



LISBON  
SCHOOL OF  
ECONOMICS &  
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**MASTER IN**  
**MATHEMATICAL FINANCE**  
**MASTER'S FINAL WORK**  
**INTERNSHIP REPORT**

**Loss Given Default: A Backtesting  
exercise**

Maria Leonor Lopes

October, 2018



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*Supervisors:*

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February 6, 2019

## **Abstract**

After January 2018, the new accounting standard IFRS 9 *Financial Instruments* was mandatory practice for all Financial Institutions. Introducing the new impairment model, which focus on expected credit losses (ECL) instead of incurred losses established previous in IAS 39 *Measurement and Recognition*. According to the new standard, the risk parameters involved in the computation of the ECL are required to be periodically revised. The Loss Given Default (LGD) is a risk input which represents the loss in case of a financial instrument defaults. Hence, the aim of the present report is to validate the risk input through a back testing exercise, considering statistical tests.

**Keywords:** Impairment Model, IFRS 9, IAS 39, Expected Credit Loss, Loss Given Default, Backtesting.

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## List of Abbreviations

A-IRB - advanced internal-ratings-based

BCM – Banking and Capital Markets

BM – Behaviour Maturity

CCF – Credit Conversion Factor

EAD –Exposure at Default

EBA – European Authority Banking

ECL – Expected Credit Loss

EIR – Effective interest rate

FSO – Financial Services Organizations

FVOCI – Fair Value through Other Comprehensive Income

FVPL – Fair Value through Profit or loss

IAS – International Accounting Standards

IASB - International Accounting Standards Board

IFRS – International Financial Reporting Standards

LGD – Loss Given Default

PD – Probability of Default

RR – Recovery Rate

## Introduction

The present work is the result of a 6-month curricular internship at EY – Ernst & Young, S.A., in the service line FSO – Advisory, with the purpose of concluding the master program in Mathematical Finance, at ISEG – Lisbon School of Economics and Management. Being a member of the *Banking and Capital Markets* team (BCM), I worked on credit risk, specifically, assessing and validating through the backtesting exercise, the Loss Given Default (LGD) risk parameter, incorporated in the *forward-looking* expected credit loss (ECL) model, described in the new *International Reporting Standards on Financial Instruments* IFRS 9.

After the 2007's global financial crisis, the delayed recognition of credit losses, computed at the time by the incurred loss model established in IAS 39 *Financial Instruments – Recognition and Measurement* was identified as a weakness in the accounting standards. Therefore, the International Accounting Standards Board (IASB) issued a new standard for financial reporting, the IFRS 9 *Financial Instruments*, which replaced the previous one. Aiming to mitigate the misrepresentation of the credit risk profile considered in credit provision calculation, include a lifetime risk analysis since origination and capture a *forward-looking* perspective in ECL, the accounting standard is organized in three components: (i) the classification and measurement of financial assets and financial liabilities, (ii) impairment, (iii) hedge accounting.

Focusing on the novelty of the impairment component, the Expected Credit (ECL) model assess the deterioration in the credit quality of financial instrument since its initial recognition. Hence, entities are obliged to identify the amount of ECL as a loss allowance. Depending on significant increase of credit risk assessment that results in to three possible staging classifications (bellow described in Figure 5- General Approach), two measurement perspectives should be considered in computing risk parameters: the 12-month ECLs and the Lifetime ECLs. Furthermore, the ECLs computation involves the following risk parameters:

- Credit Conversion Factor (CCF);
- Probability of Default (PD);
- Loss Given Default (LGD);
- Behavior Maturity (BM);
- Exposure at Default (EAD);

Additionally, these risk parameters need to include a *forward-looking* analysis that takes in to account the correlation between macroeconomic variables and the underlying impact on credit risk profile for each specific credit portfolio.

On the Financial Institution in study, I was presented with the opportunity to validate the risk parameter LGD and assess the goodness-of-fit of the model adopted for the purposes of collective analyses of impairment. Hence, the focus of my report will be the former risk input and test the performance of the model used through statistical tests. In order to contextualize the previous ideas, the present report will be structured as follows. In Chapter 2, the new standard IFRS 9 *Financial Instruments* will be presented and its impacts and the new impairment model requirements will be discussed. In Chapter 3, the model used by the financial institution in study will be described. The LGD model, with focus on backtesting methods and other methodological aspects, is explained in Chapter 4. Chapter 5 contains the model validation results and an overview of alternative approaches and the main conclusions and further research are presented in Chapter 6.

## IFRS 9 Financial Instruments

### 2.1 Reasons and effects

The incurred loss model under IAS 39 was based on a backward-looking approach, only recognizing credit events upon occurrence. Taking into account its complexity and the diverse approaches adopted by entities to compute impairment, IFRS 9 *Financial Instruments* was developed, proposing the ECL model for all financial assets considered previously.

Considering the standard IAS 39 where for different financial instruments were applied distinctive impairment models, under IFRS 9 *Financial Instruments* a single impairment model is applied to all debt instruments measured at amortized cost and at fair value through other comprehensive income, the loan commitments and financial guarantee contracts in the IFRS 9 *Financial Instruments* impairment requirements' scope, see [11] (EY, formerly Ernst&Young 2018).

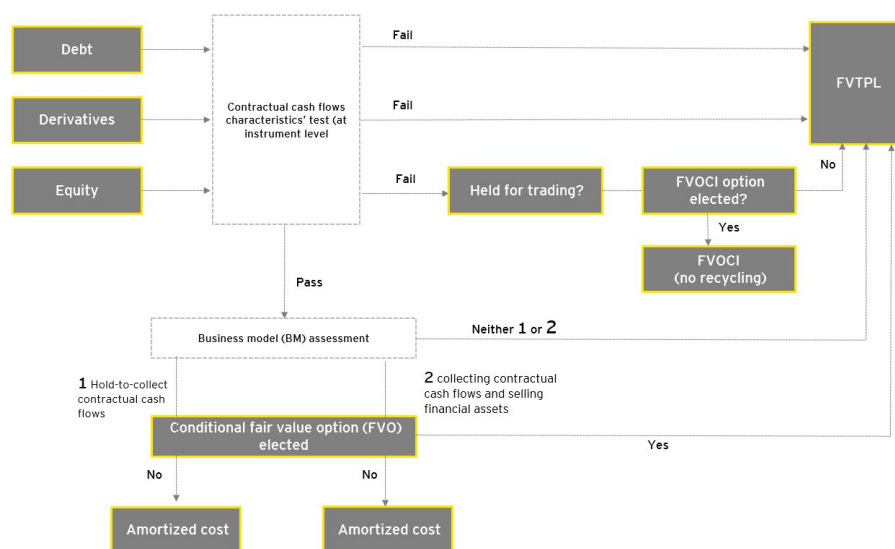
Additionally, with the new standard, the impairment requirements allow to anticipate the credit losses, resorting to 12-month and lifetime ECL allowance for all credit exposures, besides fair value through profit or loss.

