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Report 2020

MORE Score methodology

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Executive summary

The present report contains the annual validation of MORE Score methodology carried out under Section B of Chapter IV of modefinance Policies and Procedures.

The validation team, as notified to Mr. Zorzi on 14 May 2021, is the following:

- Ms. Lucia Parussini, Responsible of Review
- Mr. Andrea Sorrentino, Responsible of Quantitative and Development Function
- Mr. Simone Ziraldo, Responsible of IT Function.

The purpose of validation process is to demonstrate the discriminatory power, predictive power and historical robustness of MORE Score methodology.

According to modefinance Policies and Procedures, all relevant information have been collected concerning the credit assessment referred to the period 2016-2020. Also the financial information have been collected about the defaulted companies, where modefinance definition of default is: “Company for which missed payments on a financial obligation are officially recorded, or under administration status or under bankruptcy”. It is not compelled to verify the reliability of quantitative and qualitative data to which the methodology has been applied because the data are provided by policy certified institution.

Only scores with confidence level higher than 80% have to be taken into account in validation process according to modefinance Policies and Procedures. This confidence level, as specified in MORE methodology document, does not indicate financial confidence of the company; but it is a reflection of the variations in availability of financial data, and suggests the degree of financial detail the MORE evaluation is able to take into account for each company.

Between 2016 and 2020, 3,642,050 companies have been evaluated by MORE Score methodology with confidence level higher than 80%. At May 2021, it turns out that 82,289 of these companies have gone into default during this period. A validation set of 315,536 companies has been singled out, with 7,511 defaults. The details, on how the validation set has been defined, are given in the next Section.

Validation

It was verified the transparency and completeness of the methodology’s documentation available at https://cra.modefinance.com/en/methodologies, which is updated to July 2017.

It was verified the measures taken to ensure quality and to cleanse raw data. No MORE score has been issued for unbalanced financial statements. Unknown financial data were computed from known financials, when possible.

It was not received reports of anomalous behavior by rating analysts who daily use the methodology under validation.

In order to single out the validation set, the companies evaluated by MORE Score methodology with confidence level higher than 80% between 2016 and 2020 have been analyzed. Several aspects are considered:

- geographical coverage: the most of companies (86%) are European;
- size: the most of companies are micro (79%) and small (13%) sized enterprises, where the definition used is
  - micro sized enterprise: operating revenue less than 2,000 th EUR,
  - small sized enterprise: operating revenue more than 2,000 th EUR and less than 10,000 th EUR,
  - medium sized enterprise: operating revenue more than 10,000 th EUR and less than 50,000 th EUR,
  - large sized enterprise: operating revenue more than 50,000 th EUR;
- activity sector: the most of companies are in Commerce (51%), Services (49%) and Industrial (25%) sectors (the activity sectors are aggregations of NACE Rev.2 codes);
- MORE Score: for the last available scoring year, the most of non-defaulted companies are in classes A, BBB, BB and B (78% of non-defaulted companies), the most of defaulted companies are in classes CCC, CC, C and D (69% of defaulted companies).

Figures 1 and 2 illustrate the distributions of companies respect to these aspects, for the last available scoring year.

In the analyzed set of companies, non-defaulted ones have available financial accounts for each year between 2015 and 2019 and every year between 2016 and 2020 they have been assessed by MORE Score methodology. The defaulted companies have available financial accounts for at least one year between 2015 and 2019 and between 2016 and 2020 they have been assessed by MORE Score methodology at least once.

The validation set, smaller than the available set of companies, has been chosen so to have similar distributions per geographical area, per size, per activity sector and per MORE Score, in order to be representative of the entire set. Being European the most of scored companies, in the validation set there are only European companies. The discriminatory power, predictive power and historical robustness of MORE Score methodology, have been evaluated on this validation set.

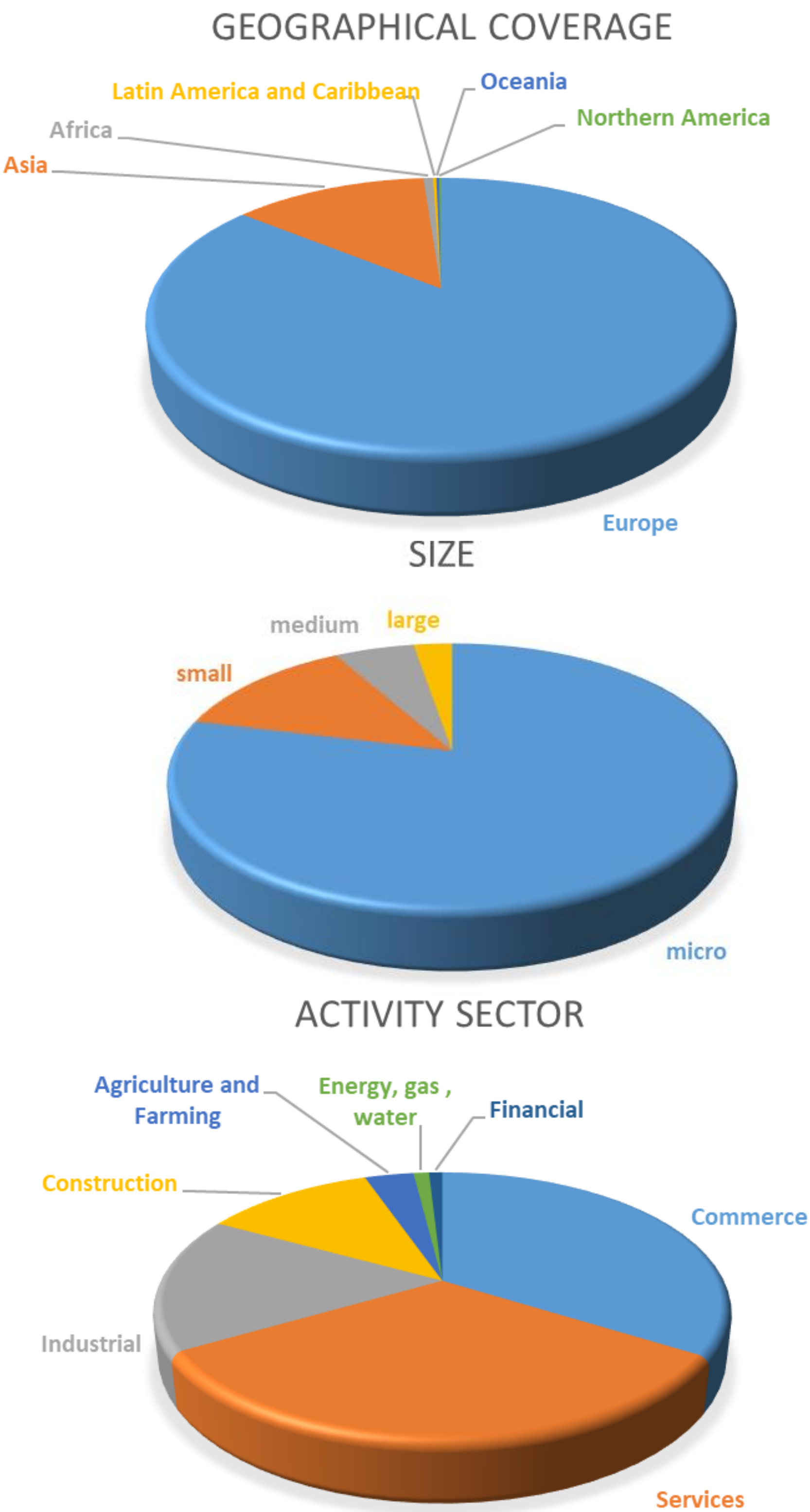
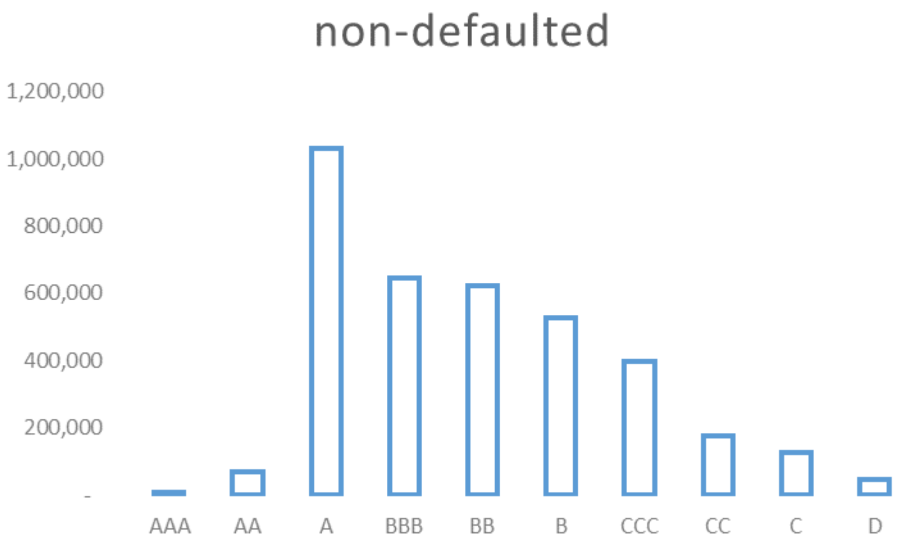


Figure 1 The observed distribution of the companies evaluated by MORE Score methodology with confidence level higher than 80% between 2016 and 2020 per major geographical areas, per size and per activity sector.



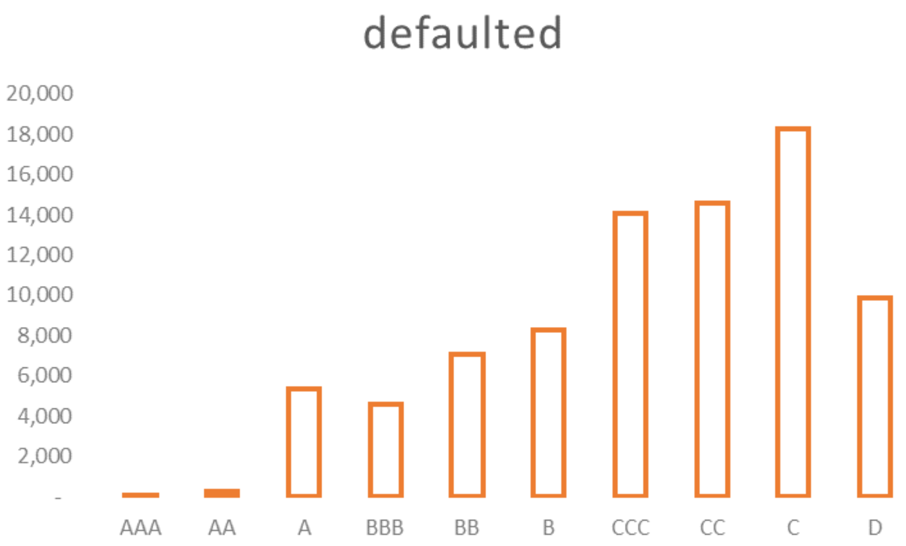


Figure 2 The observed distribution of the companies evaluated by MORE Score methodology with confidence level higher than 80% between 2016 and 2020 per last available MORE Score distinguishing between non-defaulted and defaulted companies.

The same analysis has been carried out on the set of Italian companies with turnover higher the 20,000 th EUR, which have been assessed by MORE Score methodology every year between 2016 and 2020 for non-defaulted ones and at least once between 2016 and 2020 for defaulted ones. These companies, having confidence level higher than 80%, are 15,747. At May 2021, 352 of these companies have gone into default. The companies of this set are medium sized (57%) and large sized (43%) enterprises. The most of companies are in Industrial (43%), Commerce (31%) and Services (17%) sectors, as shown in Figure 3. For the last available scoring year, the most of non-defaulted companies are in classes A, BBB, BB and B (79.0% of non-defaulted companies) and the most of defaulted companies are in classes B, CCC, CC, C and D (85.5% of defaulted companies), as shown in Figure 4.

The choice to analyze this second set of companies is due to the fact that the information on default is not mandatory, and therefore not available, in all countries. For Italian companies this information is available. Moreover, the expected long run three-year default rate has been computed on a set of companies similar to this one, that is: companies based in Italy with at least 20,000 th EUR of turnover in the most recent financial statements disclosed; companies defaulted during 2016, 2015 or 2014; non-defaulted companies, active and for which financial statements were disclosed for fiscal years: 2013, 2014, 2015.

From now on, the first validation set, which is representative of the entire set of scored companies, will be named set A; the second validation set, for which a reliable information on defaults is available, will be named set B.

The analyzed time horizons will be short term (1 year), medium term (3 years) and long term (5 years), if not otherwise specified. For 1-year time horizon, MORE Scores assessed in 2020, based on financial statements disclosed for fiscal year 2019, and the defaults during 2020 are considered. For 3-year time horizon, MORE Scores assessed in 2018, based on financial statements disclosed for fiscal year 2017, and the defaults during 2018, 2019, 2020 are considered. For 5-year time horizon, MORE Scores assessed in 2016, based on financial statements disclosed for fiscal year 2015, and the defaults during 2016, 2017, 2018, 2019, 2020 are considered.

