Euler Hermes Rating GmbH

Rating Validation Study

29 November 2019

Update of defaults per 30 June 2019

EULER HERMES Rating

A company of Allianz

Content

Introduction

Euler Hermes Rating GmbH (hereafter “EHR”) publishes this study on defaults, rating transitions and complementary statistics in accordance with Regulation (EC) No 1060/2009 (as amended) and the guidelines on the validation and review of Credit Rating Agencies’ methodologies (ESMA/2016/1575; as amended). The full report complying with these guidelines has been provided to ESMA.

This study allows users of credit ratings assigned by EHR and interested third parties to evaluate the performance and stability of these ratings based on key quantitative assessments and a qualitative discussion of these outcomes. EHR publishes an annual update of this study on a regular basis. In addition, EHR regularly publishes a semi-annual update of the list of defaulted entities.

In order to enhance data coverage, we follow the ESMA guidelines and include in some of our analyses non-regulated/private ratings, which were assigned particularly before 2010. In the following sections, we clearly note whether validation statistics therein were calculated based solely on regulated/public ratings or jointly on regulated/public and non-regulated/private ratings. Ratings can be solicited or unsolicited.

The ratings were assigned to corporates and corporate issuances, corporates structured as project financings (projects) and project finance transactions as well as single-tranche structured finance transactions. We typically refer to corporates and transactions as “entities” in the text and combine different asset classes in our analyses. Corporate issuance ratings and project finance ratings, which refer to expected loss are classified as Limited Quantitative Evidence (LQE) ratings. Their validation, hence, follows the applicable ESMA guidelines and is presented separately. Nevertheless, the corporate or project ratings underlying these expected loss ratings are included in the general validation statistics. If no separate corporate or project rating is available, we use a proxy rating (e.g., the anchor rating of a project finance transaction) or deduct the notching adjustment from the expected loss rating in order to get a pro forma proxy rating. In some instances, we also combine rating categories to Credit Quality Steps (CQS) as defined in the regulations.

In the section “SME and MidCap Ratings (**TRIB**Rating)”, we provide evidence from the methodology development process on the performance of the quantitative part of the SME rating methodologies under **TRIB**Rating, a brand of Euler Hermes Rating GmbH, following the ESMA guidelines for the validation of methodologies with limited quantitative evidence by using third party data. Issuer ratings assigned under **TRIB**Rating are nevertheless included in the general validation statistics.

As a general remark, this study covers neither credit estimates/pre-analyses nor structured finance ratings as defined in the regulations (securitisations).

This report contains a semin-annual update of the number of defaults per 30 June 2019.

Rating Distributions and Defaults

Initial ratings and rating updates

In the years 2002 through 2018, EHR assigned a total of 729 public and private ratings, of which 290 were initial ratings and 439 were rating updates (figures 1 and 2). 37 rated entities defaulted during this period.

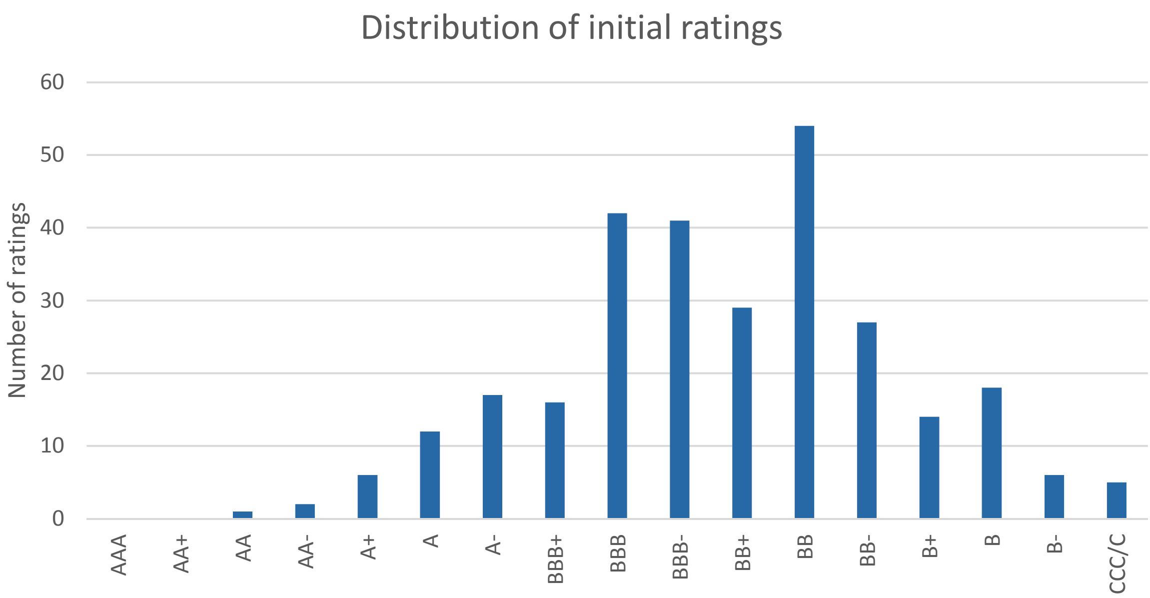

Figure 1: Distribution of initial ratings

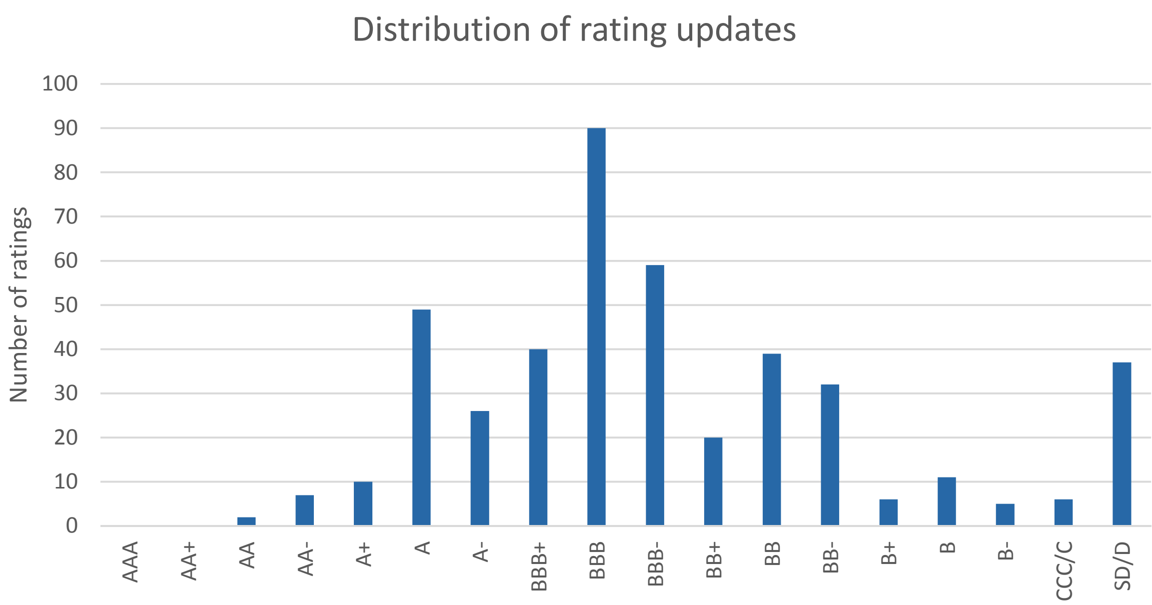

Figure 2: Distribution of rating updates

A total of 399 of all assigned ratings were public ratings (figures 3 and 4). Of these public ratings, 127 were initial ratings and 272 were rating updates. Seven entities, which were assigned a public rating defaulted during the entire period.