Nevertheless, the key difference is the forward-looking component, where forecasts of future macroeconomic factors, their probability of occurrence and multiple scenarios are incorporated in the ECLs computation.

The effects of the new established standard are: the increase of credit loss allowances of financial institutions; the higher volatility in ECL amounts, given the focus on forecasting expected credit losses; the itexpert judgment requirement, determining significant deterioration or improvement in credit risk and computing the forward-looking factor. Although this last element may hinder the comparison between financial institutions, however, given the methodological documentation support, the transparency of the process will be more evident.

## 2.2 Classification and Measurement of Financial Instruments

Under the new standard, classification and measurement of financial instruments after initial recognition will vary accordingly to their contractual cash-flow characteristics and the business model associated. Not only the financial assets are assessed at fair value through other comprehensive income (FVOCI) or fair value through profit or loss (FVTPL) but at amortized cost as well, summarized in the following scheme.



*Figure 1: Classification of financial assets, see [11](EY, formerly Ernst&Young, 2018)*

Considering the new accounting standard, “An entity shall recognize a loss allowance for expected credit losses on a financial asset that is measured in accordance with paragraphs 4.1.2 or 4.1.2A, a lease receivable, a contract asset or a loan commitment and a financial guarantee contract (. . .)” [13](IFRS 9 *Financial Instruments* (2014), §5.5.1). Hence, the financial securities mentioned previously which fall into the impairment requirements are the ones categorized as amortized cost and fair value through other comprehensive income.

The new impairment model envisions the recognition of the financial instruments’ credit quality, by evaluating its deterioration or improvement. Depending on credit deterioration since initial recognition, entities can assume three different approaches

when computing the amount of ECLs recognized as a loss allowance or provisions: (i) General Approach; (ii) Simplified Approach; (iii) the purchased or originated credit-impaired Approach.

A financial instrument is considered credit-impaired when, for instance: there is a breach of contract, i.e., a default or a past due event, or financial difficulties are acknowledged; or an active market for a financial asset disappears; or even the recognition that the borrower will enter in bankruptcy or other financial reorganization. Nevertheless, if there is an improvement in the credit quality, then the entity can recalculate the interest revenue by computing the effective interest rate (EIR) based on the initial lifetime ECLs in the estimated cash-flows, see [11] (EY, formerly Ernst&Young 2018).

Under the general approach, see Appendix A for regulatory support, to credit exposures where an increase in credit risk since initial recognition is not identified, an entity applies the 12-month ECLs. Otherwise, to credit exposures where a deterioration in the credit risk is recognized, the lifetime ECL is applied. The following figure summarizes the process.

	Stage 1	Stage 2	Stage 3
Loss allowance updated at each reporting date	12-month expected credit losses	Lifetime expected credit losses	
Lifetime expected credit losses criterion	-	Significant increase since initial recognition + Credit - Impaired	
Interest revenue calculated basen on	Effective interest rate on gross carrying amount	Effective interest rate on gross carrying amount	Effective interest rate on gross carrying amount less loss allowance

*Figure 2: General Approach, see [11](EY, formerly Ernst&Young, 2018)*

As seen in Figure 2 above, there exist three distinct stages which reflect the exposure of an instrument to credit loss. Depending on their credit quality since initial recognition, exposures which entered in default are classified as being in stage 3; exposures where

a significantly deterioration in credit quality is observable are classified in stage 2.

Exposures which don't fall in the previous categories are in stage 1.

Entities are required to compute the loss allowance based on lifetime ECLs at each reporting date under the simplified approach, see Appendix A for regulatory support.

The former approach is applicable to contract assets or trade receivables with irrelevant financial component, which are covered by the IFRS 15 *Revenue from Contracts with Customers*.

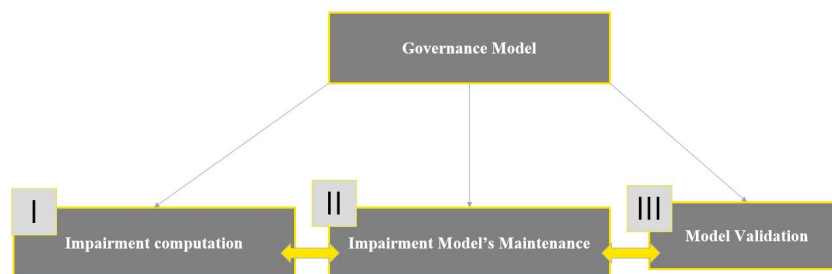
## Impairment Model Definition

The present chapter introduces the parametric model adopted by the financial entity at study, introducing the concepts of governance, portfolio's segmentation and risk parameters involved in the computation of ECLs provisions.

### 3.1 Governance Model

The aftermath of the global financial crisis, highlighted the need to align risk management and corporate finance. By ensuring a structured governance model, stipulating the member's responsibilities and periodical review of the framework as well, the two concepts started to be bridged.

The Governance Model adopted by the chosen financial entity is composed of three macro processes, which ensure the continuity of the model's life cycle. An established framework with well-defined responsibilities combined with model development and validation assures: (i) a better understanding of concepts, strengthen the quantitative analyses performed by experts; (ii) identifying possible risks which threaten the stability of the financial system. The following scheme represents the relationship behind the three macro processes considered in the impairment model life cycle.



