Creditsafe Germany

Generic Scorecard for Registered Companies

Executive Summary

Group Analytics

Version 1.0 2019

1. Executive Summary

1.1. Creditsafe Germany Generic Scorecard Overview

It is our mission to empower businesses to make confident credit decisions that support their healthy growth whilst reducing their exposure to risk. With this in mind, Creditsafe Germany has developed a new and more powerful scorecard for companies registered at the German Commercial Register (Handelsregister).

Creditsafe continually monitors and validates its credit scorecards, using the latest knowledge in the field of statistical scoring methods. We also strive to increase predictability through introducing additional information from our ever-expanding database. As we acquire new data on the German business population from first and third party sources, we assess their statistical significance in predicting commercial stability to ensure all relevant and available data is employed in our scorecard.

Consequently, the way in which companies are scored has improved. Our latest scorecard generates more informed and predictive assessments about a growing number of companies, even in cases where less information is available.

1.2. Scorecards and Segmentation

The essential concept behind Creditsafe's scoring approach is to accurately predict business behaviour (in terms of their good/bad performance over the next 12 months) using a set of characteristics that clearly identify why a business is considered to be high or low risk.

To increase the discriminative power of the scorecard, population segmentation was conducted. The aim of the segmentation was to define a set of sub-populations that, when modelled individually and combined, rank risk more effectively than a single model on the overall population. To distinguish between companies by their size (micro, small, medium and large), the foundation of the segmentation has been the application of legal requirements from the commercial code (Handelsgesetzbuch, HGB) by using information from their last stated financial accounts (§267a HGB, §267 HGB).

In addition, companies without any stated financial accounts within a time frame of 36 months, where economic activity is more uncertain, will fall into a separate segment. This is considered as well for newly established companies as they often lack financial statements.

Registered Company Scorecards

1. New — company age between 18 – 24 months, without stated financials
2. Micro — companies regarding §267a HGB
3. Small — companies regarding §267 (1) HGB
4. Medium — companies regarding §267 (2) HGB
5. Large — companies regarding §267 (3) HGB
6. No financials — company age above 24 months, without stated financials (within 36 mos.)

1.3. Model Default Definition

The performance definition was designed to clearly identify why a business is considered to be high or low risk.

	German Commercial Register
Bad	Insolvency or insolvency process will start within upcoming 12 months
Good	None of the above status definitions within upcoming 12 months

1.4. Individual PD (Probability of Default) versus Score 0 – 100

Creditsafe's new scorecards will provide a *score* between 0 and 100, *risk classes* from "E" to "A" and the local *Bonitätsindex,* representing the highest and lowest risk respectively. The scoring scale was generated using the probability of default output. It is an alternative way for customers to accept or decline credit applications whilst being representative of the risk associated with the business.

With the launch of the new scorecard, the Creditsafe score will be accompanied with a PD. The PD is determined for each individual company based on their combination of characteristics. It is important to note that the score itself is not a percentile score where the population is forced into certain positions to achieve a desired distribution. Each score is created from the probability of default, and due to the granular outcomes of the PD calculations there will be a range of PDs per score (see the "Total Population Matrix" below and the mapping within Appendix A).

1.5. Summary of Results

Total Population Matrix

Risk Class	Average PD	Bad Ratio	Min PD	Max PD	Min Score	Max Score	% of Population
A	0.11%	0.09%	0.01%	0.17%	81	100	17%
B	0.33%	0.30%	0.17%	0.61%	61	80	45%
C	1.33%	1.28%	0.61%	3.08%	35	60	29%
D	5.85%	5.61%	3.08%	99.99%	0	34	9%

Risk class A represents an average probability to default of 0.11%. The applied score range for "A" lays between 81 and 100 score points.

Total Population (Decile) Matrix

Max PD	% Bads	Observed Bad Ratio	Average Estimated PD
0.01%	1%	0.08%	0.08%
0.18%	1%	0.08%	0.16%
0.23%	2%	0.19%	0.20%
0.30%	2%	0.24%	0.26%
0.42%	3%	0.32%	0.35%
0.57%	5%	0.48%	0.49%
0.81%	6%	0.68%	0.69%
1.25%	10%	1.04%	1.02%
2.08%	15%	1.60%	1.60%
99.99%	55%	5.73%	5.59%
Total	**100%**	**1.04%**	**1.04%**

