creditsafe

Creditsafe Austria

Generic Scorecard Austria Trade Register

Executive Summary

Group Analytics

Version 1.0 2024

1. Executive Summar

1.1. Creditsafe Austria Generic Scorecard Overview

In pursuit of enhancing its data reliability and addressing challenges associated with an on-demand API for Austrian credit reports, Creditsafe has strategically entered the Austrian market. Departing from reliance on external data partners, Creditsafe Group Analytics has successfully developed set of scorecards tailored specifically for Austria.

The primary objective of this initiative is to support monitoring capabilities, make use of greater control over predictive power over time, and enable the computation of an individual probability of default based on individual company characteristics. This innovative approach not only fortifies Creditsafe's foothold in the Austrian market but also significantly contributes to a more streamlined and effective risk assessment process for companies engaged in business activities within Austria.

1.2. Scorecards and Segmentation

Creditsafe's scoring methodology is a commitment to accurately predict business behaviour over the upcoming 12 months, using a wide set of characteristics that clearly identify why a business is considered to be high or low risk."

To augment the discriminative power of the scorecard solution, a strategic segmentation process was executed. The primary objective of segmentation was to delineate distinct sub-populations, each modelled individually and then amalgamated, to yield a more effective risk ranking than a singular model applied to the overall population. The key criterion for segmentation was the size of the company, predominantly determined by total asset levels. Additionally, two specialized scorecards were developed for companies without financial accounts – one tailored for newly established entities and another for companies lacking public financials, such as sole traders. This segmentation approach enhances the precision and relevance of Creditsafe’s risk assessment models, providing a more accurate perspective for businesses operating within diverse contexts.

Following segments were defined and modelled accordingly:

Companies with financial accounts

1. Small
2. Medium
3. Large

Companies without financial accounts

4. New – companies who have not yet filed their accounts – less than 24 months old
5. Other companies – sole traders etc.

1.3. Individual PD (probability of default)

The Probability of Default (PD) is a quantitative measure assessing the likelihood that a business will fail to meet its financial obligations and turn into the insolvency process within 12 months from the day of credit assessment. Creditsafe's scorecard employs a comprehensive rating scale, ranging from 1 to 100, where higher scores indicate lower risk and vice versa. This scale is derived from the individual PD calculated by scoring algorithm.

This PD is meticulously crafted based on a unique combination of company-specific characteristics. Unlike the previous approach, where scores were directly matched, the conversion process will now feature a range of PDs per score. By maintaining the PD at a company level, this refined methodology provides a more nuanced and accurate risk assessment, empowering users with a granular understanding of the creditworthiness of each company.

