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IMPACT OF IFRS 9 STANDARDS ON DEFAULT RISK: APPLICATION TO THE AMERICAN CONTEXT

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Abstract

The aim of this paper is to test the impact of integrating forward-looking information in risk assessment, specifically to estimate customer default risk. To determine the potential impact of adopting IFRS 9 standards, we use a credit portfolio of an American institution, containing data covering the period stretching from 01- 01-1989 to 01-01-2020. In this paper, we propose a method to highlight the incorporation of the Forward-looking" variable, based on economic scenarios, in the calculation of default probabilities. Our results show that an adverse scenario reflecting a future deterioration of economic conditions will surely lead to an increase in current customer default. While a favorable scenario will lead to lower default probabilities. This has been proven by integrating the economic adjustment coefficient (EAC) into the calculation of default probabilities. The paper contributes to the literature by adding knowledge on the relationship between default risk and IFRS 9 accounting standard.

Keywords: IFRS, IASB, dynamic provisioning, credit risk, prudential regulation, and default risk

JEL Classification: G01, G3, M4

1. INTRODUCTION

With the succession of financial, economic, and health crises, banks, as well as several financial institutions, have found themselves hypersensitive to survive these crises. An example of such crises is the 2008 “subprime” crisis, which represents a tangible proof of the suffering of banking institutions. However, throughout the 2007-2008 period, credit markets were completely frozen.

Banking activity, like all business activities, opts for efficiency and profitability. Nevertheless, it is marked by its complexity and sophistication as it requires establishing a balance between profitability and risk control.

At this stage, the proper assessment and governance of risks, the most important of which is credit risk, proves to be hyper-vital for the continuity of the bank's activity as well as its financial stability (Novotny-Farkas, 2016). Among the risk assessment and management techniques, we cite scoring, and financial analysis, yet the main tool used by banks is the provisioning technique or the recognition of provisions to cover themselves against potentially expected losses (Breeden and Maxim, 2020 ; Filusch, 2021).

However, with the onset of financial crises, especially that of 2008, the provisioning method became incapable of satisfying the needs of banks to cover losses. Researchers have accused it of generating a procyclical character. This comes back directly to the source of inspiration for the application of IAS39-inspired provisioning. Testimony of banks during the 2008 “subprime” crisis proves that the IAS39- inspired provisioning has become insufficient for coverage. Indeed, the IAS39 standard is a retrospective accounting framework based on the recognition of incurred credit losses, i.e. the provision on a specific asset will only be recognized if there is a tangible proof of deterioration or loss. This results in late recognition of provisions and therefore delayed recognition of losses.

Faced with this scenario, the regulatory authorities, namely the International Accounting Standards Board, have received several complaints on this poor and obsolete model. After a long revision of regulations and reform of the IAS39 standard, in 2014 the authorities managed to replace the IAS39 system with the new IFRS, more precisely IFRS9, which came into force at the beginning of 2018. The main novelties introduced by this standard are those of the use of a new impairment model based on expected and unproven losses, which entails the integration of "Forward-looking data" in risk estimation and also the application of a new provisioning logic relevant to the dynamics of customer monitoring (Yang et al., 2020).

In this paper, we will try to test the impact of integrating forward-looking information in risk assessment to estimate customer default risk.

The rest of the paper is organized as follows. The first section presents the theoretical background and especially the basic principles of IFRS9. The second section presents the empirical design and the main results. The last section concludes the paper.

2. BASIC PRINCIPLES OF IFRS 9

With a view of urgently revise the IAS 39 standard, the IASB and its American equivalent the FASB found it necessary to fill its gaps, specifically at the level of impairment of assets and liabilities and credit risk provisioning, and to establish a new IFRS 9 system able to establish better transparency of information and good management of assets.

On July 24, 2014, the International Accounting Standards Board posted the final version of the International Financial Reporting Standard IFRS9 “Financial Instruments”. This new standard aims to introduce new rules for the classification and impairment of financial instruments based on expected loss models and provisioning based on stages (buckets).

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The table below presents the main differences between IFRS 9 and IAS 39.

Table 1: Differences between the two reforms IAS39 and IFRS9

IAS 39	**IFRS9**
Model-based on incurred or proven losses "EL"	Model-based on expected credit losses "Expected Credit Loss"
Provisioning as soon as a tangible indicator of impairment surfaces.	Provisioning at the time the credit is granted
Model-**based** on historical data	Model-based on retrospective data and takes into account "Forward-looking" prospective data

The new IFRS 9 standard is made up of three main components: classification and measurement of financial instruments, impairment, and hedge accounting. The project to implement this reform spans over two major phases. The first proposes a new methodology for classifying and valuing financial assets and the second introduces a new provisioning practice. In Europe, the standard came into effect on January 1, 2018.