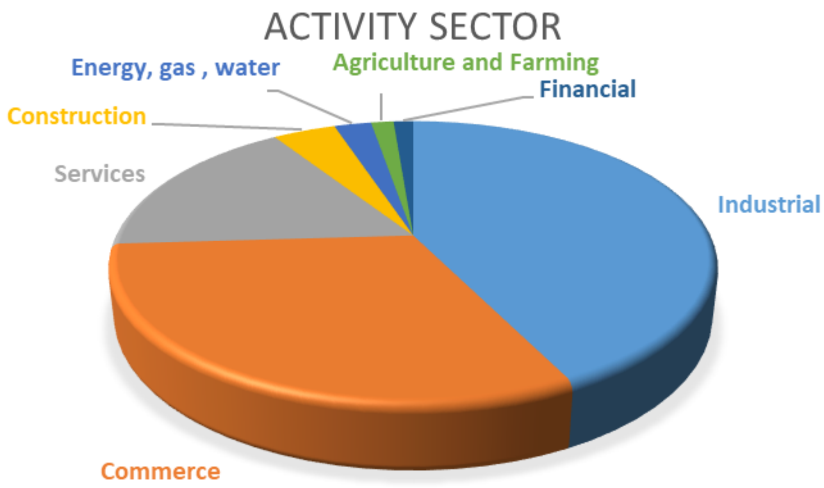
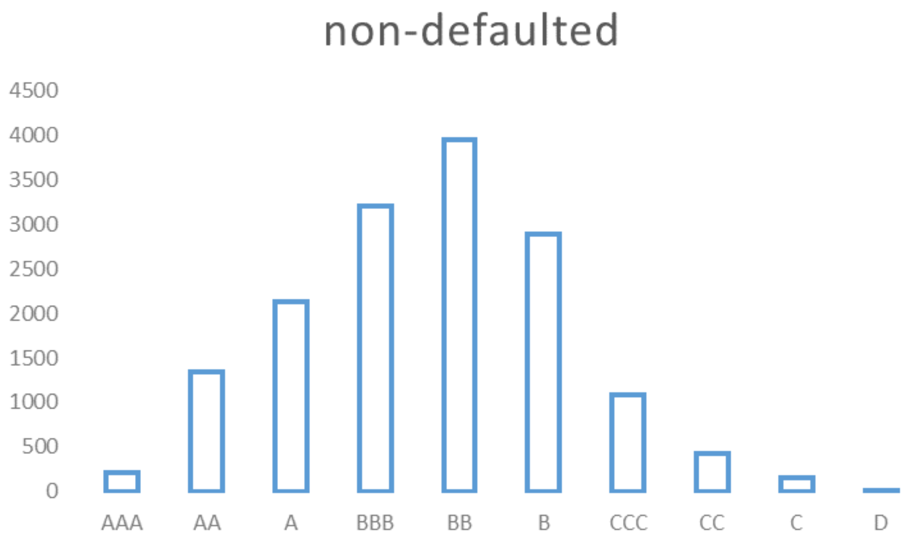


Figure 3 The observed distribution of the Italian companies with turnover higher than 20,000 th EUR evaluated by MORE Score methodology with confidence level higher than 80% between 2016 and 2020 per activity sector.



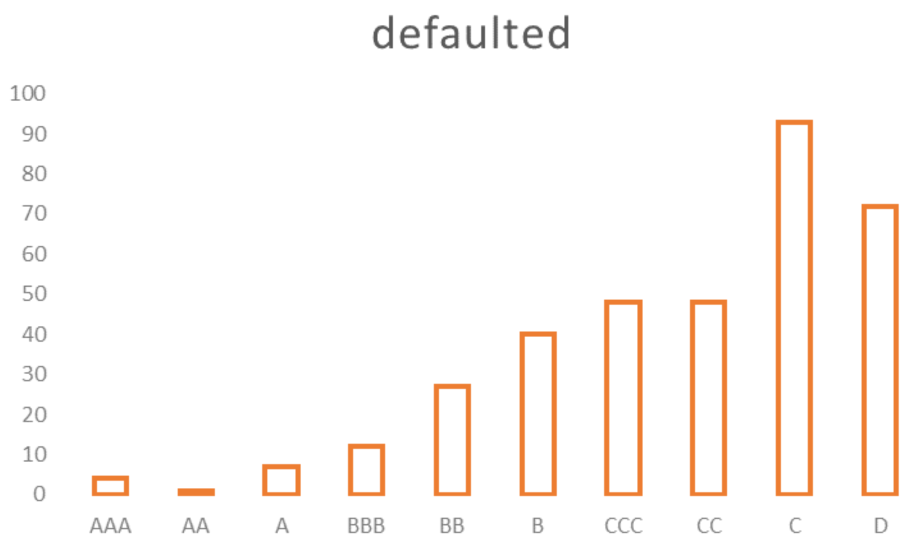


Figure 4 The observed distribution of the Italian companies with turnover higher than 20,000 th EUR evaluated by MORE Score methodology with confidence level higher than 80% between 2016 and 2020 per last available MORE Score distinguishing between non-defaulted and defaulted companies.

Discriminatory power

The discriminatory power, which denotes the ability of the methodology to discriminate ex ante between defaulted and non-defaulted companies, is demonstrated using CAP/AUC/Gini models, Kolmogorov-Smirnov statistic and the distribution of the observed default rates considering multiple time horizons: short term (1 year), medium term (3 years) and long term (5 years).

Figure 5 shows the observed CAP (Cumulative Accuracy Profile) model of set A and set B for the analyzed time horizons. In these figures, if the curve of the observed current model follows the straight line from lower left to upper right, then the methodology cannot differentiate between defaulted and non-defaulted companies, i.e. it is a random model. If the curve tends to bend to the upper left, then the model can differentiate the actual defaulted and non-defaulted companies. Analyzing the validation sets, for 1-year time horizon the current model is clearly distant from the random model and tends to the optimal one. As expected, the longer the time horizon is, the less the current model tends to the optimal model. Let us notice that the stepwise trend of curves for set B depends on the low numbers of companies, in particular the defaulted ones.

The AR (Accuracy Ratio), or Gini coefficient, is defined as the ratio of the area between the CAP of the current model and the CAP of the random model and the area between the CAP of the optimal model and the CAP of the random model. AR has a value between 0% and 100%, where 0% indicates that the model performs equal to the random model and 100% indicates the model performs perfect. The Area Under the Curve (AUC) has a similar meaning. When the value of AUC is 50%, the model makes random evaluations. When the value of AUC is 100%, this indicates that the evaluations are perfect.

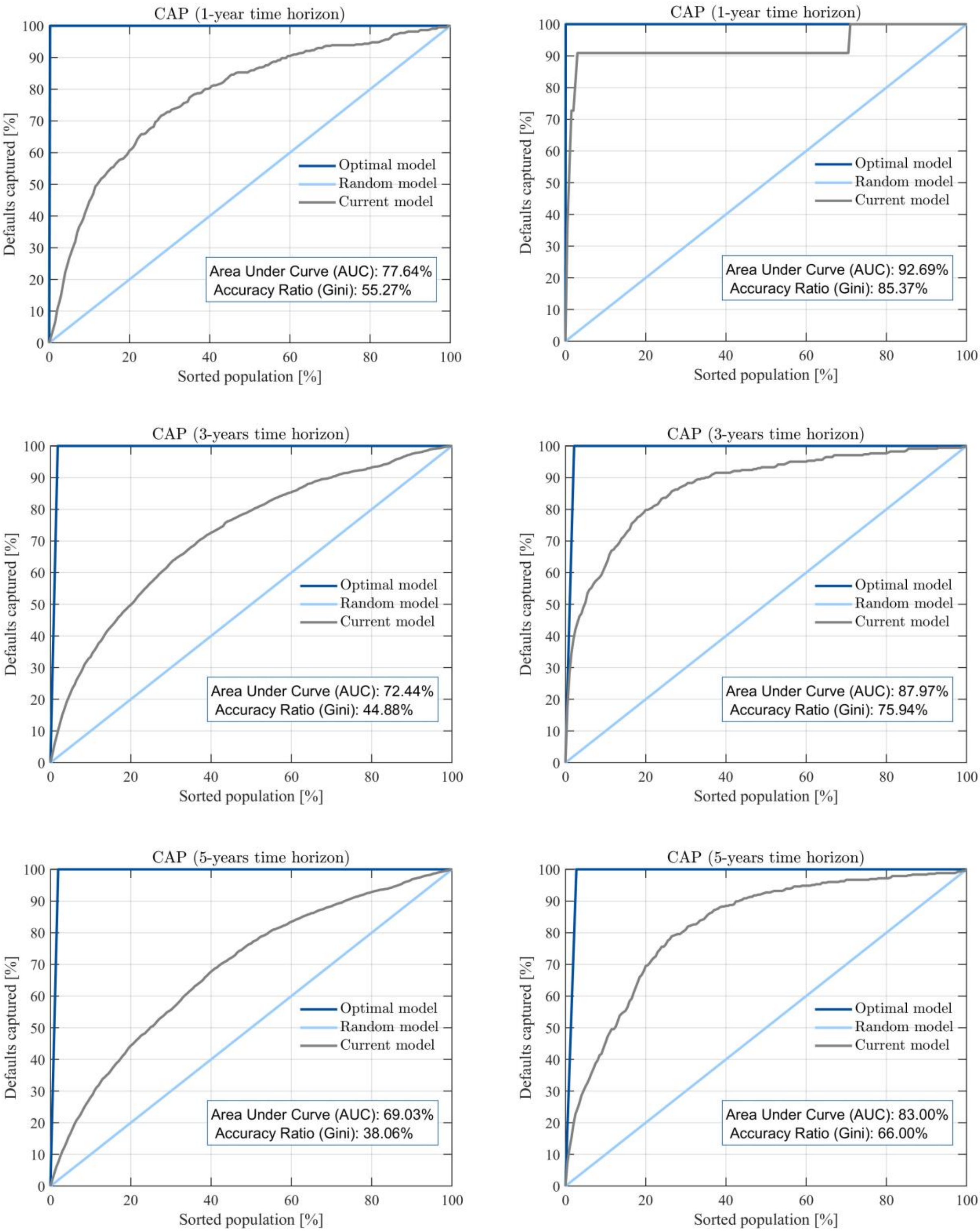
For the MORE Score model, the values of AR and AUC are reported in Table 1 for the validation set A and in Table 2 for the validation set B. The values computed on set A are extremely good for a methodology based only on financial data and a validation set where the most of companies are micro and small sized enterprises, which In general exhibit very volatile financial trends. The observed AUC and AR of the set B, made up of medium and large sized enterprises, are constantly higher than those of set A. So much so that AUC and AR computed on 5-years time horizon for set B are very close to those computed on 1-year time horizon for set A. Certainly, this shows that that the larger the companies the more discriminatory the MORE Score model is. But it should be borne in mind that the information on defaults may be incomplete for set A (information is not available in all countries) and this justifies the better discriminatory performance on set B. The analysis confirms, however, a good discriminatory power.

Table 1 Observed AUC, AR and k-statistic values for the validation set A with different time horizons.

time horizon	*1 year*	*3 years*	*5 years*
AUC %	77.64	72.44	69.03
AR %	55.27	44.88	38.06
k statistic %	43.99	33.99	28.46

Table 2 Observed AUC, AR and k-statistic values for the validation set B with different time horizons.

time horizon	*1 year*	*3 years*	*5 years*
AUC %	92.69	87.97	83.00
AR %	85.37	75.94	66.00
k statistic %	87.99	61.20	54.02



a) set A   b) set B

Figure 5 Observed CAP model for discriminatory power evaluation of MORE Score methodology with different time horizons.

The discriminatory power of MORE Score is confirmed by Kolmogorov-Smirnov test, too. The two-sample Kolmogorov-Smirnov test is computed to verify whether the MORE scores of defaulted and the MORE scores of non-defaulted companies come from the same distribution. The Kolmogorov–Smirnov statistic quantifies the distance between the empirical distribution functions of the two samples. The null distribution of this statistic is calculated under the null hypothesis that the samples are drawn from the same distribution. The decision to reject the null hypothesis is based on comparing the asymptotic *p*-value with the significance level α=5%. When $p < \alpha$, then the null hypothesis is rejected, that means the two data samples are from different distributions. The asymptotic *p*-value becomes very accurate for large sample sizes, and is believed to be reasonably accurate for sample sizes n_1 and n_2, such that $(n_1 * n_2)/(n_1 + n_2) \geq 4$, which is satisfied by the samples we have to test. Asymptotic *p*-value obtained by the Kolmogorov-Smirnov test on MORE Score is 0 for all the three different time horizons under analysis. This means that the two tested samples, scores of defaulted and non-defaulted companies, come from different distributions and the methodology is discriminant. The test statistic k values are reported in Table 1 for set A and Table 2 for set B. In Figure 6, the cumulative distribution functions of MORE scores are plotted for defaulted and non-defaulted companies for 1-year, 3-years and 5-years time horizon.

