

# **IFRS 9: Financial Instruments (Impairment)**

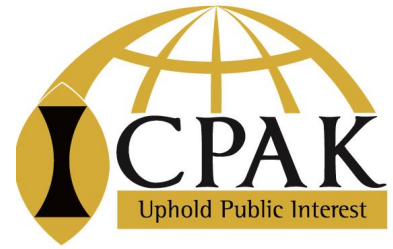
**By Ferdinand Othieno  
8 March 2018**

**Credibility.**

**Professionalism.**

**AccountAbility**

# Agenda – Impairment practical



- 1. Impairment under IFRS 9**
- 2. Defining default**
- 3. Significant increase in credit risk**
- 4. Measuring expected credit losses**

## **1. Financial Advisory**

- Transaction Services – Valuations, M&A, IPOs, Rights Issues, FDDs, Restructuring, Project Finance, Business Plans e.t.c.
- Selected clients – Safaricom, TMEA & EAC, KCB, Britam, UAP, KenGen, Home Africa, Investeq, Mwalimu National SACCO

## **2. IFRS 9 Training experience**

- Commercial Bank of Ethiopia,
- Prime Bank,
- Bank of Uganda,
- Waumini SACCO, Boresha SACCO, Awash Bank Ethiopia

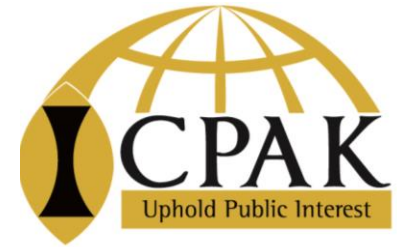
## **3. Teaching & Research**

- Dean, Institute of Mathematical Sciences, Strathmore University
- Interests – Asset Pricing, Quantitative Risk Management, Stochastic Processes in Finance

## **4. Education**

- PhD Finance (Ongoing - UCT), CFA Level 3, MSc (Banking & Finance), BBA (Finance), CPAK

# On Investing... in anything



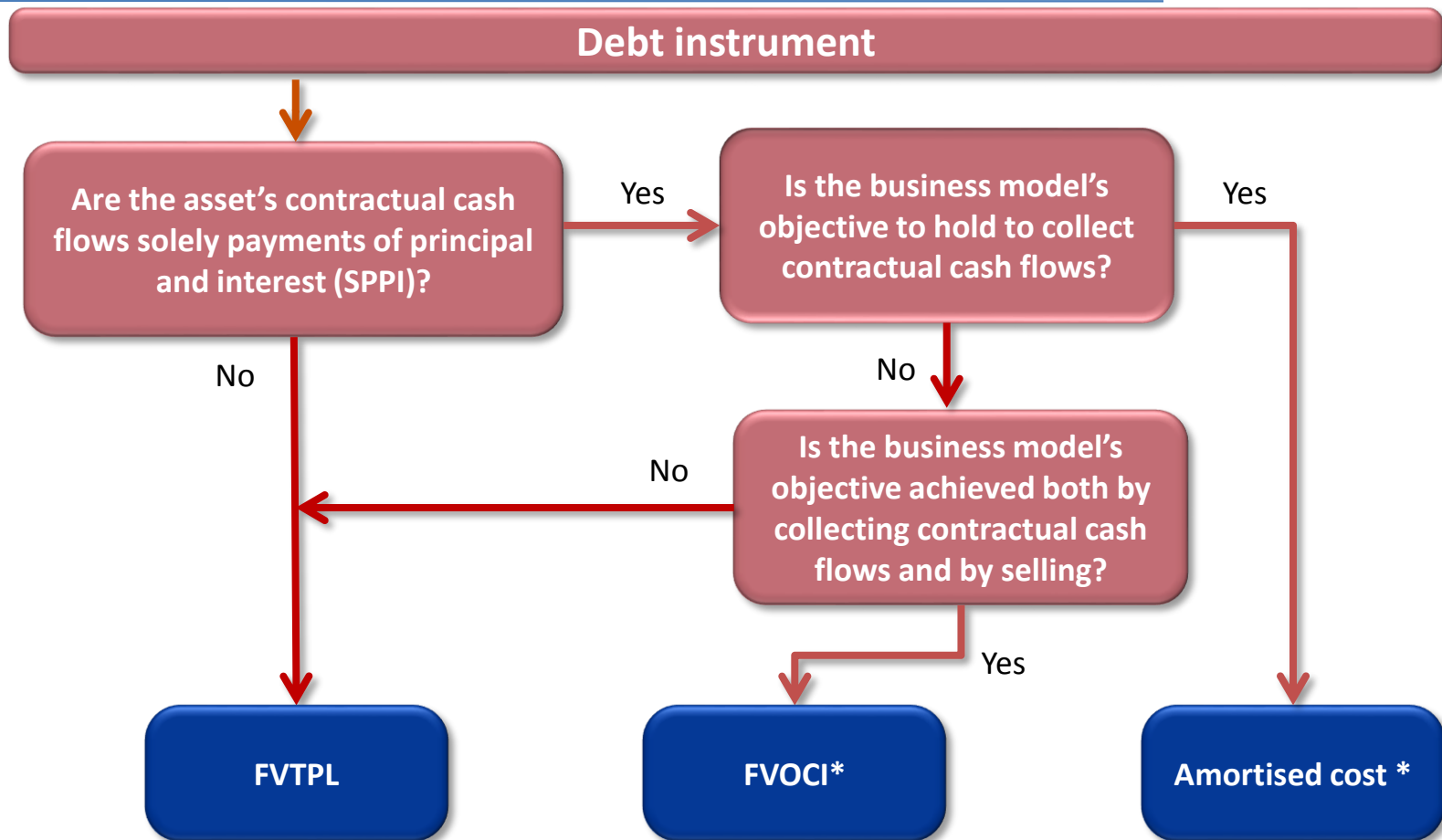
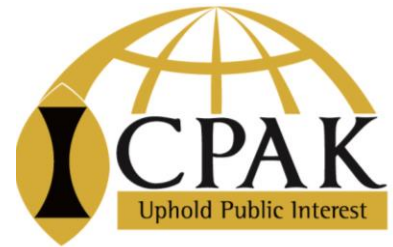
“

Investing should be more like watching paint dry or watching grass grow. If you want excitement, take \$800 and go to Las Vegas.

”