*Figure 3: Governance Model, see [16](Scandizzo, 2016)*

The macro process I - *impairment computation*

This process has three phases: parameters estimation, collective impairment analyses and consolidation. The first phase establishes the definition of requirements, methodology and assumption that will be considered in the model development, and correspondent validation, and control processes. The collective impairment analyses' phase draws on the previous by categorizing the parameters estimation in risk classes or stages, applying next the macroeconomic scenarios' probability and their respective forecasts, and at last computing the ECL's amount. Then, in the consolidation phase, the report for the analyses is presented, approved and the credit risk is monitored and mitigated.

The macro process II – *Impairment Model Maintenance*

This process englobes identified improvement opportunities or the resolution of insufficiencies, given by the local validation administration and the independent and external Audit team, then it follows the conceptual changes associated with model enhancement to reach better performance in risk estimation.

The final macro process – *Impairment Model Validation*

The third process insures the impairment model reliability and its continuous process of adjustment to changes in social-political and economic variables with impact on credit risk estimation.

For each macro process, the Institution stipulates which department of the financial institution is responsible for the activity in question, reviewing it periodically.

## **3.2 Portfolio's Segmentation**

Paragraph B5.5.4 of IFRS9 states that, "In some circumstances an entity does not have reasonable and supportable information that is available without undue cost or effort to measure lifetime expected credit losses on an individual instrument basis. In that case, lifetime expected credit losses shall be recognised on a collective basis that con-

siders comprehensive credit risk information” [13](IFRS 9 *Financial Instruments* (2014), §B5.5.4).

In our case study, paragraph B5.5.4 of IFRS 9 *Financial Instruments* had to be applied, and because of this the present report will focus on the collective assessment of impairment. Consequently, the portfolio will be disaggregated according to homogeneous risk levels with similar credit risk characteristics. Hence, the estimates of the risk parameters incorporated in the ECL’s computation tend to vary accordingly to the segmentation criteria for the portfolio.

The financial institution in study segregates its portfolio in two macro segments, which will be denoted Segment 1 and Segment 2, respectively. Then, the following features must be taken into consideration: the type of product, the client’s characteristics, his/her collateral coverage level and seniority, the contract date, the remaining time to maturity, and the payment behaviour is evaluated as well.

### **3.3 Risk Parameters**

The risk parameters considered in the impairment model take in to account the occurrence of an asset’s default, which results from the application of qualitative and quantitative triggers, being the most relevant the 90 days past due.

In order to calculate the ECL amount associated, it is necessary to take into consideration the following risk parameters.

Risk Parameter	Description
Probability of Default (PD)	<ul style="list-style-type: none"> <li>Measures the risk associated to a counterparty's default, which for simplification purposes corresponds to 90 days overdue;</li> <li>It varies according to the operation's stage, being PD<sub>12-month</sub> for stage 1 and PD<sub>lifetime</sub> for stage 2;</li> </ul>
Loss Given Default (LGD)	<ul style="list-style-type: none"> <li>Represents an operation's percentage of loss estimation after entering in default;</li> </ul>
Exposure at Default (EAD)	<ul style="list-style-type: none"> <li>Represents the exposure's amount upon each operation;</li> <li>Its computation incorporates the on and off balance exposure, taking into account as well the Credit Conversion Factor (CCF) parameter; Depending on the security's stage, the EAD assumes a 12 months or lifetime perspective;</li> </ul>
Credit Conversion Factor (CCF)	<ul style="list-style-type: none"> <li>Measures the percentage of the off balance exposure which can be converted to on balance exposure until the entry in default;</li> </ul>
Behaviour Maturity (BM)	<ul style="list-style-type: none"> <li>Measures the time period during which the entity is exposed to credit risk according to the frequency of the operation's payment.</li> </ul>

Figure 4: Summary of the Risk parameters

Even though each risk parameter presented in Figure 4 has its own computation formula, the present report focus on the ECL estimation as well as the LGD's and the impact of the latter in the loss provisions. Thus, taking into account the credit stage classification of each facility or debtor, the ECL will be calculated according to the next equations, such that for stage 1 we have

$$ECL = EAD \times PD_{12-month} \times LGD_0 \tag{1}$$

Equation 1: ECL equation for stage 1

As for stage 2,

$$ECL = \sum_{k=t}^m \frac{EAD_k \times LGD_0 \times SR_{k-1} \times PD_k}{(1+r)^k} \quad (2)$$

*Equation 2: ECL equation for stage 2*

The survival rate (SR) presented above is inversely proportional with the probability of default (PD). Let  $k$  be the random variable representing the time until the occurrence of default,  $f(k) \geq 0$ , probability density function and  $F(k)$  its the cumulative distribution function which is complementary to the survival function,  $S(k) = 1 - F(k)$ . SR is related to the hazard function, also known as the instantaneous risk, which translates the probability of defaulting at a given rate, in a time horizon, see [7](Witzany, Rychonovsky, Charamza, 2012).

The probability of default (PD) is a risk measure, representing the expectation of a counterparty entering in default within the next 12 months or the lifetime of the financial instrument. Therefore, there exists two possible approaches depending on the operation's stage, see [3] (Beygi, Makarov, Zhao, Dwyer, 2018):

(i) For stage 1, the  $PD_{12-month}$  follows the equation

$$ODR_t = 1 - \prod_{i=t}^{(t-1+12)} (1 - ODR_i) \quad (3)$$

*Equation 3: ODR 12-months equation*

where  $ODR_i$  represents the marginal observed default rate in time  $i$  and  $ODR_t$  the cumulative observed default rate of the operation being at  $t$  months in this risk position.

(ii) For stage 2, the  $PD_{lifetime}$  follows the equation

$$ODR_t = \frac{Defaults_t}{number\ of\ non - defaulting\ operations_t} \quad (4)$$

*Equation 4: ODR lifetime equation*

Where  $t$  represents the time at the risk position.