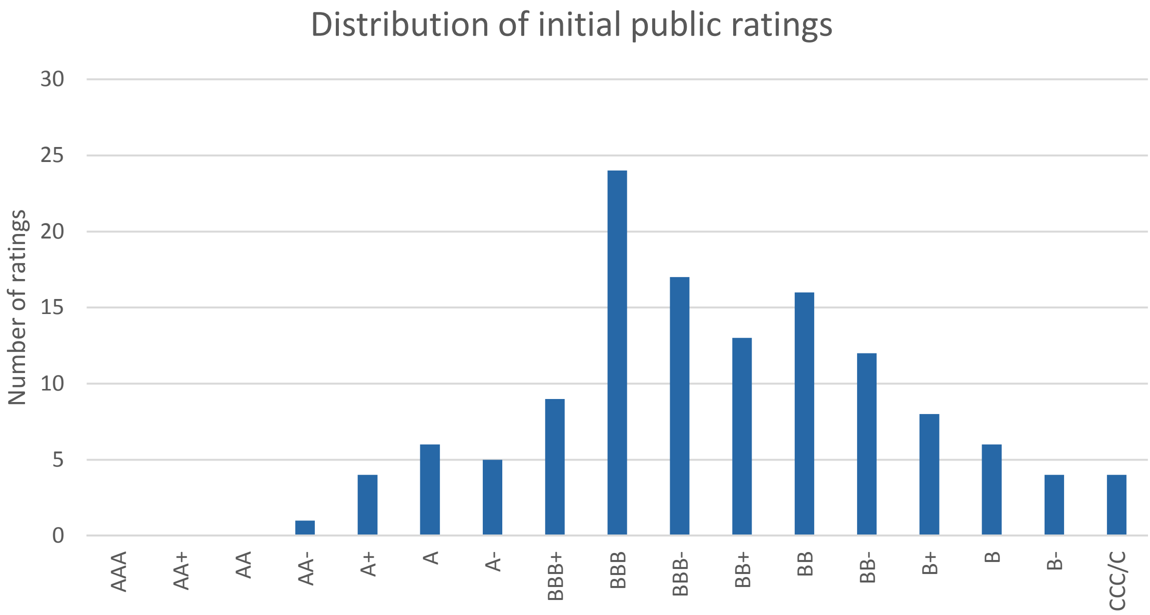

Figure 3: Distribution of initial public ratings

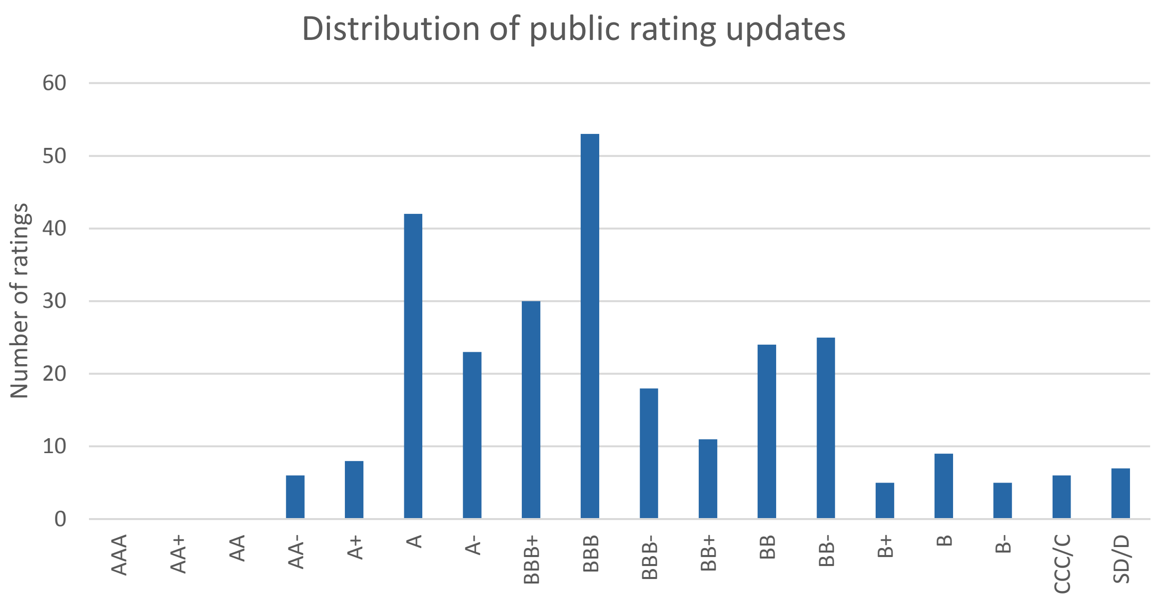

Figure 4: Distribution of public rating updates

Initial ratings were concentrated around the BB rating category, driven by the high number of ratings assigned to small and medium-sized enterprises. Another maximum can be observed around BBB and BBB- rating categories, which typically represent the lower limits for investors to invest in such entities. This was particularly the case for public ratings. The distribution of rating updates tends towards investment grade rating categories because solicited rating updates were typically only requested in case the initial ratings were already investment grade.

Defaulted rated entities (Update per 30 June 2019)

EHR publishes a semi-annual update of the number of defaults. Between 2002 and 30 June 2019, 38 rated entities defaulted of which four entities defaulted within 12 months after the last rating update (table 1). Only two ratings were being monitored at the time of default (public ratings). Of the 31 private ratings, which were assigned prior to default, four ratings were assigned to entities, which were guilty of reporting falsified accounts to the auditors and EHR. The company names of those companies to which a private rating was assigned or whose ratings were accessible only for subscribers cannot be disclosed.