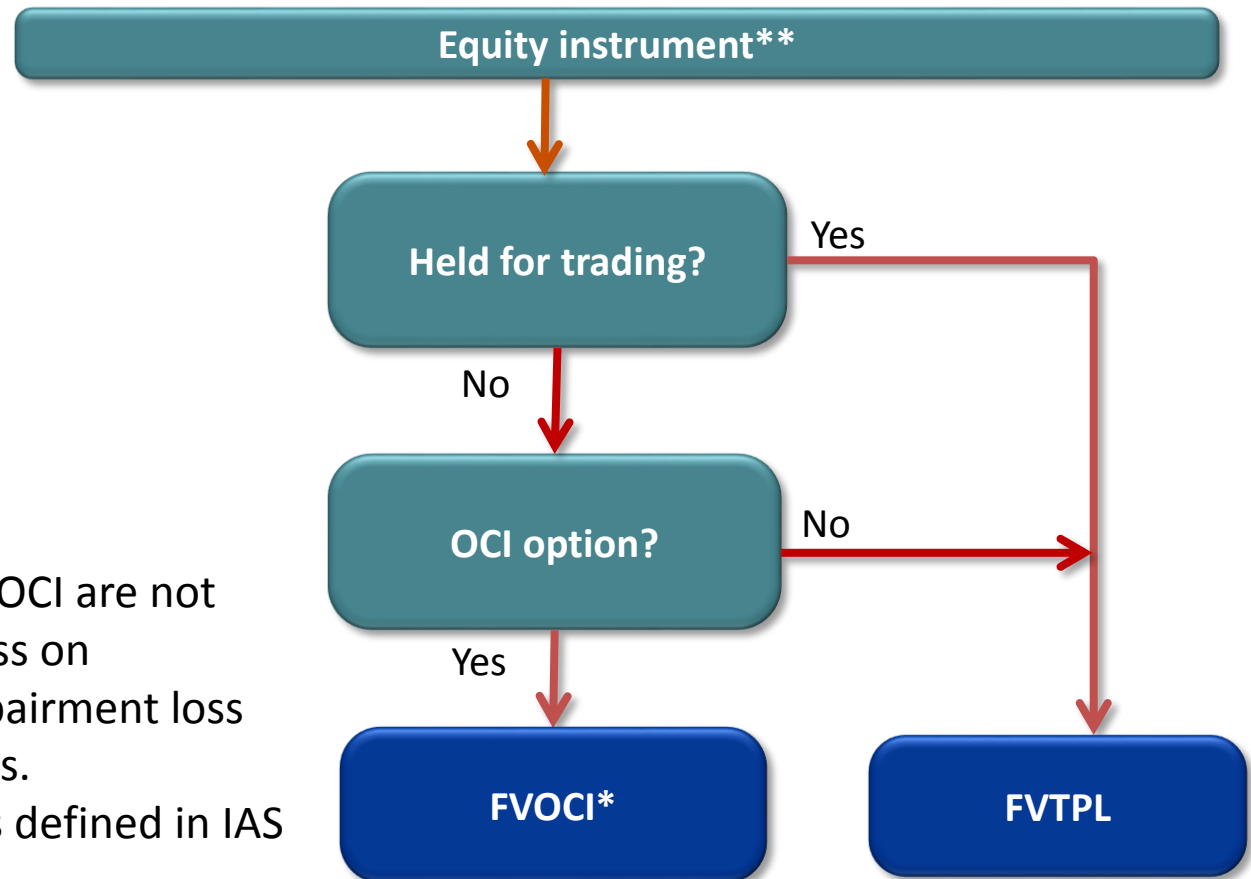
— Paul Samuelson

# Classification of Financial Assets – Debt Instruments



\* Subject to FVTPL designation option - if it reduces accounting mismatch

# Classification of equity instruments



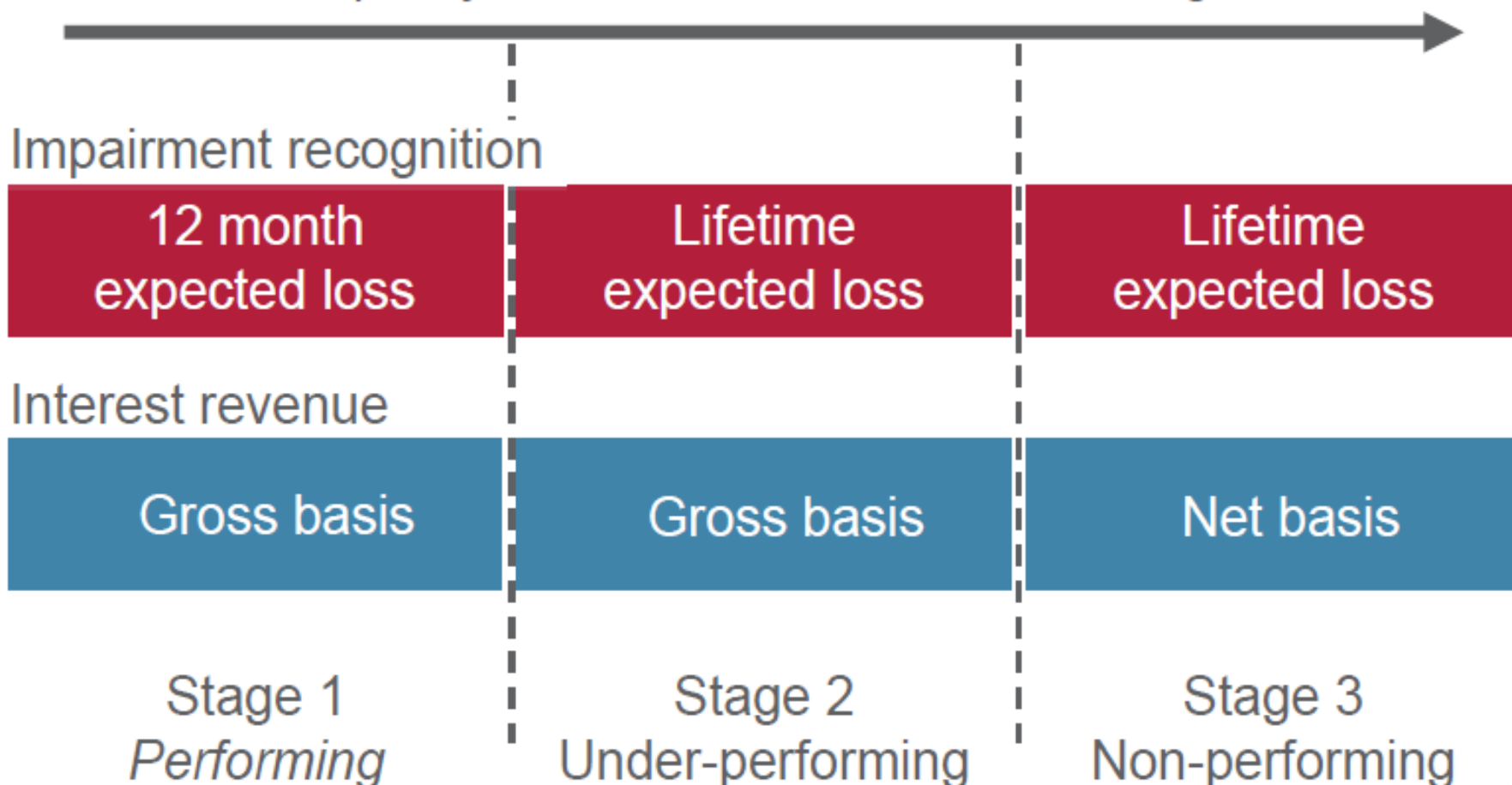
\* Amounts recognised in OCI are not reclassified to profit or loss on derecognition and no impairment loss recognised in profit or loss.

\*\* Equity instrument is as defined in IAS

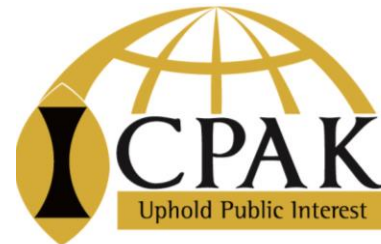
# Expected loss model – 3 stages



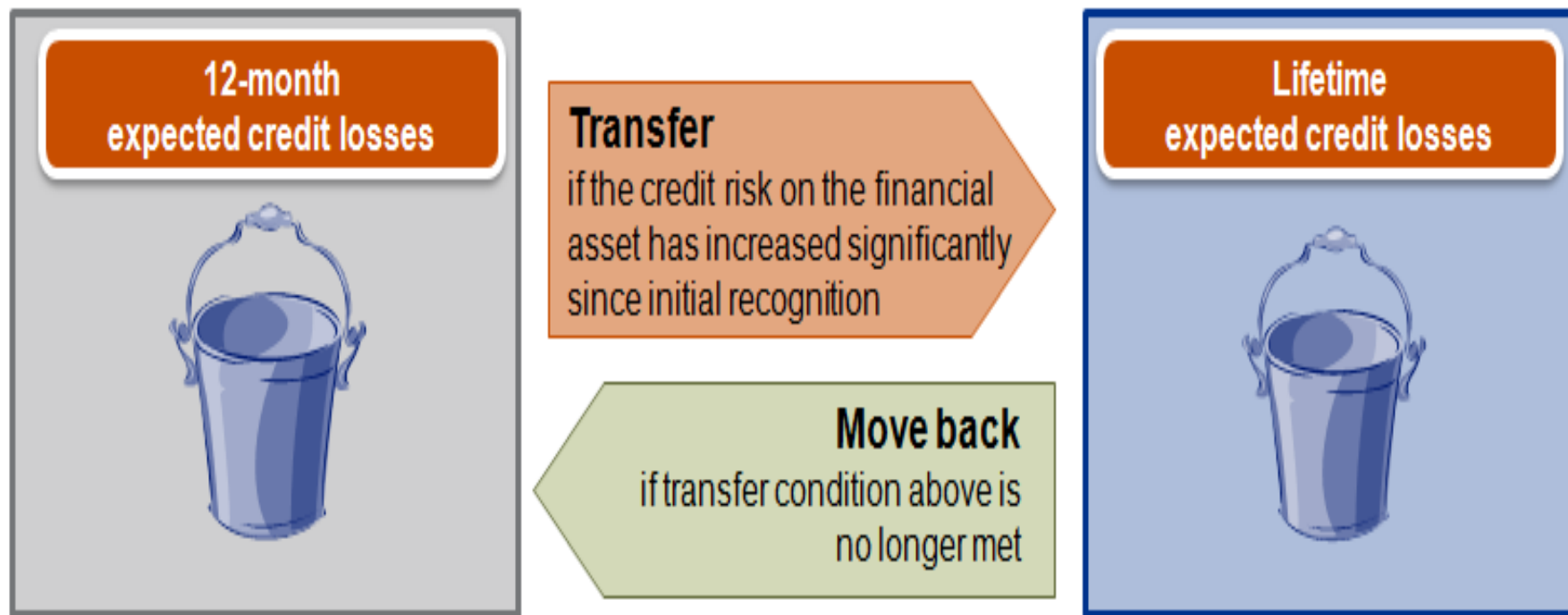
Credit quality deterioration since initial recognition



# Dual Measurement Approach

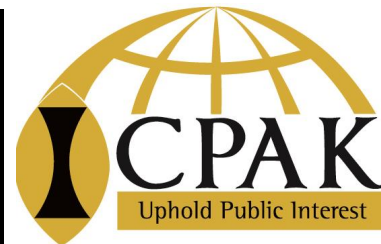


- Under the general principle, one of two measurement bases applies:
  - 12-month expected credit losses; or
  - Lifetime expected credit losses.
- The measurement basis depends on whether there has been a significant increase in credit risk since initial recognition.





# Dual Measurement Approach – Key Concepts



**12-month  
expected credit  
losses**

- Losses resulting from default events possible within 12 months after reporting date.

**Lifetime  
expected credit  
losses**

- Losses resulting from all possible default events over expected life of financial instrument.

**Significant  
increase in  
credit risk**

- Not defined.

**Default**

- Not defined.

