimum Capital Requirments, supervisors can impose additional requirments

1. Capital Conservation Buffer 2.5% CET1, stress periods
    - Restrictions on dividends distribution are imposed if the requirement is not met

CCB	CET1	Dividends
[0, 0.625%)	[4.5%, 5.125%)	0%
[0.625%, 1.25%)	[5.125%, 5.75%)	20%
[1.25%, 1.875%)	[5.75%, 6.375%)	40%
[1.875%, 2.5%)	[6.375%, 7.0%)	60%
≥ 2.5%	≥ 7.0%	100%

Additional Capital Requirements (2)

2. Countercyclical Buffer
   - Based on the economic cycle: (0, 2.5%] on top of CET1/RWA
   - As for the Capital Conservation Buffer, dividends are restricted if not met
3. Additional Systemic Surcharge for large Financial Institutions which are classified as *Globally Systematically Important Banks* (G-SIB)
   - G-SIBs are banks whose systemic risk profile is deemed to be of such importance that the bank's failure would trigger a wider financial crisis and threaten the global economy
   - A comprehensive list of G-SIBs can be found here

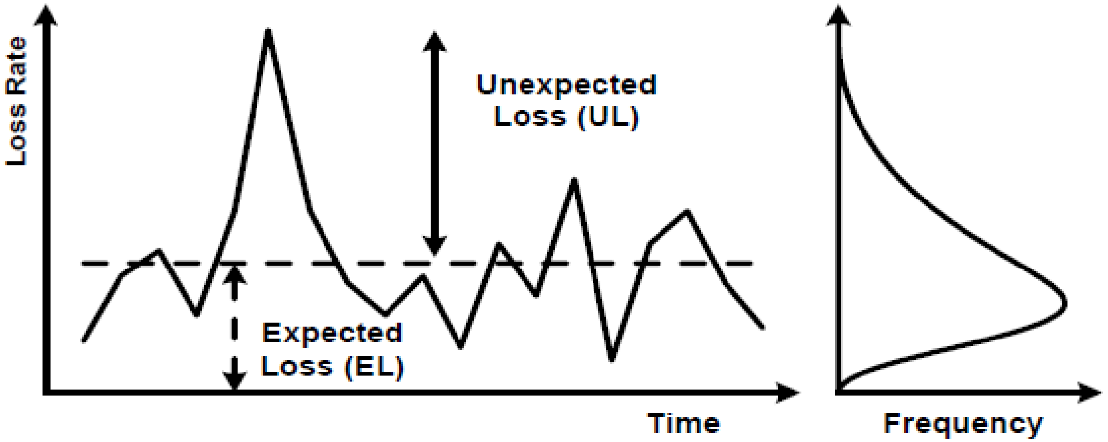
Definition of Risk

- RWAs represent the denominator of the Capital Ratios formulas
- Bank’s Assets are assigned a Risk Weight (RW) based on their risk profile
  - Credit Risk RWA
  - Market Risk RWA
  - Operational Risk RWA
- Each RWA sub-category can be computed alternately via:
  - Standardised Approach: RW are given by the regulator
  - Advanced Approach: RW are computed using Internal Models which have to be validated by regulators

Expected Loss and Unexpected Loss

- Due to the risk profile of their business, banks typically have to bear losses

Figure 1



- Banks are required to forecast *Expected Losses* (ECL), which are the *average* level of losses they can reasonably expect within a one-year time horizon
- Expected Losses have to be covered through pricing of loans and provisioning
- On the other hand, losses that exceed EL are called *Unexpected Losses* (UL) and are to be covered by banks' capital

Section 3

Credit Risk

Impacted Risk Spheres

- Idiosyncratic Risk: it is the risk related to specific features of the borrower or their assets
  - Personal Event: the borrower is investing in legal entity B, which operates in the semiconductor industry. Hence, the borrower is exposed to idiosyncratic risk related to any events that can affect the business of B.
  - Systematic Risk: it is related to the broader macroeconomic environments and its events
    - Covid-19 Crisis
    - Global Financial Crisis (2007-2009)
    - Oil Crisis (1973)

Preliminaries (1)

- Default risk is the risk that a borrower will default i.e., the risk that the borrower will become unable or unwilling to make payments
- Result: loss of either principal, interest or both
- 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 IRS) with another bank.
- Examples of defaults:
  - A company goes bankrupt.
  - As company fails to pay a coupon for some of its issued bonds upon agreed time.
  - A household fails to pay amortisation or IR on their mortgage.

