Report on a GCD LGD Model building exercise

Report on an exercise in using GCD data to build LGD models
Using GCD standard definitions to develop a range of models
Focus on Machine Learning

Thomas Alzheimer, Data Scientist and Philip Winckle, Senior Consultant
Introduction by Richard Crecel, Executive Director of Global Credit Data

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GCD is now analysing LGD Data in more detail

GCD collects in its LGD/EAD platform all recovery cash flows from defaulted loans plus loan, borrower and collateral data.

GCD data can be used to estimate:
- ultimate recovery rate,
- cure rate,
- loss given loss and many other parameters relevant for valuing NPL.

Regular publications and academic studies (for deeper insights) and dashboards

<table>
<thead>
<tr>
<th>Unsecured</th>
<th>Observed Recovery Rate</th>
<th>Time to Peak Recovery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grand Total</td>
<td>82,167</td>
<td>79%</td>
</tr>
<tr>
<td>Secured</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Senior</td>
<td>24,058</td>
<td>76%</td>
</tr>
<tr>
<td>Subordinated</td>
<td>782</td>
<td>59%</td>
</tr>
<tr>
<td>Other</td>
<td>1,611</td>
<td>81%</td>
</tr>
<tr>
<td>Total</td>
<td>26,451</td>
<td>76%</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Africa &amp; Middle East</td>
<td>1,693</td>
<td>88%</td>
</tr>
<tr>
<td>Asia &amp; Oceania</td>
<td>5,896</td>
<td>78%</td>
</tr>
<tr>
<td>Europe</td>
<td>39,509</td>
<td>81%</td>
</tr>
<tr>
<td>Latin America</td>
<td>3,978</td>
<td>69%</td>
</tr>
<tr>
<td>North America</td>
<td>30,895</td>
<td>77%</td>
</tr>
<tr>
<td>Other</td>
<td>196</td>
<td>62%</td>
</tr>
</tbody>
</table>

Many academic and internal studies available

GCD data contains detailed cashflows and recovery events to perform analyses and academic studies.

Figure 3.1: Systematic movements in DRTs

Notes: The figure illustrates the systematic movements of DRTs for resolved loans. Box plots of the DRTs per year for the US, Great Britain, and Canada are displayed, whereas, outliers are hidden due to the presentation purpose. The black horizontal lines within the box plots mark the medians. The means are represented as dashed lines in the box plots.

Source: Betz, Kellner, Rösch 2017, “Macroeconomic effects and frailties in the resolution of non-performing loans“ ; Data: GCD

LGD by Collateral Haircut Bucket

Source: Internal analysis (GCD 2017) on Real Estate Finance Europe
Banks are specially Downturn focused now

- COVID-19 has triggered an unprecedented downturn that will impact loan defaults and recoveries.
- GCD data can help model the impact of the recession on amount and timing on recovery cash flows.
Background and Purpose to this exercise

- FCG and GCD have had long cooperation, including Benchmarking and joint help to members
- In 2019 FCG volunteered to work with GCD to explore building LGD models on GCD’s full data set
- GCD set up a working group to bring member bank experience to direct the modelling
- FCG will publish the results (while guarding GCD data confidentiality)
- The resultant paper focuses on machine learning and will be available as a use example for GCD members and others
- The aim was to use different modelling methods to:
  - Test GCD data usability for forward looking models
  - Compare observed drivers to industry standards
  - Explore applicability of Machine Learning
- Has FCG achieved these goals? You be the judge!

- Opinions expressed by FCG in this document are FCG’s own and do not represent any specific views supported by GCD or its Member Banks
Authors and Acknowledgements

• This report and the underlying paper were produced by an FCG team

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Irina Cirmizi  
FCG Associate

Mats Ehnbom  
FCG Senior Manager

• The authors were given access to GCD data as part of a working group on LGD modelling meeting regularly with GCD members, who also provided helpful review of the report

• The report and this presentation represent the opinions of FCG and its employees and associates, not the official position of GCD

• The authors would like to thank GCD members and executives for their valuable contributions
### Terms: Measurement vs Prediction