# Expected Credit Losses



$$\text{Expected credit losses} = \text{PV}\{\text{Contractual CFs} - \text{E}(\text{CFs})\}$$

**Probability weighted**



Unbiased probability-weighted amount (evaluate range of possible outcomes and consider risk of credit loss even if probability is very low)

**Present value**



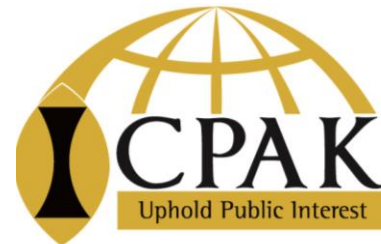
Generally calculated using original EIR or an approximation as discount rate

**Cash shortfalls**



Difference between cash flows due under the contract and cash flows that entity expects to receive

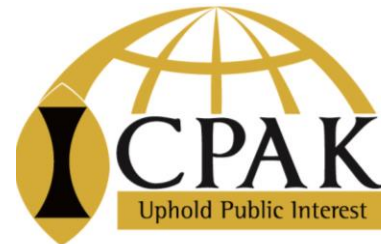
# 12-Month ECL



Recognize 12-Month ECL if there has been no significant increase in credit risk since initial recognition

- **What is 12-month ECL**
  - Portion of the lifetime ECL
  - 12-month PD times total ECL
  - It is the expected shortfall from all contractual cashflows given the PD occurring in the next 12 months
- **What is NOT 12-Month ECL**
  - Expected cash shortfall in the next 12 months
  - Credit losses on assets expected to default in the next 12 months

# Lifetime ECL

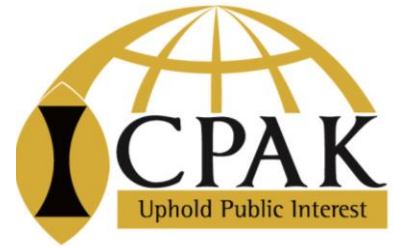


Recognize lifetime ECL if there has been significant increase in credit risk since initial recognition

- **What is lifetime ECL**

- Expected shortfalls in contractual cash flows;
- Taking into account the potential for default at any point during the life of the financial instrument;
- Note – significant increase in credit risk is more probable for good quality assets than for poorer assets; and
- Practical exception – do not recognize lifetime ECL for an asset with low credit risk

# Significant increase in credit risk



Has there been a significant increase in the instrument's credit risk?

YES

Has the entity chosen to apply the "low credit risk" operational simplification?

YES

Is the credit risk of the instrument low?

NO

YES

Recognize lifetime ECL

YES

Recognize 12-month ECL

NO

# Significant increase in credit risk

It is possible for an instrument for which lifetime ECL have been recognized to revert to 12-month ECL should the credit risk of the instrument subsequently improve

12-month  
expected credit losses



## Transfer

if the credit risk on the financial asset has increased significantly since initial recognition

## Move back

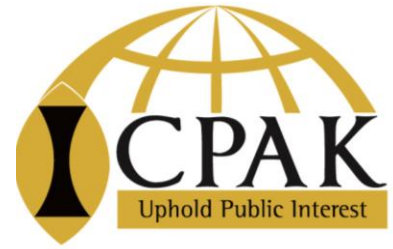
if transfer condition above is no longer met

Lifetime  
expected credit losses



# Significant increase in credit risk

## Assessing deterioration

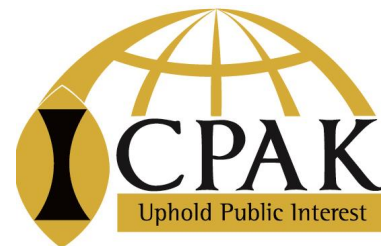


Use best information available without undue cost or effort

- **Information to consider**
  - Borrower specific
  - Macro-economic factors
  - Internal ratings
  - Internal PDs
  - External pricing
  - Credit ratings
  - Delinquencies
- **Rebuttable presumption**:- assets that are 30 days past due have deteriorated

# Significant increase in credit risk

## Assessing deterioration – Example 1



Bank B has a reporting date of 31 December. On 1 July 2017 the Bank advanced a 3-year interest-bearing loan of KES 2,000,000 to Entity A. Management estimates the following risks of defaults and losses that would result from default at 1 July 2018 and at 31 December 2018 and 2019

Date	PD next 12 months	Months 13-36	LGD	Lifetime ECL
1 July 2018	2.5%	5.0%	800,000	60,000
31 Dec 2018	3.0%	10.0%	700,000	91,000
31 Dec 2020	1.0%	2.0%	500,000	15,000

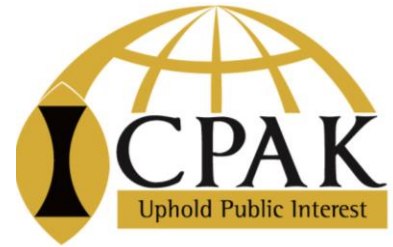
**What is the provision as at:**

- 1 July 2018
- 31 Dec 2018
- 31 Dec 2020



# Significant increase in credit risk

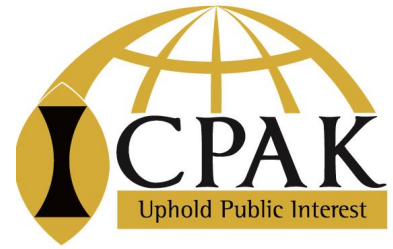
## Assessing deterioration – Example 2



- Bank X provides senior secured debt to company Y.
- At the time of origination:
  - It is expected that Y would meet the covenants in the contract
  - Stable expected revenue and cash flows in Y's industry
- Subsequent to initial recognition:
  - Y underperforms on its business plan
  - Y close to breaching its covenants
  - Prices for Y's bond's decreased, market spreads increased, not explained by market environment
- Bank X expects further deterioration in economic environment

# Significant increase in credit risk

## Defining default– Example 3

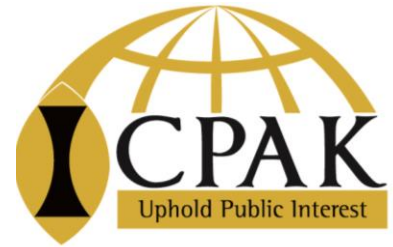


Lender A makes a 5 year amortizing loan with payments of principal and interest payable in regular monthly instalments. The borrower is also subject to six-month financial covenants.

- For this loan a definition of default based on missed payments and covenant breaches could be suitable.

# Significant increase in credit risk

## Defining default– Example 4

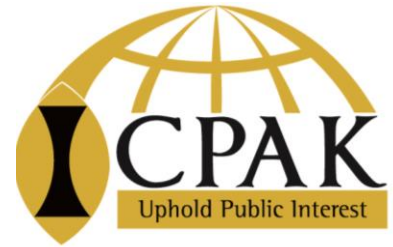


Lender B makes a 5 year loan with interest payable monthly and principal all due on maturity.

- In this case it is unlikely that a definition of default that is based solely on missed payments will be sufficient.
- This is because the main repayment is not due until maturity and hence a definition based on late payment would not capture the possibility that events take place before maturity that result in the borrower becoming unlikely to repay.

# Significant increase in credit risk

## Defining default– Example 5

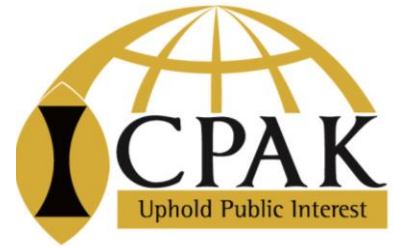


Can regulatory definition of definition of default be used for IFRS 9 purposes?

- Simply:- regulatory definitions can be used in so far as they do not conflict with the principles of IFRS 9.
- To discuss - **CBK** migration **to and from classes** and **consistency with IFRS 9**

# Significant increase in credit risk

## Defining default– Example 6

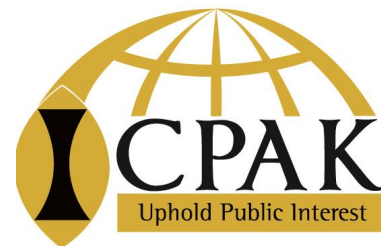


Effect of Business Combinations:- When financial assets are acquired in a business combination, the reference point for measuring the initial level of credit risk of those assets is reset to the date of the business combination.

- Entity C acquired Entity D in a business combination in June 2014. Entity D holds a loan from an associate that was considered low credit risk when first advanced in 2012. In June 2014, the risk of default on this loan was considered to be significant. At the reporting date of December 2014, the risk of default remains the same as at June 2014. Has there been a significant increase in credit risk at the reporting date of December 2014?
- **No. The date of the business combination is the reference date for the acquirer's financial statements, not the acquiree's date of initial recognition.**

# Significant increase in credit risk

## Individual & collective assessment

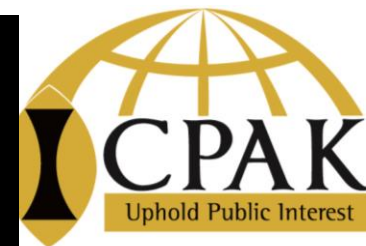


### Possible shared credit characteristics.

- Instrument type
- Credit risk ratings
- Collateral type
- Date of initial recognition
- Remaining term to maturity
- Industry
- Geographical location of borrower
- The value of collateral relative to the financial asset if it has an impact on probability of a default occurring

# Modelling ECL

# Measurement of ECL



## Expected credit losses on financial assets

### Probability weighted

Unbiased probability-weighted amount (evaluate range of possible outcomes and consider risk of credit loss even if probability is very low)

### Present value

Generally calculated using original EIR or an approximation as discount rate

### Cash shortfalls

Difference between cash flows due under the contract and cash flows that entity expects to receive



## Three building blocks

- An unbiased and probability weighted amount that is determined by evaluating a range of possible outcomes
- The time value of money
- Reasonable and supportable information about past events, current conditions and forecasts of future economic conditions.

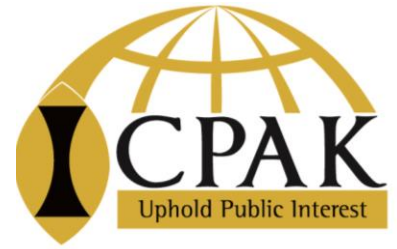
# Expected loss - introduction



Expected loss (EL) is calculated as the product of Exposure at default (EAD), Probability of default (PD), and Loss given default (LGD).

$$EL = PV\{PD * LGD * EAD\}$$

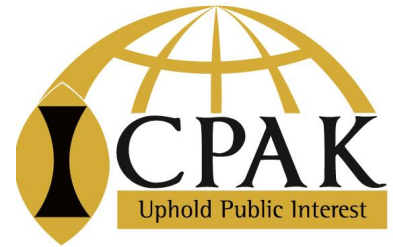
# Exposure at default



- Exposure at default (EAD), is the loss exposure stated as an amount (e.g., the loan balance outstanding).
- EAD can also be stated as a percentage of the nominal amount of the loan or the maximum amount available on a credit line.