Preliminaries (2)

- IFRS 9 sets out how an entity should classify and measure financial assets and financial liabilities
- Pre-IFRS 9 adoption: the *incurred loss* framework required banks to recognise credit losses **only** when evidence of a loss was apparent
- Under IFRS 9's ECL impairment framework
- ECLs at all times, taking into account:
  - Past events, current conditions and forecast information, and to update the amount of ECLs recognized at each reporting date
  - Changes in an asset's credit risk. It is a more forward-looking approach than its predecessor and will result in more timely recognition of credit losses

Preliminaries (3)

- PD (Probability of Default): probability that the borrower will default over a given time horizon.
- LGD (Loss Given Default): percentage loss the lender suffers given the default of the counterparty.
- EAD (Exposure at Default): outstanding amount the borrower has yet to repay to the lender at time of default.
- ECL (Expected Losses): computed using the three above components as

$$\mathrm{EL} = \mathrm{PD} \cdot \mathrm{LGD} \cdot \mathrm{EAD}$$

Basel III: Credit Risk

- Three possible approaches to measure Credit Risk:

  1. Standardised Approach (SA)

  2. Internal Ratings-Based Approach

     - Foundation Internal Ratings-Based (F-IRB) approach

     - Advanced Internal Ratings-Based (A-IRB) approach

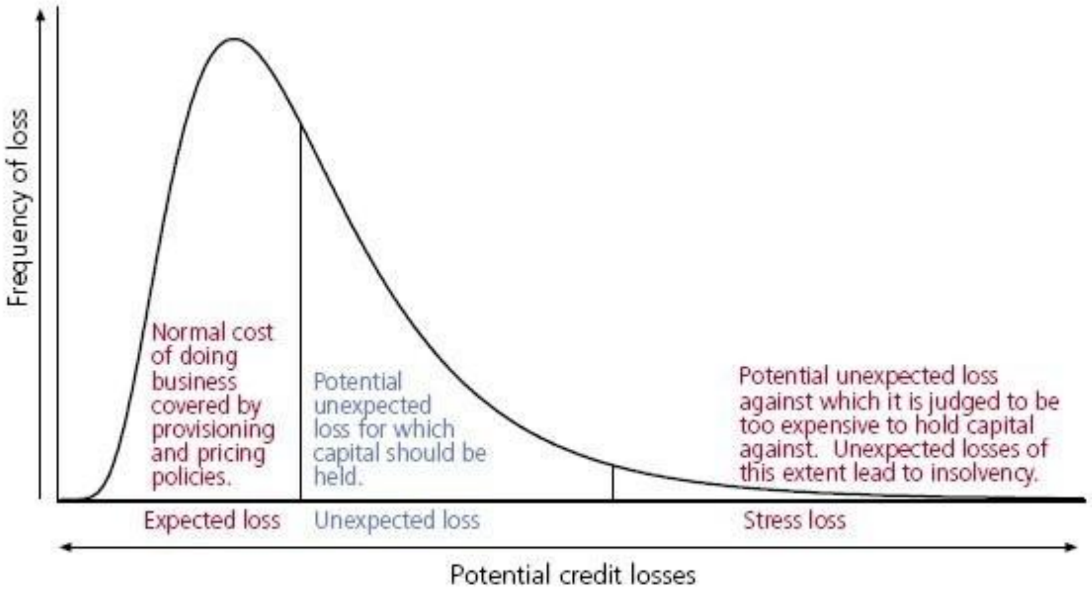
Standardised Approach (SA)

- Methodology:
  - Exposures are divided in different categories, based on the counterparty or the underlying collateral.
  - Different Risk Weights (RWs) are applied to such exposures, depending on the category the counterparties belong to and their rating.