Financial entities tend to align the criteria of credit impaired instruments for transfer to stage 3 with the definition of default. According to the Appendix A of IFRS 9 *Financial Instruments*, "A financial asset is credit-impaired when one or more events that have a detrimental impact on the estimated future cash flows of that financial asset have occurred: (...) b) a breach of contract, such as a default or past due event; (...) d) it is becoming probable that the borrower will enter bankruptcy or other financial reorganisation; (...)", in case of occurrence of the previous events, the financial institution classifies such impaired instruments as defaulted, i.e., in stage 3, given they satisfy the requirements to be in default as well. Hence, for stage 3 it follows,

$$ECL = EAD \times LGD_t \quad (5)$$

*Equation 5: ECL equation for stage 3*

Furthermore, the new accounting standard IFRS 9 presents the notion of lifetime which refers to the period between the origination date and the maturity date of a contract, as well as the three bucket approach (i.e. classification by stages), taking into account the credit quality deterioration or improvement, making an direct impact on the risk inputs computation, for instance, the distinctive approaches applied to the PDs estimates, depending on the stage of the counterparty as presented above.

Additionally, the forward-looking component is assimilated through three possible scenarios: (i) baseline; (ii) adverse; (iii) optimistic, such that for each outcome, the risk parameters are adjusted according to their correlation with the macro-economic variables. For instance, macro-economic variables such as GDP value, interest rates,

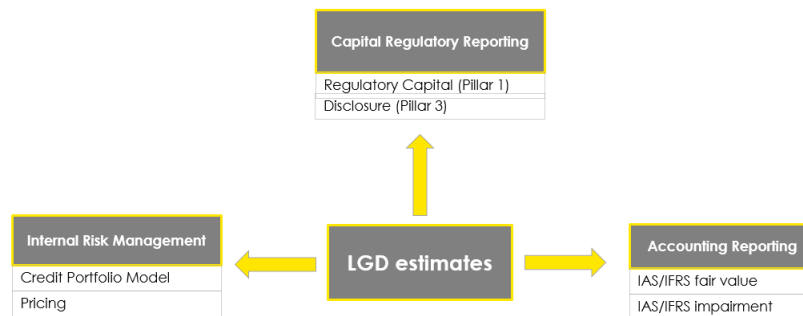
unemployment rate, Loan-to-Value (LTV) ratio are considered, projecting afterwards their shocks on the ECL's estimation.

Given the purpose of our case study, the next section presents the risk parameter LGD, under different frameworks and computational approaches.

## LGD Model

### 4.1 Loss Given Default

Depending on the context to apply LGD, a financial institution may perform the estimation of its own risk parameters and apply the estimations to distinct frameworks (e.g. capital regulatory reporting (under Basel Accord), account reporting (IAS/IFRS), Internal Risk Management (ICAAP – Internal Capital Adequacy Assessment Process)). The following figure represents a few of those applications.



*Figure 5: LGD Estimates and its applications, see [10](Engelmann, Rauhmeier, 2011)*

The present report focus on the estimation of the LGD for accounting purposes, considering numerous modelling approaches in order to estimate the former risk parameter. For instance, recovery strategies and probabilities of execution are an alternative as well as to adapting existing parametric or non-parametric statistical models under other estimation framework besides the accounting. Hence, there are some similarities between the Basel Accord II capital requirements and IFRS 9's impairment requirements, even though each application impose different requirements and estimation procedures. By adjusting the already existing Basel models to IFRS 9, financial institutions adopt good established models, smoothing the implementation process.

Introducing the Basel Accord II which stands on three pillars: (i) First Pillar, Minimum Capital Requirement; (ii) Second Pillar; Supervisory Review Process; (iii) Third Pillar,

Market Discipline. Focusing on (i), financial institutions must ensure the minimal capital requirements by having their capital ratios above the 8% threshold. The former ratio is given by the total capital, which represents the amount of capital available and its risk weighted assets (RWA), which in turn is composed of the credit risk exposure, market risk exposure and operational risk exposure, see [1](BIS, Bank for International Settlements, 2003).

Regarding the RWA's computation, the credit risk exposure is measured following two distinct approaches: (i) standardized, (ii) Internal Ratings Based (IRB). The former relies on external ratings provided by agencies like Moody's, S&P, etc. The latter evaluates the creditworthiness of the borrower using internal estimates to measure the risk in the portfolios. The assessment is yet divided: (i) foundation IRB approach, (ii) Advanced IRB approach, with both requiring risk inputs such as PD or LGD.

The process to adapt advanced internal-ratings (A-IRB) models to IFRS 9's must take into account several requirements, such as the incorporation of the future macroeconomic scenarios and their probability of occurrence through the risk inputs such as the PD and LGD, see [15](Miu, Ozdemir, 2011), are required in the IFRS 9 framework.

Paragraph B5.5.55 of IFRS9 states that, "For the purposes of measuring expected credit losses, the estimate of expected cash shortfalls shall reflect the cash flows expected from collateral and other credit enhancements (. . .)" [13](IFRS 9 *Financial Instruments* (2014), §B5.5.55). In our case, the LGD is a cyclical point-in-time (PIT) estimate such that incorporates the current state of the economy, measuring then the "accounting loss" expected.

Under the Basel II, the LGD is an a-cyclical through-the-cycle (TTC) estimation which assumes losses during a severe and plausible economic downturn, thus being considered an "economic loss", according to the Basel Committee on Banking Supervision (BCBS) "(. . .) When measuring economic loss, all relevant factors should be taken into account. This must include material discount effects and material direct and indirect

costs associated with collecting on the exposure. (...)” [2](BCBS (2004), §460). Following the previous line of thought, LGD estimation becomes the ratio between economic loss and exposure at default, see [10](Engelmann, Rauhmeier, 2011), i.e.,

$$LGD_j(t_{DF}) = \frac{EAD_j(t_{DF}) - NPV(Rec_j(t), t \geq t_{DF}) + NPV(Costs_j(t), t \geq t_{DF})}{EAD_j(t_{DF})} \quad (6)$$

*Equation 6: LGD computation under the capital framework*

From the equation above,  $LGD_j(t_{DF})$  is the loss given default of the security  $j$ ,  $EAD_j(t_{DF})$  refers to the security’s exposure at default, the NPV represents the net present value associated with all recoveries  $Rec_j$  and costs  $Costs_j$ , observed at time  $t$ .

