

Exogenous Maturity Vintage (EMV) Modelling Based on Through the Cycle Maturity Transition Matrix

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Statements in this presentation are opinions of the presenters and not necessarily represent RBS view.

Summary

Purpose of Our Research

The aim of our work was to test a PD model development methodology that could be applied in IFRS9 modelling and stress testing.

EMV Model Obtained from PLS Decomposition

Partial Least Squares regression is often used to decompose the observed cohort level default rate (organised in the panel data format) into exogenous, maturity and vintage components. Each of these components can be modelled separately.

We tested this methodology in 2017, now again with modified conditions and we believe that this approach is unreliable and should be used with caution.

EMV Model based on TTC Transition Matrix

The second approach, we based on a construction of TTC (through the cycle) transition matrix (Markov chain model). The deviations from the values in TTC matrix were modelled with the use of macro-variables.

Data

I. Monte-Carlo Simulation:

Since this is a simulation, data is generated and the outcome tested.

The settings for this simulation were obtained from the trial run of decomposition method that we believe a few lenders still use.

- Panel data for the PLS run were constructed from simulated E, M and V components
- PLS run (E, M and V components were obtained)
- Obtained E, M and V components were de-trended
- Simulated and obtained E, M and V components were compared in de-trended format

II. Our EMV model using TTC Transition Matrix (Maturity)

Internal data from RBS loans portfolio.

Rationale for EMV Methodology

EMV Model can be written as an additive model as follows:

$$\text{Vintage } DR_{\text{vintage,quarter}}^{\text{OutcomeD}} = E_{\text{OutcomeD}} + M_{\text{quarter}} + V_{\text{vintage}}$$

The model as above has the following features:

- The model predicts the stressed DR on vintage level
- Components quantify the their own effect
- Vintage component estimates the effect of time of origination (often driven by macro-economics)
- Exogenous component captures the effect of macro-economic cycle
- Maturity component reflects the dependency of default rate on age of the loan
- Attrition model is necessary for production of the portfolio default rate (portfolio DR is a volume weighted vintage DR)

Structure of Panel Data Format

Vintage	Date	Quarter	Performing	Flow to Default	Def Rate
2005Q1	2005Q1	1	129821	5217	4.02%
2005Q1	2005Q2	2	117511	4999	4.25%
2005Q1	2005Q3	3	102345	5506	5.38%
2005Q1	2005Q4	4	94561	4999	5.29%
2005Q1	2006Q1	5	81025	3705	4.57%
...
2005Q1	2014Q4	40	581	8	1.38%
2005Q2	2005Q2	1	187541	6890	3.67%
2005Q2	2005Q3	2	167890	7020	4.18%
...
2005Q2	2015Q1	40	96	1	1.04%
2005Q3
...
...
2009Q2	2009Q2	1	112021	6296	5.62%
2009Q2	2009Q3	2	98246	6321	6.43%
2009Q2	2009Q4	3	84658	6089	7.19%
2009Q2	2010Q1	4	71564	4801	6.71%
...
2009Q2	2015Q4	27	2131	11	0.52%
2009Q3
...
...

Structure of panel data:

- Data in this table is indicative. It does not hold RBS data.
- Each cohort (vintage) has its own panel in the table
- Panel Data is typically unbalanced
- The observed DR is relating to the vintage
- Observed vintage default rates relate to 3 different areas:
 - Macro-economy
 - Age of the loan
 - Risk Appetite

EMV Decomposition Method

Vintage	Date	Qtr	Exogenous Comp. Dummies					Maturity Comp. Dummies				Vintage Comp. Dummies				
			dE (2005Q1)	dE (2005Q2)	...	dE (2015Q1)	...	dM [1]	dM [2]	...	dM [40]	dV (2005Q1)	dV (2005Q2)	...	dV (2015Q1)	
2005Q1	2005Q1	1	1	0		0			0				1	0		0
2005Q1	2005Q2	2	0	1		0			0	1			1	0		0
2005Q1	2005Q3	3	0	0		0			0	0			1	0		0
2005Q1	2005Q4	4	0	0		0			0	0			1	0		0
2005Q1	2006Q1	5	0	0		0			0	0			1	0		0
...
2005Q1	2014Q4	40	0	0		0			0	0			1	0		0
2005Q2	2005Q2	1	0	1		0			1	0			0	1		0
2005Q2	2005Q3	2	0	0		0			0	1			0	1		0
...
2005Q2	2015Q1	40	0	0		1			0	0			0	1		0
2005Q3
...
...