2.1. The principles of classification and evaluation

Following a bank managers' combinatorial analysis of the management models and contract characteristics linked to each asset made, the IFRS 9 standard dictates 3 classification categories:

- Fair value through profit or loss,
- Fair value through equity,
- Amortized cost.

Thus, if the financial asset is guided by an economic model for holding purposes and obtaining cash flows at specific dates of interest and principal (Credit Risk), the asset must be valued at an amortized cost. In contrast, an asset is measured at fair value through equity if the company intends to hold and sell it while also receives the contractual cash flows.

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Figure 1 below presents a summary of the classification and valuation of financial assets.

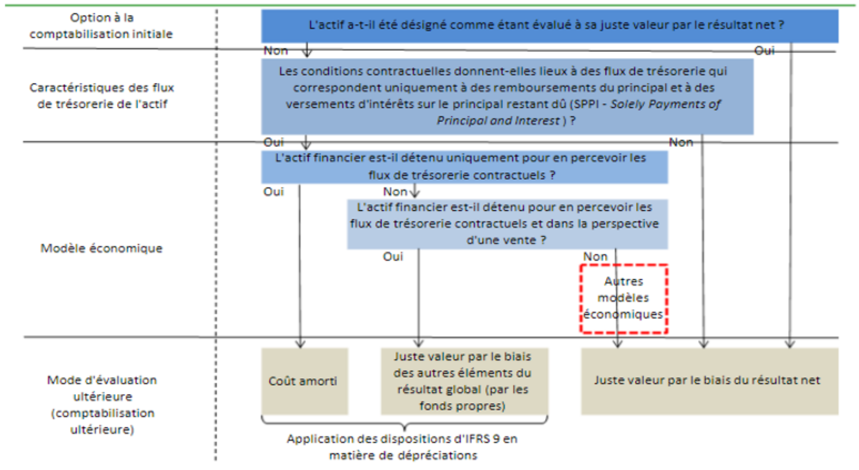

Figure 1: Classification and measurement of financial assets under IFRS9

Source: BNP PARIBAS

2.2. Depreciation

In accounting terms, depreciation means recording the potential future loss, i.e. the loss in value of an asset. In this paper, provision represents depreciation, and this provision is calculated by an assessment of the losses linked to credit (the amount of potential loss following the granting of a credit).

Thus, article B 5.5.2 of the new IFRS 9 standard stipulates that: “Expected credit losses […] are generally deemed to be recognized before the financial instrument becomes past due. Typically, credit risk increases significantly before the financial instrument is past due or other post-observable borrower-specific factors (e.g, modification or restructuring) arise. Therefore, where it is possible to obtain reasonable and supportable information that is more forward-looking than information on overdue payments without incurring undue cost or effort, that is the information that should be used to assess changes in credit risk”

The impairment component is considered to be the great innovation brought by the new IFRS9 reform. The latter admits a new impairment model which is bears on estimating "expected losses" (ECL), replacing thus the old "proven losses » model of the IAS39 standard. Assessment of expected losses is shown by the calculation of the ECL at 12 months and the ECL at maturity (Yang and Kenneth, 2018). In addition, this model requires the earlier recognition of "expected losses" through the incorporation of all prospective or future information called "Forward-looking data". This term represents a forecast coefficient of the future economic situation, which must be incorporated into the estimation of default probability and therefore the estimation of the ECL at 12 months and maturity.

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2.2.1. The ECL "expected loss" impairment model

The ECL model is defined as "the average credit loss weighted by the respective default risks that could be incurred over the life of the credit". This model is based on the recognition of expected losses from the initial recognition of financial instruments. Therefore, banks are called upon to apply this principle and no longer wait until the materialization of a significant depreciation of a receivable to record it as being a loss.

Calculation of expected credit losses requires taking into account all of the following elements:

- Good quality of historical and current data or information available.
- Weighted probabilities on possible events.
- The value of time in discounting losses.

2.2.2. Estimation of expected losses according to the "Buckets" approach

This model aims to better represent the deterioration (or improvement) of the quality of credit risk at the level of provisioning throughout the asset life (Fortésa et al., 2012; Barth and Wayn, 1995). The model implemented by IFRS 9 revolves around three "Buckets" or "Stages" which depend on the level of credit risk deterioration attached to the asset and its location in the different levels of strata (Braije, 2017; Escaffre and Sefsaf, 2010; M'rabet, 2017).

