creditsafe

Creditsafe Germany Generic Scorecard B2B

Executive Summary
Group Analytics
Version 2026

creditsafe

1. Executive Summary

1.1. Creditsafe Germany Generic Scorecard Overview

To further strengthen Creditsafe's position in the German market, a new generation of generic scorecards has been developed by Creditsafe Group Analytics. The previous scorecards were launched in 2019 and, following several years of significant growth in data coverage, predictive analytics capabilities, and market developments, it was time to undertake a comprehensive redevelopment.

Creditsafe continuously invests in improving its credit scoring solutions by applying the latest advances in statistical modelling techniques and leveraging its ever-expanding database. The new scorecards make use of a broader range of relevant and up-to-date information, enabling more accurate and predictive assessments of German businesses.

The redevelopment also reflects changes in the German regulatory environment. New requirements under the German Federal Data Protection Act (Bundesdatenschutzgesetz, BDSG), within the framework of the General Data Protection Regulation (GDPR), introduce stricter conditions for the scoring of natural persons. This particularly affects businesses outside the German Commercial Register, where the credit assessment may be linked to an individual rather than a separate legal entity. Consequently, the new scorecards have been developed for companies registered in the German Commercial Register. Businesses outside the register will no longer receive a calculated credit risk score.

This redevelopment enhances the way companies are scored, improving risk differentiation across the portfolio while increasing coverage and predictive performance, even for businesses with limited available information. As a result, customers benefit from more reliable credit risk assessments that better reflect today's business environment

1.2. Scorecards and Segmentation

The essential concept behind Creditsafe’s scoring approach is to accurately predict future business behaviors by estimating the likelihood of adverse credit events occurring within the next 12 months. This is achieved using predictive characteristics that identify and quantify the key drivers of credit risk, enabling businesses to be ranked from lowest to highest risk.

To maximize predictive performance and discriminative power, the German portfolio was segmented into several distinct sub-populations prior to model development. The rationale for this approach is that German businesses vary considerably in terms of maturity, size, regulatory reporting requirements, operational complexity, and the availability of financial information. As a result, the factors driving credit risk are not uniform across the population.

Rather than applying a single scorecard across all companies, dedicated models were developed for groups of businesses with similar characteristics and data profiles. This allows each scorecard to utilize the most relevant risk indicators for the segment concerned and provides a more accurate assessment of credit risk. Segmentation also improves model stability, increases score coverage, and enhances risk differentiation across the portfolio.

The segmentation framework was primarily driven by:

- Company maturity and operational history
- Availability and recency of financial accounts
- Legal obligation to submit financial statements
- Company size, measured by total assets

The resulting scorecard architecture consists of the following segments:

Companies with Limited or No Financial Information

1. Startup – 1 Year Financials
Newly established companies with a limited operating history and only one year of financial accounts available.

2. Startup – No Current Financials
Young businesses where current financial statements are not yet available, requiring greater reliance on non-financial and behavioral characteristics.

3. No Financials – No Obligation
Businesses that are not legally required to publish financial accounts, including municipal companies, public sector-owned entities, associations, foundations, and certain other entity types with limited financial disclosure requirements.

4. No Current Financials
Companies for which financial statements are either unavailable, outdated, or not sufficiently current for use within the statistical modelling framework.

Companies with Financial Accounts

5. Small Companies
Businesses with relatively low levels of total assets and simpler organizational structures. These companies often exhibit different risk dynamics compared with larger businesses and therefore benefit from a dedicated model.

6. Medium Companies
Businesses with greater operational scale and financial complexity than small companies, requiring a distinct risk assessment framework.

7. Large Companies
Companies with substantial asset bases, more complex business structures, and often different financial and credit risk characteristics from smaller segments.

Expert Models

8. Expert Model – Financial Institutions
Banks, insurance companies, and other financial institutions operate under specialized regulatory frameworks and exhibit risk characteristics that differ significantly from non-financial companies. Consequently, these entities are assessed using a dedicated expert model.