EMV Decomposition Method

Panel Data demonstrated in the previous chart can be used to decompose the vintage default rate into three components (E, M and V).

This can be achieved by logistic regression, PLS or any other regression method.

- The parameter estimates for the Exogenous dummies (*date*) form an Exogenous Component. This component effectively form a time-series.
- The parameter estimates for the Vintage dummies (*vintage*) form a Vintage Component.
- The parameter estimates for the Maturity dummies (*quarter*) form a Maturity Component.

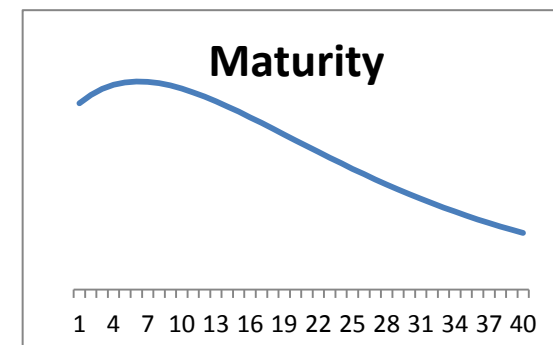
Here is indication of the SAS code:

```
proc ___ data=<panel_data>;  
class vintage date quarter;  
model Def_Rate = vintage date quarter;  
run;
```

EMV Decomposition Method: Monte-Carlo Test

We realised that the E and V components have a shape of a random walk. We tested the decomposition approach using the following steps:

1. E component is generated using random walk process
2. V component is generated using random walk process
3. Scale for M component is randomly chosen.
Scale changes the magnitude of the M component.
4. Panel data is generated using the values from 1), 2) and 3). Data contained 80 quarter vintage histories (15 years of simulated data).



$$Vintage DR_{vintage,quarter}^{OutcomeD} = E_{OutcomeD} + M_{quarter} + V_{vintage}$$

5. A decomposition is run using PLS regression. In this step, the E, M and V components are retrieved from the regression method.
6. E, M and V components retrieved from step 5 are de-trended
7. De-trended E from step 1 is compared with de-trended E obtained from step 5.
de-trended V from step 2 is compared with de-trended V obtained from step 5,
similarly for M...

We decided to repeat this process 10000 times and summarise the comparisons.

EMV Decomposition: Monte-Carlo Test Results

We calculated the “weight” of each component to estimate the component’s influence in the overall EMV structure:

$$weight\ E = \frac{\sigma_E}{(\sigma_E + \sigma_M + \sigma_V)}$$

$$weight\ V = \frac{\sigma_V}{(\sigma_E + \sigma_M + \sigma_V)}$$

$$weight\ M = \frac{\sigma_M}{(\sigma_E + \sigma_M + \sigma_V)}$$

$$comparison = |weight^{simul} - weight^{decomp}|$$

We compared the values of *weights* from the generated components and components retrieved from the decomposition after de-trending (3 comparisons). **In 63.83% of cases from 10000 iterations, the weights of all components were less than 5% apart** (difference in absolute numbers).

Vintage	Exogenous	Maturity	+/- 10%	+/- 5%	+/- 1%
OK	OK	OK	79.4%	63.83%	28.82%
OK	OK	outside	2.1%	3.1%	2.5%
OK	outside	OK	3.0%	2.3%	1.2%
OK	outside	outside	4.3%	6.8%	7.1%
outside	OK	OK	2.3%	3.0%	2.8%
outside	OK	outside	1.5%	3.7%	10.0%
outside	outside	OK	4.1%	6.1%	6.7%
outside	outside	outside	3.3%	11.2%	40.9%

If the components are not de-trended, instead of 63.83% cases, only 29.3% cases would have the weights of all the components less than 5% apart. (See our presentation from CRC Conference XV, 2017),

Through the Cycle Matrix Approach (1/2)

- We were tested certain Moody's approach that we know only partially.
- The key is to define the credit classes based on the PD estimate from IRB model. After that the TTC transition matrix is constructed.
- We calculated observed quarter transition matrices from 2008 Q1 – 2017 Q4. Let's call these matrices *point in time* M. Values in the transition matrices change over time. How far the values are from their TTC value is estimated using econometric models.

	new	CC1	CC2	CC3	CC4	CC5	Def	Close
new								
CC1								
CC2								
CC3								
CC4								
CC5								
Def								
Close								

- In our sample, the highlighted fields showed a dependency towards a typical economic cycle. Differences from the TTC values were modelled in these fields.
- The other values in the matrix are derived from the values in the highlighted fields.