In Figure 7, the MORE score distributions of defaulted and non-defaulted companies of both validation sets are represented, where the discriminatory power of the methodology is evident, especially for short and medium term time horizons. Observing the score distribution of non-defaulted companies of set A, a strange squashing of scores toward class A from classes AAA and AA can be noticed. This behavior is due to the fact that the most of the companies in the validation set are micro and small sized companies and the MORE Score model include a constraint on the maximum score class issued for micro sized enterprises, which is A. Moreover, for these companies, the creditworthiness, is more influenced by non financial factors than for larger companies. That can be conditioned by different dynamics, such as governance experience, less organized management, usually very short time planning, and so on. Larger companies have more inertia and, as a consequence, their health status too.

The MORE score distributions of defaulted and non-defaulted companies of set B are evidently closer to skew normal distributions and, reducing the time horizon, the distribution of non-defaulted moves toward healthier classes and the distribution of defaulted moves toward riskier classes.

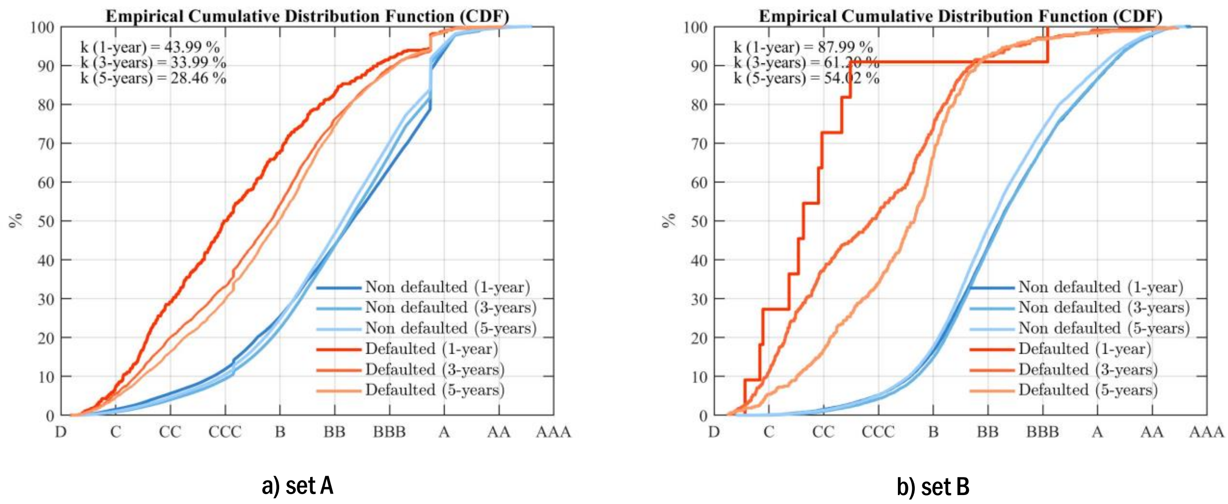


Figure 6 Test statistic k of Kolmogorov-Smirnov test for the discriminatory power evaluation of MORE Score methodology for the three years time horizons under analysis.

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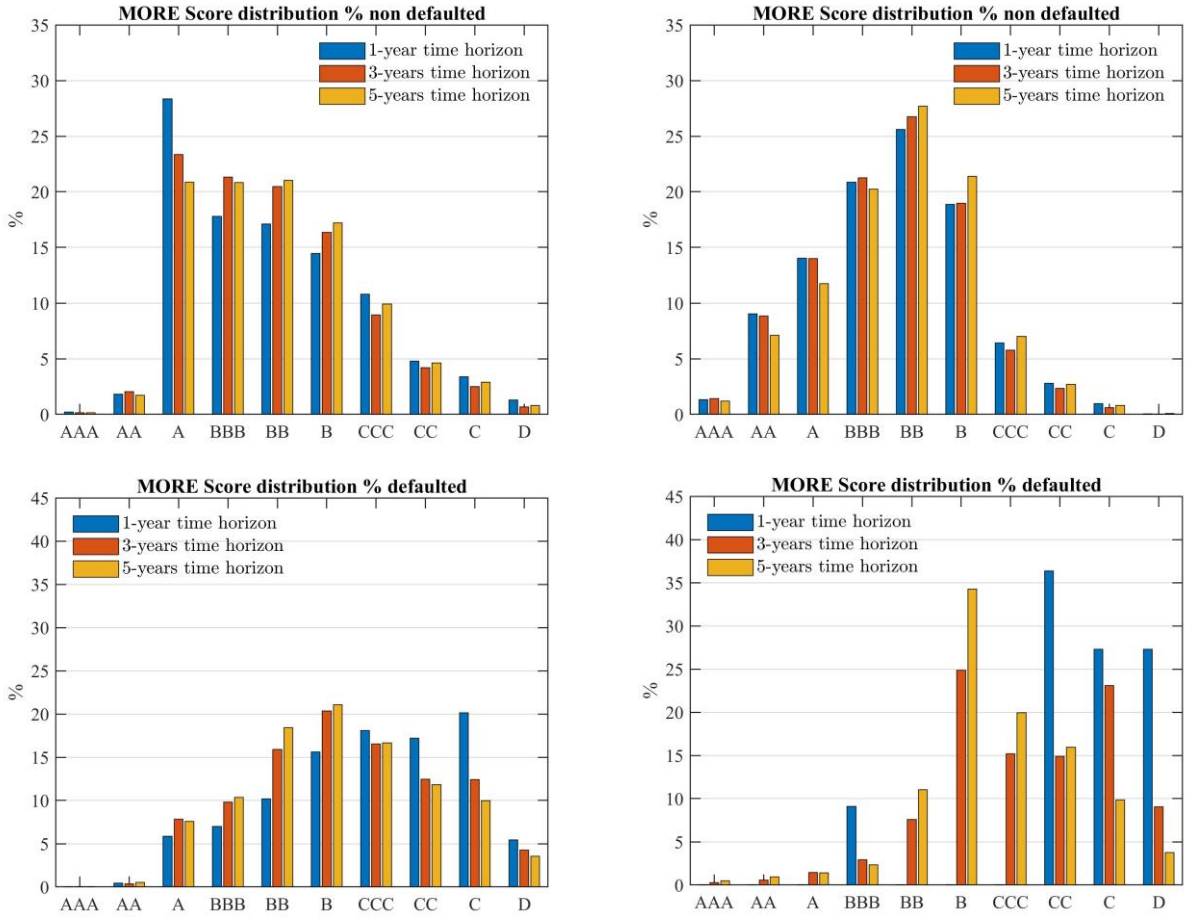

a) set A b) set B

Figure 7 MORE distribution for non-defaulted and defaulted companies of validation set with different time horizons.

Predictive power

To demonstrate the predictive power of the methodology, the expected long run three-year probabilities of default were compared to the observed default rates using the binomial test, the chi-square test and the Brier score. The expected probabilities of default are declared in modefinance Policies and Procedures and are reported in Table 3.

In Tables 4 and 5 there are the distributions of the observed default rates for the validation samples. They are plotted in Figure 8, together with the expected default rates.

There is presence of a defaulted company in class AAA in both validation sets. These companies have been individually analyzed, in particular their financial accounts. According to the officially filed accounts, it was impossible to anticipate a default, as they look quite sound. So these anomalies do not depend on malfunction of the MORE Score model.

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Table 3 Expected long run three-year default rates declared in modefinance Policies and Procedures.

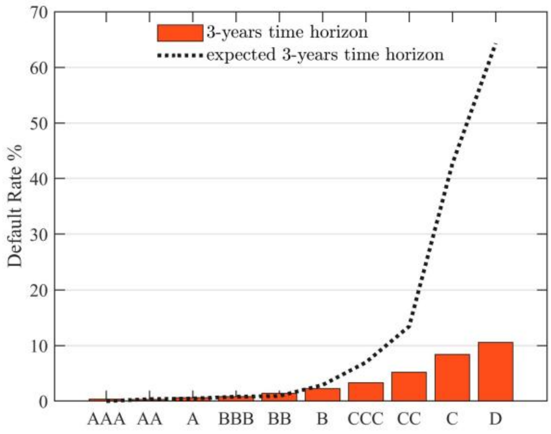
MORE	*RATING*	*Expected long run three-year default rate*
AAA	A1	0.00%
AA	A2+ A2 A2-	0.36%
A	A3+ A3 A3-	0.47%
BBB	B1+ B1 B1-	0.80%
BB	B2+ B2 B2-	0.92%
B	B3+ B3 B3-	2.91%
CCC	C1+ C1 C1-	6.97%
CC	C2	13.44%
C	C3	42.69%
D	D E F G	64.29%

Table 4 Observed default rates in validation set A.

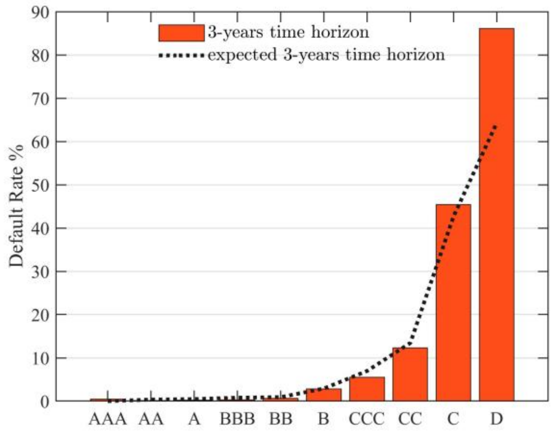
MORE	*AAA*	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*D*
non defaulted	258	3706	42188	38547	37005	29579	16164	7563	4532	1213
defaulted	1	12	262	329	533	682	554	417	415	143
observed long-run 3 year default rates %	0.39	0.32	0.62	0.85	1.42	2.25	3.31	5.23	8.39	10.55

Table 5 Observed default rates in validation set B.

MORE	*AAA*	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*D*
non defaulted	221	1361	2153	3271	4115	2920	887	362	95	5
defaulted	1	2	5	10	26	85	52	51	79	31
observed long-run 3 year default rates %	0.45	0.15	0.23	0.30	0.63	2.83	5.54	12.35	45.40	86.11



a) set A



b) set B

Figure 8 Observed default rates in validation sets.

The binomial test allows to evaluate if the observed defaults are significantly different from the expected for each class of MORE Score. The results of the binomial test, with null hypothesis H_0: observed default rate equal to expected default rate, and the alternative hypothesis H_1: observed default rate not equal to expected default rate, are reported in Tables 6 and 7.

Being the observed default rate for MORE Score AAA equal to 0%, the classes AAA and AA have been gathered. The null hypothesis has to be rejected if p-value <α or, equivalently, if test statistic $|z|>|z_{\alpha/2}|$ with significance level α. For the validation set, the null hypothesis has to be rejected with a significance level of 5% ($|z_{\alpha/2}|$=1.96) for those MORE Score classes, where the two tailed p-value is lower than 0.05, as highlighted in red in Tables 6 and 7. Let us notice that for validation set B, the default rates are very close to those expected, having the validation set the same characteristics as the sample used for the calculation of the expected long run three-year probabilities of default.

Table 6 Binomial test statistics for predictive power evaluation of MORE Score methodology on the validation set A.

Binomial-test	*AAA-AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*D*
test statistic	-0.14	4.36	1.00	10.14	-6.79	-18.54	-21.51	-48.76	-41.29
two-tailed p-value	1.000	0.000	0.305	0.000	0.000	0.000	0.000	0.000	0.000
one-tailed p-value	0.427	0.000	0.146	0.000	1.000	1.000	1.000	1.000	1.000

Table 7 Binomial test statistics for predictive power evaluation of MORE Score methodology on the validation set B.

Binomial-test	*AAA-AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*D*
test statistic	-0.67	-1.43	-3.05	-1.87	-0.16	-1.61	-0.65	0.69	2.60
two-tailed p-value	0.502	0.150	0.001	0.050	0.870	0.107	0.518	0.444	0.005
one-tailed p-value	0.735	0.933	1.000	0.975	0.558	0.949	0.738	0.199	0.001

Even the one-tail test has been performed, with null hypothesis H_0: observed default rate equal or less than expected default rate, and the alternative hypothesis H_1: observed default rate greater than expected default rate. The null hypothesis has to be rejected if p-value <α or, equivalently, if test statistic $z > z_{1-\alpha}$ with significance level α, where, for α=0.05, $z_{1-\alpha}$ =1.65. For the validation set A, the null hypothesis is not rejected for the most of MORE Score classes, in particular the risky classes. This means the observed default rates are smaller than the expected default rates for all classes and a company risks default less than claimed by the methodology. This behavior is overly prudent, which is obviously preferable than an indulgent evaluation of credit risk. For the validation set B, the null hypothesis is not rejected for all MORE Score classes, except class D. This means for this class the observed default rate is greater than the expected default rate with a probability of 99.9%.