9. Expert Model – Corporates
Large and strategically important corporate entities may have unique organizational structures, ownership arrangements, and financial profiles that are not fully captured by a standard statistical scorecard. These companies are therefore assessed through a specialized expert-based methodology.

This segmentation strategy ensures that each company is evaluated using the most appropriate methodology based on its characteristics and available information. By combining specialized scorecards across the various segments, Creditsafe achieves broader market coverage, stronger predictive power, and more accurate credit risk assessments across the German business population.

1.3. Individual PD (probability of default) versus score 1-100

Creditsafe's scorecard assigns a score from 1 to 100, where 100 represents the lowest risk and 1 the highest risk. The score is derived from the model's Probability of Default (PD) and provides a simple and intuitive measure for customers when making credit decisions.

With the launch of the new scorecard, the individual company PD is displayed alongside the Creditsafe score. Calculated using each company's unique characteristics, the PD provides a more granular view of risk, while the score continues to offer a simple and consistent basis for credit decision-making.

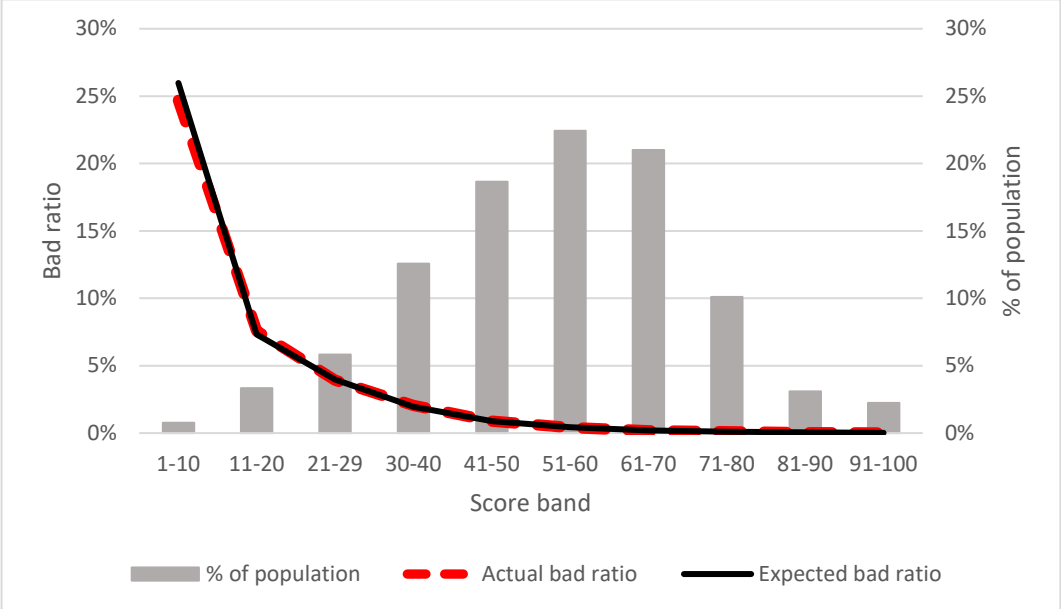
1.4. Summary of Results

The **"No Financials – No Obligation"** segment has been excluded from the population distribution analysis. While this segment represents a relatively large share of the population, it is characterized by a very low observed risk level and consists of entities that are not legally required to publish financial statements, such as municipal companies, publicly owned entities, associations, and foundations.