**Data based modelling is the art of converting historical observations to good future guesses**

<table>
<thead>
<tr>
<th>Default Event</th>
<th>Ex post (realised)</th>
<th>Measurement type</th>
<th>Ex ante (predicted)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Any one or more of:</td>
<td>Observed loss (accounting loss)</td>
<td>Credit Losses</td>
<td>EL Expected loss</td>
</tr>
<tr>
<td>• 90 days late on material payment</td>
<td>ODF (Observed Default Frequency) (also called Default Rate)</td>
<td>Default rate</td>
<td>UL Unexpected loss</td>
</tr>
<tr>
<td>• Deemed as &quot;Unlikely to pay&quot;</td>
<td>Observed EAD Observed CCF</td>
<td>Exposure at Default</td>
<td>PD (TTC or PIT) (also called Expected default frequency)</td>
</tr>
<tr>
<td>• Bankruptcy, liquidation, Chapter 11</td>
<td>Observed LGD Observed LGL Observed Cure rate Observed time to resolution</td>
<td>Loss Given Default</td>
<td>EAD CCF (credit conversion factor)</td>
</tr>
<tr>
<td>• Forced restructure</td>
<td></td>
<td></td>
<td>LGD (loss given default)</td>
</tr>
<tr>
<td>• Collateral or guarantor action</td>
<td></td>
<td></td>
<td>LGL (loss given loss)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Cure rate</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Time to Resolution</td>
</tr>
</tbody>
</table>
1. Segment credit book into model groups
2. Collect data on defaulted cases
3. Reference Data Set (RDS)
4. Calculate historical observed LGDs and other parameters
5. Model architecture or structure
6. Explore and decide on drivers and weights
7. Calibrate, add margins of conservatism and downturn
8. Validation of estimates by backtesting and benchmarking

Focus of the working group

Background and History
Scope and Method
- Model A: Historical Averages
- Model B: Regression
- Challenger Models: Machine Learning

This modelling work focused on structure, method and drivers, not on calibration
Standards available…. 

*The modelling re-used as many existing standards as possible*

1. Segment credit book into model groups
2. Collect data on defaulted cases
3. Reference Data Set (RDS)
4. Calculate historical observed LGDs and other parameters
5. Model architecture or structure
6. Explore and decide on drivers and weights
7. Calibrate, add margins of conservatism and downturn
8. Validation of estimates by backtesting and benchmarking

FCG and the working group were able to use the standards which GCD member banks have already set over the last 15 years as well as structure and drivers from GCD reports.
Data choices made

Aim was to be compatible with GCD Large Corporate LGD Report

- GCD’s full LGD/EAD data set of defaulted counterparties and loans
- Large Corporates chosen (GCD LC includes midcorp)
- Years of default restricted to 16 years; 2000 to 2015 to ensure completeness
- Standard GCD RDS used which filters out likely data quality issues
- Non-syndicated loans only
- In total 16,674 defaulted loans were in the study
- Data was prepared and modelling done at loan level, not borrower level
- When using variables with limited completion in the data set, only those with >50% completion are included.
- Data is consistently split into 80% training dataset and 20% validation set. 2 methods were used, random across all years and older vs newer.

Representativeness:
Banks using GCD data to benchmark or build a model will normally select a sub-set of the data based on borrower size, region, collateral and/or industry.

In this case we have used all these factors as model drivers, allowing us to use all data.
Methodology and Definitions

2 step approach using GCD cure and LGD definitions

- 2 step approach used throughout:
  - step 1 cure/no cure
  - step 2 recovery for no cure loans
- Outcome is a probability of cure as well as a range of recovery results.
  \[
  E(LGD) = P(\text{Cure}) \times E(LGD|\text{Cure}) + (1 - P(\text{Cure})) \\
  \times E(LGD|\text{Not Cure}) = \\
  = P(\text{Cure}) \times LGD_{\text{Cure Mean}} + (1 - P(\text{Cure})) \\
  \times E(LGD|\text{Not Cure})
  \]
- LGD was calculated using GCD’s Cap LGD 2:
  - advances after default are added back to EAD
  - all cash flows discounted at risk free Euribor
  - result is floored at 0% & capped at 150%
- Outliers are winsorized at +/-3%
• Default definition is not adjusted from GCD standard, i.e. as judged by each bank using standard Basel rules. This can include a lot of defaults which quickly revert to order.

• “Cure” is defined at loan level exactly as per GCD definition: A loan having time to resolution < 1 year, no write-off and no collateral sale or guarantee call. Alternate timing from 30 days up to 5 years was also explored, supporting 1 year as most discriminatory.

