Understanding the Spain D&B Failure Score

THIS DOCUMENT IS INTENDED TO ADDRESS THE FOLLOWING QUESTIONS:

- What is the Informa Failure Score?
- What does the Informa Failure Score predict?
- What is the availability of the Informa Failure Score?
- How is the Informa Failure Score calculated?
- How does the Informa Failure Score perform?
- What is the Relationship between the Informa Failure Score and Failure Rates?

INTRODUCTION

The Failure Score provides an overall statistical assessment on the future prospects of an active Public or Private business facing a situation of failure over the next 12 months, and is applicable to all firms with minimum information available in the Dun & Bradstreet Data Cloud.

In order to assign a risk indicator to each business in Spain, Informa developed separate assessment models to distinct business segments (Companies with Financials; Companies with no Financials; Sole Traders), given the clear dissimilarities in terms of the information each one has available, as well as the quite different observed historical failure rates.

The distribution of the scoreable universe in December 2016 is summarized in Table 1 below.

Table 1: Distribution of the Spanish scoreable universe

MODEL TYPE	SEGMENT/LEGAL FORM	# RECORDS	% RECORDS
Statistical			
• Companies with Financials	Private Limited Liability company (Sociedad de responsabilidad limitada)	614,007	21.02%
	Public Limited Liability Company (Sociedad Anónima)	57,633	1.97%
	Co-Operative Society (Sociedad cooperativa)	2,292	0.08%
	Partnership (Sociedad colectiva)	67	0.00%
	Limited partnership (Sociedad comanditaria)	67	0.00%
• Companies without Financials	Private Limited Liability company (Sociedad de responsabilidad limitada)	463,078	15.86%
	Public Limited Liability Company (Sociedad Anónima)	9,455	0.32%
	Co-Operative Society (Sociedad cooperativa)	25,844	0.88%
	Partnership (Sociedad colectiva)	499	0.02%
	Limited partnership (Sociedad comanditaria)	50	0.00%
Non-Statistical (Rules Based)	Proprietorship (Empresario individual)	1,590,111	54.45%
	Joint Property (Comunidad de Bienes)	157,264	5.39%

Until 2016, the failure risk assessment of Companies without financials was rules based. However, from 2017 such assessment changed to a statistically based analysis, which combined with the statistical model already applied to companies with financial information. In line with this change, the current document describes some of the main technical features relative to the modelling basis applied to the segment of Companies without Financials.

In addition, the document summarizes the overall performance of Companies failure risk evaluation based on the two underlying models (with financials and with no financials), that together combine to provide a common and coherent output. Based on the assessment.

Informa applies, it is possible to rank businesses based on each one's probability of failure, i.e. becoming "Bad". Such ranking may be retrieved from the outputs provided by each of the following risk classifications: a Score ranging from 1001 to 1999; a 1 - 100 Score; a 1 – 4 Risk Class. The difference between classes in each of these classifications is based on the likelihood of a business experiencing the above definition of "Bad" performance over the next 12 months.

Besides the assessment of an extensive number of Companies with financial information available in the Dun & Bradstreet Data Cloud, the risk of failure of active Spanish firms with no financial information available is accordingly assessed, based on the available demographic, trade and negative information about each one.

The performance of the Spanish Failure Score for this segment of firms confirms that the underlying analytical solution is highly effective in predicting the potential insolvency of your existing and prospective customers. The solution allows you to:

- Automate decisions for increased efficiency
- Allow faster processing of large volumes of transactions
- Free up resources to look at the time-intensive borderline decisions
- Enable more consistent decisions across the entire organization
- Reduce the costs associated with full-scale application and annual risk reviews
- Apply scores across an entire portfolio to quickly identify risk and opportunity
- Satisfy regulatory needs for timely, consistent and objective review of decisions at the account level

This document explains in greater detail how the Spanish Failure Score relative to firms with no financials was developed, after which the distributions and performance tables of the scoreable universe of Companies (with financials and without financials, both statistically-based) are shown.

FAILURE SCORE – FIRMS WITH NO FINANCIALS

WHAT THE FAILURE SCORE PREDICTS

The Failure Score predicts the likelihood of a firm facing a financial crisis over the next 12 months, materialized in the assignment of bankruptcy, insolvency proceedings, or dissolution of activity together with unsolved legal incidents.

The Spanish Failure Score was developed to meet the strict quality standards set by Dun & Bradstreet. Relative to the previous solution tailored to assess the risk of this type of firms, the new model contains several statistically based improvements and updates, providing a better understanding of the key variables that influence the future financial health of a business.