Population matrix for segment 1-7 (except: 3. No Financials – No Obligation)

Risk Class	Min PD	Max PD	Min Score	Max Score	Expected Bad Ratio	Actual Bad Ratio	% of Population
A	0,01%	0,14%	71	100	0,08%	0,07%	15%
B	0,14%	0,61%	51	70	0,32%	0,30%	43%
C	0,61%	3,00%	30	50	1,31%	1,37%	31%
D	3,00%	99,99%	1	29	6,79%	7,24%	10%

Population distribution for segment 1-7 (except: 3. No Financials – No Obligation)

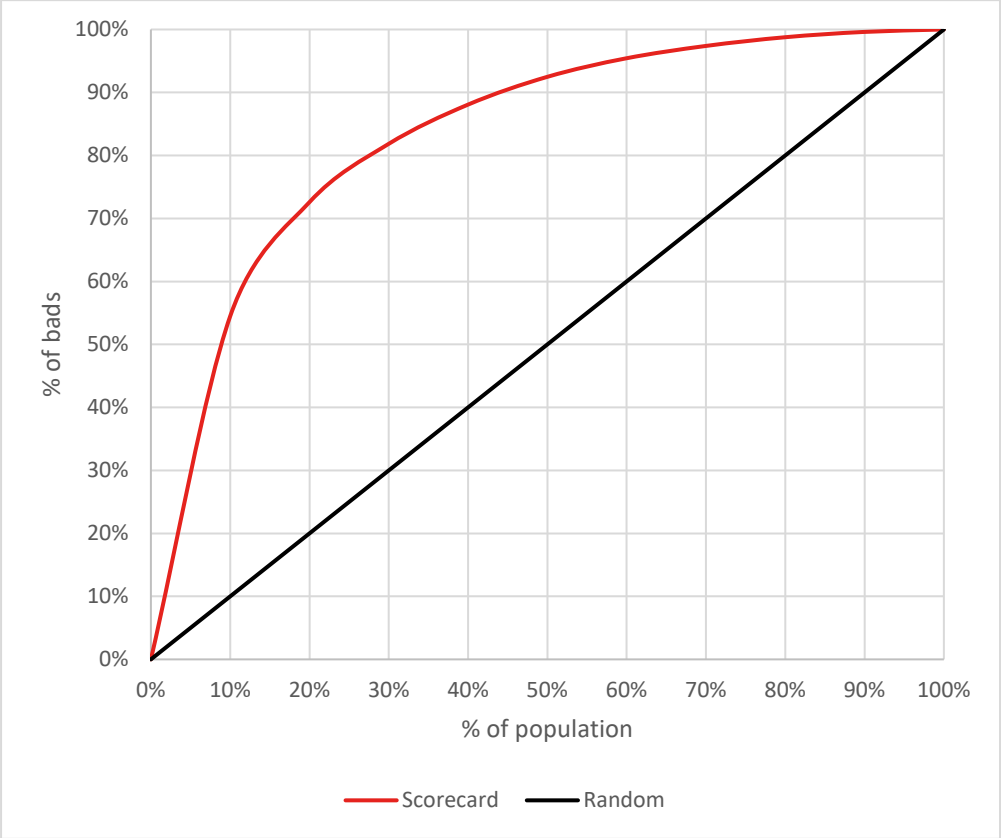


Predictive power – Gini coefficient

The Gini coefficients demonstrate strong discriminatory power across all segments of the German company population. The scorecards exhibit a high level of predictive accuracy and stability across the portfolio.

As part of its model governance framework, Creditsafe will continuously monitor and validate scorecard performance to ensure ongoing robustness, reliability, and predictive power. Regular performance assessments will be conducted to ensure that the models remain effective and aligned with changes in market conditions and portfolio characteristics.

Predictive power for segment 1-7 (except: 3. No Financials – No Obligation)



The Gini coefficient varies across the different segments, with an average value of approximately **70%**, demonstrating strong overall discriminatory power. The main exception is the No Financials – No Obligation segment, which consists primarily of associations, foundations, municipal entities, and similar organizations. As the risk drivers for these entities differ from those of traditional commercial businesses, the segment exhibits more heterogeneous risk patterns that are less suited to a standard commercial scorecard approach.

1.5. Migration matrix

The migration table shows how observations are distributed between the risk grades of the existing scorecard and the new scorecard. By comparing the classifications from the two models, the analysis provides an overview of how observations are assigned across the risk scale.