Considering capital requirements, the LGD estimation can be performed in different ways, on the basis of the chosen approach, which can be of an explicit or implicit nature. On one hand, explicit methods estimate LGDs directly from loss data, being categorized as Market LGD or Workout LGD. The former resorts to the comparison between defaulted bonds’ market prices and their par value. As oppose to the latter, where the process is based on the discounted post-default recoveries, taking into consideration workout expenses and costs associated, and then comparing the value of the resulting default deal with the EAD.

On the other hand, implicit methods infer from data which contains relevant information, being divided in implied market LGD and implied historical LGD. The former includes the credit spread on defaulted bonds. In contrast with the latter which uses the realized loss and internal long-run PD for its estimates.

When measuring the credit loss, the difference between contractual cash-flows and the cash-flows that a financial institution expects to receive, discounted at the original EIR, must be taken into account. Besides considering the future cash-flows of a defaulted entity, its collateral and guarantees are incorporated into the estimation of the LGD.

The risk parameter LGD is a percentage of the exposure outstanding at default, es-

establishing a complementary relationship with recovery rates (RR), for which the net cash-flows from the receivable generated by a workout process are observable, see [7](Witzany, Rychonovsky, Charamza, 2012). Then:

$$LGD = 1 - RR \Leftrightarrow LGD = 1 - \frac{1}{EAD} \sum_{i=1}^n \frac{CF_i}{(1+r)^{t_i}} \quad (7)$$

*Equation 7: LGD computation under the accounting framework*

The LGD represented above is bounded in the interval  $[0, 1]$ , since the workout recovery rate (RR) is supposed to represent the market RR. In the case of the LGD estimates taking negative values, it is due to low or no recoveries and collecting late fees, for instance. The EAD stands for the securities exposure at default and  $CF_i$  is its generated cash-flow. Also, the discount rate  $r$  applied affects directly the recoveries.

According to the European Banking Authority (EBA) Guidelines on PD and LGD estimation, the discounting rate considered in regulatory reporting is an interbank funding rate and a 5% add-on, in order to facilitate comparisons between LGD estimates. In contrast with the standard IFRS 9, where the use of the effective interest rate (EIR) is a requirement. Considering the accounting standard, the relevant time period covers all recoveries back to the reporting date, as oppose to the Basel models, which only assume the time interval between default and post recoveries. Besides, the cash flows are actualized in order to improve its analysis on the current date, taking into account monetary depreciation.

Another modeling approach is considering distinct default scenarios, which affect the loss measurement, and sequentially the recoveries and the discount rate as well: the pre-defaulted, at-defaulted and post-defaulted events.

Focusing on the post-defaulted events, it is considered the “cure” scenario, where the defaulted financial institution is cured after a time interval and fulfills its obligations; “restructuring” scenario, which after restructuring its counterparties, the defaulted

entity recovers by repossession or selling a collateral; “liquidation” scenario, which refers to the liquidation of all credit products.

The previous examples allow to categorize the distinct types of recovery that a financial institution recognizes. Accordingly, it may assume different strategies for computing the loss and probability associated with each scenario, see [10](Engelmann, Rauhmeier, 2011).

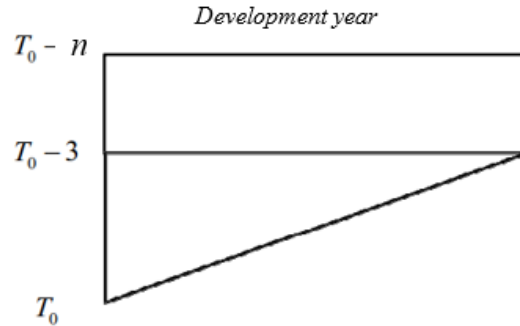
The methodology adopted by the financial entity in study is hybrid since the computation steps vary depending on the LGD type considered, namely, by segregate in LGD cash, LGD collateral and recovery costs, explained in the following section.

Beforehand the distinction between secured and unsecured exposures is needed, in order to understand the methodology adopted. Therefore, for secured exposures, a collateral is associated with the obligor’s contract in case of defaulting (i.e. LGD collateral), whereas in unsecured exposures only cash payments are considered (i.e. LGD cash). Either way, both are computed according to a workout strategy developed by the financial institution, given its impact on the recoveries and costs.

## **4.2 LGD Methodology**

### **4.2.1 LGD cash**

The LGD cash component is based on cash-flows of the cash-payments received, assuming distinct approaches for its computation, namely, by assessing the observed amounts of recoveries or by the amounts of debt between two consecutive time periods. Adopting the latter, the following step is to recognize the time when the operation defaulted and generate the respective cash-flow, throughout the workout period established.



*Figure 6: Chain Ladder representation*

By adopting the “chain-ladder” representation, the discounted recover rates are organized by seniority, being  $T_0$  the current time and then the development year, which represents how long after defaulting, the operation is liquidated or cured/restructured. Furthermore, the length of workout period is essential for incorporating time as factor on the LGD model estimation. The workout period length can be calculated using the cumulative recovery rate. By analyzing the former, it is possible to evaluate the recovery rates’ time distribution and determine when the expected recovery starts to be immaterial. Depending on the portfolio’s segmentation, distinct workout periods are considered, assuming time intervals until to 70 months. See [5] (Chalupka, Kopecsni, 2008).

#### 4.2.2 LGD Collateral

The collateral component of LGD estimation is computed apart from the cash component, yet following a similar methodology. Its estimation is based on haircut rate, which assesses collateral’s depreciation, the probability of said collateral being executed and then discounted by the exposure at default (EAD) associated.

By definition, haircuts mitigate the expected losses a lender expects to suffer given the market and liquidity risks, see [6](Chapman, 2011). Hence, the financial institution recalculates the value of the collateral by assessing the devaluation from the contract date until entering in default and from then to total liquidation. Provided with the

former time lags, it is possible to define two net recovery ratios,  $\delta_1$  and  $\delta_2$ . The pre-sale ratio  $\delta_1$  takes into account the resulting credit loss in said time interval by computing the quotient between the initial value and the collateral's evaluation value at default, in order to be discounted to the reference date. The post-sale ratio  $\delta_2$  follows a similar, yet the time points considered for its computation are the collateral's acquisition date and the default date. The haircut  $hct$  is then  $hct = 1 - \delta_1\delta_2$ .