Rating	Sovereign	Banks	Corporate	Retail	Real Estate
[AAA, AA-]	0%	20%	20%		
[A+, A-]	20%	50%	50%		
[BBB+, BBB-]	50%	50%	100%		
[BB+, BB-]	100%	100%	100%	75%	[35%, 100%]
[B+, B-]	100%	100%	150%		
[CCC+, CCC-]	150%	150%	150%		
No Rating	100%	50%	100%		

Advance Interanl-Ratings (IRB) Approach (1)

- Distinguishing ECL from UCL is critical:
  - $\mathrm{EL} = \mathrm{PD} \cdot \mathrm{LGD} \cdot \mathrm{EAD}$ represents the risk embedded in the lending activity; hence it has to be covered by pricing policies
  - UL stems from the *uncertainty* of the EL, namely it can be interpreted as the volatility of the EL. UL have to be covered through banks' own capital.



Advance Internal-Ratings (IRB) Approach (2)

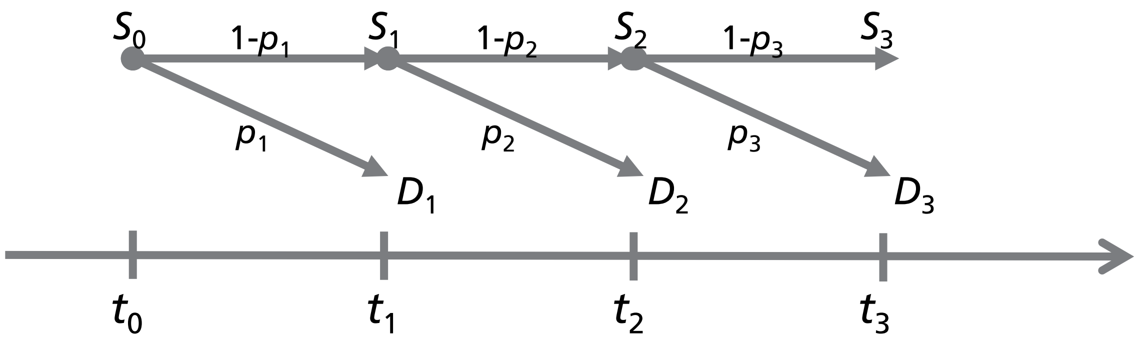
- F-IRB Approach allows banks to use their own estimates of the PD and EAD components.
- A-IRB Approach allows banks to internally estimate each model component.

Exposure	Potential approach	Default Probability PD	Loss Given Default LGD	Exposure at Default EAD	Maturity M
— Central Institutions and Central Banks (*) — Credit exposure with supervised entities — Corporates — Exposures in capital — Exposures in securities — Other assets	FOUNDATION IRB	Estimated by the Institution	Regulatory values	Regulatory values	Regulatory values
	ADVANCED IRB	Estimated by the Institution	Estimated by the Institution	Estimated by the Institution	Estimated by the Institution
— Retail credit exposures(**)	ADVANCED IRB	Estimated by the Institution	Estimated by the Institution	Estimated by the Institution	N/A

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 : $F(t) = P(\mathrm{t} \le t) = E(\mathbf{1}_{t}(t))$
  - Marginal PD: $F(t_i, t_{i+1}) = P(t_i < \mathrm{t} \le t_{i+1}) = F(t_{i+1}) - F(t_i)$
  - Forward PD, point in time (PIT): $p(t_i, t_{i+1}) = P(t_i < \mathrm{t} \le t_{i+1} \mid t_i < \mathrm{t})$
- Multi-step default tree, $p_{\mathrm{i}} = p(t_{i-1}, t_i)$:



- $F(t_i) = 1 - (1- p_1)(1- p_2)\ldots(1- p_i) = 1\text{-}s_1 s_2\ldots s_i$, where survival probability (PIT) $s_i = 1\text{-}p_i$

Section 4

Estimation of PD

Models for estimating the PD

- Models for estimating the PD can be divided into the following two categories:

1. Credit-scoring Models: these models assign a weight to a set of economic and financial indicators of a company. The higher the weight, the higher the importance of the indicator in predicting the default. Results: score which measures the borrower's PD.
2. Capital Markets Models: these models use data from the Markets to compute PDs.
   - Structural models: Merton model, KMV model
   - Reduced-form models: Jarrow-Turnbull model (extension of the Merton model)
   - Credit Default Swap (CDS) models

- We are focusing on the first category of models.

