Modeling the Loss Given Default of Retail Contracts

Abstract

Risk management is the fundamental concept in any modern financial institution that wants to be perceived as having a stable capital base and generating economically justified decisions. It has implications on different aspects of bank operations and organizational structure. Implementing the Advanced Internal Rating Based Approach (AIRB) for capital allocation or International Financial Reporting Standard number 9 (IFRS 9) for expected credit loss calculation regimes serves to enhance risk management practices and raises competitiveness on the market. The scope of risk parameters use is not limited to assessing current risk vulnerability but also positioning the institution in the forthcoming economic environment. The importance of selection and validation of the methods to measure various types of risk seems vital not only during a downturn but in any phase of the economic cycle. This makes all units vulnerable to risk exposure, interested in having as precise parameters as possible.

Not surprisingly, one of the major concerns of the financial institution risk framework is to assess the risk connected to credit activity correctly. The Basel II Capital Accord prescribes the minimum amount of regulatory capital an institution must hold to be resistant to unexpected losses and be in line with its risk appetite. Estimation of expected and unexpected losses associated with each exposure is possible within the Asymptotic Single Risk Factor Model (ASRF) framework. The AIRB standard, which adopted these proposals, imposes estimation of the three risk parameters, which are PD probability of default (PD), loss given default (LGD) and exposure at default (EAD). The first one is defined as the likelihood that a particular client will not repay his debt and fall into default in a determined extent of time. The default event is indicated by the default indicator variable that equals one if the uncertain default occurs, and zero otherwise. Loss given default stands for economic loss, expressed as a percentage of exposure, which will not be recovered if the loan goes into default. EAD is the amount expressed in a particular currency, that obligor will have to repay in case of default. It consists of the current outstanding, which was already drawn, and a part of the commitment, which can be drawn and introduces uncertainty, leading to estimate the Credit Conversion Factor (CCF). Multiplication of these three elements results in *Expected Loss (EL)*, which is a part of the loan pricing and takes a substantial role in the accounting for financial instruments (specifically impairment of financial assets) as IFRS 9 replaced the IAS 39 in 2018. What is more, PD, downturn LGD (dLGD) , downturn EAD (dEAD) and correlation parameter among loans are used as a part of the first pillar in *Unexpected Losses (UL)* calculation to obtain risk-adjusted capital requirements under Basel II Accord.

There are many areas where competitive advantage can be gained, when underlying risk of exposure can be properly reflected by risk parameters. Firstly, pricing, which reflects true risk of a client, can be used to select an acceptance level that correctly represent institution risk appetite. It leads to flexibility in the credit policy decision-making process, as the riskiness of default event and conditional loss can be managed simultaneously. What is more, even after default, collection (debt recovery) strategies can be set according to LGD estimates, where the soft collection can be assigned to cases with a low value of LGD parameter and more decisive actions otherwise. Secondly, capital requirements calculated via the advanced approach are seen as more sensitive to the underlying risk of assets, as internal models can recognize detailed risk profile absorbed by institution. Pursuing less risky assets leads to regulatory capital reduction, which can be used for other business initiatives. Last but not least, the use of in-house PD, LGD and EAD make it possible to get deep insight into the impairment process, which lead to preparing stable and forward-looking forecasts of provisions. Financial institutions that can precisely justify the value of expected losses are perceived as more valuable for potential investors, influence the market valuation and raises competitiveness on the market.

Previously, researchers and practitioners mainly focused on the individual creditworthiness expressed in PD. As a result, various methods for estimating PD have been established. On the other hand, we observed a growing research on the LGD in the last few years. Despite the importance of this parameter, both in capital requirements calculation and from accounting perspective, there is still
a lack of a standardized set of estimation methods or even an agreed list of potential risk drivers with rationale about directions in which LGD is pushed. The estimation task carries great challenge, starting from calculating the actual values, selecting sound risk drivers and functional form, ending with demonstration that an estimation method is appropriate to institutions activities and showing precise/conservative (taking into consideration specific regime) calibration results at the same time. Even if the definition of LGD according to Article 4 (22) of the Capital Requirements Regulation (CRR) is straightforward and expressed as a *ratio of the loss on exposure due to the default of the counterparty to the amount outstanding at bankruptcy*, it can be measured in four different ways. These alternatives are “workout LGD”, “market LGD”, “implied market LGD” and “implied historical LGD”. Workout LGD is based on the institution owns loss and recovery experience. It is necessary to determine all recoveries and costs observed after default, discount them and compare with the value of defaulted exposure at the moment of default.

