Modelling Exposure at Default Without Conversion Factors for Revolving Facilities

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Objective

The objective of this presentation is to:

- highlight some of the shortcomings of the Credit Conversion Factor
- propose an alternate method of estimating EAD for revolving facilities

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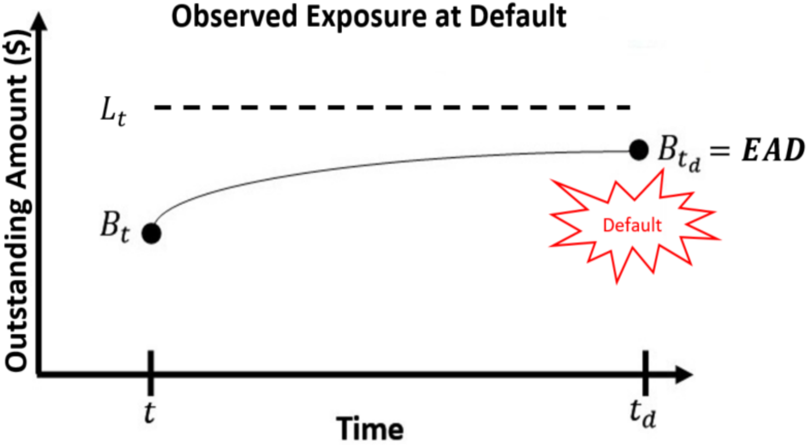
1) Summary of the Two Key Conclusions

1. The limitations of the Credit Conversion Factor
   - undefined and numerically unstable (singularity), can lack economic intuition
2. The joint behaviour of both balances and limits impacts EAD for revolving facilities
   - evidence of risk-based line management to reduce EAD

2) Background – EAD

The Basel Accord[1] defines Exposure at Default (EAD) as the **expected gross exposure of the facility upon default of the obligor**



[1] paragraph 474

2) Background – Limitations of CCF

EAD commonly modelled via transform called the Credit Conversion Factor

$$CCF = \frac{EAD - B_t}{L_t - B_t}$$

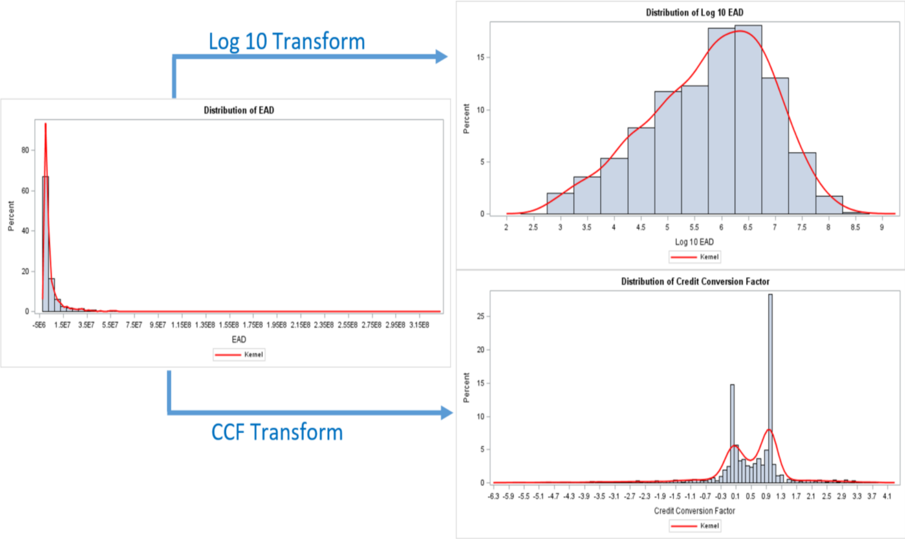
But this transform actually worsens the statistical properties, making it not "universally appropriate"[2] for measuring EAD

- Singularity ($B_t = L_t$) and numerically unstable ($B_t \approx L_t$)
- Lacks economic intuition for CCF outside the range $[0, 1]$

Truncating CCF values $[0, 1]$ may lead to biased results[3].