The probability of execution  $\beta$  measures the probability of recovering from default by selling the collateral. Depending on the portfolio's segment, the financial institution takes as assumption that after  $n$  months after entering in default the security will be executed regardless. Therefore, its computation is based on the following ratio, where  $i$  represents the time in default of the security:

$$\beta_i = \frac{\text{number of defaulted securities}_{\max(n,i)}}{\text{number of defaulted securities}_i} \quad (8)$$

*Equation 8: Collateral's execution probability*

Ultimately, the LGD's collateral component is computed as follows:

$$LGD_{\text{collateral}} = \frac{hct \times \beta}{EAD} = \frac{(1 - \delta_1\delta_2) \times \beta}{EAD} \quad (9)$$

*Equation 9: LGD collateral component*

Additionally, LGD estimates consider adjacent costs to the process, being indirect and direct costs.

### 4.3 Backtesting

After the development process, the LGD model is subject to validation process. The procedure itself considers qualitative and quantitative methods in order to assess the

model's goodness-of-fit. In this regard, the former relies on a qualitative review which evaluates the data quality, checking its time interval and assumptions assumed.

Quantitative methods applied include benchmarking and backtesting methods. While the first compares the internal model estimates with external model estimates, when available, backtesting evaluates the internal model estimates with the realized observations.

Considering the backtesting framework, the most common metrics used for assessing the predictive performance of LGD models are the error-based metrics, such as the Mean Absolute Error (MAE), the Root Maximum Squared Error (RMSE), the correlation-based metrics, (e.g. Pearson's  $r$ , Kendall's  $\tau$ , Spearman's  $\rho$ , coefficient of determination  $R^2$ ), and at last the classification-based metrics, for instance AUROC, see [16] (Scandizzo, 2016).

The metrics mentioned above present some disadvantages for assessing the LGD model. For example, in the case of insufficient observations in the portfolio, outliers in the sample can induce poor accuracy in the performance test. In fact, RMSE is seen as more conservative given the higher weightage on forecasting errors, hence disrupting the performance analyses.

Lotterman *et al* (2014) suggest an alternative backtesting approach by adopting statistical tests, to evaluate model deterioration at a specific significance level, e.g. 5%. In addition, the process is based on an out-of-time validation, where data is selected from a time period and the predictive accuracy is tested on a following time interval. Hence, the previous difficulty presented with the error based and correlation metrics ceases to exist.

#### **4.3.1 Welch's t test**

In order to calibrate the LGD model, the financial institution in study uses the Welch's t test, a central tendency error test which prevents the over or underestimating of the

LGDs estimates. Thus, the difference between the observed LGD,  $Y$ , and the estimated LGD,  $\hat{Y}$ , will be the error  $E = Y - \hat{Y}$ , assessing the error's central tendency to be equal to zero. The Welch's t test evaluates the mean error  $\mu_E$ , with the null and alternative hypothesis as follows:

$$H_0 : \mu_E = 0 \text{ vs } H_1 : \mu_E \neq 0 \quad (10)$$

*Equation 10: T test hypothesis*

Furthermore, the T statistic is given by the following ratio, where  $n$  represents the number of observations and  $s_E$  is the error's standard deviation:

$$T = \frac{\hat{E}}{\frac{s_E}{\sqrt{n}}} \sim t_{n-1} \quad (11)$$

*Equation 11: T test hypothesis*

The financial institution in study applies the previous test comparing observed and estimated recovery rates. Here, the RRs are computed considering the ratio between the sum of all recoveries of defaulted contracts at time  $t$  and the sum of initial debt of said contracts.

$$\text{Recovery rate}_t = \frac{\sum_i \text{Recovery amount}_{t,i}}{\sum_i \text{debt}_{0,i}} \quad (12)$$

*Equation 12: Numerical expression for computing the observed and estimated recovery rates*

In Equation 12, the  $\text{Recovery amount}_{t,i}$  represents the total amount of recoveries of contracts which have been in default at  $t$  months. Same for the initial debt,  $\text{debt}_{0,i}$ , which corresponds to the total amount of debt of the previous referenced contracts.

Taking into account the number of observations in the input data and the variance of the RRs, the statistic  $t$  follows the equation below and has  $v$  degrees of freedom,

$$t = \frac{\overline{RR}_{t,obs} + \overline{RR}_{t,est}}{\sqrt{\frac{s_{t,est}^2}{n_{t,est}} + \frac{s_{t,obs}^2}{n_{t,obs}}}} \sim t_{(v)} \quad (13)$$

$$v \approx \frac{\left(\frac{s_{t,est}^2}{n_{t,est}} + \frac{s_{t,obs}^2}{n_{t,obs}}\right)^2}{\frac{s_{t,obs}^4}{n_{t,obs}^2} + \frac{s_{t,est}^4}{n_{t,est}^2}} \quad (14)$$

*Equation 14: T statistic and respective degrees of freedom*

#### 4.4 Point in time Adjustment

In addition, the risk parameters estimation can be computed through two distinct approaches, Through-the-cycle (TTC) for capital purposes or Point-in-time (PIT) for provisioning purposes. The first is based on the historical information of the credit risk state of the borrower through an entire economic cycle. As oppose to the PIT approach, where the risk inputs should represent the current business cycle, including forward-looking macroeconomic information, see [10](Engelmann, Rauhmeier, 2011). The financial entity in study estimates recovery rates following the TTC approach, based on historical data collected. Then, the TTC estimates are compared with the estimates in the most recent period in order to assess the model's performance in capturing the current business cycle. In the case of misrepresentation of reality, an adjustment is applied: the variable scalar, see [3](Begin, Thomas, 2012). A variant of the variable scalar approach is most common used in A-IRB models, when converting PIT to TTC PDs. For instance, adjusting the PIT PD upward in periods of low credit losses, or downturn when high credit losses are observed.