Company	Rating type	Last rating update	Rating date	Regulated rating	Date of default
Company 1	Corporate rating	B	May 03	no	Sep 04
Company 2	Corporate rating	B	February 05	no	Apr 06
Company 3	Corporate rating	BBB-	March 05	no	June 07
Company 4	Corporate rating	B-	February 04	no	February 08
Company 5	Corporate rating	B+	Apr 06	no	Apr 08
Company 6	Corporate rating	BB	Aug 06	no	Aug 08
Company 7	Corporate rating	BB-	Aug 06	no	February 09
Company 8	Corporate rating	BB-	Nov 06	no	Apr 09
Company 9	Corporate rating	BBB-	October 06	no	June 09
Company 10	Corporate rating	BB	Sep 06	yes	Aug 09
Company 11	Corporate rating	B+	Nov 08	no	March 10
Company 12	Corporate rating	BB-	Nov 04	yes	June 10
Company 13	Corporate rating	B-	Apr 05	yes	July 10
Company 14	Corporate rating	BB	June 08	no	October 10
Company 15	Corporate rating	BB	Nov 06	no	February 11
Company 16	Corporate rating	BB	Nov 06	no	February 11
Company 17	Corporate rating	BBB-	Aug 10	no	March 11
Company 18	Corporate rating	BB	Sep 05	no	Apr 11
Company 19	Corporate rating	B	Sep 06	no	October 11
Company 20	Corporate rating	B	June 07	no	October 11
Company 21	Corporate rating	B+	February 06	no	February 12
Company 22	Corporate rating	BB	July 07	no	July 12
Company 23	Corporate rating	BB	Sep 08	no	December 12
Company 24	Corporate rating	BBB-	December 07	no	February 13
Company 25	Corporate rating	B	October 08	no	February 13
Company 26	Corporate rating	BBB-	Aug 09	no	February 13
Company 27	Corporate rating	BB+	December 08	no	March 13
Company 28	Corporate rating	BB+	July 07	no	July 13
Company 29	Corporate rating	BB	Nov 09	no	Aug 13
Company 30	Corporate rating	BB	July 07	no	January 14
Company 31	Corporate rating	BB	Aug 12	no	February 14
RENA GmbH	Corporate rating	CC	February 14	yes	March 14
Company 33	Corporate rating	BB	February 10	no	January 16
Scholz AG	Corporate rating	C	January 16	yes	May 16
Company 35	Corporate rating	BB-	October 11	no	July 16
Rudolf Wöhrl AG	Corporate rating	C	October 16	yes	December 16
Company 37	Corporate rating	B+	May 07	yes	May 17
Company 38	Corporate rating	BB-	June 2014	no	December 17

Table 1: Defaulted rated entities

Discriminatory Power, Predictive Power and Historical Robustness

Please note that all numbers, figures and tables in the following sections exclude events of default that occurred as a result of financial misstatement (e.g., reporting falsified accounts) because such events of default are not related to the performance of rating methodologies.

Throughout this chapter, we classify as LQE ratings all types of ratings whose number of historical ratings or defaults is not considered sufficient for performing certain analyses on such rating types. Based on these thresholds, all corporate issuance ratings and project finance ratings, which are based on an expected loss approach fall under this definition. Their validation is therefore presented separately in this chapter.

Discriminatory power

The discriminatory power of EHR's rating methodologies relates to the ability to rank-order the rated entities given their future status (default; recovery) at predefined time horizons. In order to demonstrate the discriminatory power, several measures and statistics are used to provide deeper insight.

As the applicable statistical measures for analysing the discriminatory power require a relatively large number of data points, we include both, public and private ratings in this analysis.

The discriminatory power of rating methodologies for issuer, project or structured finance ratings (probability of default ratings) is analysed based on the Receiver Operator Characteristic (ROC) in conjunction with the Area under Curve (AUC) for various time horizons (see Appendix A for a technical description). The outcomes suggest a high discriminatory power.

EHR also assigned 85 ratings, which refer to expected loss measures. The discriminatory power of the underlying corporate or project ratings is already captured in the above validation statistics. As neither any of these underlying entities nor the issuances/transactions themselves have defaulted, we cannot perform any additional tests for measuring the discriminatory power of rating methodologies for expected loss-based ratings. Moreover, we rely neither on third-party data nor on hypothetical transactions, since neither data for comparable transactions nor related information are publicly available to a sufficient extent. In case we observe defaults for such ratings, we will collect information, if available, on the realised recovery. Otherwise, we will base the analysis of the discriminatory power on standard recovery levels assumed in the market or presented in relevant studies.

Figure 5 shows the observed default rates across CQS for a one-year time horizon.

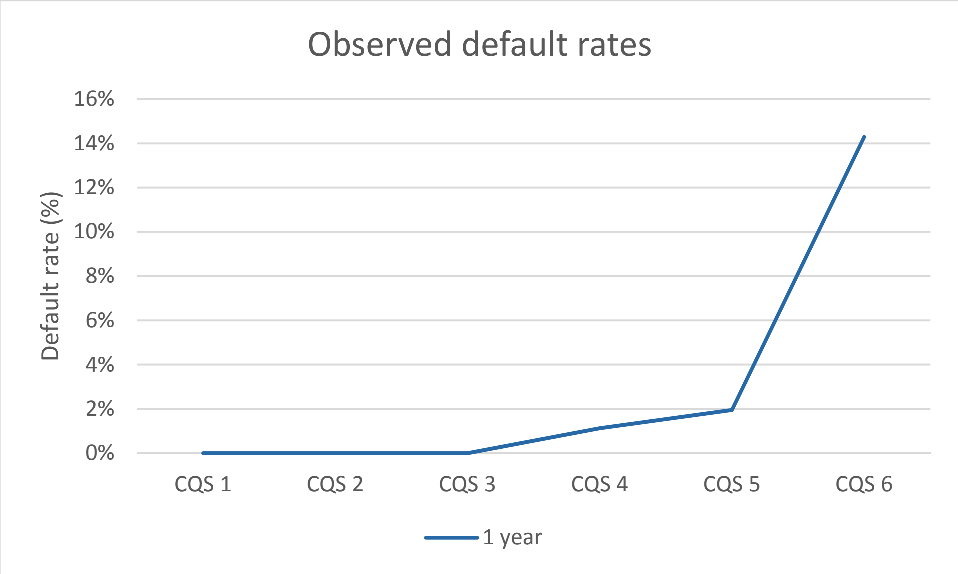

Figure 5: Observed default rates

Predictive power

Observed default rates are compared to expected default rates. This analysis is based jointly on public and private ratings.

As a means of analysing the predictive power, a two-sided binomial test is performed for every CQS against the hypothesis of observing significantly lower or higher default rates. The results do not indicate that observed default rates are significantly lower or higher than the expected values.

As the number of rated entities is comparatively low, statistical tests, which rely on a large sample and that could support the above findings on predictive power (e.g., chi squared test) are not performed.

EHR also assigned 85 ratings, which refer to expected loss measures. The predictive power of the underlying corporate or project ratings is already captured in the above validation statistics. As neither any of these underlying entities nor the issuances/transactions themselves have defaulted, we cannot perform any additional tests for measuring the predictive power of rating methodologies for expected loss-based ratings. Moreover, we rely neither on third-party data nor on hypothetical transactions, since neither data for comparable transactions nor related information are publicly available to a sufficient extent. In case we observe defaults for such ratings, we will collect information, if available, on the realised recovery and compare this to that recovery assumption applied in the rating process. Otherwise, we will base the analysis of the predictive power on standard recovery levels assumed in the market or presented in relevant studies.

Historical robustness

Historical robustness of a rating methodology relates to the stability of assigned ratings and the distribution of ratings over time. Transition matrices are presented for several time horizons and separately for initial ratings as well as initial ratings and rating updates. Additionally, upgrade/total and changed/unchanged ratios are calculated.