- **Assets in Stage 1 "Bucket 1"**

The asset qualified in the first phase displays no tangible or intangible indication of a considerable deterioration in its quality, i.e the least risky asset characterized by a very unlikely default possibility. The potential amount of expected credit losses should be assessed by calculating the 12-month forward ECL and financial income (interest) is calculated according to the effective interest rate (EI based on the gross credit amount)

In addition, if credit quality remains intact, calculation of the ECL will be applied each year until loan maturity. Finally, it is very crucial to mention that the bank must activate its credit monitoring system in this phase, because a lowering of credit quality accumulates their transitions in the second and third phases.

- **Assets in Stage 2 "Bucket 2"**

If the bank considers that the credit quality associated with an asset has deteriorated significantly from its initial recognition, consequently the value of the loss that it must recognize is equal to the ECL over the lifetime or at maturity and no longer to the next 12 months and interest is calculated according to the effective interest rate and the gross book value of the loan. The financial asset will then move into the second stage of IFRS 9. Therefore, a national recording of provisions for impairment (on a collective basis) at this stage is conducted.

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On the other hand, at this stage, even if there is no tangible indicator of loss observed, credit quality is assessed as deteriorating. The indicators that highlight this deterioration are, for example, the score, default probability, the number of days of late payment, etc.

A significant increase in credit quality may translate into an increased likelihood that a default will occur upon initial assessment. The bank has thus to identify this deterioration with the method it finds the most appropriate but taking into account:

- “The variation of the default risk since initial recognition;
- The expected life of the financial instrument and;
- Reasonable and supportable information that can be obtained without incurring undue cost or effort, which may affect credit risk. »

In addition, article 5.5.11 of IFRS9 stipulates the rebuttable presumption that: "Regardless of how an entity assesses significant increases in credit risk, there is a rebuttable presumption that the credit risk associated with a financial asset has increased significantly since initial recognition when contractual payments are more than 30 days past due. The rebuttable presumption does not apply when the entity determines that there are significant increases in credit risk before contractual payments were more than 30 days past due”.

Therefore, the entity is called upon to establish a general diagnosis of the elements that can indicate deterioration in credit risk. Figure 2 below provides a list of these elements that can provide information on deterioration in credit quality.

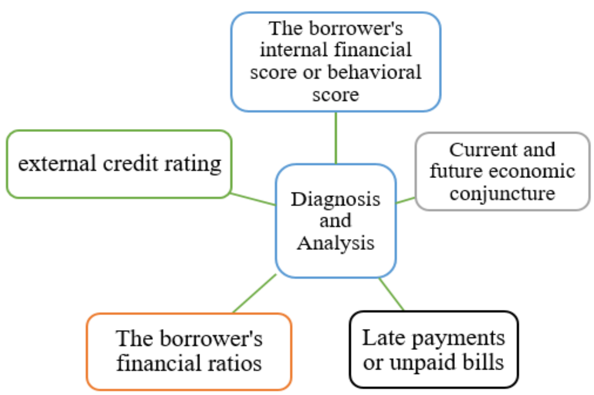

Figure 2: List of Factors Driving Recognition of Deteriorating Credit Risk

Source: Official Journal of the European Union

- **Assets in stage 3 “Bucket 3”**

If credit quality is considerably depreciated, i.e. there is a materialization of tangible and observed events of losses, for example, the non-recovery, of the principal or a delay in payment which exceeds 90, then the financial asset will migrate to the third stage.

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According to paragraph 452 of the Basel capital framework, failure of a financial asset occurs if it is exposed to the following two criteria:

- A qualitative criterion: the banking group considers it doubtful that the debtor will honor their credit commitments without the need for measures of enforcing the guarantees.
- A quantitative criterion occurs when the debtor exceeds a payment delay of 90 days, equivalent to the rebuttable presumption dictated in article B5.5.39 of the IFRS9 standard relating to the default part.

In this regard, the expected credit loss (ECL) is calculated over the entire maturity like that of the second Bucket (ECL at maturity) but the financial income is determined according to the net book value or the gross book value minus loss provisions (Lotfi, 2016; Thomas, 2009).

3. THE ECL DEPRECIATION MODEL

The main impairment component of the new IFRS 9 standard is based on the "ECL" expected credit loss model, which has just replaced the proven losses, or "Incurred losses" (IL) model used under IAS 39.

Schutte et al. (2020) consider that the IFRS 9 standard requires a large amount of data to be taken into account to estimate the ECL and the PD and LGD factors. The authors also claim that these requirements are met because there is no specific prescribed method for estimating PDs and therefore ECLs.