The table highlights where observations are classified into the same risk grades and where movements occur between different grades. These migrations reflect differences in the ranking and risk assessment of the two scorecards.

The migration analysis is a useful way to compare the classification outcomes of the existing and new scorecards and to understand how observations are redistributed between risk grades under the updated model.

		New risk grades			
		A	**B**	**C**	**D**
Previous risk grades	A	35%	52%	11%	1%
	B	19%	56%	22%	3%
	C	3%	35%	45%	18%
	D	0%	18%	52%	30%

creditsafe

2. Data Preparation & Population Design

2.1. Sample Design

The scorecards were 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. There are sufficient businesses to develop a robust scorecard.
- Each business had a 12 months' exposure period; this is sufficient for business performance to be reliably assigned.
- The window covers a full year to avoid seasonality.
- The sample window is recent enough to be representative of the future German population.

The scorecard development sample was created using business information from **1 September 2019 to 31 August 2024**, providing **60 months (5 years)** of historical information. A 12-month outcome period was then used from **1 September 2024 to 31 August 2025** to assign the good/bad population.

2.2. CS German Default Definition

The default definition applied in the German scorecard development is presented below. The purpose of this default definition is to provide a clear and robust distinction between high-risk and low-risk businesses.

Bad	Insolvency process started
Good	Not above definition

creditsafe

3. Scorecard Development

Modelling Methodology

The scorecard was developed using **stepwise logistic regression**, which is the standard modelling approach applied within Creditsafe. Logistic regression is particularly well suited for credit risk modelling as it produces an estimated **Probability of Default (PD)** for each company, enabling a direct and transparent relationship between score values and expected risk levels.

The modelling process involved extensive variable assessment, including predictive strength, stability, data quality, and business relevance. Candidate variables were evaluated through both univariate and multivariate analysis before being considered for inclusion in the final model.

Business Logic Review

In addition to statistical performance, all variables and model relationships were assessed from a business perspective. During the univariate analysis stage, variables demonstrating implausible or non-intuitive relationships with default risk were excluded from further consideration.

Following model development, a comprehensive review of the final scorecard was conducted to ensure that the results were both statistically robust and commercially meaningful. Attention was given to the risk ranking of attribute groups, ensuring that score contributions were consistent with observed default behaviour. This included validating the direction and magnitude of score impacts to confirm that higher-risk characteristics received appropriately lower scores and vice versa.

Scorecard Calibration

The final logistic regression model generates an individual PD for each company. These PD estimates were subsequently transformed into the Creditsafe **1-100 credit score scale** using the industry-standard **Points to Double the Odds (PDO)** methodology.

The calibration process was designed to ensure that the score accurately reflects the underlying probability of default while maintaining a score distribution appropriate for the German market. As a result, the Creditsafe score provides a clear and intuitive representation of credit risk, with higher scores indicating lower predicted default risk.

The table below illustrates the relationship between the estimated PD and the corresponding Creditsafe 1-100 score.