The binomial test can be applied to one score class at a time only. To check several score categories simultaneously, the chi-square (Hosmer-Lemeshow) test is applied. This test is based on the assumptions of independence, normal approximation and sample size large enough. The closer the p-value is to zero, the worse the estimation is.
In Tables 8 and 9 the results of the chi-square test are shown both for each score class and for all score classes simultaneously, with degrees of freedom DOF equal to 8 (being grouped together AAA and AA).
For one degree of freedom the critical value, with significance level α equal to 5%, is 3.84. For all score classes the test statistic is higher than the critical value, except AAA, AA and BBB analyzing the validation set A. Analyzing the validation set B the test statistic is higher than the critical value only for BBB and D. So this confirms the behavior already highlighted by two-tailed binomial test. The critical value, with significance level α equal to 5% and 8 degrees of freedom, is 15.51 So the test statistic for all score classes simultaneously is higher than the critical value and the expected default rates do not perfectly forecast the observed default rates, but with an evident better predictive power considering the statistics computed on the validation set B for the reasons already mentioned.

Table 8 chi-square test for predictive power evaluation of MORE Score methodology on the validation set A.

chi-quadro test	*AAA-AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*D*	*dof=8*
test statistic	0.0	19.3	1.1	103.4	46.3	344.5	463.4	2379.4	1707.5	2862.2
p-value	1.000	0.000	0.305	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 9 chi-square test for predictive power evaluation of MORE Score methodology on the validation set B.

chi-quadro test	*AAA-AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*D*	*dof=8*
test statistic	0.8	2.5	9.9	3.8	0.0	2.8	0.5	0.6	7.7	23.1
p-value	0.370	0.113	0.002	0.051	0.828	0.095	0.472	0.443	0.006	0.003

The Brier Score for predictive power evaluation of MORE Score methodology has also been computed and reported in Tables 10 and 11. Brier Score equal to 0 means that the methodology is total accurate respect to the expected default rates, while Brier Score equal to 1 means that the methodology is total inaccurate. For the validation set, the Brier Score is higher for classes C and D, remaining below alarming values, and is good for all other MORE Score classes. Considering the Brier score for all score classes simultaneously, with degrees of freedom DOF equal to 8, a general good behavior in forecasting default probabilities is shown.

Table 10 Brier score for predictive power evaluation of MORE Score methodology on the validation set A.

	AAA-AA	*A*	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*D*	*dof=8*
Brier-score	0.003	0.006	0.008	0.014	0.022	0.033	0.056	0.195	0.383	0.023

Table 11 Brier score for predictive power evaluation of MORE Score methodology on the validation set B.

	AAA-AA	*A*	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*D*	*dof=8*
Brier-score	0.002	0.002	0.003	0.006	0.027	0.053	0.108	0.249	0.169	0.017

The analysis of predictive power has highlighted the differences between the two validation sets, in particular the difficulty to have complete information on defaults in most countries. What can be certainly deduced is that the MORE Score methodology has a good predictive power for medium-large sized enterprises.

Historical robustness

The historical robustness of MORE Score methodology is demonstrated by producing transition matrices, alternatively named migration matrices, which describe the movement that a company takes through different scoring classes. A migration matrix completely summarizes changes in credit scores over a given time horizon. The cells of the matrix are discrete-time estimates of migration probabilities. A change in a company's score reflects the credit quality evolution of that company, either improved (upgrade) or deteriorated (downgrade). Analysis of the score transition, including default, is useful in the validation of credit risk model. All transition matrices should exhibit the same characteristic, having high probabilities in a diagonal matrix, which means the company tends to maintain its current score. The second largest probability should be around the diagonal. Meanwhile, the farther from the diagonal, the lower the rating transition. It is expected that higher scores tend to be more stable and lower scores experience more volatility. Moreover, the probability of remaining at initial score should reduce as the time horizon analyzed becomes longer.

1-year, 3-years and 5-years transition matrices are given in Tables 12, 13 and 14 for the validation set A. 1-year transition matrix is from MORE Scores 2019 to MORE Scores 2020, 3-years transition matrix is from MORE Scores 2017 to MORE Scores 2020, 5-years transition matrix is from MORE Scores 2015 to MORE Scores 2020.

Table 12 1-year transition matrix of validation set A.

from/to	*AAA*	*AA*	*A*	*BBB*	*BB*	*B*	*CCC*	*CC*	*C*	*D*	*Defaults*
AAA	58.5%	6.4%	26.9%	4.7%	0.4%	1.7%	0.4%	0.9%	0.0%	0.0%	0.0%
AA	4.5%	42.0%	44.4%	4.9%	1.6%	1.4%	0.6%	0.1%	0.1%	0.1%	0.4%
A	0.1%	2.9%	76.6%	12.7%	2.8%	2.1%	1.3%	0.4%	0.2%	0.0%	0.9%
BBB	0.0%	0.7%	28.2%	44.5%	14.9%	4.9%	3.9%	1.1%	0.5%	0.1%	1.3%
BB	0.0%	0.2%	6.7%	18.6%	46.1%	15.0%	7.1%	3.0%	1.2%	0.2%	1.8%
B	0.0%	0.1%	4.3%	5.6%	17.7%	46.2%	14.4%	5.6%	2.7%	0.4%	3.0%
CCC	0.0%	0.1%	3.6%	4.3%	8.0%	15.5%	41.7%	12.3%	6.4%	1.7%	6.2%
CC	0.0%	0.1%	1.8%	3.1%	5.8%	12.4%	22.1%	26.3%	15.5%	3.6%	9.5%
C	0.0%	0.0%	1.5%	1.4%	2.3%	4.5%	17.2%	13.1%	31.4%	11.7%	16.9%
D	0.0%	0.0%	0.8%	0.8%	0.9%	1.0%	10.6%	5.8%	14.8%	44.1%	21.2%

Table 13 3-years transition matrix of validation set A.

from/to	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	Defaults
AAA	25.1%	8.9%	44.3%	9.8%	4.3%	3.4%	2.1%	0.4%	0.9%	0.0%	0.9%
AA	5.4%	21.8%	53.1%	10.2%	3.2%	3.1%	1.4%	0.5%	0.5%	0.1%	0.7%
A	0.2%	4.0%	66.6%	15.2%	5.2%	3.7%	2.5%	0.9%	0.6%	0.1%	1.0%
BBB	0.1%	1.4%	33.3%	32.8%	16.0%	6.7%	5.0%	2.0%	1.1%	0.2%	1.5%
BB	0.0%	0.5%	12.5%	20.9%	33.2%	15.9%	8.3%	3.8%	2.0%	0.4%	2.4%
B	0.0%	0.3%	7.0%	8.9%	21.1%	35.2%	14.4%	5.8%	3.2%	0.8%	3.4%
CCC	0.0%	0.3%	7.3%	6.8%	10.8%	18.5%	29.9%	11.0%	7.3%	2.4%	5.6%
CC	0.0%	0.2%	5.3%	5.4%	9.4%	13.0%	24.4%	17.7%	12.8%	3.8%	8.0%
C	0.0%	0.2%	4.6%	3.7%	5.5%	6.9%	21.3%	12.6%	22.0%	10.4%	12.8%
D	0.0%	0.0%	3.6%	1.4%	2.5%	3.3%	17.5%	8.2%	14.7%	32.5%	16.4%

Table 14 5-years transition matrix of validation set A.

from/to	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	Defaults
AAA	13.8%	6.9%	55.9%	10.1%	2.7%	4.8%	2.1%	2.1%	1.1%	0.0%	0.5%
AA	5.7%	16.4%	51.9%	11.8%	4.3%	4.1%	2.6%	1.1%	0.6%	0.2%	1.2%
A	0.2%	4.3%	61.3%	16.2%	6.7%	4.5%	3.3%	1.3%	0.8%	0.3%	1.2%
BBB	0.2%	1.9%	37.0%	27.9%	15.0%	7.4%	5.3%	2.1%	1.4%	0.3%	1.5%
BB	0.1%	0.8%	18.7%	22.3%	27.1%	14.6%	7.9%	3.6%	2.0%	0.5%	2.4%
B	0.1%	0.5%	11.2%	12.7%	22.6%	28.3%	12.8%	5.2%	2.9%	0.7%	3.0%
CCC	0.0%	0.5%	10.9%	9.2%	14.4%	20.7%	23.0%	9.1%	5.6%	1.7%	4.9%
CC	0.1%	0.6%	9.6%	7.9%	11.5%	15.0%	22.6%	13.3%	9.6%	3.3%	6.5%
C	0.0%	0.5%	11.1%	6.7%	8.2%	10.1%	20.9%	11.4%	15.2%	7.4%	8.4%
D	0.2%	0.4%	10.6%	4.2%	5.8%	5.4%	19.1%	8.8%	13.8%	20.7%	10.9%

The computed migration matrices do not show all the expected behavior. Table 12 shows that AAA and AA companies are not stable as expected, whereas 'A' companies are highly stable. This behavior is due to the fact that the most of the companies in the validation set are micro and small sized companies and the MORE Score model includes a constraint on the maximum score class issued for micro sized enterprises, which is A. Moreover, for score class D the probability to default should be higher than the probability to improve. This can be explained with the incomplete information on defaults.

Analyzing longer time horizons, such as in Tables 13 and 14, the volatility increases for all score grades, how it is supposed to happen.

When analyzing the 1-year, 3-years and 5-years transition matrices, given in Tables 15, 16 and 17 for the validation set B, the computed migration matrices show exactly the expected behavior. Table 15 shows that healthy and adequate companies are more stable than vulnerable and risky ones considering 1-year time horizon. Moreover, a downgrade is more probable for healthy companies and an upgrade more probable for adequate, vulnerable and risky companies, except for score class D where the probability to default is higher than the probability to improve. Analyzing longer time horizons, such as in Tables 16 and 17, the volatility increases for all score grades.

Table 15 1-year transition matrix of validation set B.

from/to	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	Defaults
AAA	58.9%	30.4%	4.3%	3.4%	1.0%	1.9%	0.0%	0.0%	0.0%	0.0%	0.0%
AA	5.1%	64.5%	22.8%	4.2%	1.6%	1.2%	0.3%	0.0%	0.1%	0.1%	0.1%
A	0.2%	16.1%	57.5%	20.9%	3.3%	1.4%	0.4%	0.0%	0.0%	0.0%	0.0%
BBB	0.1%	1.8%	15.6%	60.1%	16.9%	3.6%	1.3%	0.3%	0.1%	0.0%	0.2%
BB	0.0%	0.5%	1.1%	15.2%	64.0%	14.3%	3.5%	0.9%	0.3%	0.0%	0.3%
B	0.1%	0.2%	0.7%	3.2%	19.6%	62.1%	9.9%	2.8%	0.8%	0.0%	0.5%
CCC	0.0%	0.7%	0.9%	4.1%	10.5%	25.6%	39.4%	12.4%	3.5%	0.1%	2.8%
CC	0.0%	0.0%	0.5%	1.8%	8.3%	19.6%	23.3%	33.5%	9.0%	0.0%	3.9%
C	0.0%	0.6%	0.0%	1.2%	3.0%	9.0%	9.6%	18.6%	24.0%	3.0%	31.1%
D	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	5.9%	0.0%	11.8%	11.8%	70.6%

Table 16 3-year transition matrix of validation set B.

from/to	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	Defaults
AAA	41.7%	37.7%	7.0%	3.5%	4.0%	2.5%	1.0%	1.5%	0.5%	0.0%	0.5%
AA	5.5%	50.1%	27.6%	9.7%	3.5%	2.2%	0.7%	0.2%	0.2%	0.0%	0.3%
A	1.4%	20.6%	43.7%	23.0%	6.8%	2.8%	1.0%	0.3%	0.1%	0.0%	0.2%
BBB	0.4%	5.3%	20.0%	45.4%	19.8%	5.7%	2.0%	1.1%	0.0%	0.0%	0.3%
BB	0.1%	1.5%	4.5%	20.2%	48.5%	17.6%	4.5%	1.7%	0.4%	0.0%	1.0%
B	0.1%	0.6%	1.4%	6.5%	26.0%	46.6%	9.7%	3.4%	1.5%	0.0%	4.0%
CCC	0.1%	0.8%	2.9%	6.5%	13.9%	29.8%	27.2%	9.5%	2.9%	0.0%	6.5%
CC	0.0%	1.1%	2.2%	5.6%	14.2%	19.3%	18.0%	17.5%	7.6%	0.7%	13.7%
C	0.0%	0.5%	1.5%	4.5%	6.5%	12.6%	14.6%	12.1%	11.1%	1.0%	35.7%
D	0.0%	3.3%	0.0%	0.0%	13.3%	6.7%	16.7%	3.3%	0.0%	3.3%	53.3%