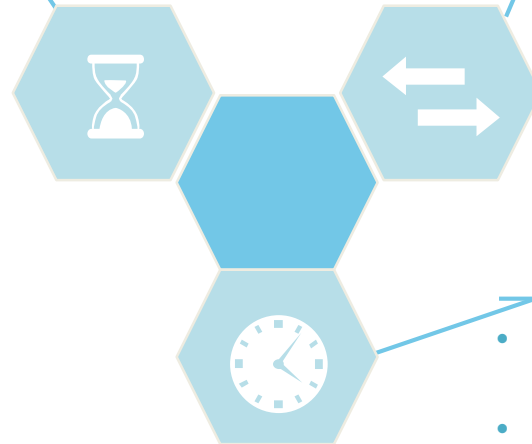
# Exposure at default

## Period of estimation



### Term loan

- For individual assessment, maximum contractual period under consideration of extension options
- For collective assessment, you might consider the average life of the loans or the loan with the largest life in the bucket



### Overdraft

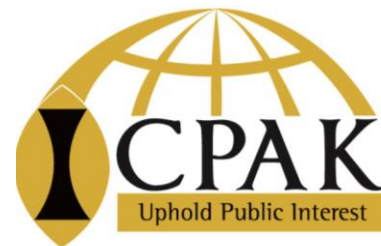
- Consider the normal life of the overdraft facilities
- Consider management policy regarding overdraft facilities

### Off-Balance Sheet

- Consider the normal life of the off balance sheet exposures
- Consider the behavior of the off balance sheet exposures
- Consider management policy regarding off balance sheet exposures
- Consider the credit conversion factor of the bank

# EAD estimation

## Effective interest rate (EIR)

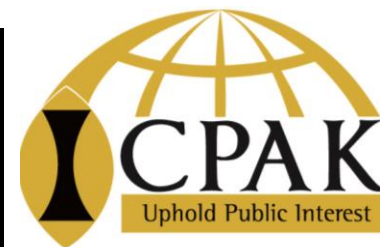


For individual assessment, the EIR will be the EIR of each exposure

For collective assessment, the EIR will be the average EIR of the exposures in the bucket or the EIR of each exposure in the portfolio

# EAD estimation

## Portfolio risk segmentation

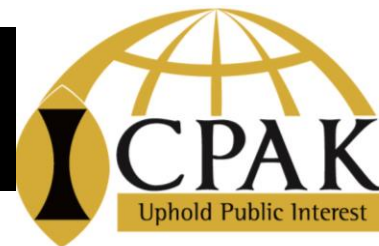


Categorize each exposures according into risk groups or similar credit risk.

SECTOR	CUSTOMER	PRODUCT	AMOUNT	RATING	STAGE
FINANCE & INSURANCE	MAXITRUST MICROFINANCE BANK LIMITED	LEASE	1,197,141.68	Grade 1 : Low Risk	Stage 1
FINANCE & INSURANCE	TFS FINANCE LIMITED	LEASE	1,882,917.24	Grade 9: Lost	Stage 3
FINANCE & INSURANCE	FIRSTGUARANTY RISK SOLUTIONS INSURANCE BROKERS LIMITED	TERM LOAN	180,521,311.92	Grade 8: Doubtful	Stage 2
FINANCE & INSURANCE	TABB MULTI GLOBAL INVESTMENT LIMITED	TERM LOAN	4,643,953.34	Grade 7: Doubtful	Stage 2
AGRICULTURE	DIRECTED SERVICES LIMITED	ADVANCES	106,351,114.31	Grade 1 : Low Risk	Stage 1
AGRICULTURE	DIRECTED SERVICES LIMITED	ADVANCES	203,709,504.80	Grade 1 : Low Risk	Stage 1
AGRICULTURE	DIRECTED SERVICES LIMITED	ADVANCES	49,010,843.93	Grade 1 : Low Risk	Stage 1
GENERAL	HILTOP INT'L CHRISTIAN CENTRE	ADVANCES	4,621,012.90	Grade 2: Watchlist	Stage 2
GENERAL	MOHAMMED HAYATU-DEEN	ADVANCES	719,797,765.89	Grade 2: Watchlist	Stage 2
GENERAL	PERFECT KITCHENS LIMITED	ADVANCES	28.23	Grade 7: Doubtful	Stage 2
MANUFACTURIN	QUALITY COOL WORKS LIMITED	ADVANCES	524,021,435.36	Grade 9: Lost	Stage 3
GENERAL	THEOPHILUS OSAZE ILUOBE	ADVANCES	46,492,910.78	Grade 3: Watchlist	Stage 2
GENERAL	WORLD EVANGELISM INCORPORATION	ADVANCES	187,358,985.48	Grade 9: Lost	Stage 3
GENERAL	APOSTLE PAUL GOSPEL OUTREACH	LEASE	1,864,246.47	Grade 9: Lost	Stage 3

# EAD estimation

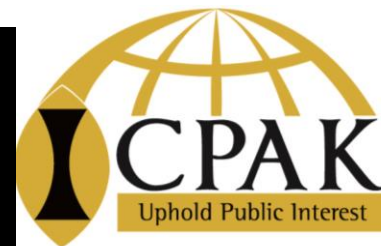
## Portfolio risk segmentation



SECTORS	Stage 1	Stage 2	Stage 3	Grand Total
ADMIN. & SUPPORT SERV.	1,760,392			1,760,392
AGRICULTURE	3,448,871,246	1,279,237,718	51,831,722	4,779,940,687
ARTS, ENTERTAINMENT & RECREATION	2,545,295	5,618,058,120	138,966,197	5,759,569,613
CONSTRUCTION	3,033,513,800	12,802,052,785	2,967,097,845	18,802,664,431
EDUCATIONAL	48,261,612	299,020,857	33,678,210	380,960,680
FINANCE & INSURANCE	1,197,141	185,165,265	1,882,917	188,245,324
GENERAL	6,285,968,539	3,733,764,184	2,450,522,818	12,470,255,541
GENERAL COMMERCE	3,095,684,600	3,647,480,412	1,483,241,424	8,226,406,436
GOVERNMENT	29,374,474,852	321,643	7,317,100	29,382,113,596
HUMAN HEALTH & SOCIAL WORK	5,566,622,216	66,171,157	57,956,112	5,690,749,487
INFORMATION & COMMUNICATION	32,485,929,114	770,673	14,622,183	32,501,321,970
MANUFACTURING	6,381,377,306	91,530,609	21,428,405	6,494,336,321
OIL & GAS	13,615,117,384	6,981,523,448	5,794,682,208	26,391,323,041
POWER & ENERGY	2,154,398,665			2,154,398,665
REAL ESTATE	1,387,881,553	584,175,467		1,972,057,020
TRANSPORTATION & STORAGE	3,751,904,019	7,544,164,930	1,719,351,385	13,015,420,335
Grand Total	111,767,069,103	44,275,673,629	15,134,034,341	171,176,777,074

# EAD estimation

## Credit conversion factor (CCF)



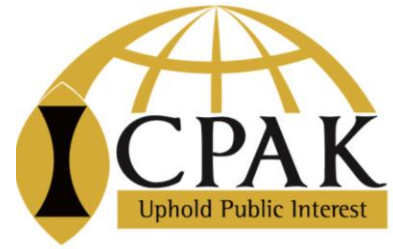
Apply the credit conversion factor of the client to the off balance sheet exposures in order to get its On-balance sheet equivalent

$$\begin{aligned} & \textit{Total On balance sheet exposure} \\ & \quad = \\ & \textit{On balance sheet exposures of the bank} \\ & \quad + \\ & \textit{(Off balance sheet exposures * CCF)} \end{aligned}$$



# EAD estimation

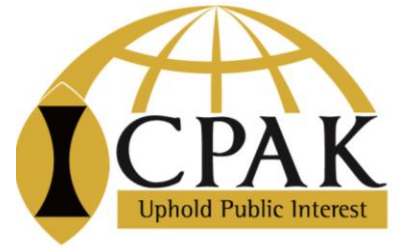
## Credit conversion factor (CCF)



- Loans with undrawn limits may change exposure over time due to available unutilized limits;
- Stage 2 assets suffer from this phenomenon more than stage 1 due to highly likely drawdown during stress events
- To consider drawdowns one needs to calculate the **credit conversion factor**
- Conversion of issued LCs and LGs into on-balance sheet items is also required for ECL calculations

# EAD estimation

## Credit conversion factor (CCF)



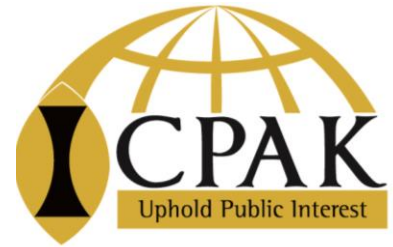
- Exposures which the bank provides future commitments, in addition to the current credit contain both on and off balance sheet values as EAD

$$EAD = \text{Drawn line} + CCF \times \text{Undrawn credit line}$$

$$CCF = \frac{\text{Increase in exposure over the period}}{\text{Available funds at the start of the period}}$$

# EAD estimation

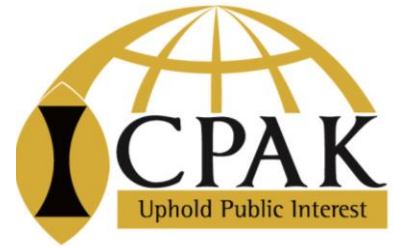
## Other considerations



- Prepayment rates
- Peculiar characteristics of the exposure
- Rescheduling and renegotiations, etc.

