

Somers' D in LGD and EAD Modeling

Impact of Input Binning on Discriminatory Power

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Discriminatory Power in IRB Modeling

- Testing discriminatory power is one of the key aspects of model assessment conducted by credit risk practitioners.
- In simple terms, within the IRB framework, discriminatory power testing evaluates whether a model provides meaningful differentiation between facilities or obligors based on the levels of risk parameters assigned and the values observed in the validation sample.
- Somers' D is commonly used to assess discriminatory power in LGD and EAD models because the final outputs of these risk parameters are typically ordinal, with a limited number of distinct values. In practice, this often corresponds to rating grades or pools.
- When calculating Somers' D, practitioners frequently adopt the ECB approach presented in the [Instructions for Reporting the Validation Results of Internal Models](#).
- However, in practice, different approaches are observed when preparing inputs for the calculation of Somers' D in LGD and EAD modeling, and there are no standard guidelines on how to approach this task.
- Given that practitioners often rely on specific thresholds for Somers' D when concluding on a model's overall discriminatory power, it is worth investigating the impact of input binning on the final decision.
- This presentation examines the potential impact of input binning on overall discriminatory power by comparing three different binning procedures applied to the realised risk parameter values, given the rating grades of the model output. Practitioners should keep in mind that the relationships between Somers' D measures shown in this simulation may not apply to every model output. Still, this work can serve as a basis for developing an appropriate method for determining what an LGD or EAD model should actually discriminate.
- The following slides first introduce the basic concept of Somers' D used to measure discriminatory power in LGD and EAD models, and then compare the results of three different binning approaches on the simulated dataset.

Somers' D in LGD and EAD Modeling

In LGD and EAD modeling, Somers' D has been adopted as a standard metric for measuring a model's discriminatory power.

Given that Somers' D is inherently a pair of asymmetric coefficients, for a contingency table (X, Y) , D_{xy} is considered an appropriate measure of the performance of X in predicting or ranking Y .

The formula for calculating the Somers' D_{xy} coefficient for a contingency table (X, Y) is:

$$D_{xy} = \frac{P - Q}{n^2 - \sum(n_j)^2}$$

where:

- P is twice the number of concordant pairs;
- Q is twice the number of discordant pairs;
- n is the total number of observations in the contingency table;
- n_j denotes the column marginal totals.

Simulation Study Design

The purpose of this simulation is to examine how the choice of binning approach for realised LGD values affects the Somers' D value, under the assumption that the final model output consists of five rating grades. The data used in this simulation are available at the following [link](#) with LGD_R, LGD_P, LGD_P_pool being realised, estimated LGD, and final model pools respectively. Other columns presented in the simulation dataset refer to the discretized values of the realised LGDs based on different binning approaches.

The following table presents a summary of the final model pools that will serve as the basis for two of the binning approaches applied to the realised LGD values.

```
##          pool no lgd_mean
## 01 (-Inf,0.2488) 498   0.1459
## 02 [0.2488,0.3225) 190   0.2702
## 03 [0.3225,0.5024) 152   0.3547
## 04 [0.5024,0.7705) 208   0.6655
## 05 [0.7705,Inf) 152    0.8291
```

Binning Approach 1:

This binning approach assumes that the realised values are discretized independently of the estimated model pools. The selected thresholds for discretizing the realised values are based on the [ECB approach for LGD and EAD models](#), which produce more than 20 unique values (page 33).

- | | |
|----------------|--|
| Segment 1: | facilities i with $0\% \leq LGD_i^R < 5\%$; |
| Segment 2: | facilities i with $5\% \leq LGD_i^R < 10\%$; |
| Segment 3: | facilities i with $10\% \leq LGD_i^R < 20\%$; |
| ... | ... |
| Segments 4–11: | 10% LGD steps |
| ... | ... |
| Segment 12: | facilities i with $100\% \leq LGD_i^R$ |

Simulation Study Design cont.

Binning Approach 2:

This binning approach assumes that the realised values are discretized based on model outputs for each pool. In other words, it relies on model-implied thresholds to discretize the realised values. As in the first binning approach, it follows the [ECB instructions for reporting on validation results](#), but applies to models that produce 20 or fewer unique values. According to the ECB instructions (page 32), for a model that outputs two facility grades, F1 and F2, realised LGD is segmented into three classes. The first class comprises all realised LGD values that are less than or equal to the estimated LGD of grade F1. The second class comprises all realised LGD values that are less than or equal to the estimated LGD of grade F2 and are not part of the first class. The third class comprises all realised LGD values that are greater than the estimated LGD of grade F2.

Binning Approach 3:

This binning approach (proposed by [Andrija Djurovic](#)) presents an adjustment of the second binning approach applied only to the last class of realised LGD. Therefore, using the same example of a model with two facility grades, F1 and F2, realised LGD values are discretized into two classes. The first class comprises all realised LGD values that are less than or equal to the estimated LGD of grade F1, while the second class consists of all realised LGD values that are greater than the estimated LGD of grade F1. For models that output more than two facility grades, the process is applied in the same way, with realised values discretized based on model estimates per pool while producing the same number of pools as the model outputs.

Simulation Results

Bootstrapped Distribution of Somers' D by Binning Approach