[2] Taplin (2007)
[3] Moral(2006)

2) Background – Example Transforms

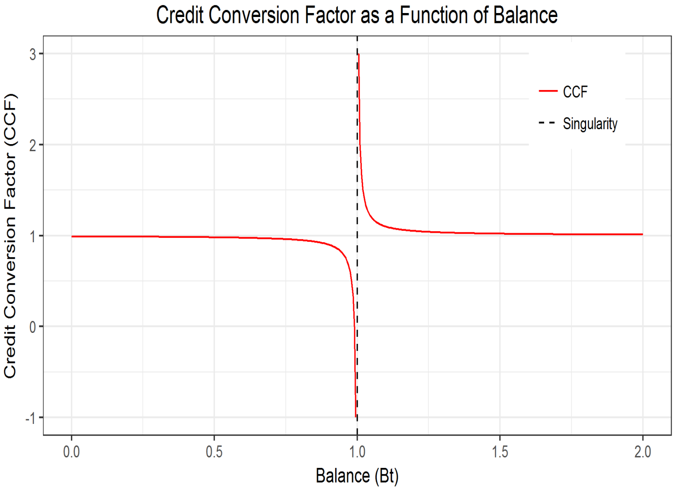


For the CCF transform, 47% of data is undefined, and for display purposes the graph is truncated at 5th and 95th percentile.

2) Background – Limitations of CCF

CCF as a function of B_t has a singularity at $B_t = L_t$

- For illustration $EAD = 0.99$ and $L_t = 1$

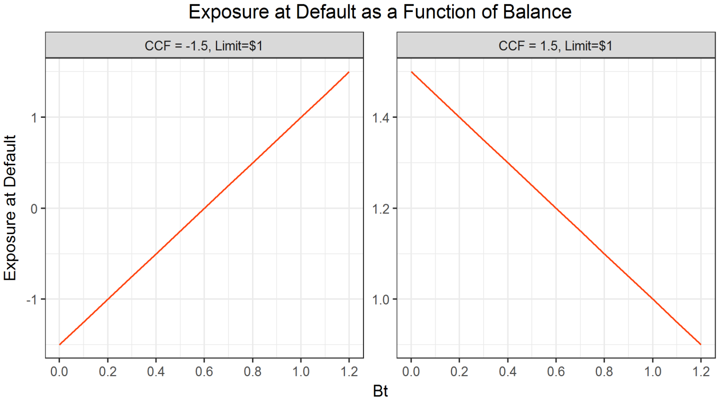


2) Background – Limitations of CCF

Using CCF, EAD as a function of B_t lacks economic intuition

$$EAD = B_t(1 - CCF) + L_t \times CCF$$

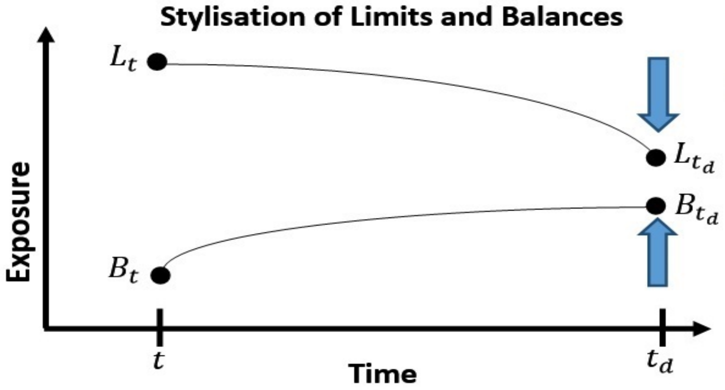
- $CCF < 0$ can lead to negative EAD estimates for small balances
- $CCF > 1$ leads to EAD estimates decreasing as balance increases



3) Methodology – Motivation

Several authors[4] recognise two counter-acting dynamics driving EAD

1. Banks manage limits for financially distressed customers
2. Financially distressed customers draw up remaining funds



[4] Araten and Jacobs (2001), Jacobs (2010) , Qi (2009), Agarwal et al. (2006), Mantel (2012)

3) Methodology – Global Credit Data (GCD)

Entire GCD[5] database contains ˜100,000 resolved defaults

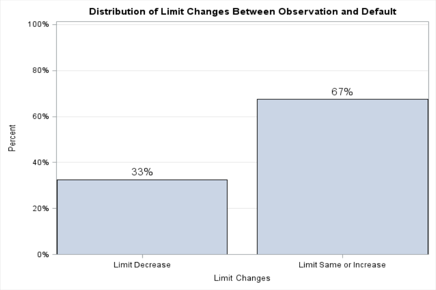
Our training data is drawn from one member's view of (GCD) database, comprising 2,144 defaulted revolving facilities from large corporates

After removing unpredictive variables, our modelling dataset contains 3 outcome variables and 10 covariates known exactly twelve months prior to default