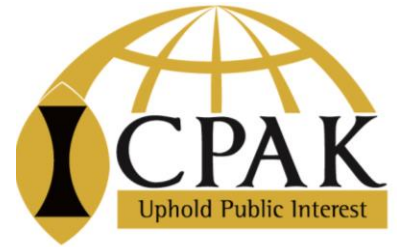
# Probability of default (PD)

# Probability of default



- Probability of default is defined as the probability of an account moving from its status as at the observation period into the default status over a defined time horizon.

# Classes of PD

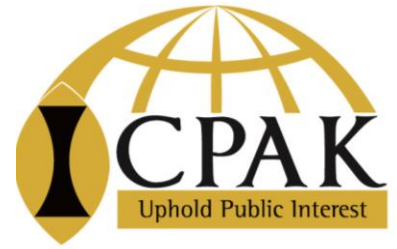


Historical PD



Forward looking PD

# Historical PD



## PD determination

### Methods

Default intensity  
method

Vintage loss method

Transition Rate Models

Financial data vendors

Rating agencies

Structural models

### Others

# Estimating PDs using transition matrices



## Example Steps

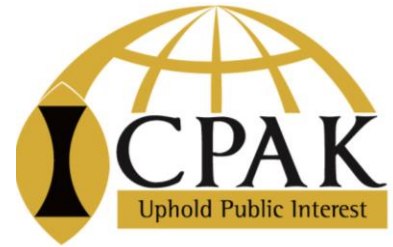
Step 1: Obtain the exposure data for the most recent consecutive periods

Step 2: Group the exposure portfolio according to similar credit risk (e.g. sectors, product).

Step 3: Group the loan portfolio according to their performance (e.g. performing, non-performing).



# Estimating PDs using transition matrices

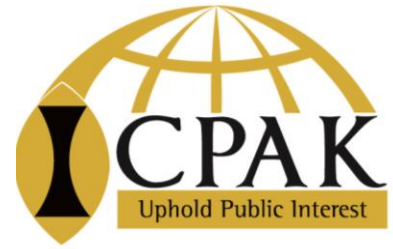


## Example Steps

Step 4: Determine the loans that moved from one state to another based on the matrix as shown below:

	Performing	Substandard	Doubtful	Loss
Performing	173,497,597,043.77	13,520,592.72	433,036,196.25	47,160,199.56
Substandard	55,421,670.89	-	150,569,775.25	-
Doubtful	414,993,605.94	-	166,181,744.15	26,018,125.37
Loss	1,231,190,046.01	-	-	951,866,417.40

# Estimating PDs using transition matrices



## Example Steps

Step 5: Compute the transition probabilities for each of the new state of event based on the matrix obtained in step 4:

	Performing	Substandard	Doubtful	Loss
Performing	99.716%	0.008%	0.249%	0.027%
Substandard	26.905%	0.000%	73.095%	0.000%
Doubtful	68.346%	0.000%	27.369%	4.285%
Loss	56.398%	0.000%	0.000%	43.602%

# Estimating PDs using transition matrices

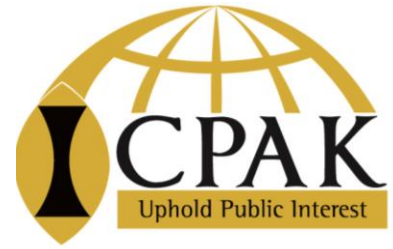


## Transition rate model (Example)- Steps

Step 6: Determine the probability of default from the array of transition probabilities

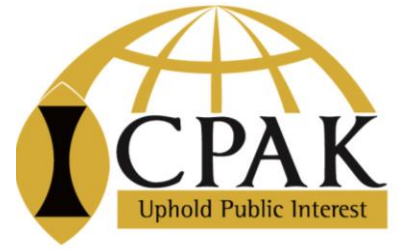
PERFORMING PD:	0.027%
SUBSTANDARD PD:	0.000%
DOUBTFUL PD:	4.285%
LOSS PD:	100%

# PDs – Forward looking adjustment



- **IFRS 9** requires financial institutions to adjust the current backward-looking incurred loss provision (as required by IAS 39) into a forward-looking expected credit loss.
- A forward-looking expected credit loss calculation should be based on an accurate estimation of **current and future probability of default (PD), exposure at default (EAD), loss given default (LGD), and discount factors.**

# Forward looking PDs

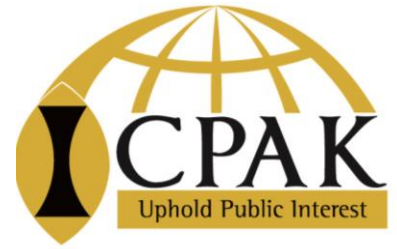


**12  
month  
PD**



**Life time PD**

# Forward looking PDs

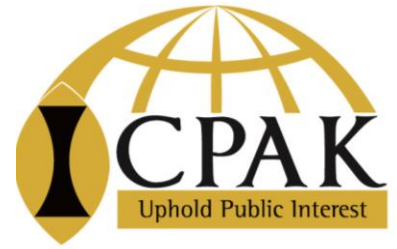


Step 1: Obtain historical probabilities of default for prior periods

Step 2: Obtain historical macroeconomic variable relating to the sector of the loan portfolio

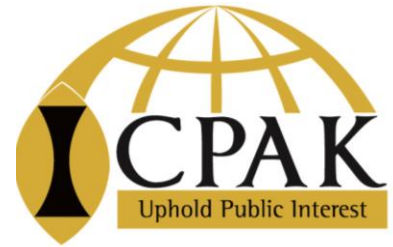
Step 3: Obtain or Forecast future macroeconomic variable using different statistical methods

# Forward PDs



Step 4: Use the macroeconomic variables and the historical PD to predict forward looking PD

# Forward looking PDs



## Forward looking PD determination

### Methods

**Regression analysis**

**Copulas**

**Probit Models**

**Logit Models**

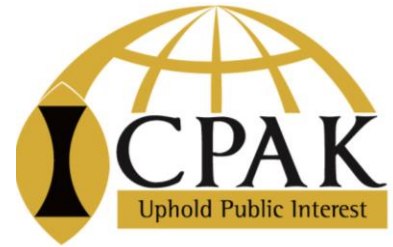
**Discriminant analysis**

**Neural networks**

**Others**



# Forward looking PDs using Logit

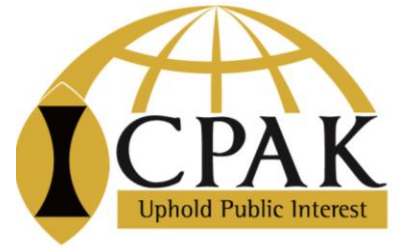


## Example Steps

Step 1: Obtain the historical PD and macroeconomic variable

Years	PD	Inflation	Unemployment rate
2008	0.0162	5.74%	0.111
2009	0.0427	12.24%	0.1
2010	0.2296	8.52%	0.008
2011	0.1966	8.06%	0.05
2012	0.0833	9.01%	0.071
2013	0.0463	15.63%	0.141
2014	0.0262	8.06%	0.078
2015	0.0627	9.01%	0.09
2016	0.1296	15.63%	0.121

# Forward looking PDs using Logit



## Example Steps

Step 2: Run a logistic regression in order to derive the regression coefficients

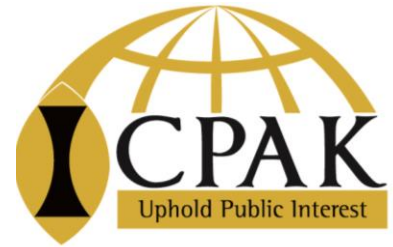
	beta*X	PD
2008	-1.89905	0.130215499
2009	-2.42524	0.081268063
2010	-5.53527	0.003929647
2011	-4.06321	0.016903136
2012	-3.35575	0.033707258
2013	-1.09511	0.250657032
2014	-3.08926	0.043552387
2015	-2.69486	0.063277273
2016	-1.77687	0.144689555

Coefficient estimates	
C	-5.607
Beta1	-2.422
Beta2	34.784

-1.62919

$$PD = \frac{1}{1 + \exp(-b'x_i)}$$

# Forward looking PDs using Logit



## Example Steps

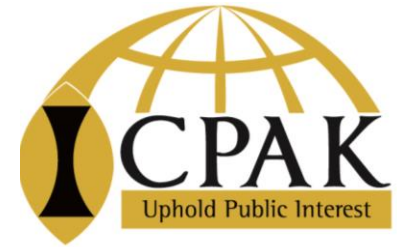
Step 3: Use the obtained regression coefficient to predict future PD based on the projected future macroeconomic variables

Year	Inflation_F	Unemployment rate_F	beta*X	PD
2017	0.158	0.135	-1.29402	0.215174
2018	0.115	0.13	-1.36381	0.203622
2019	0.093	0.125	-1.48445	0.184756
2020	0.083	0.12	-1.63415	0.163262
2021	0.08	0.115	-1.80081	0.141753
2022	0.08	0.11	-1.97473	0.121882

Coefficient estimates	
C	-5.607
Beta1	2.422
Beta2	34.784

-1.62919

# Forward looking PDs using Logit



## Example Steps

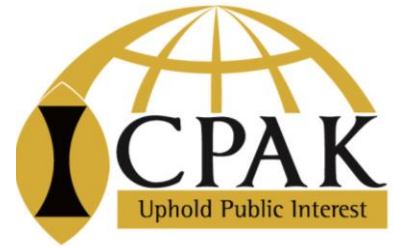
Step 4: Use the obtained regression coefficient to predict other scenarios future PD based on the projected future scenarios macroeconomic variables