Through the Cycle Matrix Approach (2/2)

- Process of obtaining the values in the other fields is explained for the Credit Class 1. Identical process is used for other credit classes.
- Each field in the row CC1, can be understood as time series (from 2008 Q1 to 2017 Q4); each value of $m(2,3)$ is predicted using macroeconomic data.
- The set of linear regressions were run:

- $m(2,1) = A + B * m(2,3)$
- $m(2,2) = A + B * m(2,3)$
- $m(2,4) = A + B * m(2,3)$
- $m(2,5) = A + B * m(2,3)$
- $m(2,6) = A + B * m(2,3)$
- $m(2,7) = A + B * m(2,3)$

	new	CC1	CC2	CC3	CC4	CC5	Def	Close
new								
CC1	0%	$m(2,1)$	$m(2,2)$	$m(2,3)$	$m(2,4)$	$m(2,5)$	$m(2,6)$	$m(2,7)$
CC2								
CC3								
CC4								
CC5								
Def								
Close								

Through the Cycle Matrix Approach (Model Use)

- For the purposes of stressed PD calculation, the stressed point-in-time transition matrices must be calculated.
- Using the macro-economic scenario, the matrix values in the highlighted fields are calculated for any point in the future. The values in the other fields are calculated from the values in highlighted fields.
- The purpose of the set of linear regressions is to keep the sum of probabilities in each row = 100%.

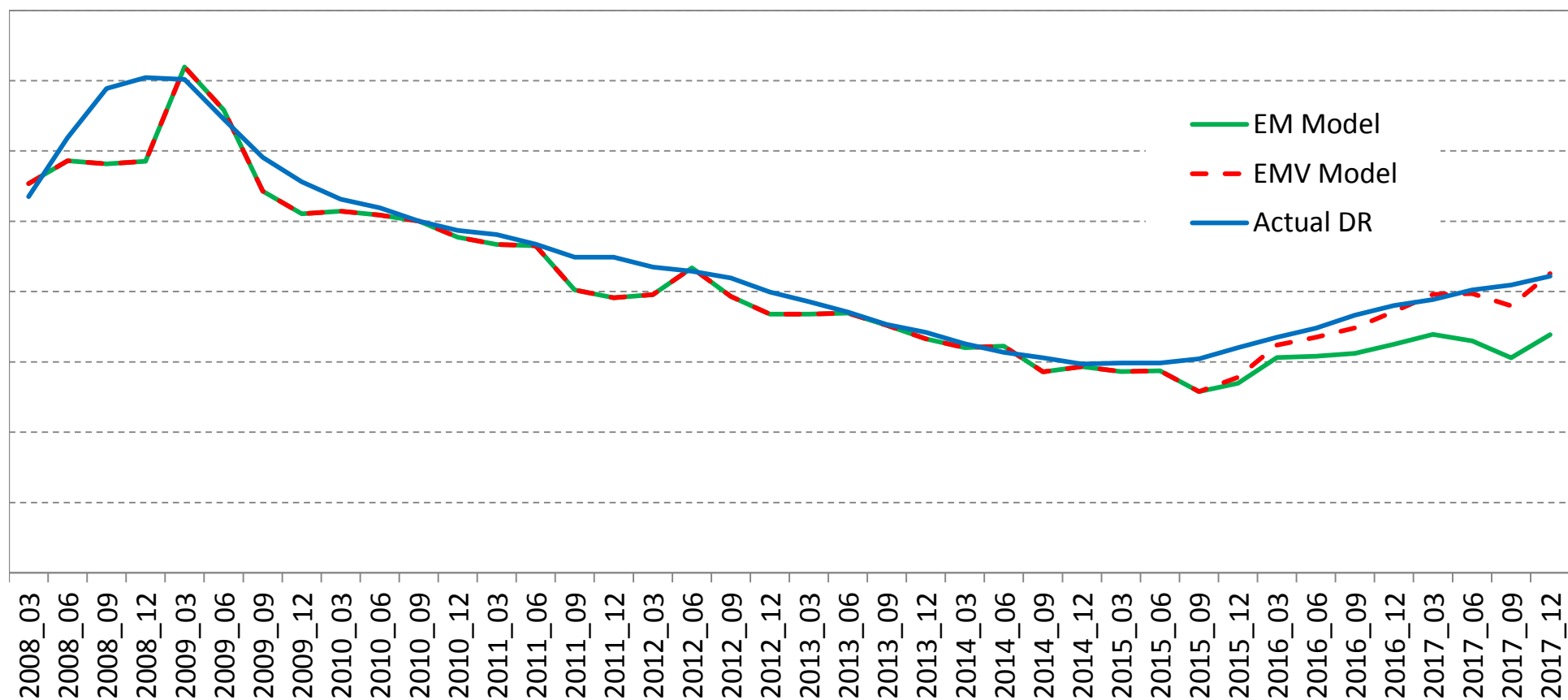
	new	CC1	CC2	CC3	CC4	CC5	Def	Close
new								
CC1	0%	m(2,1)	m(2,2)	m(2,3)	m(2,4)	m(2,5)	m(2,6)	m(2,7)
CC2								
CC3								
CC4								
CC5								
Def								
Close								