In our study, the scalar is based on the deviation between the estimated parameter and the adjustment amount necessary in order to the RR estimate predicts the current economic scenario. Thus, the new estimate follows the next equation:

$$Recovery Rate_{new} = Recovery Rate_{old} (1 + scalar) \quad (15)$$

*Equation 15: Recovery rate adjusted*

## Model Quantitative Review

Following the description of the methodology, the next step involves reviewing the parametric model adopted by the financial institution, in order to compute the ECL provisions on a collective basis, and consequentially the risk parameters, namely the LGD parameter.

Additionally, and according to the methodology used by the European Central Bank in Asset Quality Review (AQR) – Phase 2 Manual 2014, the quantitative review should evaluate models in four scopes: (i) Model Use, which assesses the suitability of the model and applicability of its outputs (how well the outputs are being applied); (ii) Model Assumptions, which weighs on the limitations of the model and the techniques adopted; (iii) Input Data, which assesses the data quality used on the models and (iv) Model Calibration, which evaluates the goodness of fit of the models and the methodology adjacent.

Attending the case study of the present report, the model calibration can be exercised through backtesting, which is a requirement established in the EBA guidelines on LGD estimation, paragraph 159.b, “The assumptions underlying the expected future costs and recoveries as well as the adjustment to the observed average LGD should be: (i) proven accurate through backtesting;” and paragraph 170 “Institutions should perform backtesting and benchmarking of their ELBE and LGD in-default estimates (. . .)”.

In the next section some statistical tests are described as the most common metrics used to perform LGD backtesting in the Financial Institution in study.

### 5.1 Welch t test

The Financial Institution in study evaluates its estimations by using Welch’s t test, mentioned previously in Chapter 4. Hence, given the input for the back testing exercise, the data is structured in order to present the total amount of recoveries and the total amount of debt through period, followed by the computation of the estimated and

observed recovery rates. In order to organize and analyse graphically the data, for each segment a correspondent curve of estimated recovery rates is associated.

Next, the statistics (i.e. mean, variance), the variables  $n_{obs}$  and  $n_{est}$ , corresponding to the observed and estimated contracts respectively, the T statistic and degrees of freedom  $v$  are calculated in order to compute the p-value.

Afterwards, it follows the assessment of the statistical relevance of each period, to evaluate if further corrections to the curve are needed, for instance the point-in-time adjustment. The process involves comparing the p-values to the significance level of 5%, creating an auxiliary variable *test\_period*. Assuming that the p-value is superior to 5%, we sum the  $n_{obs}$  of each period which passes the test. Then, the percentage of accepted periods is given by the ratio of the variable *test\_period* over the total sum of  $n_{obs}$ . The curve is statistical relevant with the condition that the percentage of accepted periods is above 50%.

The results are shown in 1 stated bellow.

## 5.2 Wilcoxon Signed Rank Test

In the present section, the Wilcoxon signed rank test is proposed as different approach by assessing the median of the errors by curve of each segment, i.e., segment 1 and segment 2. The statistical test has the following hypotheses:

$$H_0 : \eta_E = 0 \text{ vs } H_1 : \eta_E \neq 0 \quad (16)$$

*Equation 16: Wilcoxon signed rank test*

Beforehand, the input data is organized such that the errors are computed as the differences between observed recovery rates and predicted recovery rates. Then, a flag *wilcox\_error* is created taking the value 1 if the error is positive and 0 otherwise.

Afterwards, the absolute values of the errors are ranked in ascending order and the test

statistic  $Z$  is computed as the sum of the positive values' rank, the variable  $r_{plus}$ , and  $n$  error observations.

$$Z = \frac{r_+ - \frac{n(n+1)}{4}}{\sqrt{\frac{n(n+1)(2n+1)}{24}}} \sim N(0, 1) \quad (17)$$

*Equation 17: Wilcoxon statistic Z*

The Wilcoxon metric  $w_t$  accompanies the previous test to facilitate the assessment of the model's performance. The additional metric is computed as the ratio of the rank sum of negative errors over the total sum of positive and negative errors.

$$w_t = \frac{\sum r_-}{\sum r_- + r_+} \quad (18)$$

*Equation 18: Wilcoxon metric*

The  $w_t$  is bounded between 0 and 1. In case of assuming values near 1, the errors tend to be overestimated (i.e. the LGD model is over performing), as taking values of 0.5, there is no upward or downward bias in the estimation of the errors (i.e. the LGD model is unbiased). In case of assuming values approximately 0, then the model is underestimating its errors (i.e. the LGD model is under performing).

### 5.3 Results

The results can be shown in the following table.

	Welch T	Wilcoxon Signed Rank	Wilcoxon metric
<b>Seg 1</b>			
<b>Type I</b>			
Curve 1	54,47%	1,82%	0,644
Curve 2	69,56%	28,68%	0,539
Curve 3	83,20%	0,01%	0,758
Curve 4	55,54%	1,30%	0,654
Curve 5	61,77%	1,91%	0,643
<b>Type II</b>			
Curve 1	55,62%	9,62%	0,590
Curve 2	72,34%	24,85%	0,453
Curve 3	45,73%	24,85%	0,453
Curve 4	71,63%	0,02%	0,746
Curve 5	62,66%	36,65%	0,524
<b>Seg 2</b>			
<b>Type I</b>			
Curve 1	77,85%	35,42%	0,479
<b>Type II</b>			
Curve 1	60,54%	0,06%	0,321

*Table 1: Comparison of statistical tests*

Taking into account the results presented above, the T Welch test accepts all curves, except the curve from segment 1, type of product II and characteristic's type represented in Curve 3, failing by 4% approximately. The test suggests a reasonable estimation of LGD curves, assuming values in the interval [55%; 84%].

On the other hand, the Wilcoxon test accepts its null hypothesis for five curves. Thus, the LGD estimates present no bias associated, i.e., the model is a good-fit. Yet, the remaining curves present a Wilcoxon metric  $w_t$  higher than 0.5, suggesting an overestimation of the risk parameter.

When comparing the former metric with T test, both are concordant with the majority of the curves, except for curve 3 segment 1, type of product I and segment 1, type of product II, Curve 4. While the Welch T test accepts the curves with high percentage, the  $w_t$  metric assumes that the LGDs are overestimated, suggesting a scalar adjustment in order to approximate the LGD estimates to the observed.