According to Article B5.5.17 of IFRS9, "An entity shall measure expected credit losses on a financial instrument in a way that reflects:

a) an objective amount based on probability weights, which is determined by evaluating a range of possible outcomes;
b) the time value of money; and
c) reasonable and supportable information about past events, current conditions, and forecasts of future economic conditions that are obtainable at the balance sheet date without incurring excessive cost or effort. »

We notice that the "time value of money" feature is reflected in the ECL estimation formulas by incorporating the effective interest rate (EIR) from the discounting of the amounts of the provisions as well as the notion of asset life. For the component pertaining to information on past and future economic conditions, it is integrated into the calculation of the ECL by taking into account the "Forward-looking" data in the estimation of default probability (Miu and Ozdemir, 2017; Vanek and Hample, 2017; Zhang and Tony, 2019)

There is a variety of estimation practices. In the literature, we distinguish between direct and indirect modeling practices. The direct method is a total loss method while the indirect method is a loss component method who's ECL includes a variable to be explained by PD, LGV, and EAD (McPhail and McPhail, 2014). We will focus only on the indirect method.

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The expected credit loss model is as follows:

$$\boldsymbol{ECL}\ (\boldsymbol{t}) = \sum_{\boldsymbol{t=0}}^{\boldsymbol{T}} [\mathbf{PD}(\mathbf{t}) \times \mathbf{EAD}(\mathbf{t}) \times \mathbf{LGD}(\mathbf{t})] / (\mathbf{1} + \boldsymbol{k})^{\boldsymbol{t}}$$

With:

t € [0; ...; T] according to the staging (12 months for stage 1, at maturity for stage 2.3).

PD: Default Probability (PD at 12 months for stage 1, the PD lifetime for stage 2.3 lifetime exposure at Default

LGD: Lost given default

K: annual effective interest rate

Such an estimation model has some advantages which can be summarized as follows:

Each risk parameter (PD, LGD, EAD) is driven distinctly by distinct factors, providing a more dynamic and forward-looking view of the effect of economic conditions.

Default probability at maturity which incorporates forward-looking macroeconomic scenarios can be directly used in the assessment of significant increases in credit risk (Aptivaa, 2016b).

3.1. Credit losses

According to article B5.5.29, a loss of credit can be defined as:

“In the case of financial assets, a credit loss is the present value of the difference between the following two values:

a) The contractual cash flows that are due to the entity under the terms of the contract; and

b) The cash flows that the entity expects to receive”

3.2. Year expected credit losses

Section B5.5.43 of IFRS9 defines 12-month expected credit loss as “The next 12-month expected credit losses are a portion of lifetime expected credit losses, i.e. lifetime cash flow shortfalls that would occur in the event of a default within 12 months of the reporting date (or a shorter period if the expected life of the financial instrument is less than 12 months), weighted by default probability”.

3.3. Probability of default (PD)

According to the Global Public Policy Committee (GPPC, 2016), probability of default can be defined as "an estimate of the probability of default over a given time horizon" (Rhys and Spooner, 2016).

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Under IFRS9, to calculate the 'ECL we consider the following probabilities of default:

- Probability of default at 12 months: This is the probability of occurrence of default estimated over the next 12 months (or for a financial instrument whose maturity is less than 12 months), it is used in the assessment of ECL at 12 months “Bucket 1”
- Probability of default at maturity "PDs Lifetime": presents the estimated potential life time probability default during the life of the instrument, it is used to estimate ECL at maturity for assets placed in stratum 2 or stratum 3.

3.3.1. Probability of default at 1 year

To estimate PD, we use the results of its specific internal rating model as a starting point to reach PDs under IFRS9 after some adjustments are made. If not, the bank has to design a new model to estimate PD. The variables in this model must correlate with credit risk.

3.3.2. Probability of default "lifetime"

For the estimation of "lifetime" probability, the bank takes advantage of the results of its model to calculate PDs at 12 months and to extrapolate them over longer time horizons, as it has to design a specific model to calculate PDs at maturity.

It should be noted that default probability is considered the main component to estimate expected credit losses. Therefore, it must incorporate macroeconomic variables as well as variables including credit risk. Second, this probability must be adjusted and calibrated based on past, current, and future exposures. In addition, the base model must take into account the rate of migration between the different levels of “Buckets”. In this regard, taking into account forward-looking information as well as the analysis of different economic scenarios is extremely fundamental for a better design compatible with the requirements of IFRS9.

3.4. “Exposure at default” EAD

The concept of exposure at default (EAD) is the amount that reflects the amount owed by the borrower in the event of the occurrence of a default. In other words, it is the part of the receivable that is exposed to default risk taking into account interest, principal, and contractual amortization. Although EAD is considered a key element in the estimation of ECL, IFRS9 does not explicitly require banks to implement ECL assessment models. However, it calls on banks to properly assimilate the effect of variation in amounts at risk, i.e. outstanding amounts, over time so as not to fall into the trap of estimating a biased ECL. This is explained by the failure to take into account a decrease or an increase in exposure, which is likely to generate an overestimation or an underestimation of the ECL respectively.