Credit Scoring Models: Linear Discriminant Analysis (1)

- Linear discriminant analysis is a *classification technique*: companies are divided between reliable and insolvent based on available data via the use of a *discriminant function*.
- Assuming a linear combination of *n* independent variables, then the z-score of the *i*-th company is

$$z_j = \sum_{j=1}^{n} \gamma_j x_{i,j}$$

- γ_j: picked such as the distance between the means z_A and z_B is maximized.
- Wilk's Lambda is used in order to evaluate the model performance

$$\Lambda = \frac{\sum_{i \in A} (z_i - z_A)^2 + \sum_{i \in B} (z_i - z_B)^2}{\sum_{i=1}^{n} (z_i - \overline{z})^2}$$

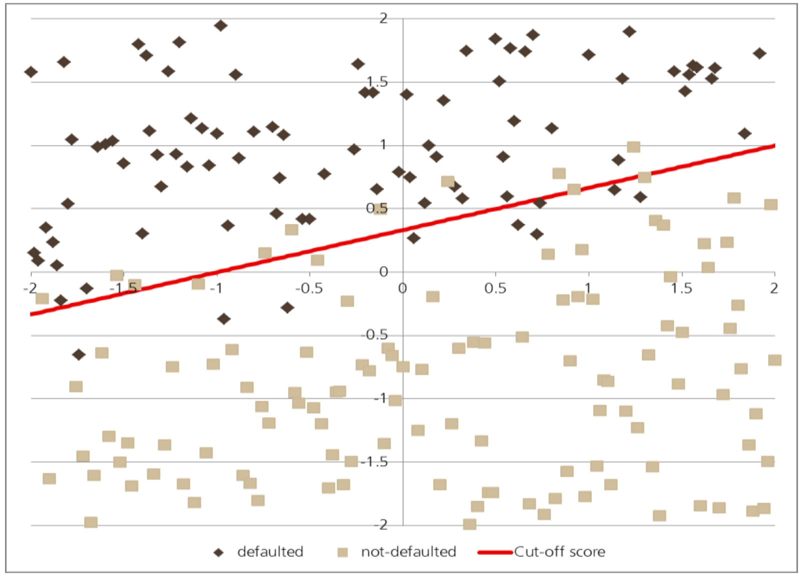
- High predictive power is achieved when the ration is closer to 0. Can you tell why?

Credit Scoring Models: Linear Discriminant Analysis (2)

- Altman Z-Score is the best-known discriminant score for listed companies.
- It is computed using a linear combination of five financial ratios each with its own weight (importance)

$$Z = 1.2A + 1.4B + 3.3C + 0.6D + E$$

  - A = Working Capital / Total Assets
  - B = Retained Earnings / Total Assets
  - C = Earnings before Interest and Taxes / Total Assets
  - D = Market Capitalisation / Debt
  - E = Sales / Total Assets



- The higher the score, the safest the company being analysed.
- Cut-off between reliable and risky companies is 1.81.
- PDs are derived from scores via *mapping functions*:
  - Different mapping functions based on the industry the company operates in.
  - Plugging the Z-Score into such functions yields the PD

Credit scoring Models: Regression Models (1)

- PDs can be estimated using regression models. To do so, four crucial steps:

1. Sample selection
2. Independent variables selection
3. Coefficient estimate: if OLS is assumed, the model equation is the following

$$y_i = \alpha + \sum_{j=1}^{m} \beta_j x_{i,j} + \varepsilon_i$$

4. PD computation: by using the estimated regression coefficients and the observed values of the independent variables

Credit scoring Models: Regression Models (2)

- Based on the functional specification of the *link type*, we obtain different regression models
- In PD modeling, practitioners often use:
  - Logit Models
  - Probit Models
- In the following slides we focus on those two link types.