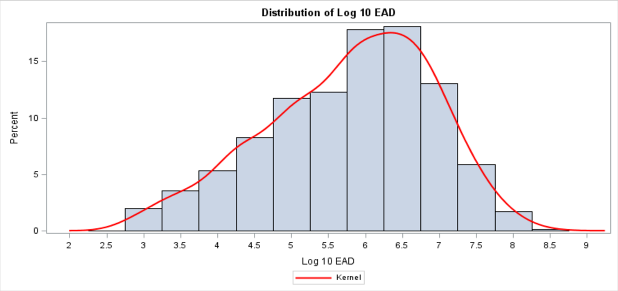
- 3 outcome variables: exposure at default (EAD), limit at default, and the date of default
- 3 entity variables: lender risk grade, operating company indicator, number of loans
- 7 facility variables: limit, balance, time to maturity, seniority, syndication, guarantee/collateral, leveraged deal

[5] www.globalcreditdata.org

3) Methodology – Limit Decrease and Log10 EAD

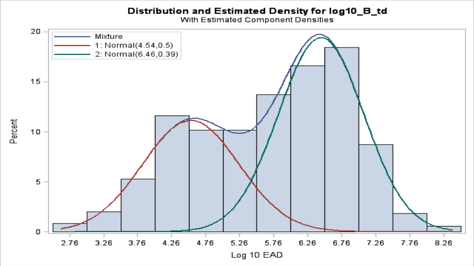


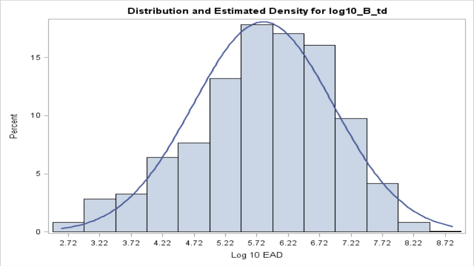
33% of facilities have a limit decreases



Average EAD is €5.7 million

3) Methodology – Log10 EAD Given Limit Decrease





Log10 EAD, given a limit decrease

Log10 EAD, given no limit decrease

Average EAD is 20% lower given a limit decrease

3) Methodology – Model Overview

To capture the observed dynamics in limit decreases and Log10 EAD, we construct 3 model components

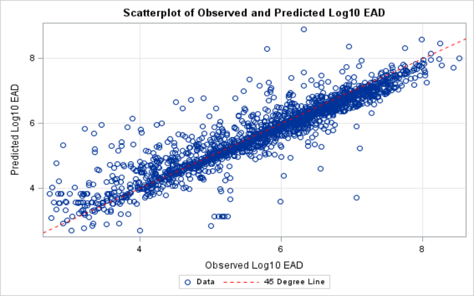
1. logistic regression to predict the probability of a limit decrease
2. finite mixture model with 2 normal densities to predict Log10 EAD, given a limit decrease
3. ordinary least squares regression to predict Log10 EAD, given no limit decrease

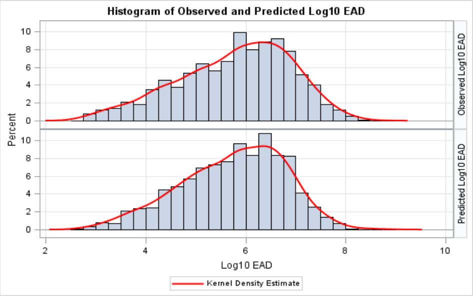
Each of these model components are fit separately using both SAS 9.4, with the results replicated in R version 3.4.0

3) Proposed Methodology – Accuracy

The fitted models produces a good degree of predictive accuracy

- The scatter plot shows predicted and observed values cluster around as 45 degree line
- The histograms show the distribution of predicted and observed values are quite similar