The Score was statistically derived combining variables from complementary type of variables that at each moment characterize a business, from where the most predictive explanatory variables were identified. These include not only information from the financial statements, but also information on trade experiences, as well as demographic and negative information.

The legal events which constitute failure in Spain include:

- Insolvency Proceedings
- Dissolved through Dissolution with unpaid debts, Liquidation and Winding Up
- Struck-off the Register (Cierre de Hoja Registral) due to irrecoverable debt

The expression "Bads" used in this document denotes businesses that have registered one or more of the above legal events. In turn, "Goods" means businesses that do not have any of the above legal events.

Any business that is classified as "Bad" is always identified with the respective situation of "Bad". However, as long as businesses are still active and observe one of the previous situations of "Bad" (e.g., Insolvency Proceedings), they have a risk class, which is the highest risk class. All cases that are already out of business, regardless of being or not being "Bad", are classified as NQ (Not Qualified).

AVAILABILITY OF THE FAILURE SCORE

As of December 2016, the entire active business universe in Spain was 3,413,580. This included Companies, Sole Proprietorships and other legal forms including associations, as well as businesses in Public Administration.

Out of this total, 97.6% (3,270,699) belonged to the private sector, of which 35.9% (1,172,992) were 'Companies'. In line with what is portrayed in Table 1, there is 1,172,992 'Companies' in the Private sector, 57.4% (674,066) of which have financial information updated in the Dun & Bradstreet Data Cloud; the failure score for this segment has been implemented in November 2014.

The Failure Score for companies without financials is available for approx. 475,000 Spanish registered businesses (42.5% of private sector). The number corresponds to a significant number of Spanish firms registered in the Chamber of Commerce.

The following cases are not considered for scoring and are outside of the 'Scoreable Universe':

- Businesses which are Out of Business, Foreign Registered Businesses
- Businesses in the following sectors - Financial, Insurance, Holding activities
- Businesses in Administration, Associations, Foundations

The D&B Failure Score will not be calculated for branches. Automatic trade-up to the headquarter location score will take place for branch locations.

The minimum level of data requirement is composed by:

- Company name
- Company address
- Foundation Date or Share Capital
- A valid Standard Industry Code (Nace Rev 2)
- Legal form

Cases which do not meet these criteria are not considered as part of the scoreable universe, and have a score of blank or null and the Risk Indicator will be null or 'dash'.

MODEL DEVELOPMENT PROCESS

The models built for the Spanish Failure Score enhance the potential benefits from the extensive Data Cloud. In addition to its comprehensiveness, this database is monitored according to strict quality processes, providing a timely and consistent Data Cloud. Such quality allowed the achievement of high performance for the Failure Score, which ultimately facilitates and leverages the data.

The predictive factors behind the Failure Score and the way they combine were chosen based on the use of robust statistical techniques, together providing mathematical equations composed by the selected variables and weights that are able to translate into a single number the risk of Failure of the businesses assessed.

The model development process applied to companies without financials required the selection of the multiplicity of factors characterizing each business at a certain period in time. In order to derive a powerful statistical model, Informa retrieved predictive information (photos) of active firms (only firms without financials) in two different points in time (31.12.2012 and 31.12.2013) relative to their respective:

- Demographic data and activity signs: includes business legal form, age since constitution, age of balance sheet, number of employees, physical address, industry type and other related information of a particular firm.
- Trade data: comprises information from trade experiences.
- Negative data: contains information pertaining to legal incidents related to potential payment difficulties.

The dataset with the two previous photos was merged with the information about the failure status 12 months after each photo. In order to maintain the logic close to a hazard model, any case in failure at the end of the first photo (31.12.2012), was excluded from the second photo, even if at the time it remained active.

With the data of the two photos, a total of over 950,000 million cases were analyzed, out of which near 16,000 cases were "Bad".

From the various potential predictive factors initially considered, the selection was based on the individual predictive power of each one and the way they combine, so as to avoid duplicating similar information, but also not to leave behind relevant information.

Appendix A contains a more comprehensive list of data elements which are used in calculating the score.

SCORING SYSTEM AND MODEL SELECTION

In order to identity the best combination of predictors, a forward and backward stepwise selection of variables was used. The final model was the one that best results revealed in terms of:

- Discriminatory power
- Lack of multicollinearity problems
- Comprehensiveness of information about each assessed entity
- Economic meaning of the relation between variables
- Robustness to out of sample and out of time tests

SCORING OUTPUTS – SCORE VALUES

Based on the combined use of both models, namely for companies with and without financials, Informa is able to retrieve several common outputs and, as such, generate the estimated performance per score range. Accordingly, indicators and tables shown in this document pertain to both models during 2016[1].