Regression Models (3): Probit Model

$$\mathbb{E}[Y \mid X] = P[Y = 1 \mid X] = \Phi(\beta_0 + \beta_1 X)$$

- Binary dependent *Y* variable
- S-shape: due to the symmetry of the PDF of the Random Variable (RV)

$$P[Y = 1 \mid X_1, X_2, \ldots, X_k] = \Phi(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_k X_k)$$

- Where is the CDF of a Normal distribution.
- The predicted probability that $Y = 1$ given $X_1, X_2, \ldots, X_k$ can be calculated in two steps

1. Calculate the distribution z
2. Calculate its CDF

Regression Models (4): Logit Model

$$\mathbb{E}[Y \mid X] = P[Y = 1 \mid X] = \Phi(\beta_0 + \beta_1 X)$$

- Binary dependent *Y* variable
- S-shape: due to the symmetry of the PDF of the Random Variable (RV)

$$P[Y = 1 \mid X_1, X_2, \ldots, X_k] = F(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \beta_k X_k)$$

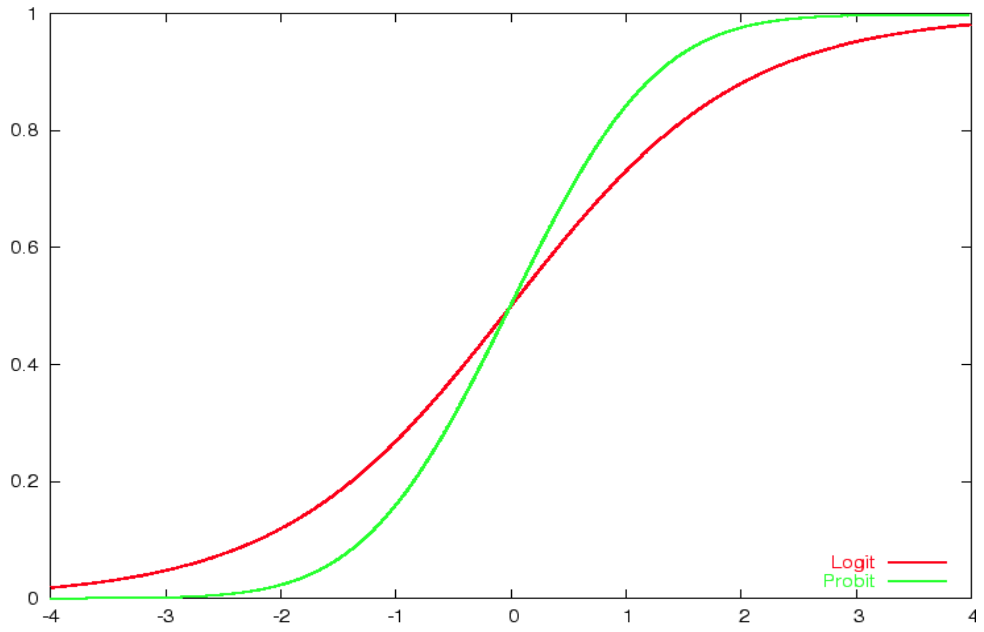
- Where is the CDF of a Normal distribution.
- The predicted probability that $Y = 1$ given $X_1, X_2, \ldots, X_k$ can be calculated in two steps

1. Calculate the distribution z
2. Calculate its CDF

Regression Models (5): Logit Model

- In the logit model it is <u>assumed</u> that

$$P[Y = 1 \mid X_1, \ldots, X_k] = \frac{1}{1 + e^{\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k}}$$



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 standardized 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 as 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 dependent variable

- In the probit model it is assumed that
  - $P(Y = 1 \mid x_1, \ldots, x_k) = F(b_0 + b_1 x_1 + \ldots + b_n x_n)$,
    the CDF of the standard normal distribution.
- The reqression coefficients of the probit model are effects on F 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 logit 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 generalized 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.

Forecast

Measuring the risk consists in understanding which different states of the world we can encounter

A way to forecast it is considering what can happen at time t_1 being at time t and having different scale of pieces of information at time t (filtrations)

However, as predictions and simulations different techniques can be used, some of them are:

Monte Carlo Simulation	Value at Risk (VaR)	Expected Shortfall (ES)

These are concepts out of our lesson scope and that will be explained in the following classes.