Tables 2 to 4 present upgrade and downgrade events for public and public/private ratings assigned between 2002 and 2017. The year refers to the year in which the rating was assigned, with an upgrade, downgrade, default or no change event in the subsequent year. Rated entities without a rating in the subsequent year are not covered.

Please note that the validation statistics in this section are presented separately for non-LQE and LQE-ratings. For LQE-ratings, we only show statistics jointly calculated for public and private ratings in order to increase the number of available ratings.

Year	Upgrades	Downgrades	Unchanged	Default	Sum	Upgrade/ Total Ratio[1]	Changed/ Unchanged Ratio[2]
2002	0	0	2	0	2	0.00	0.00
2003	1	2	1	0	4	0.25	3.00
2004	2	0	6	0	8	0.25	0.33
2005	3	0	6	0	9	0.33	0.50
2006	2	2	5	0	9	0.22	0.80
2007	1	2	5	0	8	0.13	0.60
2008	0	1	3	0	4	0.00	0.33
2009	1	0	4	0	5	0.20	0.25
2010	2	0	8	0	10	0.20	0.25
2011	0	3	6	0	9	0.00	0.50
2012	1	4	6	0	11	0.09	0.83
2013	2	1	10	1	14	0.14	0.30
2014	1	2	13	0	16	0.06	0.23
2015	2	0	17	2	21	0.10	0.12
2016	1	0	19	0	20	0.05	0.05
2017	1	2	24	0	27	0.04	0.13
total	**20**	**19**	**135**	**3**	**177**	**0.11**	**0.29**

Table 2: One-year upgrades and downgrades – public ratings (probability of default-based)

[1] excluding defaults

Year	Upgrades	Downgrades	Unchanged	Default	Sum	Upgrade/ Total Ratio[2]	Changed/ Unchanged Ratio[2]
2002	0	0	2	0	2	0.00	0.00
2003	2	2	1	1	6	0.33	4.00
2004	4	1	7	0	12	0.33	0.71
2005	3	1	8	0	12	0.25	0.50
2006	2	3	8	0	13	0.15	0.63
2007	2	3	8	0	13	0.15	0.63
2008	1	1	3	0	5	0.20	0.67
2009	2	0	6	0	8	0.25	0.33
2010	8	1	18	0	27	0.30	0.50
2011	5	6	16	0	27	0.19	0.69
2012	3	4	10	0	17	0.18	0.70
2013	2	2	17	1	22	0.09	0.24
2014	1	5	24	0	30	0.03	0.25
2015	2	2	26	2	32	0.06	0.15
2016	1	2	29	0	32	0.03	0.10
2017	1	2	34	0	37	0.03	0.09
total	**39**	**35**	**217**	**4**	**295**	**0.13**	**0.34**

Table 3: One-year upgrades and downgrades – public and private ratings (probability of default-based)

Year	Upgrades	Downgrades	Unchanged	Default	Sum	Upgrade/ Total Ratio[3]	Changed/ Unchanged Ratio[4]
2011	1	0	0	0	1	1.00	n/a
2012	0	0	0	0	0	n/a	n/a
2013	0	0	0	0	0	n/a	n/a
2014	0	0	0	0	0	n/a	n/a
2015	0	3	7	0	10	0.00	0.43
2016	0	2	12	0	14	0.00	0.17
2017	0	0	15	0	15	0.00	0.00
total	**1**	**5**	**34**	**0**	**40**	**0.03**	**0.18**

Table 4: One-year upgrades and downgrades – public and private ratings (expected loss-based)

An overall changed/unchanged ratio of 0.29 for public ratings and 0.34 for public and private ratings emphasises the high stability of EHR's ratings. Similar patterns can be observed for expected loss-based ratings.

Tables 5 through 10 show relative and absolute rating transitions of public ratings (probability of default-based) for time horizons ranging from one to three years. Similarly, tables 11 through 22 show relative and absolute rating transitions of public and private ratings (probability of default-based and expected loss-based) for time horizons from one to three years. Please note that relative values refer to actual ratings assigned in the subsequent period. Entities without a rating in the subsequent period (migration to NR) are not considered. As a consequence, relative values for migration to rating categories SD and D do not correspond to default rates. These rating transitions suggest a high degree of rating stability, particularly for investment grade ratings. More information on the calculation of rating transitions is provided in Appendix B.

[2] excluding defaults

[3] excluding defaults

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				100%														
A+				17%	83%													
A						97%	3%											
A-						7%	93%											
BBB+							6%	88%	6%									
BBB								3%	90%	8%								
BBB-									13%	63%	25%							
BB+										22%	44%	22%	11%					
BB												71%	14%		5%		5%	5%
BB-											18%	27%	27%	9%	9%			9%
B+													100%					
B														20%	40%	20%	20%	
B-														50%		50%		
CCC/ C															33%	33%		33%

Table 5: Rating transitions – public ratings (probability of default-based; relative values) – 1 year

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				4														
A+				1	5													
A						32	1											
A-						1	14											
BBB+							1	14	1									
BBB								1	36	3								
BBB-									1	5	2							
BB+										2	4	2	1					
BB												15	3		1		1	1
BB-											2	3	3	1	1			1
B+													4					
B														1	2	1	1	
B-														1		1		
CCC/ C															1	1		1

Table 6: Rating transitions – public ratings (probability of default-based; absolute values) – 1 year

To From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				100%														
A+				25%	75%													
A						97%	3%											
A-						17%	83%											
BBB+							14%	71%	7%	7%								
BBB								7%	90%	3%								
BBB-								17%	17%	17%	17%	17%	17%					
BB+										14%	29%	29%	14%	14%				
BB												53%			27%			20%
BB-												17%	50%	17%				17%
B+											50%		50%					
B													25%			25%	25%	25%
B-																		
CCC/ C																		100%

Table 7: Rating transitions – public ratings (probability of default-based; relative values) – 2 years

To From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				3														
A+				1	3													
A						28	1											
A-						2	10											
BBB+							2	10	1	1								
BBB								2	27	1								
BBB-								1	1	1	1	1	1					
BB+										1	2	2	1	1				
BB												8			4			3
BB-												1	3	1				1
B+											1		1					
B													1			1	1	1
B-																		
CCC/ C																		1

Table 8: Rating transitions – public ratings (probability of default-based; absolute values) – 2 years

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				100%														
A+				33%	67%													
A						96%	4%											
A-						22%	78%											
BBB+							25%	67%	8%									
BBB								4%	78%	9%		4%	4%					
BBB-									20%	20%	20%	40%						
BB+										25%	25%	13%	25%					13%
BB												22%			11%		11%	56%
BB-										17%		33%		17%	17%			17%
B+																		
B													33%					67%
B-																		
CCC/ C																		100%

Table 9: Rating transitions – public ratings (probability of default-based; relative values) – 3 years

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				2														
A+				1	2													
A						23	1											
A-						2	7											
BBB+							3	8	1									
BBB								1	18	2		1	1					
BBB-									1	1	1	2						
BB+										2	2	1	2					1
BB												2			1		1	5
BB-										1		2		1	1			1
B+																		
B													1					2
B-																		
CCC/ C																		1