Table 17 5-year transition matrix of validation set B.

from/to	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	Defaults
AAA	33.6%	40.7%	15.0%	4.3%	1.4%	2.1%	1.4%	1.4%	0.0%	0.0%	0.0%
AA	7.4%	44.0%	27.1%	11.6%	4.7%	3.2%	0.8%	0.7%	0.2%	0.0%	0.2%
A	2.2%	23.9%	37.8%	21.5%	8.3%	4.1%	1.3%	0.4%	0.1%	0.0%	0.3%
BBB	0.9%	10.6%	24.8%	37.7%	17.6%	5.1%	2.0%	0.6%	0.2%	0.0%	0.5%
BB	0.2%	3.0%	8.7%	25.1%	39.1%	15.8%	4.3%	2.0%	0.5%	0.0%	1.3%
B	0.2%	1.6%	3.0%	10.4%	30.7%	37.1%	8.3%	2.8%	1.3%	0.0%	4.6%
CCC	0.0%	1.2%	3.6%	8.4%	21.0%	29.7%	18.8%	8.0%	2.3%	0.1%	7.0%
CC	0.2%	1.7%	4.2%	7.5%	16.0%	24.4%	19.6%	11.9%	2.3%	0.4%	11.9%
C	1.3%	1.9%	4.5%	10.3%	7.7%	14.1%	17.3%	10.9%	10.9%	1.9%	19.2%
D	0.0%	0.0%	0.0%	15.0%	20.0%	20.0%	5.0%	25.0%	0.0%	0.0%	15.0%

For the analysis of transition matrices, several indicators can be observed. One of the most important indicators in evaluating the quality trend of score model is rating activity, calculated from the sum of rating shifts, both the upgrades and the downgrades, divided by the number of scored companies at the beginning of the analyzed time horizon. The rating stability is the number of stable scores divided by the number of scored companies at the beginning of the analyzed time horizon and the default rate is the number of defaulted companies divided by the number of scored companies at the beginning of the analyzed time horizon. The sum of rating activity, rating stability and default rate must be 100%.

Another important indicator is rating drift. Rating drift is calculated by the total number of upgrades subtracted by the number of downgrades and divided by the number of scored companies at the beginning of the analyzed time horizon. A positive rating drift shows that the number of upgrades has surpassed the downgrades, more specifically indicating an improvement of credit risk scoring. Conversely, a negative rating drift shows that the number of downgrades has surpassed the upgrades, ergo a decline of credit risk scoring. In brief, rating drift indicates whether a score shows any improvement or decline over a certain period of time.

In Tables 18 and 19 these historical robustness indicators are reported for the validation set A and validation set B, respectively. For the analyzed time horizons, and for both validation sets, the majority of score transitions tended to be positive, which means that the number of upgrades exceeded the downgrades and it can be concluded that the sample of company scores improved over the long term. The rating activity increases for longer time horizons and the rating stability decreases, as it is reasonable.

Table 18 Historical robustness indicators for the validation set A.

	1-year	*3-years*	*5-years*
rating activity	45.5%	57.9%	65.3%
rating stability	51.4%	39.1%	31.9%
default rate	3.0%	3.0%	2.9%
rating drift	-0.4%	2.9%	12.8%

Table 19 Historical robustness indicators for the validation set B.

	1-year	*3-years*	*5-years*
rating activity	40.1%	53.3%	61.6%
rating stability	58.9%	44.1%	35.6%
default rate	1.0%	2.6%	2.8%
rating drift	-0.4%	3.6%	17.3%

In Table 20 and 21 the rating activity and the rating drift for each score class are given for validation set A. Healthy score grades have high rating activity. A negative rating drift corresponds to healthy classes, which means the number of downgrades are higher than upgrades and, being this value high in absolute terms, they are significantly more. The low value of absolute rating drift for classes BBB and BB means that the number of downgrades and upgrades are very close for adequate companies and downgrade and upgrade have almost the same probability to happen.

Table 20 Rating activity for each score class analyzing the validation set A on different time horizons.

rating activity	*1-year*	*3-years*	*5-years*
AAA	41.5%	74.0%	85.6%
AA	57.6%	77.5%	82.4%
A	22.4%	32.4%	37.5%
BBB	54.2%	65.8%	70.6%
BB	52.1%	64.4%	70.5%
B	50.8%	61.4%	68.7%
CCC	52.1%	64.5%	72.2%
CC	64.2%	74.3%	80.2%
C	51.8%	65.2%	76.3%
D	34.8%	51.1%	68.4%

Table 21 Rating drift for each score class analyzing the validation set A on different time horizons.

rating drift	*1-year*	*3-years*	*5-years*
AAA	-41.5%	-74.0%	-85.6%
AA	-48.6%	-66.7%	-71.0%
A	-16.5%	-24.1%	-28.5%
BBB	3.6%	3.7%	7.6%
BB	-0.9%	3.6%	13.3%
B	4.6%	13.2%	25.3%
CCC	11.2%	23.1%	39.3%
CC	26.1%	41.1%	54.4%
C	28.5%	44.4%	61.6%
D	34.8%	51.1%	68.4%

Looking at the rating activity per classes for the validation set B, shown in Table 22, here we have an evident difference between healthier classes and riskier ones for 1- year time horizon. The healthier classes are more active than riskier and have a negative rating drift (Table 23). The rating drift grows with the worsening of the class and become positive for class B. For class CC it has the maximum value for all analyzed time horizons.

Table 22 Rating activity for each score class analyzing the validation set B on different time horizons.

rating activity	*1-year*	*3-years*	*5-years*
AAA	41.1%	57.8%	66.4%
AA	35.5%	49.6%	55.7%
A	42.4%	56.1%	61.9%
BBB	39.7%	54.3%	61.8%
BB	35.7%	50.5%	59.6%
B	37.4%	49.3%	58.3%
CCC	57.8%	66.3%	74.3%
CC	62.6%	68.8%	76.3%
C	44.9%	53.3%	69.9%
D	17.6%	43.3%	85.0%

Table 23 Rating drift for each score class analyzing the validation set B on different time horizons.

rating drift	*1-year*	*3-years*	*5-years*
AAA	-41.1%	-57.8%	-66.4%
AA	-25.2%	-38.6%	-41.0%
A	-9.8%	-11.9%	-9.7%
BBB	-4.6%	-3.0%	10.9%
BB	-2.2%	2.3%	14.3%
B	10.3%	20.1%	33.4%
CCC	25.9%	41.6%	53.5%
CC	44.6%	52.1%	70.8%
C	38.9%	51.3%	66.0%
D	17.6%	43.3%	85.0%

Table 24 Average of the scores given to defaulted companies (ADR) in the validation set A at different distances from default (DD).

DD	*1*	*2*	*3*	*4*	*5*
ADR	CCC	B	B	B	B

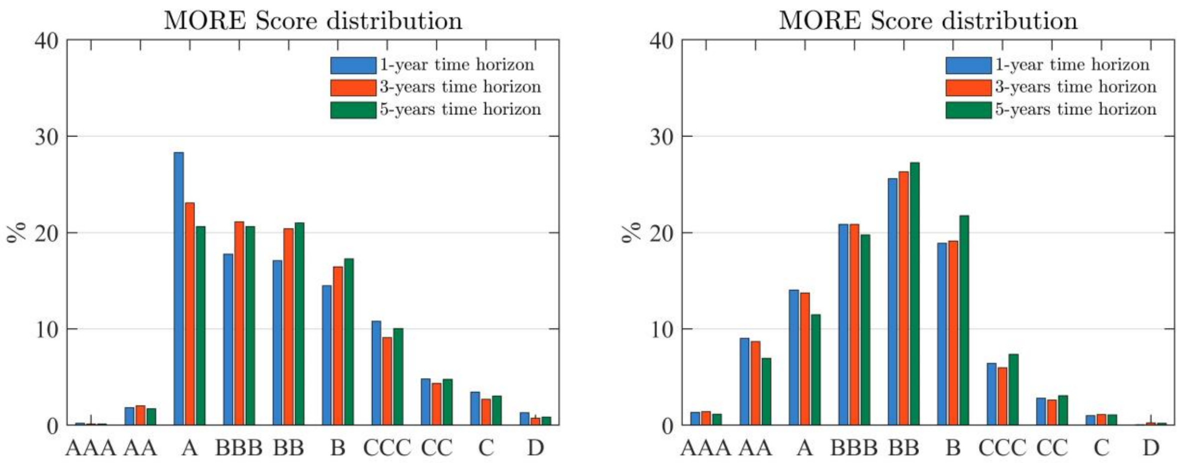
Table 25 Average of the scores given to defaulted companies (ADR) in the validation set B at different distances from default (DD).

DD	*1*	*2*	*3*	*4*	*5*
ADR	CC	CCC	CCC	CCC	B

Another aspect of stability is the average of the scoring attributed to defaulted companies approaching the default status. These values are given in Table 24 for the validation set A and in Table 25 for the validation set B.

As the MORE score decrease approaching the default, the methodology is stable according to modefinance Policies and Procedures.

To further prove the stability of the MORE scores the analysis of the scores' distributions and the univariate analysis of the key determinants of credit scores are performed on different time horizons.
In Figure 9 the MORE Score distribution is plotted for both the validation sets. The distribution is not exactly Gaussian for set A. Especially there is an abnormal value of A class percentage, respect to other classes. This behavior, as already explained, is due to the fact that the most of the companies in the validation set are micro and small sized companies and the MORE Score model include a constraint on the maximum score class issued for micro sized enterprises, which is A. Analyzing the distribution of scores for the validation set B (which includes only medium and large size companies), plotted in Figure 9 b), they are clearly more stable without statistical fluctuations. The distribution weakly shifts toward lower classes with longer time horizons.



a) set A b) set B

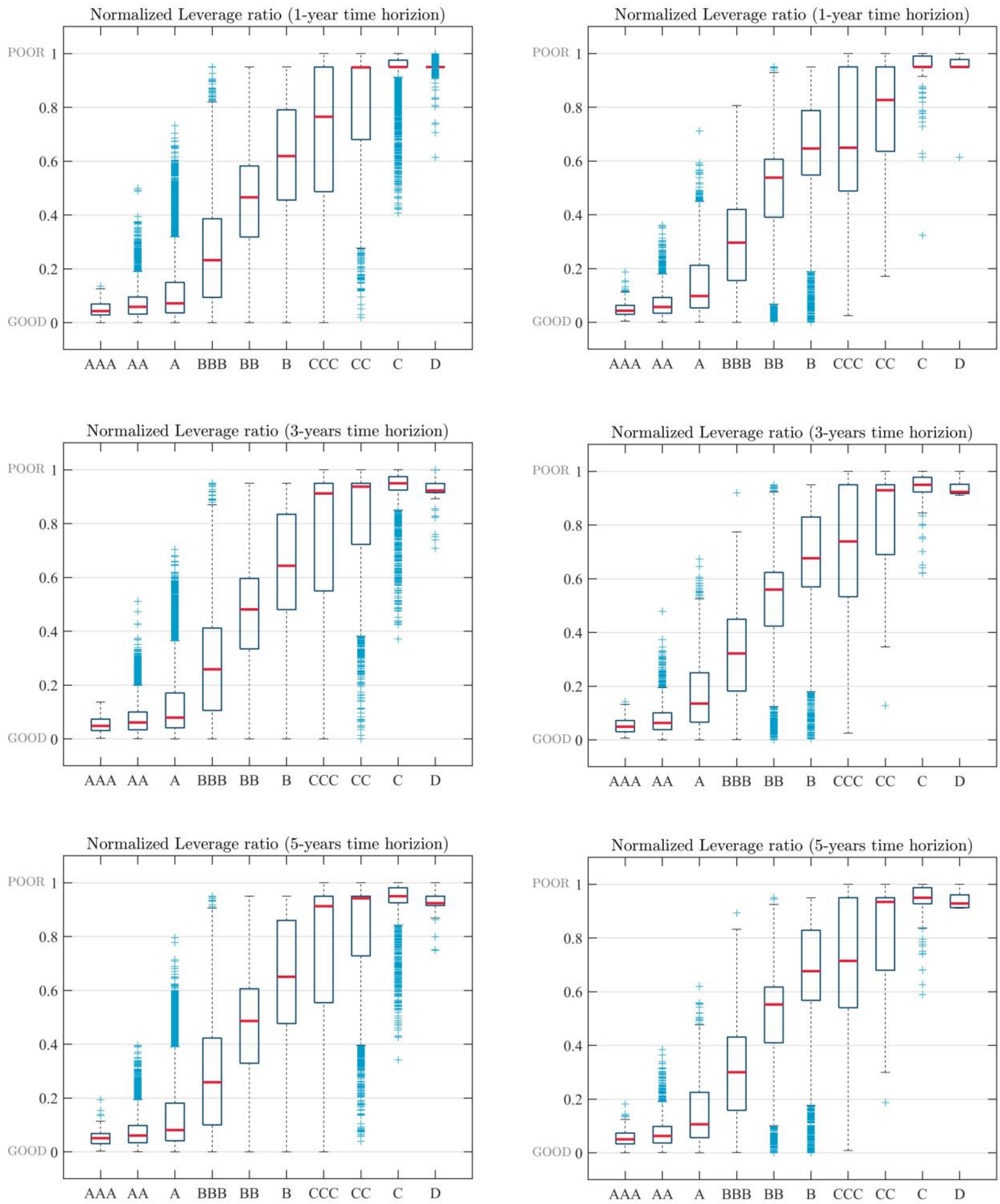
Figure 9 MORE Score distribution on different time horizons for the validation set.