Receiver Operating Characteristic (ROC) (1)

- The ROC curve says *how much the model is capable of distinguishing* between classes. The higher the AUC (**area under the curve**), the 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 will 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): probability that an actual default is classified as such:

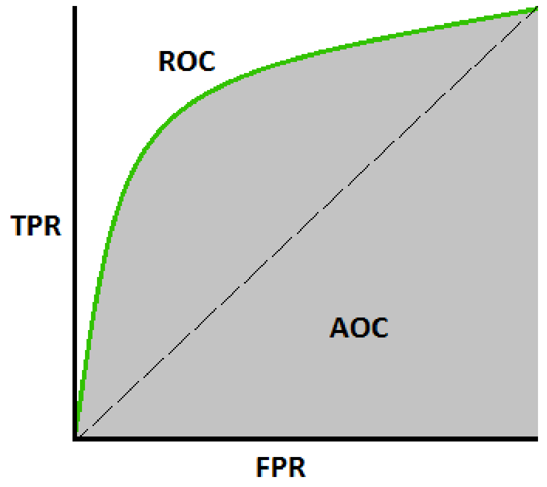
    TPR = TP / (TP + FN)

  - Specificity: probability that a non default is classified as such

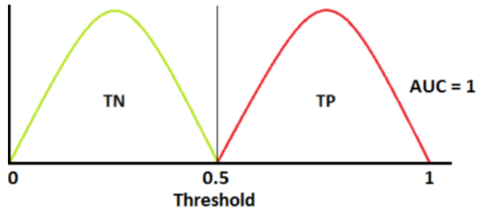
    Specificity = TN / (TN + FP)

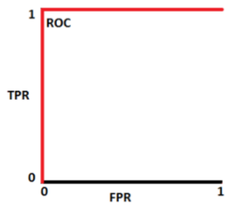
  - FPR (False Positive Rate): probability that a non-default is classified as a default

    FPR = 1 – Specificity = FP / (TN + FP)

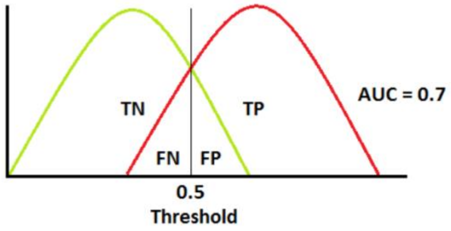


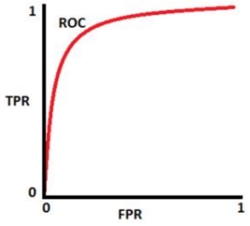
Receiver Operating Characteristic (ROC) (2)



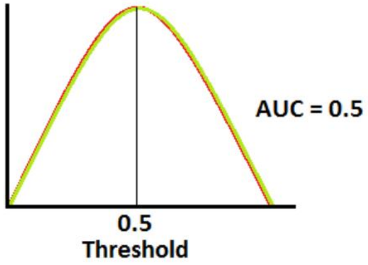


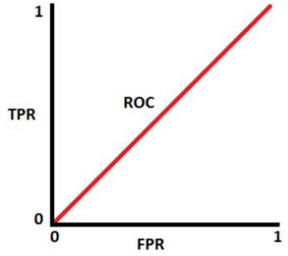
An ideal situation. When two curves do not overlap at all means model has an ideal measure of separability i.e., it perfectly distinguishes between 0s and 1s.



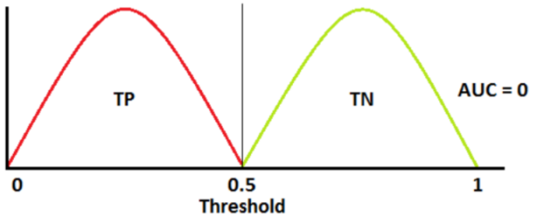


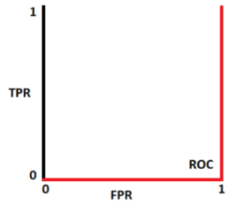
When two distributions overlap, we introduce type 1 and type 2 error. Depending upon the threshold, we can minimize or maximize them. AUC = 0.7 means there is a 70% chance that model will be able to distinguish between 1s and 0s.





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





What does AUC = 0 mean?

https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5

Section 5

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!

References

https://www.econometrics-with-r.org/11-2-palr.html
https://www.bis.org/fsi/fsisummaries/ifrs9.htm