• Estimated LGD for cured loans is not set at 0 but instead equal to the average observed LGD for all cured loans (around 0.5%)
Models Built

Baseline models then Machine Learning challengers

8 models in total
Each of the 4 models is a set of 2 models:
- P(cure)
- LGD(not cure)

Baseline model A:
- Historical Averages
  - Cure & LGD estimated
  - based on historical averages
  - simple list of known risk drivers

Baseline model B:
- Regression
  - Cure & LGD estimated
  - based on logistic and linear regressions
  - larger list of known risk drivers

Challenger model:
- Machine Learning same drivers
  - Cure & LGD estimated
  - using ML models
  - same risk drivers as Baseline B

Dataset Extension:
- Regression and ML, more drivers
  - Cure & LGD estimated
  - using both ML and Regression models
  - larger choice of drivers

5 risk drivers
22 risk drivers
22 risk drivers
>22 risk drivers
Performance Measurement

**ROC, AUC and MAE**

- Probability of cure accuracy performance can be measured similar to PD model performance by using a Receiver Operating Characteristic (ROC) curve and measuring the Area Under the Curve (AUC). Similar to a GINI coefficient.

- LGD for non-cure cases requires different techniques. The method used was Mean Absolute Error (MAE), which is an average of absolute errors:

  \[ MAE = \frac{\sum_{i=1}^{n}|E(LGD|\text{Not Cure})_i - (LGD|\text{Not Cure})_i|}{n} \]

As with most error measures it does not properly take account of the inherent “error” when predicting a bimodal distribution.

- Shapley Additive Explanations (SHAP) are used to assess individual risk drivers’ power of prediction. The ranking shows what features contribute the most to the predictions and to what extent.
Traditional Modelling

Model A: Historical Averages

• naïve model that attempts to predict future LGD based on the historical average LGDs within the different subgroups of the dataset (we can call them drivers).

• Observed LGD is calculated for each group based on the combination of the probability of the cure and observed LGD in the case of non-cure:

  \[ P(\text{Cure}) = \frac{\# \text{ cured loans}}{\# \text{ loans}} \]

  \[ E(\text{LGD} \mid \text{Not Cure}) = (\text{LGD}_{\text{mean}} \mid \text{Cure} = N) \]

5 groupings (drivers) were used:

1. **Collateral Label** – a dummy variable based on whether the loan is secured or not. In case there is no information on collateral behind the loan, it is treated as non-secured.

2. **Collateral Type** – Collateral types securing the loan which the lender can usually get control of and sell if necessary.

3. **Seniority Code** – is a more detailed equivalent of Seniority Label provided within GCD RDS, consisting of five values: Super senior, Pari-passu, Junior, Equity and Unknown.

4. **Country of Residence** – is a variable describing the borrower’s country of residence. (performed better than Country of Jurisdiction)

A simple placement of data into 1,183 buckets, based on combinations of the variable values

Buckets with 0 cases are not included, but 374 buckets only had one case.

- Actual cure cases recorded were 20% (left hand picture)
- Predicted cure has the same rate but, like any 2 state event, the model only predicts a probability of cure greater than 0 and less than 1 (right hand picture)

- Cure model accuracy is similar to PD models
- The random split of development/test data provides higher predictive power, indicating that years may differ
- Mean absolute error for LGD is also lower for random split data sets
Traditional Modelling

Model B: Logistic and Linear Regressions

Background and History

Scope and Method

Model A: Historical Averages

Model B: Regression

Challenger Models: Machine Learning

Conclusions

• \( P(\text{Cure}) \) was modelled using a logistic regression (appropriate for binary outcomes)

\[
P(\text{Cure}) = \frac{1}{1 + e^{-(\alpha + \sum \beta_i x_i)}}
\]

• \( E(\text{LGD} \mid \text{Not Cure}) \) used a linear regression of known LGD risk drivers

\[E(\text{LGD} \mid \text{Not Cure}) = \alpha + \sum \beta_i x_i\]

• Remember that \( E(\text{LGD} \mid \text{Cure}) \) is a constant and not modelled

An extra 22 drivers were trialled in addition to the 5 of Model A.