- Stressed point-in-time matrix is then used to calculate, how the portfolio is split into the segments in the future.
- Values of newly approved loans are predicted by a separate model.
- Explained model as it is can be understood as EM model. Vintage component can be built-in as a shift applied to TTC transition matrix.

EMV – Illustration of Model Fit (Historical Data)

Development of Observed and Predicted Default Rate

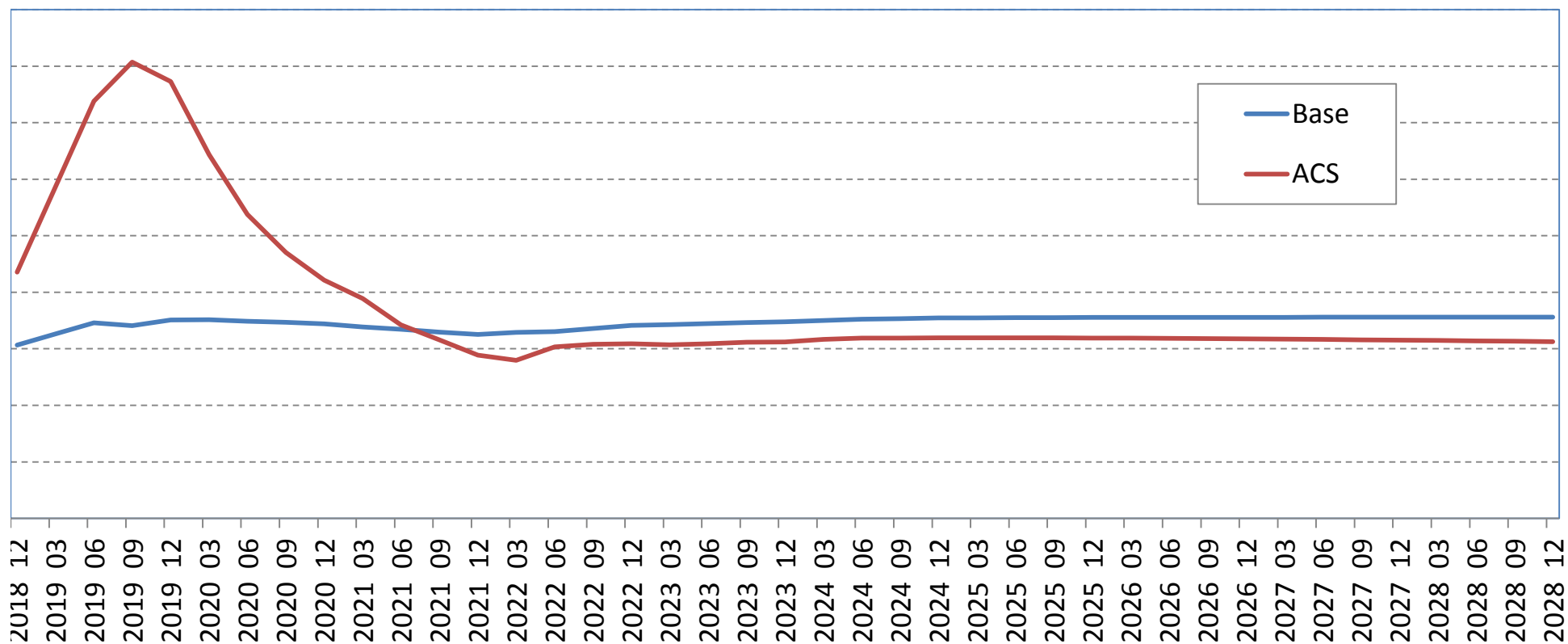
The chart shows the indicative development.



Through the Cycle Matrix Approach (Projections)

Development of Projected Annual Default Rate

The chart shows the indicative development of Base and ACS scenarios of the same year.



Questions / Comments

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