3.5. “Lost Given default” LGD

A third fundamental component of the expected credit loss model is that of loss-given default. It can be defined as “LGD= 1 –RR” with RR as the estimated recovery rate. More formally, LGD presents the assessment of the part of the debt lost after taking into account

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the guarantees recovered. In addition, LGD assessment must incorporate all future information. Therefore, modeling of this component is often independent of the different “Bucket” levels at which the financial asset is placed.

3.6. The effective interest rate (EIR)

ECLs are valued in a way that reflects the time value of money. This results in the incorporation of the effective interest rate in the calculation of the ECL. In other words, default-related cash shortfalls are discounted to the balance sheet date. For a financial asset, the bank uses the effective interest rate (EIR) (the same rate used to recognize financial income). The impact of discounting is significant as failure events and/or allied shortfalls may occur in the far future.

3.7. The expected life or maturity of the asset

Credit life or maturity presents the time allocated to the debtor to repay their debts; it is the maturity of the financial asset.

3.8. Mato forecasts or “Forward-looking”

IFRS 9 requires that default probabilities, more explicitly Forward-looking losses, must incorporate all forward-looking data reflecting information on future economic conditions or also called “ForwardLookingdata” information.

Thus, taking into account a set of possible prospective macroeconomic scenarios in the estimation of default probabilities is essential to finally guarantee an unbiased ECL. This translates more particularly into a non-linear relationship between all of these possible scenarios and the expected credit losses associated with them.

To be consistent with the directives of the standard in terms of integration of information, the bank must choose terms of measuring ECL, either by:

A weighted average of all credit losses chosen from the scenarios established.

The adjustment of default probabilities is estimated under the main scenario to take into account the non-linearity that may persist across the different possible scenarios.

To apply these two approaches, it is necessary to identify:

- The number of macroeconomic scenarios, representing the consideration of a set of scenarios (in particular, a main scenario, an unfavorable scenario). These scenarios can be identified according to facts and circumstances.
- Homogeneity of the parameters: when defining a given scenario, any correlation between the economic variables (GDP, inflation rate, unemployment, etc.) must be taken into account.

It is important to mention that the added value of the “Forward-looking data” estimation lies in identifying the most probable or frequent macroeconomic scenario based on "reasonable and justifiable information" and not on forecasting, worst-case or best-case scenarios (Oeyen and Oliver, 2019).

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4. EMPIRICAL FRAMEWORK

We recall that the IFRS9 standard requires the consideration of all forward-looking information on macroeconomic variables in the calculation of default probabilities "PDsLifetime" and "PD at 12 months". This set of information represents the Forward-looking Data".

In this section, we will try to propose a method to highlight the incorporation of the Forward-looking" variable, based on economic scenarios, in the calculation of default probabilities.

4.1 Estimation of the forward-looking" variable: The economic adjustment coefficient

The method used is based on Vaněk and Hampel (2017). The method is easy to apply because of its flexibility and simplicity. It amounts to estimating a variable called the economic adjustment coefficient to highlight the effect of projections of macroeconomic scenarios on default probability.

4.2. Model Presentation

The estimate of this economic adjustment coefficient (EAC) is based on a linear regression of the non-performing loan (NPL) ratio on the different macroeconomic variables. We take as variables the unemployment rate and Gross Domestic Product growth. This gives the following regression model:

$$\boldsymbol{\Delta NPL = \beta 0 + \beta 1 \Delta Unemployment + \beta 2 \Delta GDP + \varepsilon}$$

With:

NPL: the non-performing loan ratio is defined as the ratio between non-performing loans and total receivables.

Δ Unemployment: variation in the unemployment rate

Δ GDP: variation in GDP

4.3. Sample and descriptive statistics of the variables

The estimation is conducted on an American sample. The used data are:

- Variation in the unemployment rate in percentage in the United States, with a quarterly frequency.
- The NPL ratio is presented by non-performing loans (more than 90 days past due plus non-incriminated) against the total loans of all US banks: we have taken a percentage change as well as a variation of the value, and the frequency is quarterly at the end of the period.
- Variation in the American GDP in percentage with a quarterly frequency.

All data is taken from the Federal Reserve Economic Data (DFRED) Economic research. We use a sample of 124 observations, i.e. a total period from 01-01-1989 to 01-01-2020.

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Table 2: Descriptive statistics

Variables	N	Mean	Standard Deviation
USNPTL_CHG	124	-,0175	,19410
UNRATE (Variation of the unemployment rate in %)	124	-,014	,2757
GDP (Variation of GDP in %)	124	1,132	,6262

During the study period, we notice that the dependent variable presents an average decrease of 1.75% with a standard deviation of 19.41%.