Table 10: Rating transitions – public ratings (probability of default-based; absolute values) – 3 years

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				100%														
A+				11%	89%													
A						97%	3%											
A-						5%	90%	5%										
BBB+							4%	79%	17%									
BBB								4%	85%	10%		1%						
BBB-									19%	72%	9%							
BB+									7%	27%	27%	27%	13%					
BB									3%	8%	3%	67%	11%		3%		3%	3%
BB-											12%	29%	35%	12%	6%			6%
B+													80%	20%				
B														13%	50%	13%	13%	13%
B-														50%		50%		
CCC/ C															33%	33%		33%

Table 11: Rating transitions – public and private ratings (probability of default-based; relative values) – 1 year

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				4														
A+				1	8													
A						36	1											
A-						1	18	1										
BBB+							1	19	4									
BBB								3	61	7		1						
BBB-									8	31	4							
BB+									1	4	4	4	2					
BB									1	3	1	24	4		1		1	1
BB-											2	5	6	2	1			1
B+													4	1				
B														1	4	1	1	1
B-														1		1		
CCC/ C															1	1		1

Table 12: Rating transitions – public and private ratings (probability of default-based; absolute values) – 1 year

To From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA			100%															
AA-				100%														
A+				13%	75%	13%												
A						94%	3%				3%							
A-						11%	67%	17%	6%									
BBB+							11%	68%	11%	11%								
BBB								5%	82%	9%		2%	2%					
BBB-								3%	27%	53%	7%	3%	7%					
BB+								9%		36%	18%	18%	9%	9%				
BB										8%		42%	8%		17%			25%
BB-											11%	11%	44%	22%				11%
B+											25%		25%					50%
B													17%		17%	17%	17%	33%
B-																		
CCC/ C																		100%

Table 13: Rating transitions – public and private ratings (probability of default-based; relative values) – 2 years

To From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA			2															
AA-				3														
A+				1	6	1												
A						32	1				1							
A-						2	12	3	1									
BBB+							2	13	2	2								
BBB								3	47	5		1	1					
BBB-								1	8	16	2	1	2					
BB+								1		4	2	2	1	1				
BB										2		10	2		4			6
BB-											1	1	4	2				1
B+											1		1					2
B													1		1	1	1	2
B-																		
CCC/ C																		1

Table 14: Rating transitions – public and private ratings (probability of default-based; absolute values) – 2 years

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				100%														
A+				20%	80%													
A						93%	3%					3%						
A-						17%	67%	8%	8%									
BBB+							18%	65%	12%	6%								
BBB								5%	74%	12%		7%	2%					
BBB-									40%	40%	8%	8%						4%
BB+								7%		29%	14%	14%	21%					14%
BB									6%	6%		18%	6%		6%		6%	53%
BB-										20%		20%		10%	10%			40%
B+																		100%
B													25%					75%
B-																		
CCC/ C																		100%

Table 15: Rating transitions – public and private ratings (probability of default-based; relative values) – 3 years

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-				2														
A+				1	4													
A						27	1					1						
A-						2	8	1	1									
BBB+							3	11	2	1								
BBB								2	32	5		3	1					
BBB-									10	10	2	2						1
BB+								1		4	2	2	3					2
BB									1	1		3	1		1		1	9
BB-										2		2		1	1			4
B+																		2
B													1					3
B-																		
CCC/ C																		1

Table 16: Rating transitions – public and private ratings (probability of default-based; absolute values) – 3 years

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/C	SD/D
AAA																		
AA+																		
AA																		
AA-																		
A+																		
A																		
A-							86%	14%										
BBB+								100%										
BBB						14%			86%									
BBB-										80%	20%							
BB+											50%		50%					
BB												50%	50%					
BB-													100%					
B+																		
B																		
B-																		
CCC/C																		

Table 17: Rating transitions – public and private ratings (expected loss-based; relative values) – 1 year

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/C	SD/D
AAA																		
AA+																		
AA																		
AA-																		
A+																		
A																		
A-							6	1										
BBB+								10										
BBB						1			6									
BBB-										4	1							
BB+											2		2					
BB												1	1					
BB-													5					
B+																		
B																		
B-																		
CCC/C																		

Table 18: Rating transitions – public and private ratings (expected loss-based; absolute values) – 1 year

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/C	SD/D
AAA																		
AA+																		
AA																		
AA-																		
A+																		
A																		
A-							80%	20%										
BBB+								100%										
BBB									100%									
BBB-										50%	50%							
BB+											33%		67%					
BB													100%					
BB-													100%					
B+																		
B																		
B-																		
CCC/C																		

Table 19: Rating transitions – public and private ratings (expected loss-based; relative values) – 2 years

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/C	SD/D
AAA																		
AA+																		
AA																		
AA-																		
A+																		
A																		
A-							4	1										
BBB+								6										
BBB									3									
BBB-										1	1							
BB+											1		2					
BB													2					
BB-													2					
B+																		
B																		
B-																		
CCC/C																		

Table 20: Rating transitions – public and private ratings (expected loss-based; absolute values) – 2 years

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-																		
A+																		
A						100%												
A-							100%											
BBB+								75%	25%									
BBB									100%									
BBB-											100%							
BB+													100%					
BB													100%					
BB-																		
B+																		
B																		
B-																		
CCC/ C																		

Table 21: Rating transitions – public and private ratings (expected loss-based; relative values) – 3 years

To / From	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC/ C	SD/ D
AAA																		
AA+																		
AA																		
AA-																		
A+																		
A						1												
A-							2											
BBB+								3	1									
BBB									2									
BBB-											1							
BB+													2					
BB													1					
BB-																		
B+																		
B																		
B-																		
CCC/ C																		

Table 22: Rating transitions – public and private ratings (expected loss-based; absolute values) – 3 years

Non-systemic Deviations

Table 23 shows correlations between the overall economic trend and the annual average probability of default-based ratings as well as annual one-year default rates. It covers the full period from 2002 to 2018. We apply time series of annual GDP growth rates in Germany and the European Union as proxies for economic development. Rating categories are mapped on a numerical scale, ranging from 1 (AAA) to 21 (C). An asterick indicates a correlation being statistically significant at the 10%-level.

Annual average ratings on the aforementioned numerical scale are negatively correlated with GDP, i.e., economic upswings correlate with better ratings, economic downswings correlate with worse ratings. This shows that our ratings capture a significant part of the overall economic conditions. These ratings are, however, not fully correlated with the economic trend. This is in line with the assumption that credit ratings are supposed to be relatively stable over time and do not fully anticipate the economic cycle. This is also underpinned by the analysis of the historical robustness.

Since annual one-year default rates are not significantly correlated with the overall economic trend, we may assume that our rating portfolio does not fully reflect the overall economy. A possible explanation could be that ratings are more likely to be requested by entities, which are comparably strong to withstand economic downturns. This pattern is in line with our rating distributions. The number of investment grade ratings is significantly higher than that of speculative grade ratings.