The key determinants of MORE Score methodology are: Leverage ratio, Assets to debt, Current ratio, Quick ratio, Cash conversion Cycle, ROI, ROE, Asset turnover, Profit margin, Interest paid coverage. The analyzed ratios are normalized from 0 to 1, where 0 is a good value and 1 is a poor value.

The ratios are analyzed with box plots in Figures 10-19. A boxplot is a method for graphically depicting groups of numerical data through their quartiles. The spaces between the different parts of the box indicate the degree of dispersion and skewness in the data, and show outliers. The definition of outlier is the classical: an outlier is an extreme value that differs greatly form other values in a set of values. An extreme value is considered to be an outlier if it is at least 1.5 interquartile ranges below the first quartile or at least 1.5 interquartile ranges above the third quartile. On each box, the central red mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the '+' symbol.

Several observations can be done.

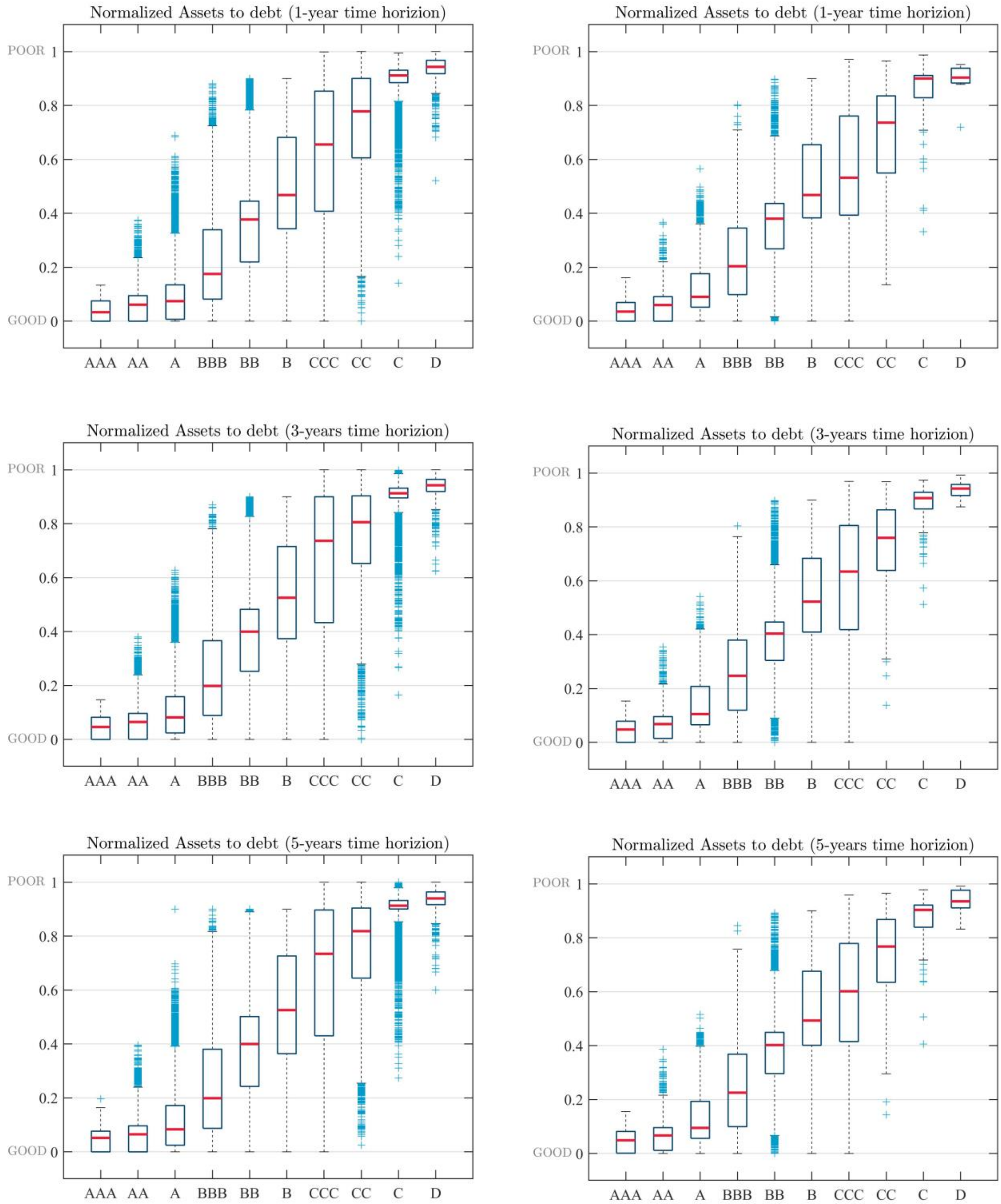
Leverage ratio and Assets to debt are solvency ratios and describe the level of capitalization of the entity, its capability of facing hypothetical periods of stress with own resources. From Figures 10 and 11 they are significantly discriminatory to evaluate the credit risk.



a) set A

b) set B

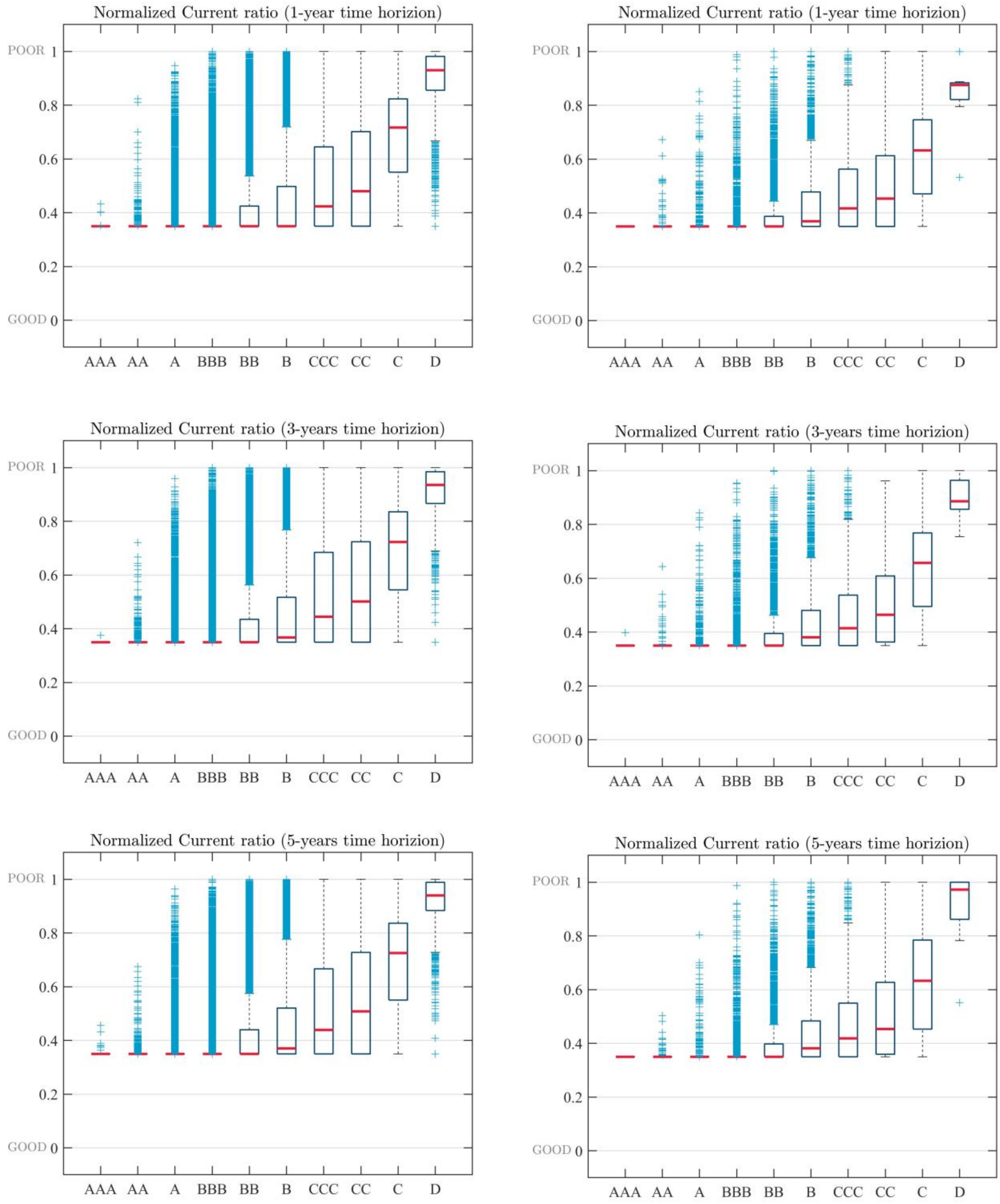
Figure 10 Boxplot of observed normalized Leverage Ratio.



a) set A

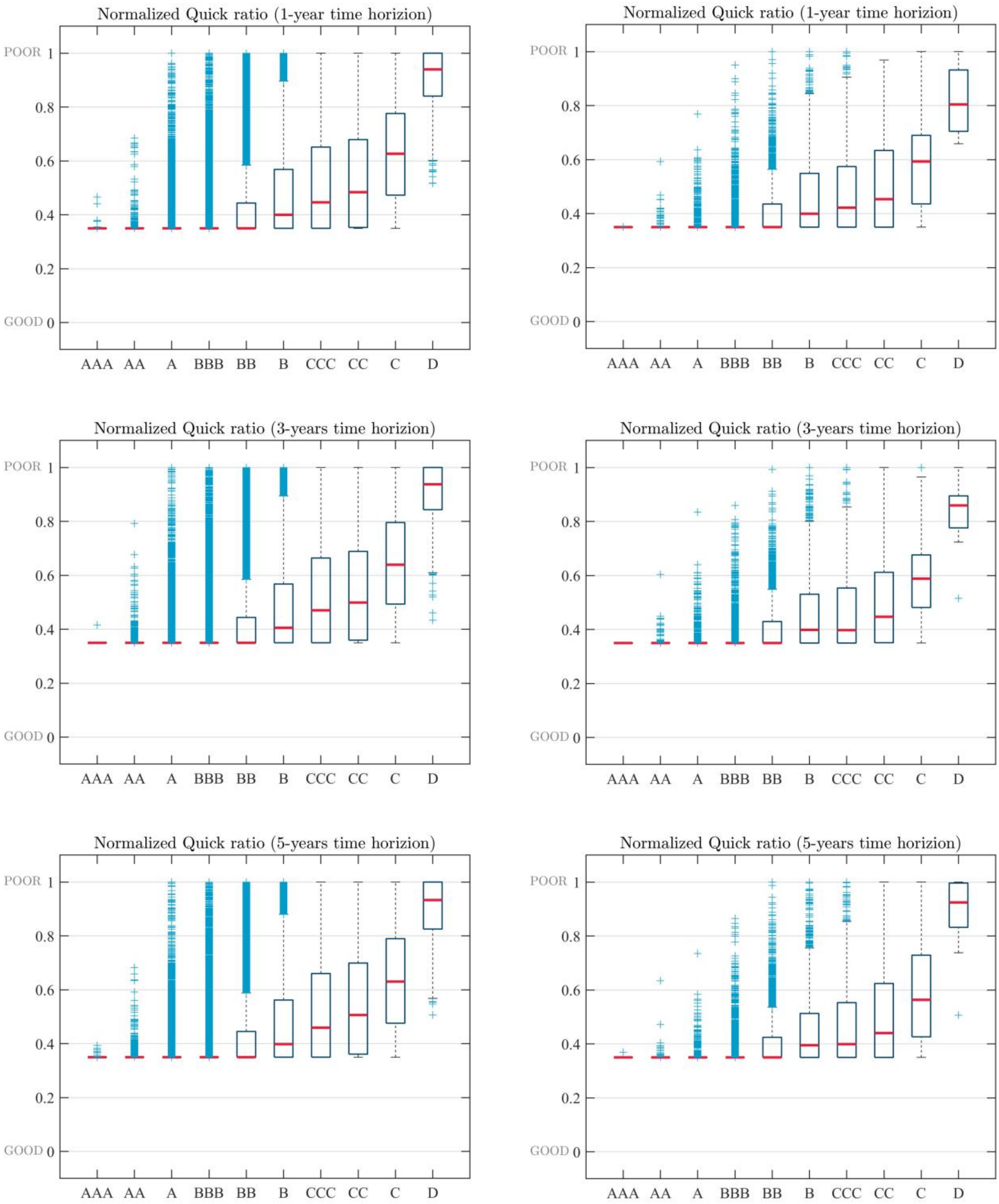
b) set B

Figure 11 Boxplot of observed normalized Assets to debt.



a) set A b) set B

Figure 12 Boxplot of observed normalized Current ratio.



a) set A

b) set B

Figure 13 Boxplot of observed normalized Quick ratio.