Thus, the unemployment rate and GDP show respective averages of -1.4% and 1.132 and standard deviations of 27.57% and 62.62%.

Figures 3 and 4 below show the variation in GDP, the unemployment rate, and NPL from 01/01/1989 to 01/01/2019.

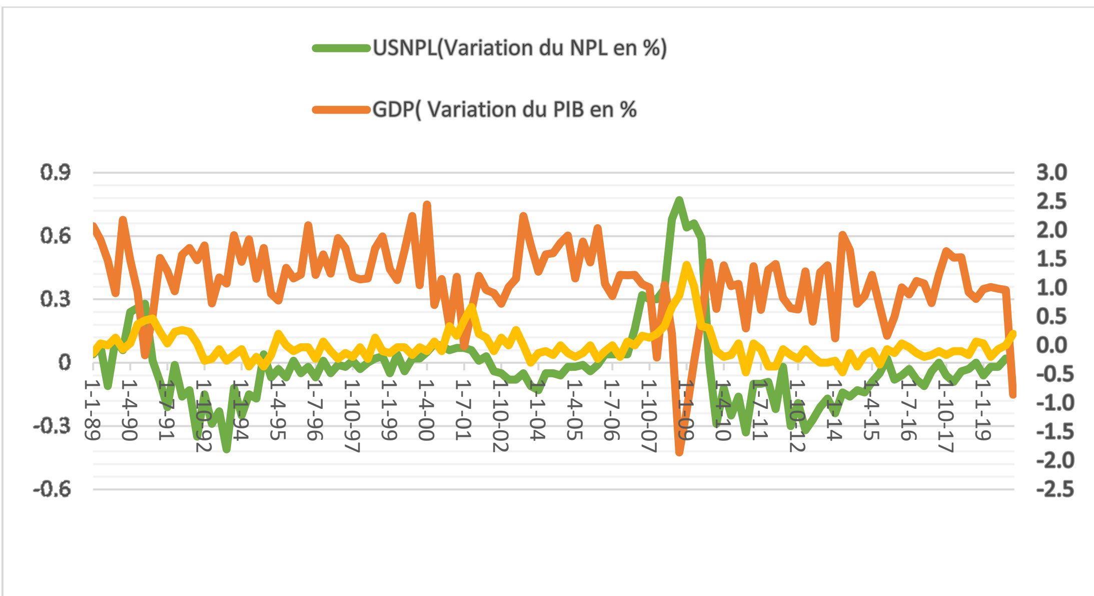

Figure 3 : Variation of GDP rate, Unemployment rate, and NPL in percentage

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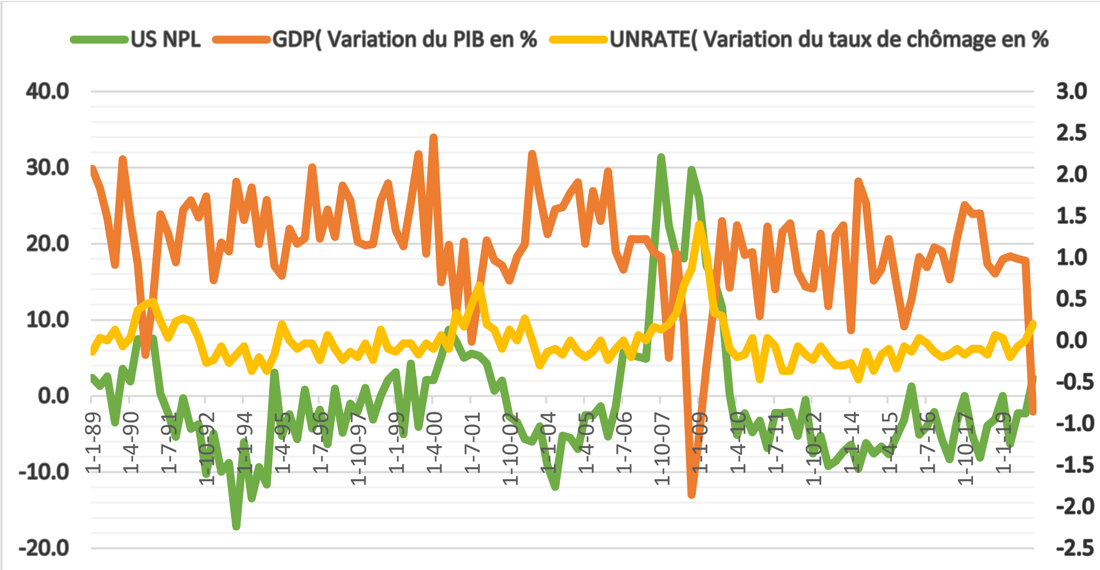

Figure 4 : Variation of the value of non-performing loans associated with a percentage variation of GDP and unemployment rate

These figures show the serious repercussions of the 2008 economic crisis. According to the curves representative of the variables, the extreme values are recorded in the second quarter of 2009.