Summarised as these types:

1. Borrower risk ratings
2. Various borrower size measures
3. Loan limit usage
4. Collateral cover via LTV
5. Real Estate as proportion of Collateral
6. Loan guarantee cover
7. Borrower industry

In both cases \( \alpha \) is the intercept of the model \( \beta_i \), is a slope coefficient and \( x_i \) is the value of the models \( i \) risk-driver.
Traditional Modelling

Regression

<table>
<thead>
<tr>
<th>Rank</th>
<th>Feature Estimating Cure</th>
<th>Score</th>
<th>Feature Estimating LGD</th>
<th>Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>DA_Country_Of_Residence</td>
<td>684</td>
<td>DA_Country_Of_Residence</td>
<td>176</td>
</tr>
<tr>
<td>2</td>
<td>Country_Of_Jurisdiction</td>
<td>609</td>
<td>Country_Of_Jurisdiction</td>
<td>173</td>
</tr>
<tr>
<td>3</td>
<td>Primary_Industry_Code</td>
<td>92.75</td>
<td>Primary_Industry_Code</td>
<td>76.80</td>
</tr>
<tr>
<td>4</td>
<td>Mean_Entity_Sales_log</td>
<td>72.08</td>
<td>EAD_2/Initial_Loan_Amount</td>
<td>73.41</td>
</tr>
<tr>
<td>5</td>
<td>Initial_Lender_Borrower_Risk_Rating</td>
<td>71.19</td>
<td>EAD_1/Initial_Loan_Amount</td>
<td>46.88</td>
</tr>
<tr>
<td>6</td>
<td>EAD_2/Initial_Loan_Amount</td>
<td>57.25</td>
<td>Initial_Loan/Limit</td>
<td>44.69</td>
</tr>
<tr>
<td>7</td>
<td>Default_Loan/Limit_2</td>
<td>54.26</td>
<td>Initial_Loan_Amount_3log</td>
<td>40.04</td>
</tr>
<tr>
<td>8</td>
<td>Initial_Share_Real_Estate</td>
<td>52.80</td>
<td>Default_Share_Other</td>
<td>27.90</td>
</tr>
<tr>
<td>9</td>
<td>Default_LTV</td>
<td>47.61</td>
<td>Mean_Guarantee_Percentage</td>
<td>26.52</td>
</tr>
<tr>
<td>10</td>
<td>Default_Share_Real_Estate</td>
<td>46.52</td>
<td>Default_Lender_Borrower_Risk_Rating</td>
<td>13.65</td>
</tr>
</tbody>
</table>

- Top 3 drivers were the same for \( P(Cure) \) and \( E(LGD \mid Not\ Cure) \)
- Countries of residence and jurisdiction are normally the same, so no surprise that they both scored highly. In a bank model these would be combined due to high correlation
- Top 10 Driver list differs from the “naïve” list of Model A, although the top 2 overlap

- Cure model accuracy is improved over model A, using the random split of development/test data
- Mean absolute error for LGD is about the same as Model A
- Outcomes are improved for extended driver set (see later results)

<table>
<thead>
<tr>
<th>Regression</th>
<th>Metric</th>
<th>Metric Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic, predicting CURE</td>
<td>AUC</td>
<td>0.7224</td>
</tr>
<tr>
<td>Linear, predicting LGD</td>
<td>MAE</td>
<td>0.2664</td>
</tr>
</tbody>
</table>
Challenger Models

Machine Learning

- A variety of ML methods were used, all based on Decision Trees
- Gradient Boosting Decision Tree (GBDT) plus RFC was chosen for \( P(Cure) \)
  - Python based extreme gradient boosting was used to deal with the non-linear relationship between dependent and independent variables.
  - Random Forest Classifier (RFC) was also used to achieve best model and avoid overfitting
- Random Forest Regressor (RFR) was used for \( E(LGD \mid \text{Not Cure}) \)
- 2 other methods (Neural Networks and Support Vector Machine) were investigated but needed more data

The models were first run on the same 27 variables as the regression models (constrained).

Then the analysis was extended across the data set with 11 extra drivers found:

1. Loan Spread
2. Base Rate
3. Total Rate (Base plus Spread)
4. US Segment
5. Facility Type
6. Nature of Default
7. Rank of Security
8. Committed Indicator
9. Leveraged Finance Indicator
10. Financial Currency
11. Public-Private Indicator
Each model’s hyperparameter setup was optimized using scikit-learn’s GridSearchCV.