GDP	Annual average rating (on a numerical scale)	Annual 1y default rate
Germany (annual growth rate)	-0.53*	-0.02
European Union (annual growth rate)	-0.66*	0.19

Table 23: Correlation between economic trend and ratings as well as default rates

Figure 6 shows the evolution of the annual GDP growth in Germany and the European Union as well as the annual average rating.

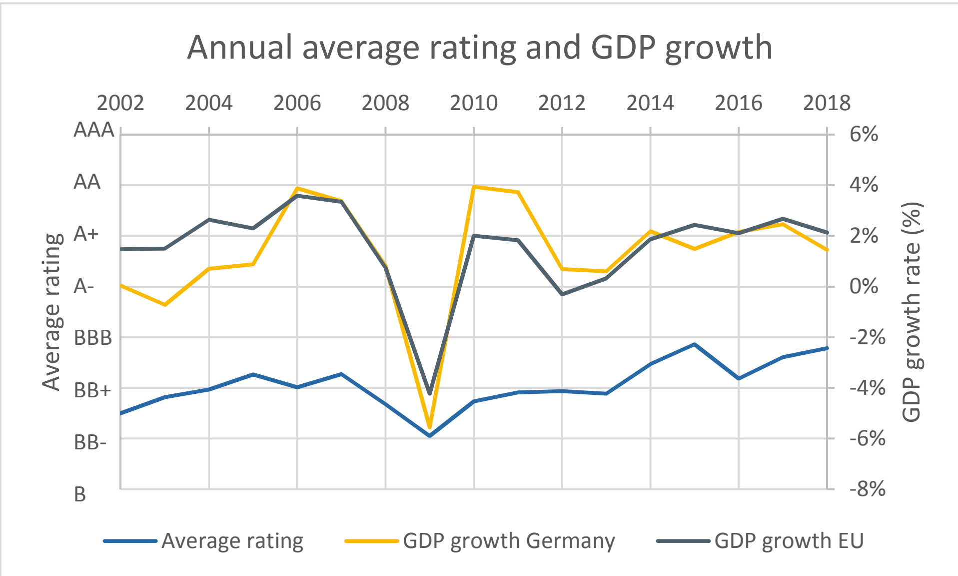

Figure 6: Annual average rating and GDP growth

Critical Thresholds

EHR’s Methodology Review Function has defined critical thresholds, which apply to the various measures presented in the above chapter. The Methodology Review Function deems these thresholds sufficient and appropriate for the purpose of validating EHR’s rating methodologies.

These critical thresholds are currently not met.

If any threshold is met in the future, we will follow our predefined process for reviewing rating methodologies as set out in the EHR-internal guideline on methodology development and review.

SME and MidCap Ratings (**TRIB**Rating)

The SME rating methodologies published under **TRIB**Rating, a brand of Euler Hermes Rating GmbH, are new rating methodologies that apply to non-financial small and medium-sized corporates (SMEs) and MidCaps in Germany, France, Italy, Spain, Switzerland[4], Belgium and Netherlands. These rating methodologies include a scorecard, which is a reference tool that can be used to explain the factors that are generally most important in assigning ratings to SMEs and MidCaps. The scorecard is a summary that does not include every rating consideration: other quantitative or qualitative considerations that may not lend themselves to a presentation in a scorecard format can also affect assigned ratings, as is discussed in the methodology reports, available on our website (www.tribrating.com).

The scorecard contains a grid with three broad factors: two are qualitative, the Sector Profile and Business Profile, and one is quantitative, the Financial Profile. These three broad factors, which have one or more sub-factors, are complemented by four notching adjustments. The financial profile, also referred to as to the financial grid or quantitative grid, comprises several sub-factors, which are all measured using ratios and metrics constructed from an issuer's financial accounts.

Because the SME rating methodologies are new, there is only limited history of assigned credit ratings available to assess these against. In order to validate these rating methodologies, we therefore follow the ESMA guidelines for the validation of methodologies with limited quantitative evidence. Specifically, the validation of these methodologies is based on the use of third party data and hence relies on the data sample used to develop the methodology.

The initial dataset used in the methodology development process for Germany comprised ca. 39,000 distinct German SMEs and MidCaps over the period 2002 to 2015, with sales typically between €10 million and €500 million, and default markers included. The number of distinct companies conditional on these having financial accounts two years prior to default was subsequently reduced to ca. 37,000 and then further reduced to ca. 24,000 in the working sample (by excluding additional SMEs and MidCaps in order to preserve the distribution of the original sample by broad risk categories (as assessed by separate risk measures)).

The initial dataset used in the methodology development process for France comprised ca. 45,000 distinct French SMEs and MidCaps over the period 2007 to 2016, with sales typically between €10 million and €500 million, and default markers included. Conditional on having financial accounts two years prior to default, the number of distinct companies was reduced to ca. 42,000 (working sample).

For Italy, the initial dataset used in the methodology development process comprised ca. 49,500 distinct Italian SMEs and MidCaps over the period 2005 to 2016, with sales typically between €10 million and €500 million, and default markers included. Conditional on having financial accounts two years prior to default, the number of distinct companies was reduced to ca. 45,000 (working sample).

The initial dataset used for Spain comprised ca. 32,000 distinct Spanish SMEs and MidCaps over the period 2005 to 2016, with sales typically between €10 million and €500 million, and default markers included. Conditional on having financial accounts two years prior to default, the number of distinct companies was reduced to ca. 25,500 (working sample).

The initial dataset used for Belgium comprised ca. 21,000 distinct Belgian SMEs and MidCaps over the period 2003 to 2019, with sales typically between €10 million and €500 million, and default markers included. Conditional on having financial accounts two years prior to default, the number of distinct companies was reduced to ca. 20,500 (working sample).

[4] The methodology for Switzerland was built on the basis oft he SME rating methodology for Germany. On the basis of data and statistics from 839 Swiss SMEs with revenues typically between €10 million and €500 million, the applicability of the SME rating methodology for Germany to Switzerland was derived from the comparability of the key financial ratios of the SMEs in these two countires. Thereforе, no specific section on statistics for Swiss SMEs is presented in this report.

The initial dataset used for Netherlands comprised ca. 27,500 distinct Durch SMEs and MidCaps over the period 2003 to 2019, with sales typically between €10 million and €500 million, and default markers included. Conditional on having financial accounts two years prior to default, the number of distinct companies was reduced to ca. 17,000 (working sample).

In order to conduct an out-of-sample robustness test, we further divided each working sample into two-thirds (“in-sample”) and one third (“out-of-sample”).We estimate a two-year probability of default econometric model using the in-sample data separately for each country.[5] This model allows us to select those financial metrics we consider most significant for anticipating defaults[6] in the respective country, and to set their weights (relative importance of each metric in the financial grid) and ranges to score each individual financial metric.

While the SME rating methodologies include both, quantitative and qualitative factors, the historical data analysed here speaks only to the quantitative part, and specifically to the financial component of the scorecard. However, we believe that the financial grid can be used to validate the SME rating methodologies because adding the qualitative layer of the methodology to the financial grid is thought to further improve the methodology’s discriminatory power.