4.4. Regression and Results

Given the time nature of our series, and before proceeding with the estimation of the model, we must carry out a test of heteroscedasticity as well as a test of stationarity to decide on the most accurate estimation method. The results of these tests from the EViews 10 software are as follows:

- **Stationarity test**

We applied the Augmented Dickey-Fuller Test (ADF 1981) to estimate the stationarity of the series.

The assumptions of the ADF Test are as follows:

H0: the series has a unit root (the series is not stationary)

H1: the series does not have a unit root. Stationarity verified

The decision rule:

If Prob < α= 5%, then we reject H0 and retain H1

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Table 3: Stationarity Test

Null Hypothesis: US_NPL has a unit root				
Exogenous: Constant				
Leg Length: 4 (Automatic - based on SIC, maxlag=12)				
			t-Statistic	**Prob.***
Augmented Dickey-Fuller test statistic			-3.190387	0.0230
Test critical values:	1% level		-3.485586	
	5% level		-2.885654	
	10% level		-2.579708	
*MacKinnon (1996) one-sided p-values.				

The Prob from the table is 0.0230 which is lower than the P-value at the 5% threshold. We reject the null hypothesis of non-stationarity and we consider that H1 is verified. Therefore, the studied series is indeed stationary.

- **Heteroscedasticity test**

In a linear regression, the assumption that the model's errors are heteroscedastic leads to non-significant coefficients as estimated by the OLS method.

The test hypotheses are as follows:

H0: The variances of the errors are homoscedastic

H1: The variances of the errors are heteroscedastic

The decision rule:

If the Prob> P-value=5%, then we accept H1, the residuals are homoscedastic, we can opt to use the OLS method for the regression.

Table 4: Heteroscedasticity test

Heteroskedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	1.326836	Prob. F(2,122)	0.2691
Obs*R-squared	2.661044	Prob. Chi-Square(2)	0.2643
Scaled explained SS	9.030501	Prob. Chi-Square(2)	0.0109

We notice that the probability is higher than the threshold of 5%, and the hypothesis of homoscedasticity is verified. We will opt for an estimation with the ordinary least squares method.

After checking stationarity and homoscedasticity of residuals. We used SPSS 25 software to run the linear regression. The results are presented in the following tables:

Table 5 : Quality of regression model

Model	**R**	**R-square**	**Adjusted R-square**	**Standard error of the estimate**
1	,724[a]	,524	,516	,13508

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R-square represents the linear determination coefficient, it gives an idea about model fit quality. We obtained an R-square of 0.524, a coefficient far from 0, which indicates a good prediction quality of the model. Below, we present the results of the regression model.

Table 6 : Results of the regression model

Coefficients						
Model		**Non-standardized-Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
		B	**Standard Error**	**Bêta**		
1	(Constant)	,010	,029		,345	,731
	GDP (Variation of GDP in %	-,018	,023	-,059	-1,982	,0436
	UNRATE (Variation of the unemployment rate in %	,486	,053	,690	9,196	,001
a. Dependent Variable: USNPTL_CHG						

The results of the significance test revealed that both variables are significant for a p-value of 10% and a t-statistic of 1.96 (values of 0.0436 and 0.01 are less than 10%).

The results show that a variation in the unemployment rate of one unit (1%) implies a percentage variation of the NPL of 0.69%, the two variables positively correlate. A variation of GDP of 1% leads to a variation of the NPL of -0.59%, the two variables negatively correlate.

4.5. Integration of macroeconomic scenario projections

After showing the presence of a relationship between non-performing loans and all macroeconomic variables, we can conclude that the introduction of an economic adjustment coefficient can detect the effect of variations in future economic conditions. This can be highlighted from the application of some future scenarios of macroeconomic variables (variation in GDP and the unemployment rate).

- A central scenario tracing stability in economic conditions
- An adverse scenario retracing a deterioration in economic conditions

The data of the different scenarios are taken from the "Trading economics (TD)" for a total period of 6 quarters. They are presented in the following table:

Table 7 : Macro-economic forecasts under different conditions

Scenarios	**Unfavorable Scenario Opposing)**		**Central Scénario (Base)**	
Projections	**ΔGDP**	**ΔUnemployment**	**ΔGDP**	**ΔUnemployment**
T2 2021	-1.2	0.2	2.1	-0.2
T3 2021	-0.8	0	2.2	-0.1
T4 2021	0.2	0.1	2.0	-0.2
T1 2022	0.1	-0.1	1.8	0.1
T2 2022	0.5	0	2.1	-0.3
T3 2022	1	0.1	2.0	-0.1

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Then, the results of the estimation allow us to write the following regression equation:

Economic adjustment factor $(CAEt) = 0.29 - 0.59\Delta GDPt + 0.69\Delta Unemploymentt$

Estimating the CAE of each quarter requires the combined use of the regression equation and the macroeconomic forecasts above.

