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
Table of Contents

1 Summary of the Two Key Conclusions

2 Background

3 Proposed Methodology

4 Findings
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\textsuperscript{1} defines Exposure at Default (EAD) as the expected gross exposure of the facility upon default of the obligor.

\textsuperscript{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)
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\textsuperscript{4} recognise two counter-acting dynamics driving EAD:

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

\textsuperscript{4}Araten and Jacobs (2001), Jacobs (2010), Qi (2009), Agarwal et al. (2006), Mantel (2012)
3) Methodology – Global Credit Data (GCD)

Entire GCD\textsuperscript{5} database contains \(\sim 100,000\) 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 unpredictable 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

\textsuperscript{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
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
Lenders engage in risk-based 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

- Probability of a Limit Decrease
  - Limit at Observation
  - Frequency
  - Limit at Observation
  - a) [Low, 100]
  - b) (100, 2000]
  - c) (2000, 8000]
  - d) (8000, High]

- Probability of a Limit Decrease
  - Utilisation
  - Frequency
  - a) Pct Balance
  - b) Zero Balance

- Probability of a Limit Decrease
  - Number of Loans
  - Frequency
  - Number of Loans
  - a) 1
  - b) 2+

- Probability of a Limit Decrease
  - Seniority
  - Frequency
  - Seniority
  - a) Super Senior
  - b) Pari-Passu
  - c) Sub-Junior/Eq
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

I would like to thank

- my supervisor, Associate Professor Jun Ma from Macquarie University, in Sydney Australia
- my manager, James O’Donnell from Westpac Bank, in Sydney Australia

who generously gave considerable time and much valued feedback which has greatly increased the quality of this presentation. Thank-you.
Questions?

Contact Details:

- Mark Thackham
- au.linkedin.com/in/markthackham
- http://hdl.handle.net/1959.14/1195692 (masters thesis - statistics)
References


Bank for International Settlements (2006). International convergence of capital measurement and capital standards a revised framework comprehensive version


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

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Level</th>
<th>DF</th>
<th>Estimate</th>
<th>Std Err</th>
<th>Wald</th>
<th>Pr &gt; ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1</td>
<td></td>
<td>-1.3948</td>
<td>0.2886</td>
<td>23.36</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Log10 Limit</td>
<td>1</td>
<td></td>
<td>0.2454</td>
<td>0.049</td>
<td>25.07</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Log10 Months to Maturity</td>
<td>1</td>
<td></td>
<td>-0.2769</td>
<td>0.072</td>
<td>14.77</td>
<td>0.0001</td>
</tr>
<tr>
<td>Zero Balance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zero Balance Yes</td>
<td>1</td>
<td></td>
<td>-0.5362</td>
<td>0.1376</td>
<td>15.19</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Zero Balance No</td>
<td>0</td>
<td></td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Loans</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Loans 2+</td>
<td>1</td>
<td></td>
<td>-0.4377</td>
<td>0.1023</td>
<td>18.31</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Seniority</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seniority Super Senior</td>
<td>1</td>
<td></td>
<td>-1.0925</td>
<td>0.195</td>
<td>31.37</td>
<td>&lt;.0001</td>
</tr>
<tr>
<td>Seniority Pari-Pasu</td>
<td>0</td>
<td></td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Seniority Sub/Junior/Eq</td>
<td>1</td>
<td></td>
<td>0.1192</td>
<td>0.1692</td>
<td>0.496</td>
<td>0.4812</td>
</tr>
<tr>
<td>Downturn Flag</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Downturn Flag Yes</td>
<td>1</td>
<td></td>
<td>-0.3635</td>
<td>0.1303</td>
<td>7.779</td>
<td>0.0053</td>
</tr>
<tr>
<td>Downturn Flag No</td>
<td>0</td>
<td></td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
## 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

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Level</th>
<th>DF</th>
<th>Estimate</th>
<th>Std Err</th>
<th>Wald</th>
<th>Pr &gt;ChiSq</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1</td>
<td>0.2969</td>
<td>0.0524</td>
<td>32.12</td>
<td>&lt; .0001</td>
<td></td>
</tr>
<tr>
<td>Log10 Limit</td>
<td>1</td>
<td>0.9447</td>
<td>0.0093</td>
<td>10210.3</td>
<td>&lt; .0001</td>
<td></td>
</tr>
<tr>
<td>Log10 Months To Maturity</td>
<td>1</td>
<td>0.0431</td>
<td>0.0136</td>
<td>9.99</td>
<td>0.0016</td>
<td></td>
</tr>
<tr>
<td>Zero Balance</td>
<td>Yes</td>
<td>1</td>
<td>-0.1214</td>
<td>0.0241</td>
<td>25.30</td>
<td>&lt; .0001</td>
</tr>
<tr>
<td>Zero Balance</td>
<td>No</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Syndication</td>
<td>Yes</td>
<td>1</td>
<td>-0.1393</td>
<td>0.0427</td>
<td>10.65</td>
<td>0.0011</td>
</tr>
<tr>
<td>Syndication</td>
<td>No</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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 relationship.

\(^6\) Mantel (2012)
\(^7\) Jacobs (2011)