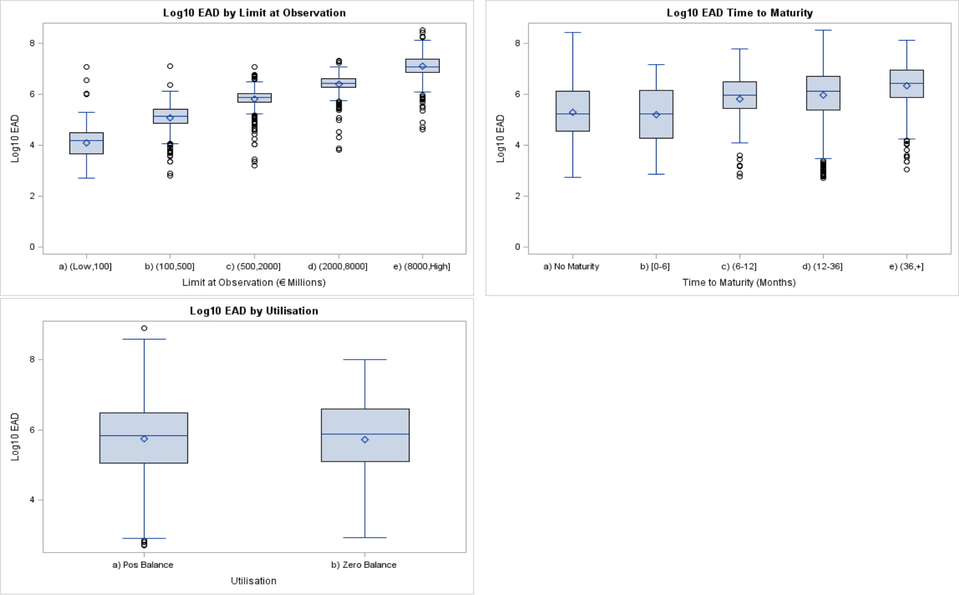


4) Findings – Drivers of Higher EAD

Obligors are active in drawing balances

- Loans more likely to lead to higher EAD have:
  - higher limits
  - higher utilisation
  - longer maturity
  - non-syndicated deals
  - loans to holding companies

4) Findings – Drivers of Higher EAD



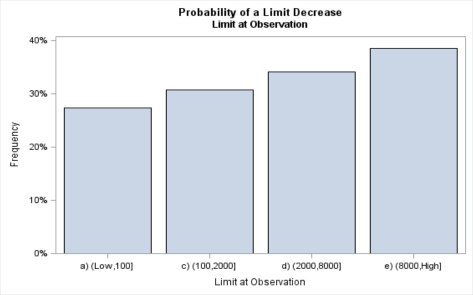
4) Findings – Risk-Based Line Management

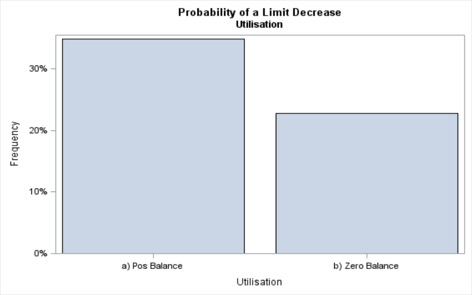
Lenders engage in risk-base line management to reduce EAD

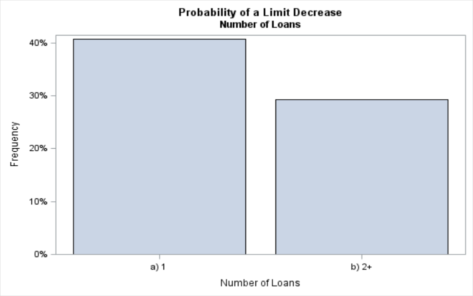
- Loans more likely to decrease limit have:
  - higher limits
  - higher utilisation
  - not in a super-senior position
  - customers with less than 2 loans

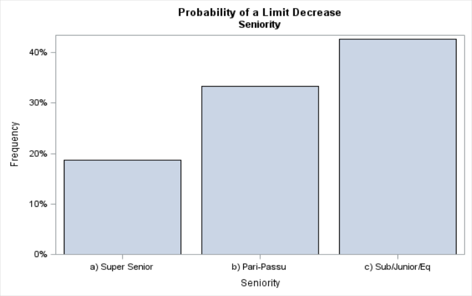
Interestingly, loans that have a shorter time to maturity are less likely to have a limit decrease.

4) Findings – Risk-Based Line Management









4) Findings – Recap of Two Key Conclusions

To recap, there are two key conclusions. Our model

1. Avoids the limitations of using CCF
   - No need to delete data points due to undefined or unintuitive response values

2. Captures the joint behaviour of both balances and limits, allowing us to identify
   - Discovery of risk-based line management
   - Confirms that both limits and balances drive realised EAD

Acknowledgements

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Thank-You!

Questions?