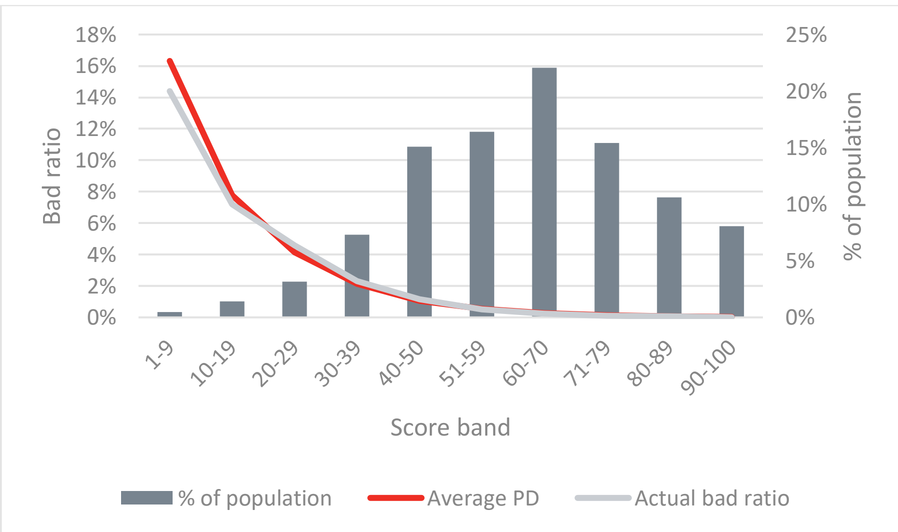
1.4. Summary of results

1.4.1. Population matrix for companies with financial accounts

A-D band	min PD	max PD	min score	max score	Expected bad ratio	Actual bad ratio	% of population
A	0,001%	0,18%	71	100	0,09%	0,06%	34%
B	0,18%	0,72%	51	70	0,38%	0,35%	38%
C	0,72%	3,03%	30	50	1,41%	1,52%	22%
D	3,03%	99,99%	1	29	6,26%	6,20%	5%
Total					0,81%	0,81%	100%

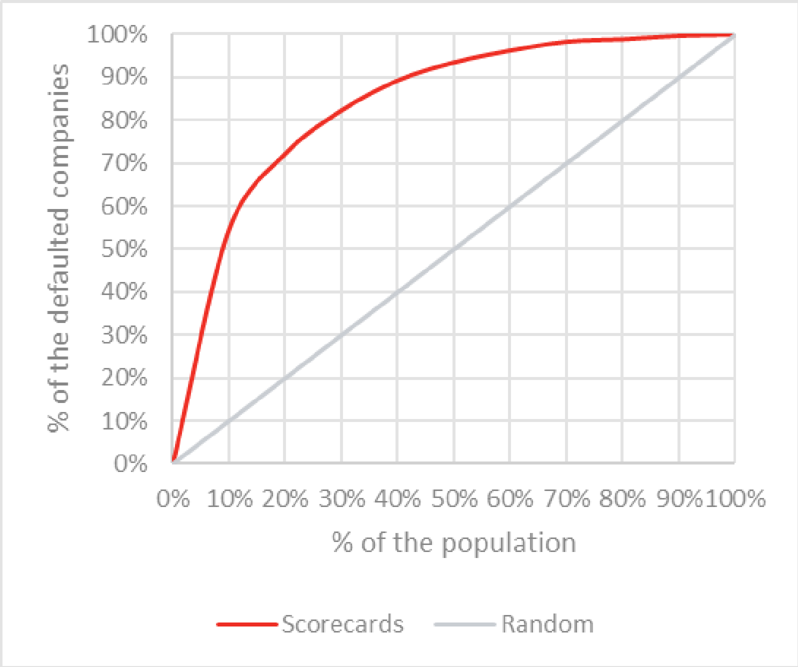
In the population matrix, above, describes the international Score Bands, Probability of Defaults (PDs), the associated minimum and max scores as well as the expected bad ratios, the actual bad ratios, and the percentage of the population in respectively A to D band.

The distribution of the scores for companies with financial accounts describes below where the X-Axis: Score Bands, Y-Axis Left: bad ratios, Y-Axis Right: the percentage of the population in each score band.



1.4.2. Predictive Power & Gini coefficient

In assessing the predictive power of Creditsafe's scorecards, the Gini coefficients emerge as a compelling measure of discrimination, showcasing exceptional performance across diverse segments within the Austrian company population.



The graph above describes the percentage of the population, with financial accounts, with the highest risk finding the percentage of the defaulted companies. That means, in the graph above, that 10 percent of the companies with the highest risk find 55 percent of all the defaulted companies. The Gini coefficient, a key indicator to measure the predictive power of the scorecards, attains levels of up to 71, demonstrating the remarkable predictive power of Creditsafe's scorecards across various segments.

1.4.3. Validation and Continuous Monitoring

Creditsafe's commitment to scorecard robustness is underscored by a continuous monitoring and validation process. The ongoing validation efforts serve to fortify the scorecards' reliability, ensuring they consistently meet the high standards set by the organization.