Loss Given Default is the estimate of losses that the bank will face when customer or facility default. It is expressed as a percentage of EAD:

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|  | $$LGD\_{i}=1-RR\_{i}=1-\frac{\sum\_{t}^{}CF\_{it}d\_{t}}{EAD\_{i}}$$ | (1) |

where $CF\_{it}$ is the net cash flow at time *t* that comprises both positive and negative flows. Recoveries consist of principal, interest and post-resolution payments, the book value of collateral realization, received fees, commissions, waivers and received money from selling loan to third party after write-off. On the costs side, there are legal expenses, administrator and receiver fees, liquidation expenses, staff salaries and additional drawings. Second element $d\_{t}$ denotes discount factor, as all cash flows need to be expressed in a value appropriate at the moment of default. These could be risk-free rate plus premium in case of the AIRB approach, or effective interest rate for IFRS 9 purposes. In the “workout approach” actual LGD is calculated for each default to achieve ultimate goal, which is assigning LGD estimate to non-defaulted and currently defaulted portfolio. Thus, it is a conditional parameter that aims to approximate how significant the loss will be if a non-defaulted client goes into default or a non-conditional parameter for defaulted customers when in-default loss is estimated. The estimation process can be divided into several steps described in Figure 1.

The presented thesis consists of four essays dealing with the modeling and estimation of the LGD for retail contracts. In brief, four concepts are presented. First, the recommendation for unfinished defaults inclusion in the modeling sample is determined, as an inevitable part of the process not well developed in the literature so far. Second, the inclusion of new risk drivers connected to client behavior after granting credit is analyzed. Third, a new form of LGD decomposition is proposed, based not directly on the LGD distribution but rather on events that leads to the bi-modal shape. At last, forecast averaging way of macroeconomic variables inclusion in the LGD model is presented as a possible technique to combine idiosyncratic bank data with systematic factors related to macroeconomics.

Figure 1 Model development steps.

First essay *Modeling Recovery Rate for Incomplete Defaults using Time Varying Predictors* discuss The Internal Rating Based (IRB) approach, which requires that financial institutions estimate the Loss Given Default (LGD) parameter not only based on closed defaults but also considering partial recoveries from incomplete workouts. This is one of the key issues in preparing bias-free samples, as there is a need to estimate the remaining part of the recovery for incomplete defaults before including them in the modeling process. In this paper, a new approach is proposed, where parametric and non-parametric methods are presented to estimate the remaining part of the recovery for incomplete defaults, in pre-defined intervals concerning sample selection bias. Additionally it is shown that recoveries are driven by different set of characteristics when default is aging. As an example, a study of major Polish bank is presented, where regression tree outperforms other methods in the secured products segment, and fractional regression provides the best results for non-secured ones.

*Beyond contract. Client behavior from origination to default as the new set of the Loss Given Default risk drivers* highlights the need to look for new risk factors that could help in the estimation of the LGD parameter. The most recent literature on this topic, mainly focuses on the estimation methods and less on variables used in explaining LGD variability. The following study attempts to expand the part of modelling process by constructing a set of client behavior based predictors, which can be used to construct more precise models. The paper investigates economic justifications by means of empirical studies to examine the potential usage. The main novelty introduced in the paper is establishing connection between LGD and behavior of contract owner, not just the contract itself. Such approach results in the reduction of the values of selected error measures and consecutively improves forecasting ability. The effect is more visible in a parametric method (Ordinary Least Squares) than in a non-parametric (Regression Tree). The research suggests incorporating client-oriented information into LGD models.

Modeling loss in the case of default is a crucial task for financial institutions to support the decision making process in the risk management framework. It has become an inevitable part of modern debt collection strategies to keep promising loans on the banking book and to write off those that are not expected to be recovered at a satisfactory level. Research tends to model Loss Given Default directly or to decompose it based on the dependent variable distribution. Such an approach neglects the patterns which exist beneath the recovery process and are mainly driven by the activities made by collectors in the event of default. *LGD decomposition using mixture distributions of in-default* events propose a solution, that integrates cures, partial recoveries, and write-offs into one equation, defined based on common collection strategies. Furthermore, various levels of data aggregation are applied to each component to reflect the domain that influences each stage of the default process. To assess the robustness of our approach, we propose a comparison with two benchmark models on two different datasets. We assess the goodness of fit on out-of-sample data and show that the proposed decomposition is more effective than state-of-the-art methods, maintaining a strong level of interpretability.

Finally, *Forecast combination approach in the Loss Given Default estimation*, examines a novel method of including macroeconomic variables into Loss Given Default models. The approach is transparent, and it easily translates changes in the overall credit environment into Expected Loss estimates, which is one of the crucial points that was recently introduced in the IFRS 9. We propose a forecast combination procedure that, separates the contract-based variables from the macroeconomic indicators. Two models are prepared and benchmarked to a single ordinary least-squares (OLS) model. To combine the forecasts we use three approaches: the equal weighting scheme, the Granger-Ramanathan Method, and Mallows Model Averaging. We tested our predictions on out-of-time data and found that the forecast combination outperforms the single OLS model in terms of the selected forecast quality metrics.

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