Estimates	
C	-5.607
Beta1	2.422
Beta2	34.784

-1.62919

PD	Inflation	Unemployment rate		beta*X	PD
2017	0.208	0.155	2017	-0.71942	0.327520269
2018	0.165	0.165	2018	-0.26745	0.433532218
2019	0.143	0.175	2019	0.13366	0.533365289
2020	0.133	0.185	2020	0.505714	0.623801247
2021	0.13	0.195	2021	0.860817	0.702831376
2022	0.13	0.205	2022	1.208655	0.770060962

# Forward looking PDs using Logit

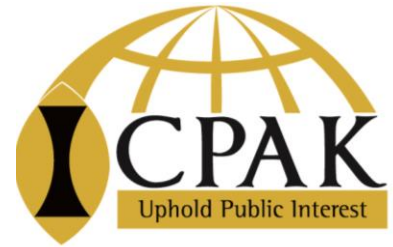


## Example Steps

Step 5: Derive the final probability of default by computing the expected value of the PD for all the scenarios

<b>FINAL PD</b>	
2017	0.22
2018	0.24
2019	0.26
2020	0.28
2021	0.29
2022	0.31

# Forward looking PDs using Logit



## Example Steps

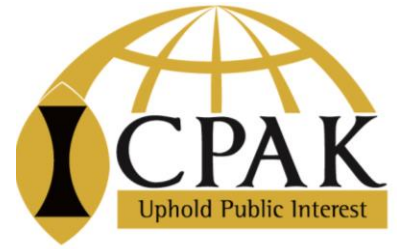
**Step 6: Compute the marginal probability of default**

Year	PD	1-PD	MPD
2016	14.47%	85.53%	
2017	21.68%	78.32%	18.54%
2018	24.10%	75.90%	16.14%
2019	26.13%	73.87%	13.29%
2020	27.85%	72.15%	10.46%
2021	29.32%	70.68%	7.95%
2022	30.56%	69.44%	5.85%

$$MPD_s[t] = \prod_{k=1}^t (1 - PD\_COND_s[k]) - \prod_{k=1}^{t-1} (1 - PD\_COND_s[k])$$

Loss given default (LGD)

# Loss Given Default



Loss given default is represents the likely percentage loss if the borrower defaults.



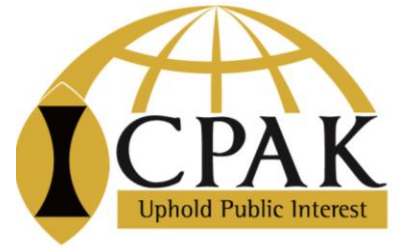
# LGD types

**Historical LGD**



**Forward looking  
LGD**

# Historical LGD



## Historical Loss given default (LGD) Determination

### Methods

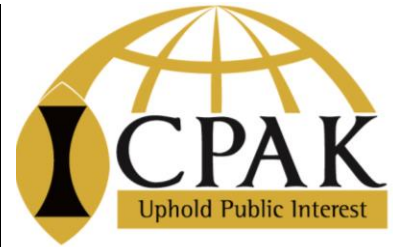
Financial data vendors  
terminals

Structural model

Basel guidelines

Etc.

# Forward LGD

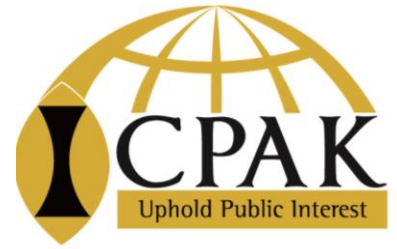


Step 1: Obtain historical Loss given default (LGD) for prior periods

Step 2: Obtain historical macroeconomic variable relating to the sector of the loan portfolio

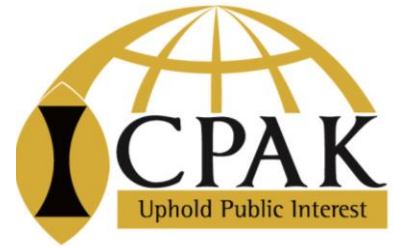
Step 3: Forecast future macroeconomic variable using different statistical methods

# Forward looking LGD



Step 4: Use the macroeconomic variable and the historical LGD to predict forward looking LGD

# Forward looking LGD



## Forward looking Loss given default (LGD)

### Methods

Gaussian Copula model

Regression analysis

Probit model

Logit model

Etc.

# Expected credit loss- Computation

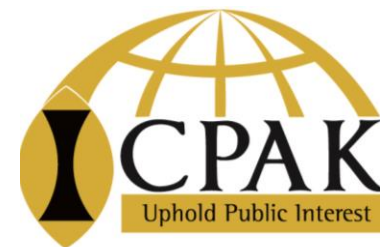
# ECL Computation



Expected credit loss is calculated as the product of Exposure at default(EAD), probability of default (PD), and loss given default(LGD).

$$\mathbf{ECL = PV\{EAD \times PD \times LGD\}}$$

# ECL Computation

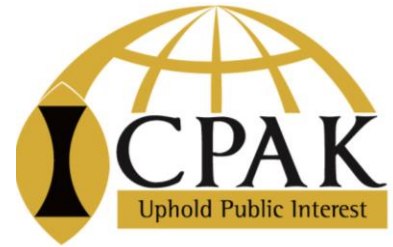


Stage 1-(12 month expected credit loss)								
	EAD (Ksh million)	PD	Survival Prob.	T	Pr def (t-1 < D < =t)	LGD	PV (EL)	12 month ECL (%)
1	3,448,871,246.45	0.12317	1	1.000	0.12317	0.0542	21,421,743.29	100.00%
							<b>21,421,743.29</b>	
Interest rate		0.074						

Stage 2-(Lifetime expected credit loss)								
	<b>1,279,237,718.75</b>							
	EAD (Ksh million)	PD	Survival Prob.	T	Pr def (t-1 < D < =t)	LGD	PV (EL)	Lifetime ECL (%)
1	1,023,390,175.00	0.12317	1	1.000	0.12317	0.0542	6,356,514.94	99.33%
2	767,542,631.25	0.08188	0.876832421	0.750	0.05385	0.0008	27,740.63	0.43%
3	511,695,087.50	0.06047	0.805034887	0.500	0.02434	0.0012	12,368.60	0.19%
4	255,847,543.75	0.05291	0.756351444	0.250	0.01001	0.0016	3,046.39	0.05%
							<b>6,399,670.56</b>	
Interest rate		<b>0.074</b>						



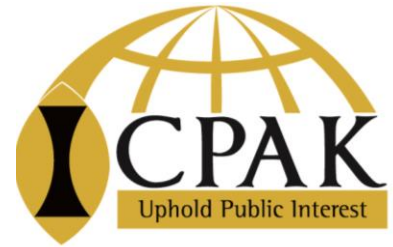
# ECL Computation



Stage 3-(Lifetime expected credit loss)								
	<b>51,831,722.77</b>							
	<b>EAD (Ksh million)</b>	<b>PD</b>	<b>Survival Prob.</b>	<b>T</b>	<b>Pr def (t-1 &lt; D &lt; =t)</b>	<b>LGD</b>	<b>PV (EL)</b>	<b>Lifetime ECL (%)</b>
1	41,465,378.22	1	1	1.000	1.00000	0.05	2,091,062.70	98.63%
2	31,099,033.66	1	1	0.750	0.75000	0.00	15,654.93	0.74%
3	20,732,689.11	1	1	0.500	0.50000	0.00	10,293.99	0.49%
4	10,366,344.55	1	1	0.250	0.25000	0.00	3,084.11	0.15%
							<b>2,120,095.73</b>	
<b>Interest rate</b>		<b>0.074</b>						

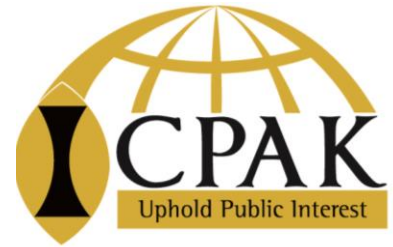
# Macroeconomic considerations

# Incorporating macroeconomic variables



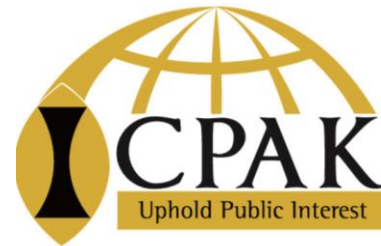
Expected loss parameters should reflect best estimate that reflects **current situation** and **reasonable and supportable macroeconomic forecasts**.

# Incorporating macroeconomic variables



1. Obtain historical macroeconomic variables
2. Determine the macroeconomic variables that affect impairment parameters
3. Project future macroeconomic variables under various scenarios

# Incorporating macroeconomic variables



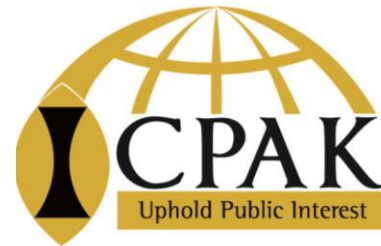
## 1. Obtain historical macroeconomic variables

### Sources

Established agencies such as :  
Bureau of statistics,  
Central bank,  
Federal agencies,  
International organizations,  
etc.

Financial data vendors terminal such as:  
Bloomberg,  
Thomson Reuters,  
BMI Research International,  
etc.