The proposed Wilcoxon Signed rank test is viewed as an alternative for the Welch's t test when the assumption of the t test for a normal distribution is questioned, see [14] (Lottermann, *et al*, (2014)). Given the data set of the back testing exercise being superior to 200 contracts, the t-student tends to converge to a normal distribution, by the Central Limit Theorem. Thus, the T test is preferred by the financial institution, for which the results from the test prevail.

## Conclusion

The present report has had its focus on the new accounting standard IFRS 9 *Financial Instruments*, emphasizing the risk parameter Loss Given Default (LGD).

The purpose of the report was to validate the risk parameter LGD and assess the goodness-of-fit of the model adopted by the financial institution in study, under the accounting framework. Thus, evaluating its backtesting exercise and propose a different approach, the Wilcoxon Signed rank test.

On one hand, the Welch T test is a parametric statistical test which relies on the LGD distribution for its evaluation of the estimates. On the other hand, the Wilcoxon Signed rank test is a non-parametric test which assesses only the ranks of the absolute value errors, discarding the requirement of a distribution. Moreover, the Wilcoxon metric  $w_t$  presented allows a better understanding on the bias estimation of the risk parameter.

Taking into consideration the Wilcoxon metric, the majority of the curves accepted by the Welch test have no upward or downward bias, i.e.,  $w_t$  takes values approximately around 0.5. Moreover, such curves are accepted by the Wilcoxon Signed rank test, which allows to conclude that the observed and estimated recovery rates assume a symmetrical distribution around 0 and do not take dissimilar values. Thus, the LGD model is a good-fit.

Yet, when the two test are not concordant, the financial institution at study applies a point in time scalar adjustment afterwards to its estimations, mitigating the misrepresentation of the economic reality.

## References

- [1] Basel Committee on Banking Supervision, (2003). *Part 2: The First Pillar - Minimum Capital Requirements*. Bank for International Settlements.
- [2] Basel Committee on Banking Supervision, (2003). *International Convergence of Capital Measurement and Capital Standards*. Bank for International Settlements.
- [3] Begin, B., Thomas, S.. (2012). *Basel II retail modelling approaches PD Models*. PricewaterhouseCoopers.
- [4] Beygi, S., Makarov, U., Zhao, J. and D. Dwyer (2018). *Modeling Methodology, Features of a Lifetime PD Model: Evidence from Public, Private and Rated Firms*. Moody's Analytics.
- [5] Chalupka, R., Kopecsi, J. (2008). IES Working Paper 27/2018. *Modelling Bank Loan LGD of Corporate and SME Segments, A Case Study*. IES FSV. Charles University.
- [6] Chapman, J., Chiu, J., Molico, M. (2011) *Liquidity Provision an Collateral Haircuts in Payments Systems*. Bank of Canada Review.
- [7] Charamza P., Rychnovsky, M., Witzany, J. (2012). *Survival Analyses in LGD Modelling*. European Financial and Accounting Journal, vol. 7, no. 1.
- [8] EBA (2017). *Guidelines on PD estimation, LGD estimation and the treatment of defaulted exposures*. European Banking Authority.
- [9] ECB (2014). *Asset Quality Review, Phase 2 Manual*. European Central Bank.
- [10] Engelmann B. and Rauhmeier R. (2011). *The Basel II Risk Parameters, Estimation, Validation, Stress Testing – with Applications to Loan Risk Management*. Second edition, Springer.

- [11] EYGM Limited, 2018. *Impairment of financial instruments under IFRS 9 - Applying IFRS*
- [12] Frankland, R., Kindgom, J., Smith, A.. (2014) *Through the Cycle and Point in Time*. Institute and Faculty of Actuaries.
- [13] IFRS Foundation, 2014. *IFRS Standard 9 Financial Instruments*. IASB.
- [14] Lotterman, G., *et al.* (2014). *A Proposed Framework for Backtesting Loss Given Default Models*. Ghent University.
- [15] Miu, P. and Ozdemir B., (2017). *Adapting the Basel II advanced internal-ratings-based models for International Financial Reporting Standard 9*. Journal of Credit Risk.
- [16] Scandizzo, S. (2016). *The Validation of Risk Models, A Handbook for Practitioners*.

## Appendix A

Relatively to the general approach, IFRS 9 Financial Instruments refers the following paragraphs:

Paragraph	Description
5.5.3	“( . . . ) at each reporting date, an entity shall measure the loss allowance for a financial instrument at an amount equal to the lifetime expected credit losses if the credit risk on that financial instrument has increased significantly since initial recognition.”
5.5.5	“( . . . ) if, at the reporting date, the credit risk on a financial instrument has not increased significantly since initial recognition, an entity shall measure the loss allowance for the financial instrument at an amount equal to 12-month expected credit losses.”
5.5.7	“If an entity has measured the loss allowance for a financial instrument at an amount equal to lifetime expected credit losses in the previous reporting period, but determines at the current reporting date that paragraph 5.5.3 is no longer met, the entity shall measure the loss allowance at an amount equal to 12-month expected credit losses at the current reporting date.

*Table 2: Regulatory support regarding the General Approach*

In the new standard, the simplified approach is enunciated on the next paragraph:

Paragraph	Description
5.5.15	<p>“( . . . ) an entity shall always measure the loss allowance at an amount equal to lifetime expected credit losses for:</p> <p>(a) trade receivables or contract assets that result from transactions that are within the scope of IFRS 15, ( . . . );</p> <p>(b) lease receivables that result from transactions that are within the scope of IFRS 16; ( . . . )</p>

*Table 3: Regulator support regarding the Simplified Approach*

For credit-impaired financial assets, IFRS 9 Financial Instruments presents the following paragraph in order to access the ECL amount to determine.

Paragraph	Description
5.5.13	<p>“( . . . ) at the reporting date, an entity shall only recognise the cumulative changes in lifetime expected credit losses since initial recognition as a loss allowance for purchased or originated credit-impaired financial assets.</p>

*Table 4: Regulator support credit.impaired financial assets*