2. Data Preparation & Population Design

2.1. Sample Design Overview

The basis for Creditsafe's scorecards is a carefully designed sample of Austrian data extracted from the organisation's extensive data pool. The design of the sample follows the following principles:

- *Economic Activity Recognition*: The generic sample is tailored to identify economically active companies, ensuring there is a robust foundation for scorecard development.
- *Exposure Period Consistency*: Each business within the sample is allocated a 12-month exposure period, allowing for the reliable assignment of business performance.
- *Mitigating Seasonality*: The sample window spans a full year to mitigate the impact of seasonality on business performance assessments.
- *Representative Time Frame*: The sample window is recent enough to be representative of the future Austrian population, ensuring the scorecards remain relevant.

The scorecard development sample was created taking business information from 1st of January 2022 back to 31st of December 2016, giving 5 years of information. A 12-month outcome period was then used from 1st of January 2022 to 31st of December 2022 to assign the good/bad population.

2.2. Definition of defaulted companies

The default definition defined for the Austrian scorecard development are described below.

Bad	Insolvency or Insolvency process started within upcoming 12 months
Good	None of the insolvency status definitions under "Bad" arose within upcoming 12 months

3. Scorecard development

3.1. Modelling Methodology

Stepwise Logistic Regression has been used to develop the scorecards. This is the preferred methodology within Creditsafe. Logistic Regression has the benefit of outputting a predicted probability to be bad the next coming 12 months. The principles of logistic regression also enable to explain, due to the algorithm behind the calculation, the exact reason why the specific company get a certain probability of default.

3.2. Checking Business Logic

Even if a variable has predictive power, it is still necessary to check that its relationship with the outcome is logical and as expected. The first check on business logic therefore will be performed during the univariate analysis, discarding the variables that are not suitable from a business perspective.

It is necessary however to perform another overall check the model resulting from the regression. If the analysis had been performed correctly the model should be predictive and correct from a mathematical point of view. It is still necessary to check its validity from the business point of view.

3.3. Scorecard Calibration

The logistic model generates individual Probability of Default (PD) values for each company and model. These PDs are subsequently transformed into a 1-100 Creditsafe score using the "double the odds" principle. This means that with every decrease of 10 score points, the PD increases with factor 2.

The chosen value for the transformation aligns the Creditsafe score with the PD at the required point. Moreover, it ensures synchronization with the score distribution anticipated by the Austrian market, optimizing relevance and utility.

The resulting Creditsafe score serves as a direct and transparent representation of the underlying Probability of Default. This alignment provides users with a clear and accessible measure, facilitating a comprehensive assessment of a credit:

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Attachment 1: PD table - Score versus Probability of the default (PD)