# Incorporating macroeconomic variables



2. Determine relationship between macroeconomic variables and impairment parameters

**Determine co-movement  
between the parameter  
and macroeconomic  
variable**

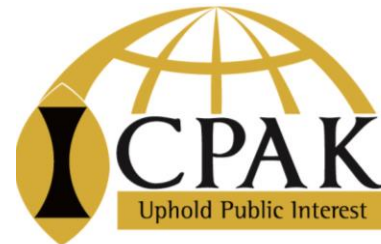
# Incorporating macroeconomic variables



## 2. Determine the macroeconomic variables that affect impairment parameters

PD	FX rate	Inflation rate	Natural gas	Oil production (Mbpd)	Oil price	Unemployment Rate	Federation account (Ksh'Billion)	Foreign reserves (U\$bn)	Money supply	Treasury rate	Prime lending rate %
0.08	0.02	12.24	-0.31	0.02	0.02	10.06	0.07	0.34	0.14	13.64	16.79
0.05	0.00	8.52	0.36	-0.03	-0.03	10.00	0.14	-0.02	0.09	10.85	16.72
0.03	0.01	8.06	0.17	-0.09	-0.09	7.80	0.01	-0.20	0.17	10.50	16.55
0.06	0.22	9.01	-0.40	-0.49	-0.49	9.00	-0.22	-0.17	0.07	9.39	16.85
0.13	0.44	15.63	-0.05	-0.18	-0.18	12.10	-0.10	-0.09	0.14	10.11	16.86

# Incorporating macroeconomic variables

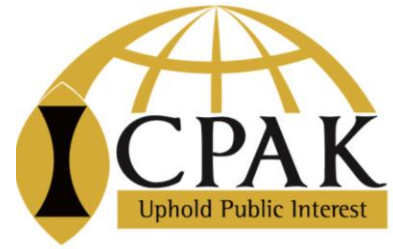


Determine relationship between macroeconomic variables and impairment parameters

Macro variable	PD
PD	1
Exchange rate	0.84124403
Inflation rate	0.97184738
Natural gas	-0.83091417
OIL PRODUCTION (Mbpd)	-0.60326576
Oil price	-0.58957609
Average electricity generation (mw)	-0.18147444
Unemployment	0.91431328
Federation account (n' billion)	-0.86292538
Foreign reserves (u\$bn)	-0.40968455
Money supply	0.47932666
Treasury rate	0.0744141
Population	0.51798166
Prime lending rate%	0.78578389



# Incorporating macroeconomic variables



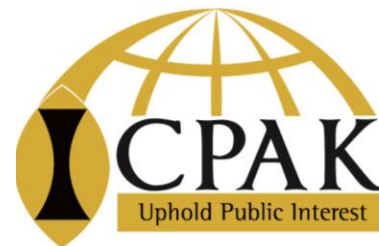
## 3. Obtain or Project future macroeconomic variables under various scenarios and assign probability to them

### Sources

Established agencies such as :  
Bureau of statistics,  
Central bank,  
Federal agencies,  
International organizations,  
etc.

Statistical techniques such as:  
regression analysis,  
stochastic models,  
Auto-regressive  
moving average,  
exponential  
smoothing

# Incorporating macroeconomic variables



## 3. Project future macroeconomic variables under various scenarios and assign probability to them

HISTORICAL DATA				
	MACRO ECONOMIC VARIABLES			
	CRUDE OIL PRICE (US\$)	INFLATION RATE (%)	AVERAGE FOREX RATE (Ksh/US\$)	
SECTORS				Year
TRANSPORTATION	27.6	6.93	102.11	2000
	23.12	18.87	111.94	2001
	24.36	12.87	120.97	2002
	28.1	13.93	129.36	2003
	36.05	15.38	133.50	2004
	50.64	17.85	132.15	2005
	61.08	8.38	128.65	2006
	69.08	5.41	125.83	2007
	94.45	11.53	118.57	2008
	61.06	12.59	148.88	2009
	77.45	13.76	150.30	2010
	107.46	10.85	153.86	2011
	109.45	12.24	157.50	2012
	105.87	8.52	157.31	2013
	96.29	8.06	158.55	2017
	49.49	9.01	193.28	2015
	40.76	15.63	278.15	2016

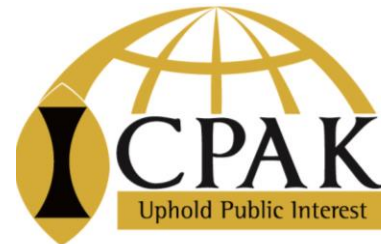
# Incorporating macroeconomic variables



## 3. Project future macroeconomic variables under various scenarios and assign probability to them

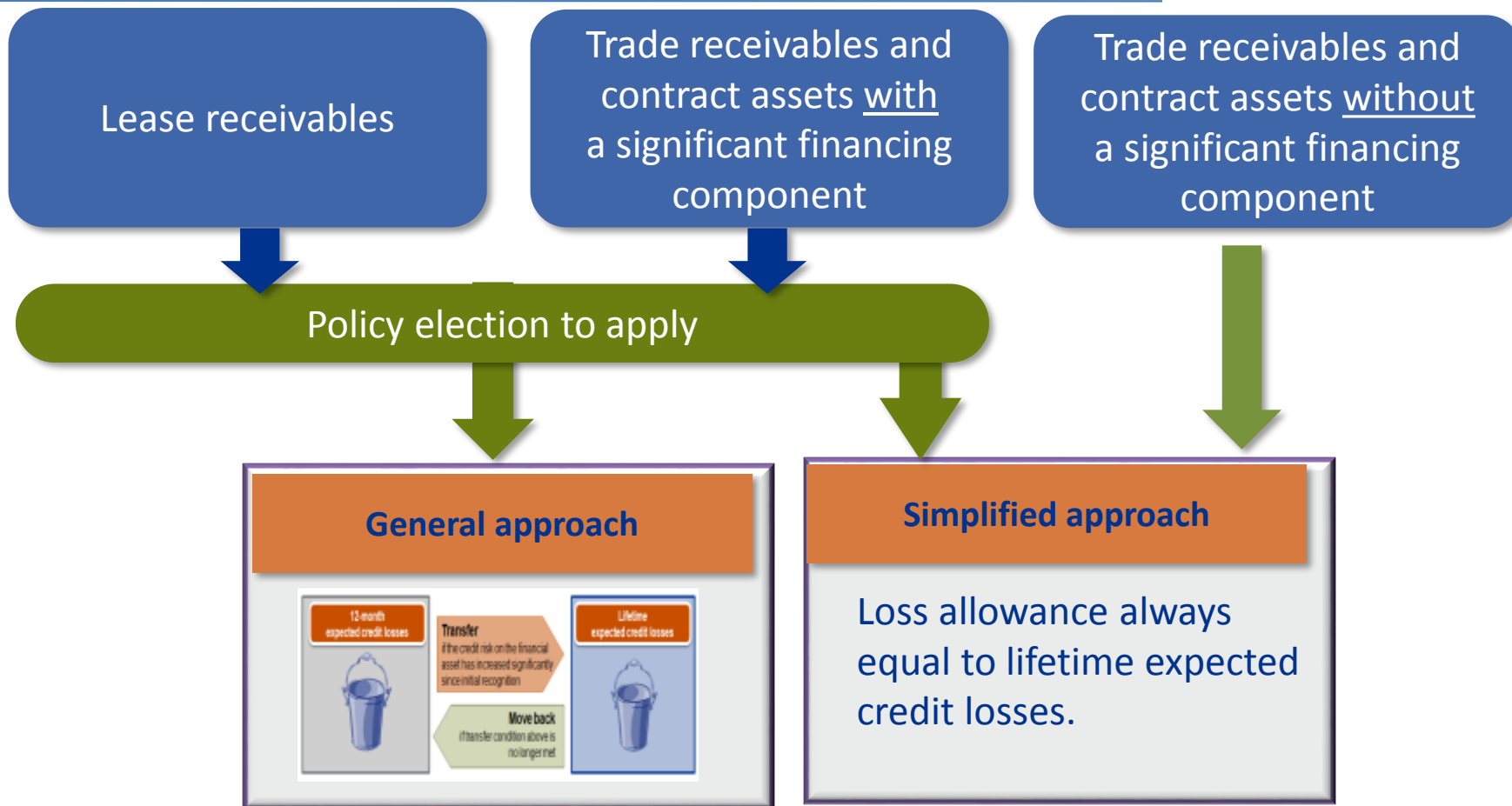
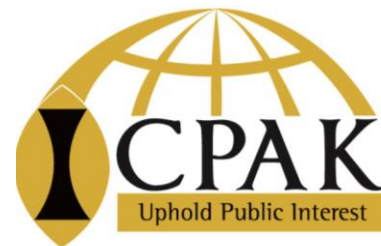
SECTORS	CRUDE OIL PRICE (U\$)	INFLATION RATE (%)	AVERAGE FOREX RATE (Ksh/US\$)	SCENARIOS (YRS)
TRANSPORTATION				WORST
	30	20.8	462.5	2017
	35	16.5	462.5	2018
	40	14.3	450	2019
	45	13.3	455	2020
	50	13	460	2021
	55	13	460	2022
				BASELINE
	45	15.8	362.5	2017
	50	11.5	362.5	2018
	55	9.3	350	2019
	60	8.3	355	2020
	65	8	360	2021
	70	8	360	2022
				BEST CASE
	60	13.8	282.5	2017
	65	9.8	282.5	2018
	70	7.3	370	2019
	75	6.3	375	2020
	80	6	280	2021
	85	6	280	2022

# What is the Estimation Period?



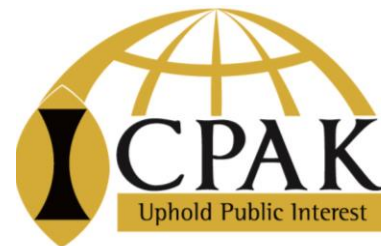
- Generally the maximum contractual period over which entity exposed to credit risk:
  - E.g. loan commitments - maximum contractual period entity has present contractual obligation to extend credit.
- Exception for certain financial instruments that:
  - Include both loan and undrawn commitment component.
  - Can be contractually withdrawn with little notice.
  - Ability to cancel does not limit the lender's exposure.
- Measure expected credit losses over the period entity is exposed to credit risk.