Please note that issuer ratings assigned under **TRIB**Rating are included in the general validation statistics.

Distribution and default rates Germany

As shown in table 35, about one third of the working sample of approximately 24,000 of the German SMEs and MidCaps whose data was used to develop the methodology were scored BBB or higher purely based on the financial profile, which is a key component of the scorecard. The distributions by rating categories were found to be robust, i.e. very similar across the different sub-samples.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	1.2%	1.2%	1.2%
A	8.9%	8.7%	8.8%
BBB	22.3%	22.1%	22.2%
BB	36.5%	37.1%	36.7%
B	27.5%	27.3%	27.4%
CCC or lower	3.6%	3.5%	3.6%

Table 35: Financial scores distribution by broad rating categories

Table 36 presents the two-year cumulative default rates (see Appendix C for a technical description) by broad rating categories derived from the financial profile. Default rates generally increase with lower rating categories derived from the financial profile, indicating that the ratings derived from financial profiles are a good predictor of default risk.[7]

[5] We estimate a two-year rather than a one-year probability of default model to maximise the number of observations, which can be used in the model estimation process and to develop a financial grid, which takes into account long-run rather than short-run effects.
[6] For the purpose of model development, we have built a default indicator that used information on legal bankruptcy as well as specific payment incidents, which together were thought to best approximate default events. For more details on the definition of ratings and default, please see the “Basic Principles for Assigning Credit Ratings and Other Services” available on our website (www.ehrg.de).
[7] The only exception is the AA or higher default rate for the in-sample being higher than the single-A default rate. This is due to the small number of SMEs and MidCaps rated AA or higher.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	0.37%	0.17%	0.30%
A	0.27%	0.55%	0.36%
BBB	0.70%	0.82%	0.74%
BB	2.02%	2.11%	2.05%
B	4.78%	4.62%	4.73%
CCC or lower	10.04%	10.64%	10.24%

Table 36: Two-year cumulative default rates by broad rating categories derived from financial profiles

Distribution and default rates France

As shown in table 37, about one quarter of the working sample of approximately 42,000 of the French SMEs and MidCaps whose data was used to develop the methodology were scored BBB or higher purely based on the financial profile, which is a key component of the scorecard. The distributions by rating categories were found to be robust, i.e. very similar across the different sub-samples.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	0.2%	0.2%	0.2%
A	3.5%	3.6%	3.5%
BBB	18.5%	18.8%	18.6%
BB	41.1%	40.8%	41.0%
B	29.3%	29.5%	29.4%
CCC or lower	7.2%	7.0%	7.2%

Table 37: Financial scores distribution by broad rating categories

Table 38 presents the two-year cumulative default rates (see Appendix C for a technical description) by broad rating categories derived from the financial profile. Default rates generally increase with lower rating categories derived from the financial profile, indicating that the ratings derived from financial profiles are a good predictor of default risk.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	0.00%	0.00%	0.00%
A	0.28%	0.47%	0.34%
BBB	0.78%	0.80%	0.78%
BB	1.87%	1.80%	1.85%
B	4.91%	4.83%	4.88%
CCC or lower	10.61%	10.41%	10.54%

Table 38: Two-year cumulative default rates by broad rating categories derived from financial profiles

Distribution and default rates Italy

As shown in table 39, about one third of the working sample of approximately 45,000 of the Italian SMEs and MidCaps whose data was used to develop the methodology were scored BBB or higher purely based on the financial profile, which is a key component of the scorecard. The distributions by rating categories were found to be robust, i.e. very similar across the different sub-samples.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	1.4%	1.4%	1.4%
A	9.6%	9.5%	9.6%
BBB	19.5%	19.6%	19.5%
BB	36.9%	37.5%	37.1%
B	29.6%	29.1%	29.4%
CCC or lower	3.0%	2.8%	2.9%

Table 39: Financial scores distribution by broad rating categories

Table 40 presents the two-year cumulative default rates (see Appendix C for a technical description) by broad rating categories derived from the financial profile. Default rates generally increase with lower rating categories derived from the financial profile, indicating that the ratings derived from financial profiles are a good predictor of default risk.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	0.00%	0.00%	0.00%
A	0.16%	0.13%	0.15%
BBB	0.27%	0.30%	0.28%
BB	1.03%	0.90%	0.99%
B	3.77%	3.39%	3.64%
CCC or lower	22.15%	18.76%	21.02%

Table 40: Two-year cumulative default rates by broad rating categories derived from financial profiles

Distribution and default rates Spain

As shown in table 41, about one third of the working sample of approximately 25,500 of the Spanish SMEs and MidCaps whose data was used to develop the methodology were scored BBB or higher purely based on the financial profile, which is a key component of the scorecard. The distributions by rating categories were found to be robust, i.e. very similar across the different sub-samples.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	1.2%	1.3%	1.2%
A	9.7%	9.9%	9.8%
BBB	20.2%	20.2%	20.2%
BB	33.6%	32.8%	33.3%
B	20.2%	20.7%	20.4%
CCC or lower	5.1%	5.1%	5.1%

Table 41: Financial scores distribution by broad rating categories

Table 42 presents the two-year cumulative default rates (see Appendix C for a technical description) by broad rating categories derived from the financial profile. Default rates generally increase with lower rating categories derived from the financial profile, indicating that the ratings derived from financial profiles are a good predictor of default risk.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	0.00%	0.00%	0.00%
A	0.34%	0.18%	0.29%
BBB	0.44%	0.55%	0.48%
BB	1.90%	1.80%	1.86%
B	6.84%	6.58%	6.75%
CCC or lower	20.04%	19.53%	19.87%

Table 42: Two-year cumulative default rates by broad rating categories derived from financial profiles

Distribution and default rates Belgium

As shown in table 43, about one third of the working sample of approximately 20,500 of the Belgian SMEs and MidCaps whose data was used to develop the methodology were scored BBB or higher purely based on the financial profile, which is a key component of the scorecard. The distributions by rating categories were found to be robust, i.e. very similar across the different sub-samples.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	2.4%	2.2%	2.4%
A	13.6%	13.8%	13.7%
BBB	22.9%	23.7%	23.2%
BB	33.6%	33.6%	33.6%
B	24.8%	24.2%	24.6%
CCC or lower	2.6%	2.5%	2.6%

Table 43: Financial scores distribution by broad rating categories

Table 44 presents the two-year cumulative default rates (see Appendix C for a technical description) by broad rating categories derived from the financial profile. Default rates generally increase with lower rating categories derived from the financial profile, indicating that the ratings derived from financial profiles are a good predictor of default risk.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	0.00%	0.12%	0.00%
A	0.12%	0.12%	0.12%
BBB	0.39%	0.31%	0.35%
BB	1.14%	1.22%	1.13%
B	3.88%	4.19%	3.86%
CCC or lower	12.65%	12.62%	12.30%

Table 44: Two-year cumulative default rates by broad rating categories derived from financial profiles

Distribution and default rates Netherlands

As shown in table 45, about one third of the working sample of approximately 17,000 of the Dutch SMEs and MidCaps whose data was used to develop the methodology were scored BBB or higher purely based on the financial profile, which is a key component of the scorecard. The distributions by rating categories were found to be robust, i.e. very similar across the different sub-samples.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	0.8%	0.7%	0.8%
A	6.9%	6.8%	6.9%
BBB	24.6%	24.3%	24.5%
BB	39.5%	39.7%	39.6%
B	23.6%	23.6%	23.6%
CCC or lower	4.4%	4.5%	4.4%

Table 45: Financial scores distribution by broad rating categories

Table 46 presents the two-year cumulative default rates (see Appendix C for a technical description) by broad rating categories derived from the financial profile. Default rates generally increase with lower rating categories derived from the financial profile, indicating that the ratings derived from financial profiles are a good predictor of default risk.