Table 8 : Assessment of the Economic Adjustment Coefficient under macroeconomic conditions

Projections	Unfavorable Scénario (opposing)	Central Scénario (Base)
T2 2021	1.136	-1.08
T3 2021	0.736	-1.077
T4 2021	0.241	-1.02
T1 2022	0.162	-0.7
T2 2022	-0.005	-1.1
T3 2022	-0.231	-0.95

4.6. Incorporation of macroeconomic adjustment in the calculation of default probabilities

As mentioned at the beginning of this section, the aim of this method is to assess default probabilities at different horizons while integrating adjustments to reflect the Forward-looking" variable.

Then, the last step is to incorporate the effects of the economic adjustment coefficient into the calculation of default probabilities. This is done using the Markovian model and the adjustment of transition matrices.

Consider the transition matrix Q with:

$$\mathbf{Q} = \begin{bmatrix} \boldsymbol{P1,1} & \boldsymbol{P1,2} \ldots & \boldsymbol{P1,r} \\ \vdots & \vdots & \vdots \\ \boldsymbol{Pr-1,1} & \boldsymbol{Pr-1,2} & \boldsymbol{Pr-1,r} \\ \mathbf{0} & \mathbf{0} & \mathbf{1} \end{bmatrix}$$

With :

- r: is the number of grades of the rating within the matrix P
- Pi and j are default probabilities
- 0<Pi,j<1 with i,j € [1…r] and ∑Pi,j= 1

If we calculate default probability at a horizon n, the formula is as follows:

$$\mathbf{S_{t+n}=S_t \times (P_{t+1})^n \; (1)}$$

With:

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- n: the estimation horizon (example: default probability at 4 years n = 4)
- St: represents a state vector such that (1 × r) state vector St. If, for example, there are four rating grades (r=4) and the process is initiated in the second step, this can be written as St = (0 1 0 0).

However, this estimation of default probability at n years does not take into account the Forward-looking" vision.

Once the incorporation of the macroeconomic forecasting factor is taken into account, equation (1) will be rewritten as follows:

$$\mathbf{S_{t+n}=S_t \times (P_{t+1}) \times (P_{t+2}) \times (P_{t+3}) \ldots . \times (P_{t+n})\ (2)}$$

Then, an adjustment of default probabilities results in the following relationship:

$$\mathbf{P_{i,\,j}{}' = \frac{CAEt \times (2(i-1))}{2 \times (r-1)(r-1)} + Pi, j\,\text{avec} \in [1 \ldots r\text{-}1]}$$

With Pi, j: default probability at a specific stage

According to the results of the assessment of the economic adjustment coefficient, we notice that most coefficients estimated for an unfavorable scenario have a positive sign, which leads to an increase in default probability. Similarly, under a favorable scenario, most of the estimated coefficients are negative, then we expect a drop in default probabilities.

5. CONCLUSION

In this paper, we highlighted the importance of adopting IFRS 9 standards within banks. Indeed, it is not a question of a simple implementation phase but on the contrary, a whole complex project which needs good planning of the environment and the banking mechanisms. A credit institution must first properly plan, organize, manage and control the different implementation phases. To highlight the novelties introduced by IFRS9, we have emphasized the forward-looking nature of the IFRS9 standards when incorporating the different macroeconomic scenarios in the estimation of default probabilities and we have highlighted the impact of these projections on the foreseeable variation of customer defaults. Like Vaněk and Hampel (2017), we apply the technique of assessing default probabilities while integrating the Forward-looking" vision. This technique requires first the estimation of an adjustment coefficient able to capture the effect of future economic conditions and second carrying out a study of possible future scenarios and finally incorporating them into the calculation of default probabilities. This technique is advantageous in terms of ease of application and adaptation to the requirements of IFRS9. We conclude that the bank must obtain all the verifiable and prospective justifiable data for the construction of the ECL model. Then, the bank is called upon to establish the various economic projections based on the study of the scenarios of the macroeconomic variables (GDP, unemployment ...) and to incorporate them into the estimation of the model. Our results show that an adverse scenario reflecting a future deterioration of economic conditions will surely lead to an increase in current customer default. While a favorable scenario will lead to a lower default probability. This has been proven by

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integrating the economic adjustment coefficient (EAC) into the calculation of default probabilities.

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