# Simplified Approach for Trade and Lease Receivables and Contract Assets



**Practical expedient to calculate expected credit losses – provision matrix.**

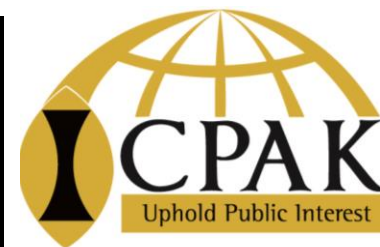
# Simplified approach – Provision matrix



- Company M has receivables of KES 30 Million in 2018
- The customer base consists of a large number of small clients
- The receivables have similar credit characteristics and they do not have a significant financing component
- The company uses a transition matrix based on historical information (adjusted for forward looking estimates)
- M estimates the following provision matrix

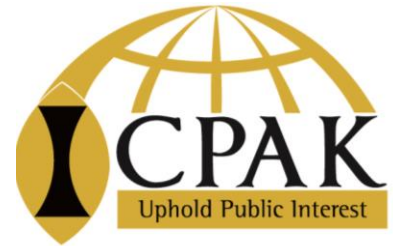
Current	1-30 Days	31-60 Days	61-90 Days	>90 Days
0.3%	1.6%	3.6%	6.6%	10.6%

# Simplified approach – Provision matrix



Current	Amount	Default rate	Lifetime ECL
Current	15,000,000	0.3%	45,000
1-30 Days	7,500,000	1.6%	120,000
31-60 Days	4,000,000	3.6%	144,000
61-90 Days	2,500,000	6.6%	165,000
>90 Days	1,000,000	10.6%	106,000

# Interest Recognition



Initial  
recognition

Significant increase  
in credit risk

Asset becomes  
credit-impaired



Impairment  
loss

12-month expected  
credit losses

Lifetime expected credit losses

Interest on assets not  
impaired at initial  
recognition

EIR applied to gross amount

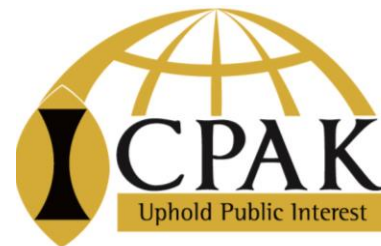
EIR applied  
to amortised cost

Interest on assets  
impaired at initial  
recognition

Credit-adjusted EIR applied to amortised cost



# Which rate for discounting



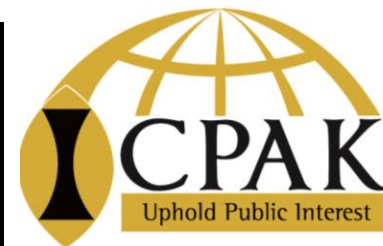
Asset	Rate
Fixed rate assets	Effective interest rate determined at initial recognition
Variable rate assets	Current effective interest rate
Purchased or originated credit impaired financial assets	Credit-adjusted effective interest rate determined at initial recognition
Lease receivables	Same discount rate as used in the measurement of the lease receivable
Loan commitments	Effective interest rate, or an approximation of it, that will be applied when recognising the financial asset resulting from the loan commitment

# Which rate for discounting



Asset	Rate
Loan commitments for which the effective interest rate cannot be determined	A rate that reflects the current market assessment of the time value of money and the risks specific to the cash flows (unless adjustment has instead been made to the cash shortfalls)
Financial guarantee contracts	A rate that reflects the current market assessment of the time value of money and the risks specific to the cash flows (unless adjustment has instead been made to the cash shortfalls)

# Disclosures



## Quantitative disclosures

Reconciliation of opening to closing amounts of loss allowances showing key drivers of change

Reconciliation of opening to closing amounts of GCAs showing key drivers of change

GCAs by credit risk grade

Write offs, recoveries and modifications

## Qualitative disclosures

Inputs, assumptions and estimation techniques for estimating ECL

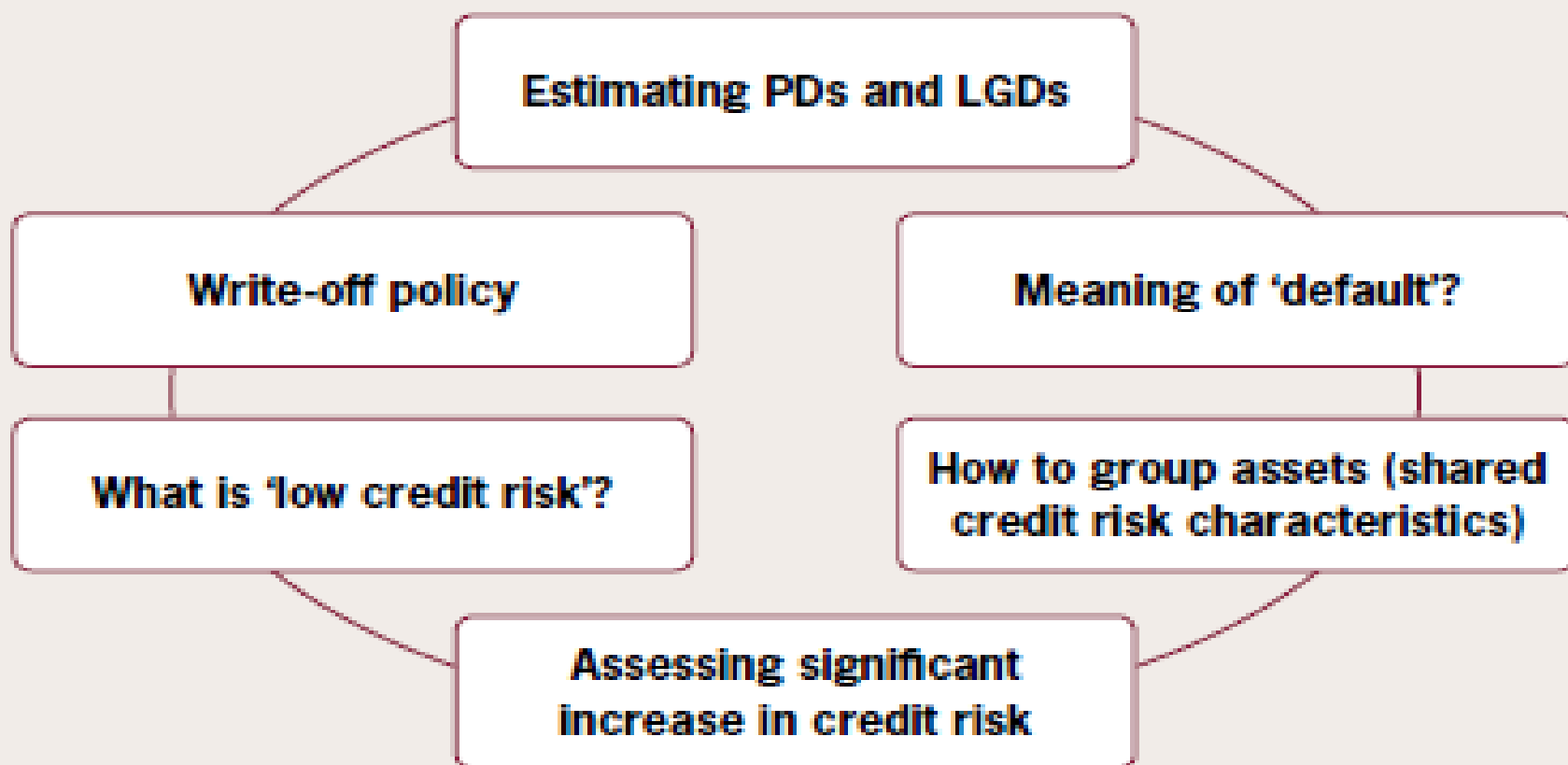
Inputs, assumptions and estimation techniques to determine significant increases in credit risk and default

Inputs, assumptions and techniques to determine credit-impaired assets

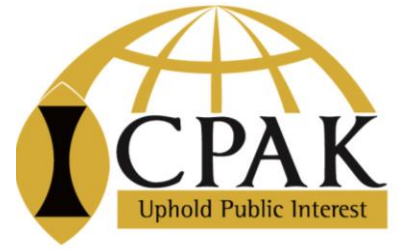
Wrote off policies, modification policies and collateral

# Key challenges - ECL

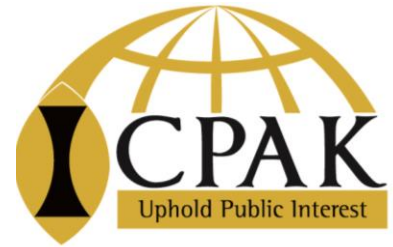
## Key implementation challenges



# Questions & comments



# Contact details



Ferdinand Okoth Othieno

Dean, Strathmore Institute of Mathematical Sciences

[fothieno@strathmore.edu](mailto:fothieno@strathmore.edu)

[fokoth@gmail.com](mailto:fokoth@gmail.com)

+254 721 722 872

The views and opinions expressed in this presentation are those of the presenter (s) unless identified as those of other parties. The information contained herein is of a general nature and is intended for educational purposes only. Although the presenter has strived to provide accurate and timely information, there can be no guarantee that such information is accurate as of the date it is received or that it will continue to be accurate in the future. No one should act on such information without appropriate professional advice after a thorough examination of the particular situation.