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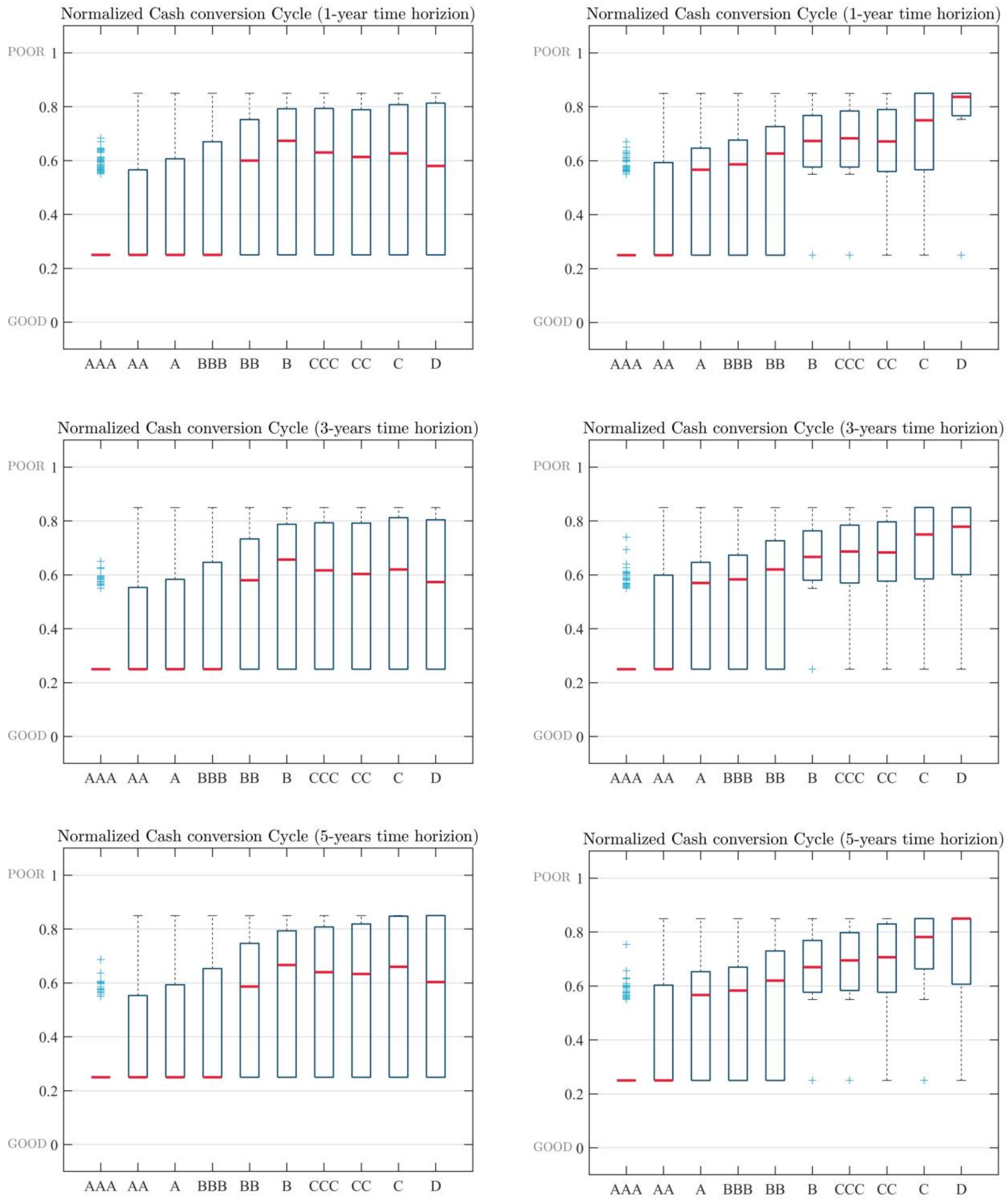
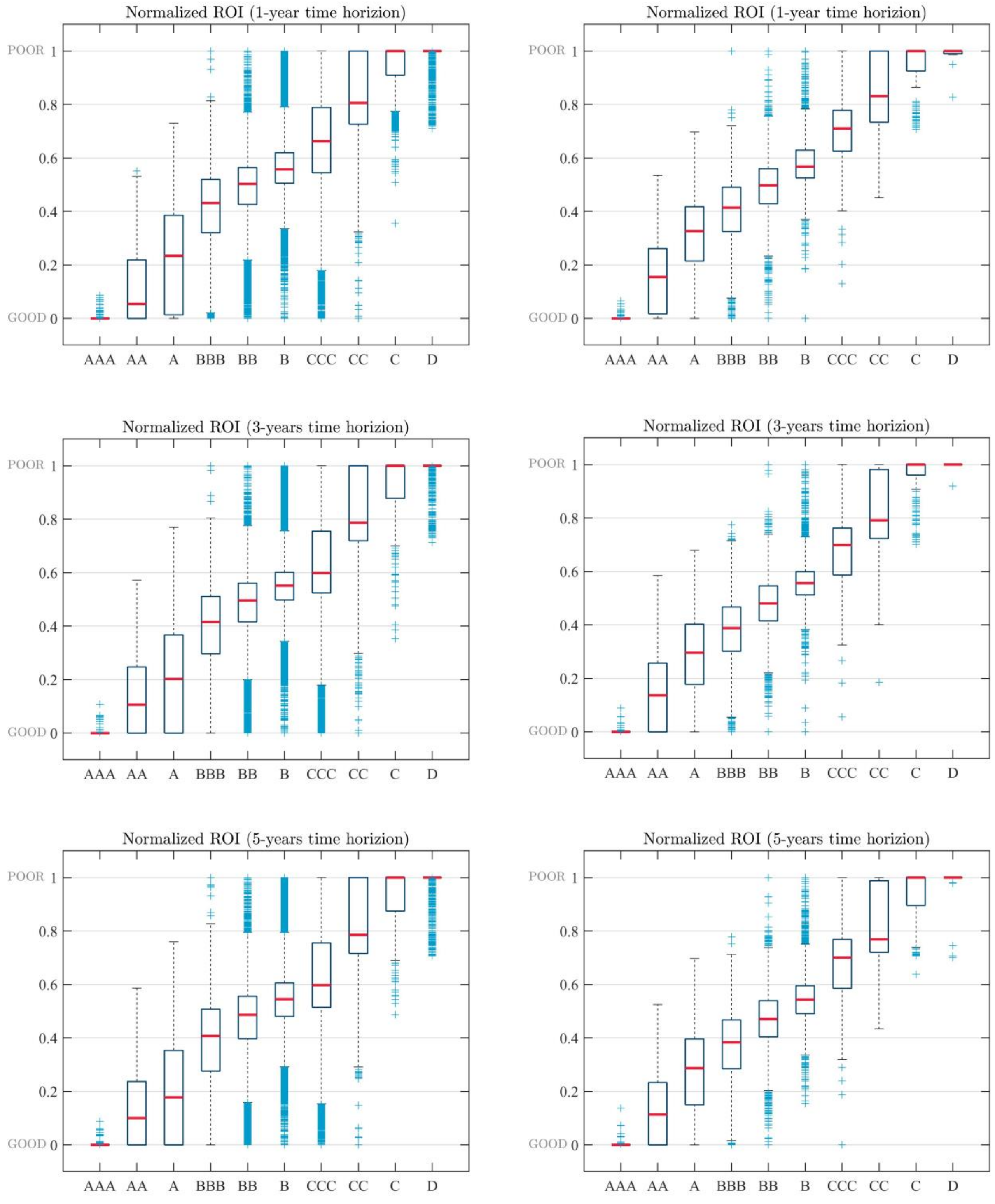


a) set A

b) set B

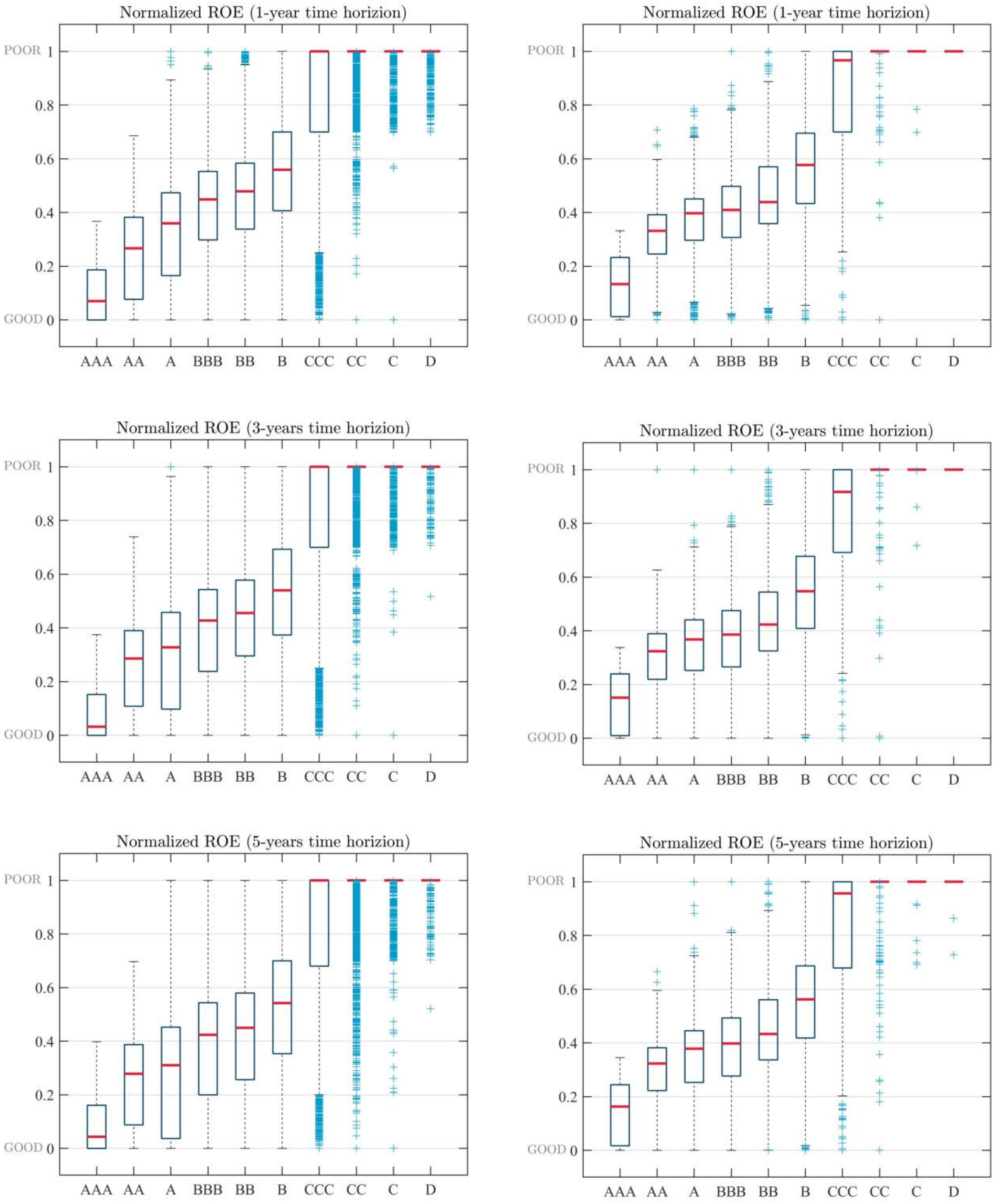
Figure 14 Boxplot of observed normalized Cash conversion Cycle.