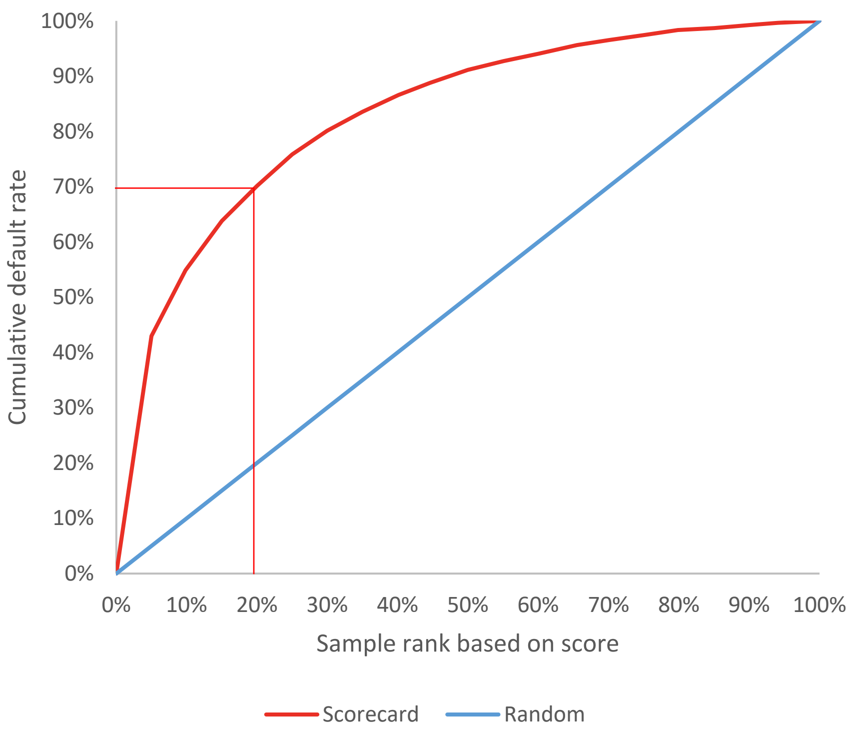
Population ranking (10 equally sized groups) by PD shows strong discrimination between high and low risk.

Total Population Gini

The Gini coefficient represents excellent discrimination across all segments of the German company population. For further comfort around the robustness of the scorecard, Creditsafe validated the scorecards using an out-of-time validation technique. The results have shown that all attributes were within the statistical range of tolerance and desired level of accuracy.

Creditsafe continuously monitors and validates the scorecard to maintain a robust forecast.

Cumulative Accuracy Profile



The overall Gini coefficient for the total German population is above 69. Approximately 20 percent of the population with the highest risk capture 70 percent of the defaulting companies.

2. Data Preparation & Population Design

The scorecard was developed from a generic sample of German data, extracted from the Creditsafe data pool.

The selection of the sample definition satisfied the following:

- The generic sample was created to recognise economically active companies and has shown that there are sufficient businesses in each and every model segment to develop a robust scorecard.
- For business performance to be reliably assigned as well as to avoid seasonality, each company was given a 12-months' exposure period.
- The sample window was recent enough to be representative of the future German company population.

The development sample was created taking business information from 1st April 2014 up to and including 31st March 2017, giving a 36 months information window. To assign the binary outcome variable ("good or bad"), a 12-month horizon was used, starting 1st April 2017 up to and including 31st March 2018.

3. Scorecard Development

3.1. Modelling Methods

Stepwise logistic regression has been used to develop the scorecard. This is the preferred method within Creditsafe. Logistic regression models the probabilities for classification problems with binary outcomes ("good or bad") and has the benefit that its output is more informative and accurate than other classification algorithms. Like any regression approach, it expresses the relationship between an outcome variable and each of its predictors. The logistic regression not only gives a measure of how relevant a predictor is (coefficient size), but also its direction of association (positive or negative).

3.2. Scrutiny of Business Logic

Not only statistical evidence is applied while developing the scorecard and selecting ingoing parameters, but also all variables are verified to be comprehensible, logical and allegeable.
Within the Creditsafe product line the information that is used to determine the risk is displayed for a maximum level of detail and transparency. The way Creditsafe shows information about a company and its related businesses helps to get the full picture and understand the reciprocal interdependencies within a group structure.

3.3. Scorecard Calibration

The output from the logistic model produces individual PDs for each of the companies and each of the models, respectively. These PDs have been transformed into a 0 – 100 score using "points double the odds" principles.

This technique was chosen to allow the score and PD to match at the point required, as well as matching the score distribution expected by the German market of today. This score is a direct representation of the underlying PD. The table in Appendix A details the relevant PD in relation to the Creditsafe 0 – 100 score.