creditsafe

Score		Min		Max	Band	Score		Min		Max	Band
100	>	0,0001%	<=	0,0155%		50	>	0,6141%	<=	0,6617%	
99	>	0,0155%	<=	0,0167%		49	>	0,6617%	<=	0,7130%	
98	>	0,0167%	<=	0,0180%		48	>	0,7130%	<=	0,7683%	
97	>	0,0180%	<=	0,0195%		47	>	0,7683%	<=	0,8278%	
96	>	0,0195%	<=	0,0210%		46	>	0,8278%	<=	0,8918%	
95	>	0,0210%	<=	0,0226%		45	>	0,8918%	<=	0,9608%	
94	>	0,0226%	<=	0,0244%		44	>	0,9608%	<=	1,0350%	
93	>	0,0244%	<=	0,0263%		43	>	1,0350%	<=	1,1149%	
92	>	0,0263%	<=	0,0283%		42	>	1,1149%	<=	1,2009%	
91	>	0,0283%	<=	0,0305%		41	>	1,2009%	<=	1,2935%	
90	>	0,0305%	<=	0,0329%		40	>	1,2935%	<=	1,3931%	C
89	>	0,0329%	<=	0,0355%		39	>	1,3931%	<=	1,5002%	
88	>	0,0355%	<=	0,0383%		38	>	1,5002%	<=	1,6155%	
87	>	0,0383%	<=	0,0412%		37	>	1,6155%	<=	1,7394%	
86	>	0,0412%	<=	0,0445%	A	36	>	1,7394%	<=	1,8727%	
85	>	0,0445%	<=	0,0479%		35	>	1,8727%	<=	2,0159%	
84	>	0,0479%	<=	0,0517%		34	>	2,0159%	<=	2,1699%	
83	>	0,0517%	<=	0,0557%		33	>	2,1699%	<=	2,3354%	
82	>	0,0557%	<=	0,0601%		32	>	2,3354%	<=	2,6007%	
81	>	0,0601%	<=	0,0647%		31	>	2,6007%	<=	2,7935%	
80	>	0,0647%	<=	0,0698%		30	>	2,7935%	<=	3,0002%	
79	>	0,0698%	<=	0,0752%		29	>	3,0002%	<=	3,2217%	
78	>	0,0752%	<=	0,0811%		28	>	3,2217%	<=	3,4589%	
77	>	0,0811%	<=	0,0874%		27	>	3,4589%	<=	3,7129%	
76	>	0,0874%	<=	0,0942%		26	>	3,7129%	<=	3,9848%	
75	>	0,0942%	<=	0,1016%		25	>	3,9848%	<=	4,2758%	
74	>	0,1016%	<=	0,1095%		24	>	4,2758%	<=	4,5870%	
73	>	0,1095%	<=	0,1181%		23	>	4,5870%	<=	4,9196%	
72	>	0,1181%	<=	0,1273%		22	>	4,9196%	<=	5,2750%	
71	>	0,1273%	<=	0,1372%		21	>	5,2750%	<=	5,6546%	
70	>	0,1372%	<=	0,1479%		20	>	5,6546%	<=	6,0598%	
69	>	0,1479%	<=	0,1594%		19	>	6,0598%	<=	6,4920%	
68	>	0,1594%	<=	0,1718%		18	>	6,4920%	<=	6,9527%	
67	>	0,1718%	<=	0,1852%		17	>	6,9527%	<=	7,4436%	
66	>	0,1852%	<=	0,1997%		16	>	7,4436%	<=	7,9661%	
65	>	0,1997%	<=	0,2152%		15	>	7,9661%	<=	8,5219%	D
64	>	0,2152%	<=	0,2320%		14	>	8,5219%	<=	9,1127%	
63	>	0,2320%	<=	0,2501%		13	>	9,1127%	<=	9,7400%	
62	>	0,2501%	<=	0,2695%		12	>	9,7400%	<=	10,4056%	
61	>	0,2695%	<=	0,2905%	B	11	>	10,4056%	<=	11,1111%	
60	>	0,2905%	<=	0,3131%		10	>	11,1111%	<=	11,8581%	
59	>	0,3131%	<=	0,3375%		9	>	11,8581%	<=	12,6482%	
58	>	0,3375%	<=	0,3637%		8	>	12,6482%	<=	13,4828%	
57	>	0,3637%	<=	0,3920%		7	>	13,4828%	<=	14,3635%	
56	>	0,3920%	<=	0,4225%		6	>	14,3635%	<=	15,2915%	
55	>	0,4225%	<=	0,4553%		5	>	15,2915%	<=	16,2681%	
54	>	0,4553%	<=	0,4907%		4	>	16,2681%	<=	17,2943%	
53	>	0,4907%	<=	0,5288%		3	>	17,2943%	<=	18,3711%	
52	>	0,5288%	<=	0,5699%		2	>	18,3711%	<=	19,4991%	
51	>	0,5699%	<=	0,6141%		1	>	19,4991%	<=	99,9900%	