a) set A

b) set B

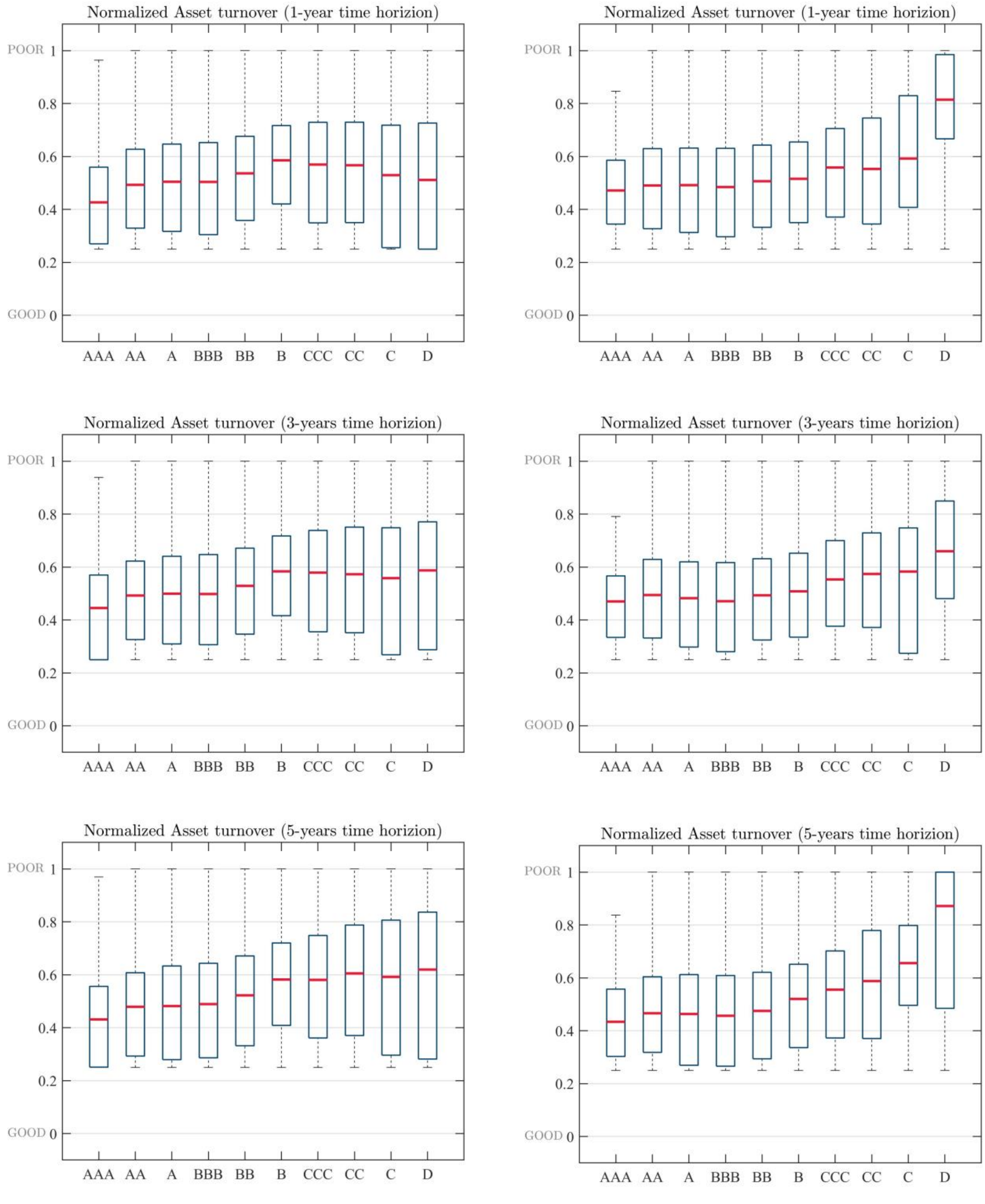
Figure 15 Boxplot of observed normalized ROI.



a) set A

b) set B

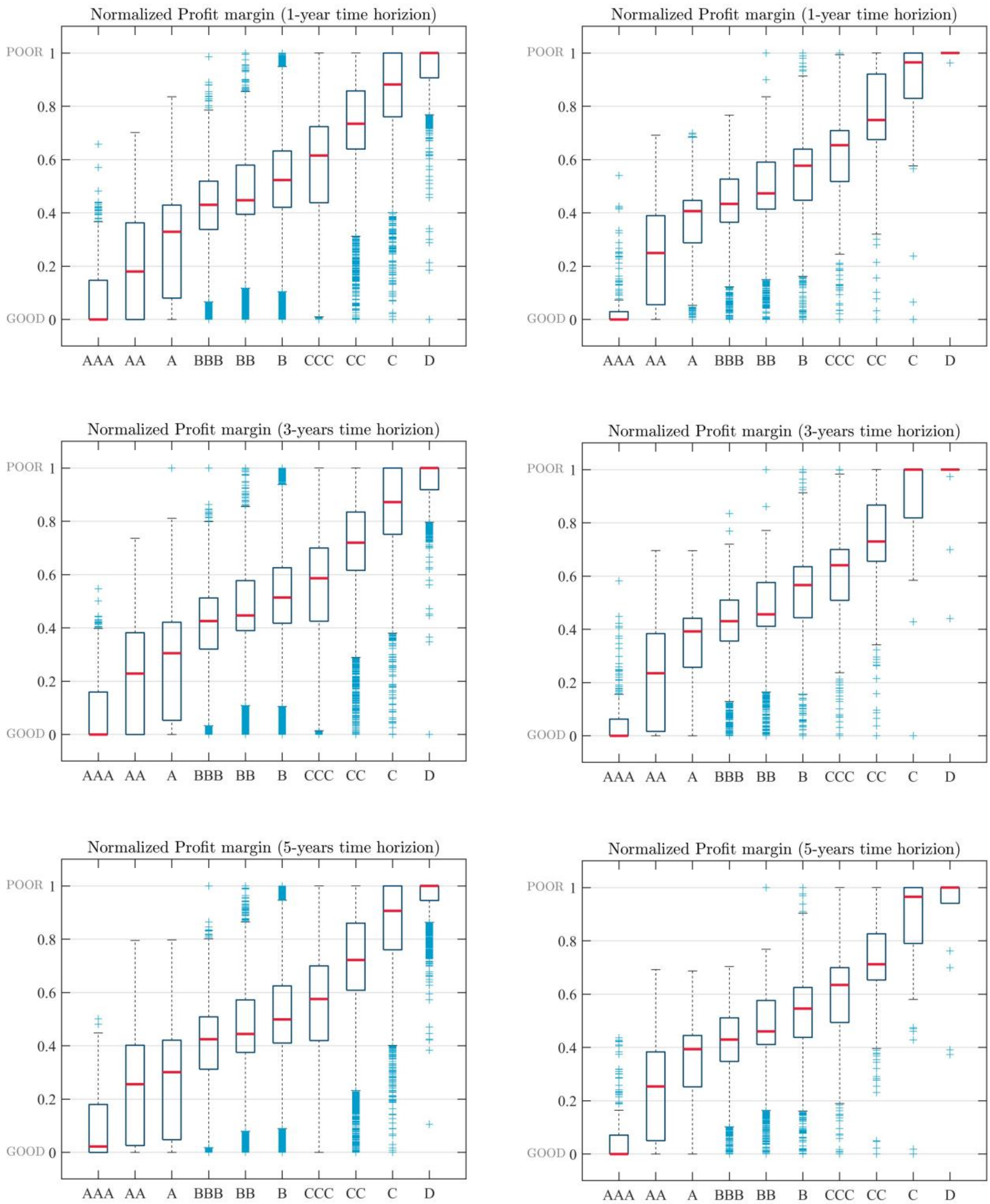
Figure 16 Boxplot of observed normalized ROE.



a) set A

b) set B

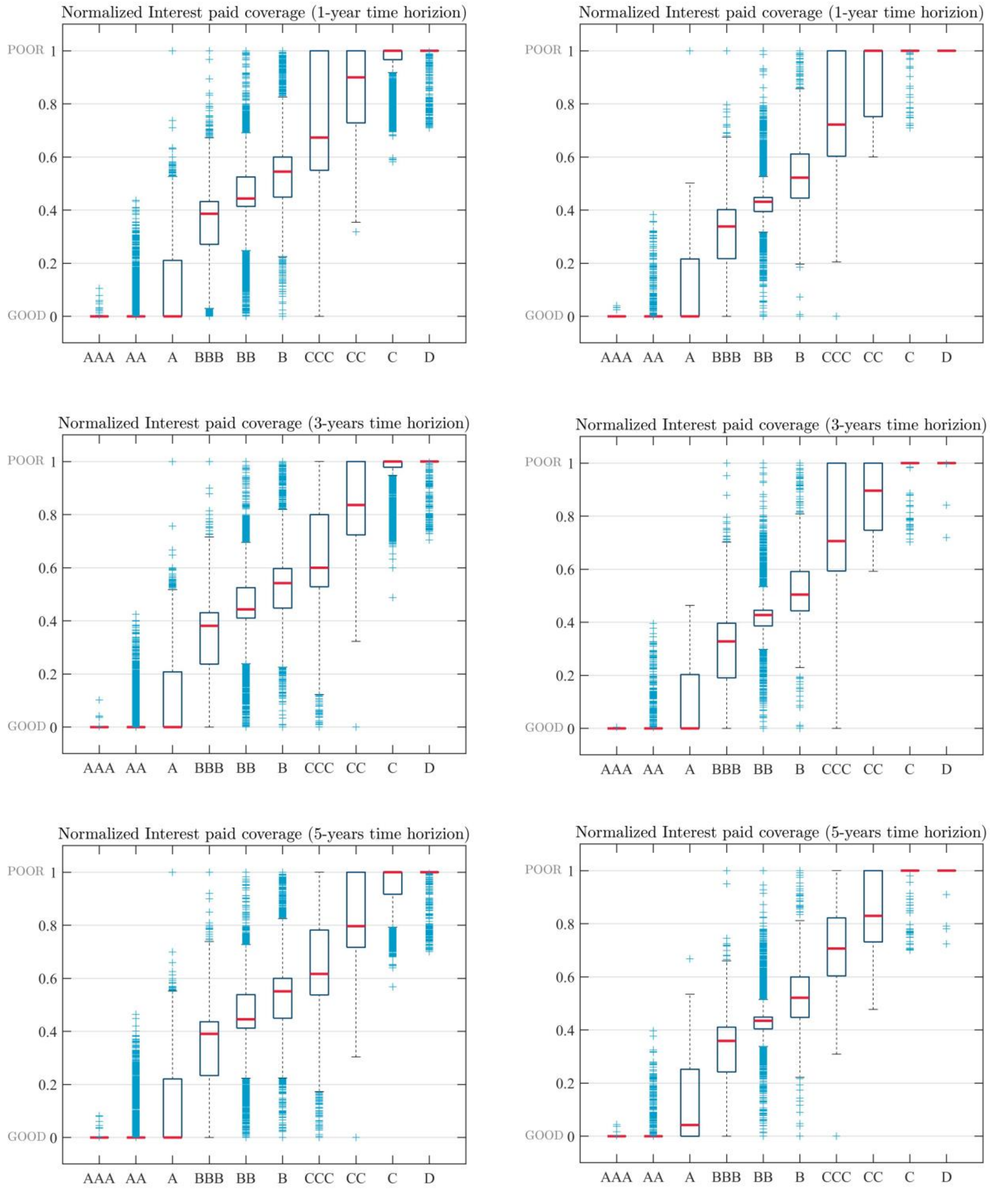
Figure 17 Boxplot of observed normalized Asset turnover.



a) set A

b) set B

Figure 18 Boxplot of observed normalized Profit margin.



a) set A

b) set B

Figure 19 Boxplot of observed normalized Interest paid coverage.

Current ratio, Quick ratio and Cash conversion Cycle are liquidity ratios, which analyze the ability of the company to meet its short-term financial commitments. In Figures 12, 13 and 14 it is evident these ratios have several outliers for healthy classes, especially for validation set A. The values of ratios have low dispersion for risky classes, except for Cash conversion cycle. The values of Cash conversion cycle are quite dispersed for both healthy and risky classes and results weakly discriminatory to evaluate the credit risk. For validation set B it is evident the values are less dispersed and the liquidity ratios are sufficiently discriminatory to evaluate the credit risk.

ROI, ROE, Asset turnover and Profit margin are profitability and economic equilibrium ratios. They explain the capacity of the company to generate revenues. The profitability of a company depends not only on the margins generated, but also on the assets that must be employed to generate these profits. From Figures 15-18 it is evident these ratios have a good discriminatory power, except for Asset turnover which seems poorly significant for credit risk evaluation in MORE Score methodology. However, this ratio should be analyzed along with margins indicators, to properly factor the buiness nature of the company.

Interest paid coverage ratio is used to determine how easily a company can pay interest on outstanding debt. From the analysis, the behavior of the ratio is highly discriminatory for the MORE Score evaluation.

Conclusion

According to modefinance Policies and Procedures, the methodology has not to be reviewed:

- its discriminatory power is extremely good, especially when medium and large size enterprises are evaluated, in particular the AUC is higher than 60% for short (77.64% for set A, 92.69% for set B), medium (72.4% for set A, 87.97% for set B) and long (69.03% for set A, 83.00% for set B) time horizon;

- the predictive power resulted good by comparing the expected and observed long run three-years default rates, when a confident information on defaults is available. It resulted poor only for the validation set for which the information on defaults could be incomplete. However, not all the triggers are activated so to require a methodology review;

- the methodology has been proved to be stable and the average of the scoring attributed to defaulted companies decreases by approaching the default status.

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