SCORE		Min PD		Max PD	Band	SCORE		Min PD		Max PD	Band
100	>	0,00001	<=	0,0002441	A	50	>	0,0072366	<=	0,0077519	C
99	>	0,0002441	<=	0,0002616	A	49	>	0,0077519	<=	0,0083037	C
98	>	0,0002616	<=	0,0002804	A	48	>	0,0083037	<=	0,0088944	C
97	>	0,0002804	<=	0,0003005	A	47	>	0,0088944	<=	0,0095267	C
96	>	0,0003005	<=	0,000322	A	46	>	0,0095267	<=	0,0102035	C
95	>	0,000322	<=	0,0003451	A	45	>	0,0102035	<=	0,0109278	C
94	>	0,0003451	<=	0,0003699	A	44	>	0,0109278	<=	0,011703	C
93	>	0,0003699	<=	0,0003965	A	43	>	0,011703	<=	0,0125324	C
92	>	0,0003965	<=	0,0004249	A	42	>	0,0125324	<=	0,0134198	C
91	>	0,0004249	<=	0,0004554	A	41	>	0,0134198	<=	0,0143692	C
90	>	0,0004554	<=	0,000488	A	40	>	0,0143692	<=	0,0153846	C
89	>	0,000488	<=	0,0005231	A	39	>	0,0153846	<=	0,0164706	C
88	>	0,0005231	<=	0,0005606	A	38	>	0,0164706	<=	0,0176319	C
87	>	0,0005606	<=	0,0006008	A	37	>	0,0176319	<=	0,0188736	C
86	>	0,0006008	<=	0,0006439	A	36	>	0,0188736	<=	0,0202008	C
85	>	0,0006439	<=	0,0006901	A	35	>	0,0202008	<=	0,0216194	C
84	>	0,0006901	<=	0,0007395	A	34	>	0,0216194	<=	0,0231352	C
83	>	0,0007395	<=	0,0007926	A	33	>	0,0231352	<=	0,0247545	C
82	>	0,0007926	<=	0,0008494	A	32	>	0,0247545	<=	0,0264842	C
81	>	0,0008494	<=	0,0009103	A	31	>	0,0264842	<=	0,0283312	C
80	>	0,0009103	<=	0,0009756	A	30	>	0,0283312	<=	0,030303	C
79	>	0,0009756	<=	0,0010456	A	29	>	0,030303	<=	0,0324075	D
78	>	0,0010456	<=	0,0011205	A	28	>	0,0324075	<=	0,0346529	D
77	>	0,0011205	<=	0,0012008	A	27	>	0,0346529	<=	0,0370479	D
76	>	0,0012008	<=	0,0012869	A	26	>	0,0370479	<=	0,0396017	D
75	>	0,0012869	<=	0,0013792	A	25	>	0,0396017	<=	0,0423237	D
74	>	0,0013792	<=	0,001478	A	24	>	0,0423237	<=	0,0452241	D
73	>	0,001478	<=	0,0015839	A	23	>	0,0452241	<=	0,0483131	D
72	>	0,0015839	<=	0,0016974	A	22	>	0,0483131	<=	0,0516018	D
71	>	0,0016974	<=	0,001819	A	21	>	0,0516018	<=	0,0551014	D
70	>	0,001819	<=	0,0019493	B	20	>	0,0551014	<=	0,0588235	D
69	>	0,0019493	<=	0,0020889	B	19	>	0,0588235	<=	0,0627804	D
68	>	0,0020889	<=	0,0022385	B	18	>	0,0627804	<=	0,0669846	D
67	>	0,0022385	<=	0,0023988	B	17	>	0,0669846	<=	0,0714488	D
66	>	0,0023988	<=	0,0025705	B	16	>	0,0714488	<=	0,0761862	D
65	>	0,0025705	<=	0,0027545	B	15	>	0,0761862	<=	0,0812103	D
64	>	0,0027545	<=	0,0029516	B	14	>	0,0812103	<=	0,0865347	D
63	>	0,0029516	<=	0,0031628	B	13	>	0,0865347	<=	0,0921731	D
62	>	0,0031628	<=	0,0033891	B	12	>	0,0921731	<=	0,0981394	D
61	>	0,0033891	<=	0,0036314	B	11	>	0,0981394	<=	0,1044475	D
60	>	0,0036314	<=	0,0038911	B	10	>	0,1044475	<=	0,1111111	D
59	>	0,0038911	<=	0,0041692	B	9	>	0,1111111	<=	0,1181438	D
58	>	0,0041692	<=	0,0044671	B	8	>	0,1181438	<=	0,1255587	D
57	>	0,0044671	<=	0,0047861	B	7	>	0,1255587	<=	0,1333686	D
56	>	0,0047861	<=	0,0051279	B	6	>	0,1333686	<=	0,1415856	D
55	>	0,0051279	<=	0,0054939	B	5	>	0,1415856	<=	0,1502211	D
54	>	0,0054939	<=	0,0058859	B	4	>	0,1502211	<=	0,1592856	D
53	>	0,0058859	<=	0,0063057	B	3	>	0,1592856	<=	0,1687884	D
52	>	0,0063057	<=	0,0067552	B	2	>	0,1687884	<=	0,1787376	D
51	>	0,0067552	<=	0,0072366	B	1	>	0,1787376	<=	0,9999999	D