GridSearchCV search for the best parameters using a fraction of the training data as a validation set (cross-validation). It repeats each unique parameter setup k-times (usually k=3) and picks the parameters with the highest average score:

- For classification, the scoring is AUC
- For regression, the scoring is MAE

The best mix of cure and lgd models were then chosen as the main model.
Challenger Models

ML same drivers outcome

<table>
<thead>
<tr>
<th>Rank</th>
<th>XGBC (Cure)</th>
<th>RFR (LGD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Country Of Jurisdiction</td>
<td>Country Of Jurisdiction</td>
</tr>
<tr>
<td>2</td>
<td>DA Country Of Residence</td>
<td>DA Country Of Residence</td>
</tr>
<tr>
<td>3</td>
<td>Default Share Real Estate</td>
<td>Primary Industry Code</td>
</tr>
<tr>
<td>4</td>
<td>Initial Lender Borrower Risk Rating</td>
<td>EAD 1/Initial Loan Amount</td>
</tr>
<tr>
<td>5</td>
<td>Mean Entity Sales log</td>
<td>Mean Entity Sales log</td>
</tr>
<tr>
<td>6</td>
<td>Mean Guarantee Percentage</td>
<td>Default Loan/Limit 2</td>
</tr>
<tr>
<td>7</td>
<td>Initial LTV</td>
<td>EAD 1 log</td>
</tr>
<tr>
<td>8</td>
<td>Initial Share Other</td>
<td>Mean Entity Assets log</td>
</tr>
<tr>
<td>9</td>
<td>Default Lender Borrower Risk Rating</td>
<td>Default Share Other</td>
</tr>
<tr>
<td>10</td>
<td>Primary Industry Code</td>
<td>Default Loan/Limit 1</td>
</tr>
</tbody>
</table>

When compared with traditional regression:

- The cure model shows stronger predictiveness
- The LGD model shows reduced error

- Top 10 Driver list differs from the “naïve” list of Model A, although the top 2 overlap. Driver lists also differ strongly from the Regression models.
- Exactly as for Model B the Countries of residence and jurisdiction both scored highest.
- Interestingly the $P(\text{Cure})$ model 3rd ranked driver differs from $E(\text{LGD} \mid \text{Not Cure})$. It suggests that more real estate in the collateral mix gives a higher cure chance. Industry code seems to matter less for cure.
Challenger Models

**ML Extended drivers outcome**

- Rank of Security emerges as top Cure driver
- Other extended drivers feature strongly for both \( P(\text{Cure}) \) and \( E(\text{LGD} \mid \text{Not Cure}) \)
- The drivers for each phase of the model are now more diverse, which may better meet business and credit expectations

<table>
<thead>
<tr>
<th>Rank</th>
<th>XGBC (Cure)</th>
<th>RFR (LGD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rank Of Security</td>
<td>Country Of Jurisdiction</td>
</tr>
<tr>
<td>2</td>
<td>Country Of Jurisdiction</td>
<td>Facility Type</td>
</tr>
<tr>
<td>3</td>
<td>DA Country Of Residence</td>
<td>Primary Industry Code</td>
</tr>
<tr>
<td>4</td>
<td>Collateral Type</td>
<td>Nature Of Default</td>
</tr>
<tr>
<td>5</td>
<td>Mean Guarantee Percentage</td>
<td>DA Country Of Residence</td>
</tr>
<tr>
<td>6</td>
<td>Nature Of Default</td>
<td>EAD 1/Initial Loan Amount</td>
</tr>
<tr>
<td>7</td>
<td>Public Private Indicator</td>
<td>Collateral Type</td>
</tr>
<tr>
<td>8</td>
<td>Mean Entity Sales log</td>
<td>Default Loan/Limit 2</td>
</tr>
<tr>
<td>9</td>
<td>Total Rate</td>
<td>Mean Entity Assets log</td>
</tr>
<tr>
<td>10</td>
<td>Mean Entity Assets log</td>
<td>NOM DEFAULT AMOUNT 1</td>
</tr>
</tbody>
</table>

Top risk-drivers ranked. Underscore indicates risk-driver from the extended list.