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- http://hdl.handle.net/1959.14/1195692 (masters thesis - statistics)

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APPENDIX 1: Parameter Estimates

Component 1: Logistic regression to predict the probability of a limit decrease

Parameter	Level	DF	Estimate	Std Err	Wald	Pr >ChiSq
Intercept		1	-1.3948	0.2886	23.3614	<.0001
Log10 Limit		1	0.2454	0.049	25.0674	<.0001
Log10 Months to Maturity		1	-0.2769	0.072	14.7743	0.0001
Zero Balance	Yes	1	-0.5362	0.1376	15.1947	<.0001
Zero Balance	No	0	0	.	.	.
Number of Loans	1	0	0	.	.	.
Number of Loans	2+	1	-0.4377	0.1023	18.3131	<.0001
Seniority	Super Senior	1	-1.0925	0.195	31.3727	<.0001
Seniority	Pari-Pasu	0	0	.	.	.
Seniority	Sub/Junior/Eq	1	0.1192	0.1692	0.496	0.4812
Downturn Flag	Yes	1	-0.3635	0.1303	7.7791	0.0053
Downturn Flag	No	0	0	.	.	.

APPENDIX 1: Parameter Estimates

Component 2: Finite mixture model estimating Log10 EAD given on a limit decrease

FMM Component	Parameter	Level	Estimate	Std Err	z Value	Pr > $\|z\|$
1	Intercept		-0.5494	0.1365	-4.03	<.0001
1	Log10 Limit		1.0106	0.02226	45.4	<.0001
2	Intercept		-2.3157	0.05419	-42.73	<.0001
2	Log10 Limit		1.0033	0.004809	208.65	<.0001
2	Zero Balance	No	2.2238	0.04177	53.25	<.0001
2	Zero Balance	Yes	0	.	.	.
Prob(1)	Intercept		0.4377	0.1798	2.43	0.0149
Prob(1)	Log10 Months to Maturity		-0.5998	0.155	-3.87	0.0001
Prob(1)	Operating Company	Yes	1.2303	0.2238	5.5	<.0001
Prob(1)	Operating Company	No	0	.	.	.

Component 3: OLS estimating Log10 EAD given no limit decrease

Parameter	Level	DF	Estimate	Std Err	Wald	Pr >ChiSq
Intercept		1	0.2969	0.0524	32.12	<.0001
Log10 Limit		1	0.9447	0.0093	10210.3	<.0001
Log10 Months To Maturity		1	0.0431	0.0136	9.99	0.0016
Zero Balance	Yes	1	-0.1214	0.0241	25.30	<.0001
Zero Balance	No	0	0	.	.	.
Syndication	Yes	1	-0.1393	0.0427	10.65	0.0011
Syndication	No	0	0	.	.	.

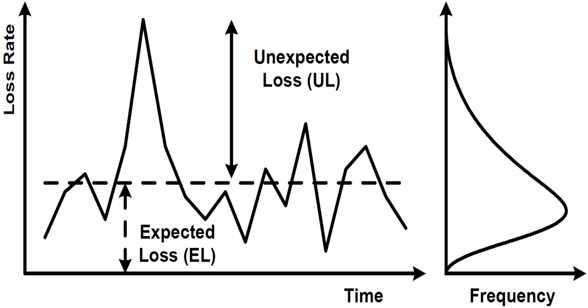
APPENDIX 2: How EAD Features in EL and UL

An estimate of EAD is required for estimating both

- Expected Loss (EL) and
- Unexpected Loss (UL)

$$EL = PD \times EAD \times LGD$$

$$UL = \left(\Phi \left[\frac{\Phi^{-1}(PD) + \Phi^{-1}(0.999)\sqrt{R}}{\sqrt{1-R}} \right] LGD - PD \times LGD \right) EAD$$

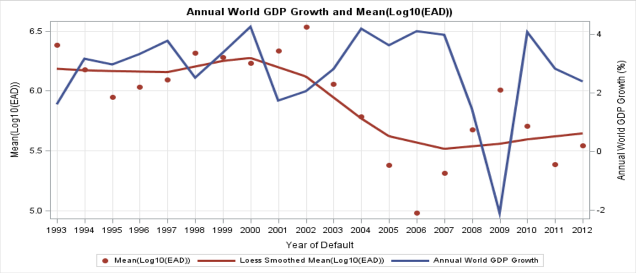


APPENDIX 3: Weak Evidence of Counter-Cyclicality

Mild evidence of counter-cyclicality, where EAD was lower during a downturn

This counter-cyclicality finding agrees with findings from other studies using the GCD[6] data and Moodys[7] URD data

Taken together, this casts doubt on the existence of a downturn-EAD



[6] Mantel (2012)
[7] Jacobs (2011)