Appendix A

Mapping of score, risk class, Bonitätsindex and PD

Score	Risk Class	Bonitätsindex	Min PD	Max PD	Score	Risk Class	Bonitätsindex	Min PD	Max PD
100	A	1	0.0000100%	0.0528626%	49	C	3.5	1.2202944%	1.2988722%
99	A	1	0.0528626%	0.0542218%	48	C	3.5	1.2988722%	1.3821664%
98	A	1.1	0.0542218%	0.0592421%	47	C	3.6	1.3821664%	1.4707224%
97	A	1.1	0.0592421%	0.0634715%	46	C	3.6	1.4707224%	1.5648623%
96	A	1.2	0.0634715%	0.0679686%	45	C	3.6	1.5648623%	1.6649261%
95	A	1.2	0.0679686%	0.0721685%	44	C	3.7	1.6649261%	1.7712734%
94	A	1.3	0.0721685%	0.0770269%	43	C	3.7	1.7712734%	1.8842834%
93	A	1.3	0.0770269%	0.0818924%	42	C	3.7	1.8842834%	2.0043564%
92	A	1.4	0.0818924%	0.0874660%	41	C	3.8	2.0043564%	2.1321234%
91	A	1.4	0.0874660%	0.0931298%	40	C	3.8	2.1321234%	2.2669599%
90	A	1.5	0.0931298%	0.0991896%	39	C	3.8	2.2669599%	2.4112899%
89	A	1.5	0.0991896%	0.1056855%	38	C	3.9	2.4112899%	2.5638182%
88	A	1.6	0.1056855%	0.1122359%	37	C	3.9	2.5638182%	2.7257253%
87	A	1.6	0.1122359%	0.1197525%	36	C	3.9	2.7257253%	2.8983972%
86	A	1.7	0.1197525%	0.1272244%	35	C	3.9	2.8983972%	3.0813624%
85	A	1.7	0.1272244%	0.1359742%	34	D	4	3.0813624%	3.2751712%
84	A	1.8	0.1359742%	0.1448033%	33	D	4	3.2751712%	3.4807321%
83	A	1.8	0.1448033%	0.1542049%	32	D	4	3.4807321%	3.6987015%
82	A	1.9	0.1542049%	0.1640193%	31	D	4.1	3.6987015%	3.9293871%
81	A	1.9	0.1640193%	0.1748582%	30	D	4.1	3.9293871%	4.1746370%
80	B	2	0.1748582%	0.1861889%	29	D	4.1	4.1746370%	4.4323689%
79	B	2	0.1861889%	0.1982524%	28	D	4.2	4.4323689%	4.7092683%
78	B	2.1	0.1982524%	0.2111591%	27	D	4.2	4.7092683%	4.9911676%
77	B	2.1	0.2111591%	0.2248816%	26	D	4.2	4.9911676%	5.3060622%
76	B	2.2	0.2248816%	0.2394938%	25	D	4.3	5.3060622%	5.6343252%
75	B	2.2	0.2394938%	0.2550276%	24	D	4.3	5.6343252%	5.9771161%
74	B	2.3	0.2550276%	0.2715392%	23	D	4.3	5.9771161%	6.3227567%
73	B	2.3	0.2715392%	0.2891743%	22	D	4.4	6.3227567%	6.7238722%
72	B	2.4	0.2891743%	0.3078898%	21	D	4.4	6.7238722%	7.1239729%
71	B	2.4	0.3078898%	0.3279106%	20	D	4.5	7.1239729%	7.5341038%
70	B	2.5	0.3279106%	0.3491591%	19	D	4.5	7.5341038%	8.0128676%
69	B	2.5	0.3491591%	0.3717424%	18	D	4.6	8.0128676%	8.4695060%
68	B	2.6	0.3717424%	0.3958199%	17	D	4.6	8.4695060%	8.9912809%
67	B	2.6	0.3958199%	0.4214924%	16	D	4.7	8.9912809%	9.5073797%
66	B	2.7	0.4214924%	0.4487777%	15	D	4.7	9.5073797%	10.0670199%
65	B	2.7	0.4487777%	0.4778208%	14	D	4.8	10.0670199%	10.6091641%
64	B	2.8	0.4778208%	0.5087845%	13	D	4.8	10.6091641%	11.2595416%
63	B	2.8	0.5087845%	0.5416900%	12	D	4.9	11.2595416%	11.8877826%
62	B	2.9	0.5416900%	0.5767112%	11	D	4.9	11.8877826%	12.5176216%
61	B	2.9	0.5767112%	0.6139827%	10	D	5	12.5176216%	13.3125722%
60	C	3	0.6139827%	0.6536471%	9	D	5	13.3125722%	14.0336249%
59	C	3	0.6536471%	0.6958559%	8	D	5	14.0336249%	14.8388071%
58	C	3.1	0.6958559%	0.7406965%	7	D	5	14.8388071%	15.6394936%
57	C	3.1	0.7406965%	0.7885601%	6	D	5	15.6394936%	16.3775573%
56	C	3.2	0.7885601%	0.8394072%	5	D	5	16.3775573%	17.3374178%
55	C	3.2	0.8394072%	0.8935035%	4	D	5	17.3374178%	18.3052775%
54	C	3.3	0.8935035%	0.9510527%	3	D	5	18.3052775%	19.2662787%
53	C	3.3	0.9510527%	1.0122706%	2	D	5	19.2662787%	20.2732966%
52	C	3.4	1.0122706%	1.0773861%	1	D	5	20.2732966%	21.3022813%
51	C	3.4	1.0773861%	1.1467552%	0	D	5	21.3022813%	99.9999999%
50	C	3.5	1.1467552%	1.2202944%	-	E	6	-	