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>XGBC + RFR</td>
<td>0.85</td>
<td>0.216</td>
</tr>
<tr>
<td>Baseline B</td>
<td>0.76</td>
<td>0.259</td>
</tr>
</tbody>
</table>

- The cure model shows stronger predictiveness from the changed and enlarged driver set
- The LGD model shows reduced error
Overall Comparative Results

**ML vs traditional**

- All models have the same structure (2 phase) allowing direct comparison
- The predictive benefit for using ML to model $P(Cure)$ is evident in the higher AUC of 0.82
- The AUC of 0.85 for the extended drivers ML model (not in graph) confirms the statistical benefit

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
<th>MAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline A</td>
<td>0.71</td>
<td>0.260</td>
</tr>
<tr>
<td>Baseline B</td>
<td>0.72</td>
<td>0.266</td>
</tr>
<tr>
<td>XGBC + RFR</td>
<td>0.82</td>
<td>0.224</td>
</tr>
<tr>
<td>Baseline B extended risk drivers</td>
<td>0.76</td>
<td>0.259</td>
</tr>
<tr>
<td>XGBC + RFR extended risk drivers</td>
<td>0.85</td>
<td>0.216</td>
</tr>
</tbody>
</table>

- Progressing from simple historical description using 5 simple drivers to high tech ML models using 38 drivers shows improved accuracy in both cure rate prediction and LGD error.
The bimodal shape of actual LGD is difficult to model

The 2 phase approach attempts to model the first zero mode

Both Baseline models A and B produce centre weighted estimates

The shape of the ML distribution best reflects the actual.

It is the authors’ firm belief that given good data quality and a sound choice of model features, the increased predictive power from Machine Learning models goes some way to offsetting the increased model risk it entails!
Conclusions

A GCD LGD Model Report

• The strong standards already set by GCD in data template, calculations and variable selection provide a good starting point for LGD modelling
• The Large GCD dataset does need to be reduced by an appropriate RDS before starting modelling
• A range of simple and more complex LGD models can be successfully built on GCD data with strong predictive power
• Splitting modelling into cure and non-cure phases using GCD’s cure definition was successfully used, with alternate cure definitions tested
• Machine Learning techniques confirm the industry standard drivers already identified by the working group
• ML seems to add a useful dimension to the modelling effort, at the very least by suggesting consideration of different driver weightings
Q: Could these methods be applied to other segments/asset classes?
A: Yes, not done yet but there was nothing unique about Large Corp for these models.

Q: Why didn’t you split out collaterals for separate modelling?
A: The models take account of secured status as a dummy variable and also with collateral type. Collateral value is also assessed with the starting LTV variable. One method would be to separate all collateralised loans to separate value based models and use these techniques only for unsecured loans.

Q: Is ML worth the extra effort and the lack of transparency?
A: As an extra modelling tool, the ML proved valuable in at least identifying key drivers, which could then be used in more traditional modelling, even if ML is a step too far for validators or regulators.

Other questions?
Appendix

Cure definition sensitivity

• Cure definition is critical for splitting data into the 2 modelling streams of \(P(Cure)\) and \(E(LGD \mid Not\ Cure)\)

• The GCD cure definition seems a bit arbitrary (1 year, no loss, no g’tee call, no collateral use)

• To test if the predictive power of the baseline models could be improved further, the cure was redefined by varying either the time to resolution or allowed LGD band.

• MAE for both baseline models A and B could be improved slightly by reducing the Time to Resolution restriction

• Relaxing the LGD restriction gives varying results depending on the model

• Overall, the effect is not strong enough to suggest altering the existing simple and long used metric.

<table>
<thead>
<tr>
<th>Cure Definition</th>
<th>MAE Baseline A</th>
<th>MAE Baseline B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Definition</td>
<td>0.260</td>
<td>0.267</td>
</tr>
<tr>
<td>TTR &lt; 30d</td>
<td>0.259</td>
<td>0.267</td>
</tr>
<tr>
<td>TTR &lt; 100d</td>
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<tr>
<td>TTR &lt; 200d</td>
<td>0.263</td>
<td>0.267</td>
</tr>
<tr>
<td>TTR &lt; 2y</td>
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<tr>
<td>TTR &lt; 3y</td>
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<tr>
<td>TTR &lt; 5y</td>
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<tr>
<td>LGD &lt; 1%</td>
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<tr>
<td>LGD &lt; 2%</td>
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<td>0.302</td>
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<tr>
<td>LGD &lt; 3%</td>
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<td>0.268</td>
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<tr>
<td>LGD &lt; 5%</td>
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<td>0.269</td>
</tr>
<tr>
<td>LGD &lt; 10%</td>
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<tr>
<td>LGD &lt; 20%</td>
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<tr>
<td>LGD &lt; 30%</td>
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<tr>
<td>LGD &lt; 50%</td>
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<tr>
<td>LGD &lt; 75%</td>
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<td>0.320</td>
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</table>

Heatmap of model error, dark green is lowest MAE