Broad rating category	In-sample	Out-of-sample	In- and out-of-sample
AA or higher	0.00%	0.00%	0.00%
A	0.24%	0.80%	0.38%
BBB	0.72%	0.84%	0.69%
BB	1.75%	1.88%	1.62%
B	3.88%	3.43%	3.31%
CCC or lower	10.14%	8.24%	8.53%

Table 46: Two-year cumulative default rates by broad rating categories derived from financial profiles

Discriminatory power

To further assess how the financial profiles rank-order default risk, we calculate the average defaulter position (AP; see Appendix D for a technical description), which is a widely used measure of the discriminatory power of rating models. By this measure, the typical German SME and MidCap defaulter within the sample carried a lower financial profile than 74% of all other sampled SMEs and MidCaps, two years in advance of default. This is true across the three samples. The average position for France is 73% across the three samples, and 80% for Italy, 78% for Spain, 80% for Belgium and 71% for Netherlands. Adding the qualitative layer of the methodology to the financial profile is thought to further improve the methodology's discriminatory power.

Appendix A: Receiver Operator Characteristic

In order to calculate the Receiver Operator Characteristic (ROC) for probability of default-based ratings, rated entities are rank-ordered according to their assigned ratings from lowest to highest. For every rating category, two key figures are calculated: Sensitivity and Specificity. Sensitivity refers to the ratio of defaults in a specific rating category plus defaults in lower rating categories over all defaults in a certain time horizon (hit rate). Specificity is the ratio of non-defaulted entities with a better rating than that specific rating category over all non-defaulted entities in that time horizon. The ROC curve plots the cumulated values of Sensitivity over (1-Specificity).

A perfect rating model would assign exclusively the lowest rating category to entities with a future default status while it would assign exclusively the highest rating category to entities with a future non-default status. Figure 10 shows the theoretical ROC curve (blue line). On the other hand, a rating methodology assigning ratings randomly would result in a ROC curve illustrated in orange.

Additionally, the Area under Curve (AUC) is calculated in order to demonstrate the discriminatory power as a single performance measure. It is defined as the area under the (actual) ROC curve. As a consequence, the AUC can range between 0 and 1, with values above 0.5 suggesting for a reasonable rating model. Higher values correspond to higher discriminatory power.

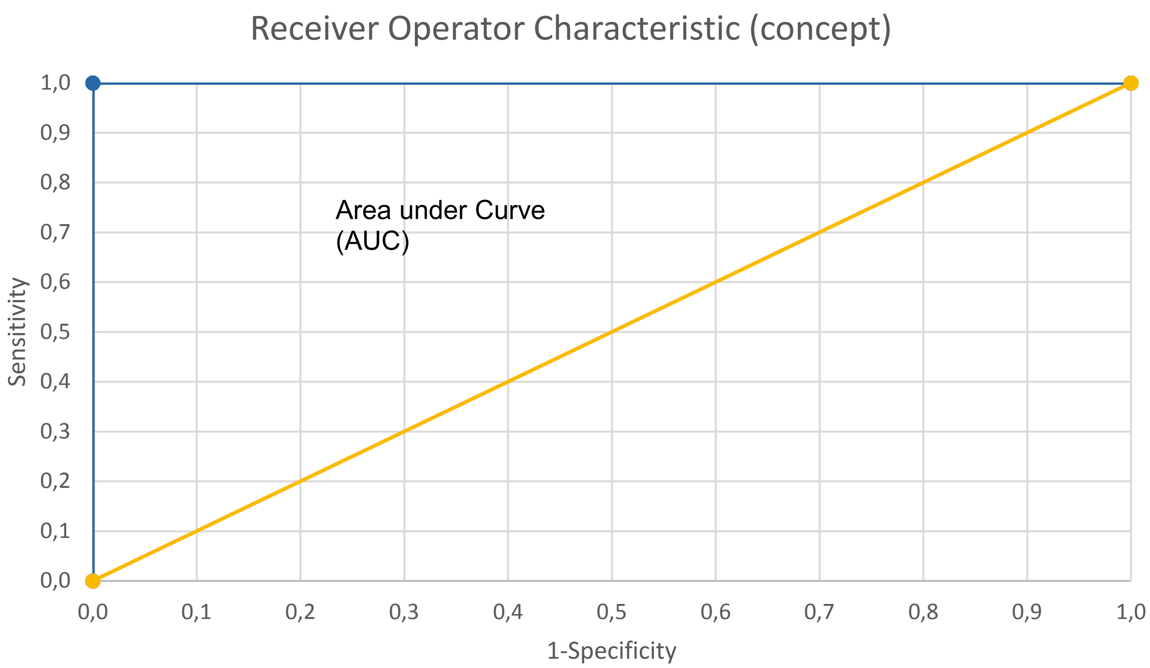

Figure 10: Receiver Operator Characteristic (concept)

Appendix B: Rating transitions

Rating transitions for certain time horizons are calculated based on the rating change between two given points in time. We use the rating at the end of a calendar year as a reference point for the assigned rating for that corresponding year. As a result, any changes that may occur during a year are not taken into account for calculating transition rates as the relevant rating is the end of year rating.

For example, if a rated entity is assigned a BB- rating in March 2014, and no rating update changed the rating during 2014, we assume the 2014 end of year rating to be BB-. If there is a rating upgrade in February 2015 to BB and another upgrade takes place in December 2015, assigning a BB+ rating, the 2015 end of year rating would be BB+. This results in a one-year rating transition from BB- to BB+.

Appendix C: Cumulative default rates

Cumulative default rates are calculated by averaging the default experience of cohorts made up of rated entities formed at yearly frequencies throughout the study period. The average cumulative default rate tells us the historically-observed probability of default for an entity within a particular rating category that would have otherwise remained outstanding during a specified length of time.

Appendix D: Average Position

We define the position of any entity in a given cohort as the share of entities rated equal to or better than it, assuming each entity occupies the midpoint of its rating category. The average position (AP) is simply the average position of the defaulted entities. Intuitively, a more powerful rating system should have low-rated defaulters and high-rated non-defaulters, meaning the average position of defaulters should be high for an effective rating system. AP is bounded between 0% and 100%, with 100% indicating perfect sorting power, 50% indicating no power and 0% indicating perfectly negative power.

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