The Failure Score for all scoreable companies (excluding Sole Proprietorships) assigns the following measurements of risk:

- A "Raw Score" of 1001 - 1999, where 1001 is applicable to businesses that have the highest probability of failure, and 1999 represents businesses with the lowest probability of failure. This Score provides a direct relationship between the score and the level of risk. The marginal odds of being good doubles for each 40 point increase. For example, a score of 1250 <=> odds of being good = 8, 1290 <=> odds of being good = 16, 1330 <=> odds of being good = 32, etc. This score enables a customer to utilize more granular cutoffs to drive the automated decision-making process.

- A "Score" of 1 - 100, where 1 represents businesses that have the highest probability of failure, and 100 represents businesses with the lowest probability of failure. This Score 1-100 shows how the risk of a business compares to other businesses in the Dun & Bradstreet Data Cloud, and is most effectively used by customers to rank order their portfolios, from highest to lowest risk of business failure. In order to maintain full coherence between the outputs of both models (firms with financials and without financials), the "Score 1 - 100" does not necessarily represent the exact percent of businesses with a score below the upper raw score corresponding to the percentile, but is an approximation of that percentage.
  Note: Andorra companies will continue, as today, on a percentile based 1 - 100 score.

- A "Risk Class" of 1 - 4, which is a segmentation of the universe into four distinct risk groups, where 1 denotes businesses that have the lowest probability of failure, and 4 denotes businesses with the highest probability of failure. 3 stands for businesses near the national average probability of failure. This Risk Class enables a customer to quickly segment its new and existing accounts into various risk groups for high-level analysis and reporting.

Table 2 shows the distribution of firms according to the respective Failure Risk Cass in the Spanish database, as well as the respective Failure Score ("Score 1 - 100") ranking and the Raw Score.

Table 2: Distribution of Failure Score of firms in the Spanish database[2]

FAILURE RISK CLASS	FAILURE SCORE 1 - 100	RAW SCORE	% OF BUSINESSES WITHIN EACH CLASS
1	90 - 100	1542 - 1999	17.78%
2	57 - 89	1459 - 1541	32.72%
3	17 - 56	1377 - 1458	33.04%
4	1 - 16	1001 - 1376	16.46%

MODEL PERFORMANCE[3]

Informa took into consideration different indicators to evaluate the model performance in terms of its discriminatory power:

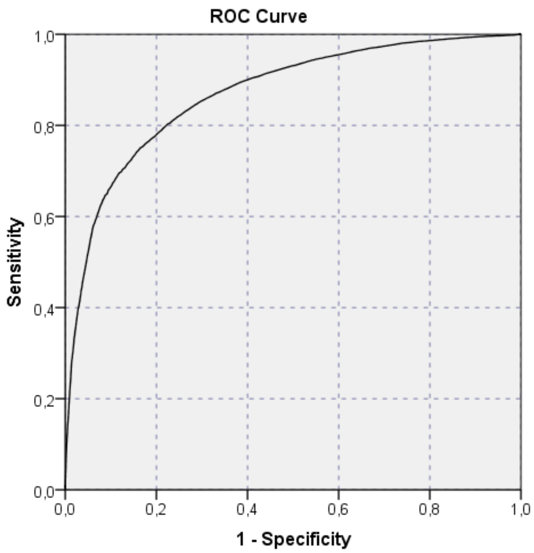
- Ranking accuracy by model, decile or quintile
- Close match between predicted and actual bad rates
- The Kolmogorov-Smirnoff statistic distance between cumulated distribution of good and bad cases as rank ordered by the model
- Predictive Index or Cumulative Accuracy Profile assessment of model gains compared to a random classifier
- The lift Gain chart with emphasis on showing the improvement in capturing BADS at the 10th and 20th scores

[1] Observation point 12/31/2015 and performance windows 01/01/2016 – 12/31/2016
[2] Model Non-Statistical excluded
[3] Model Non-Statistical excluded

One way to measure model performance is by examining a trade-off curve. A trade-off curve or a Receiver Operating Characteristic curve is a plot of ascending accumulation of “Good” businesses vs. “Bad” businesses. It is useful for illustrating model performance both at a particular score and across the spectrum of score distribution.

The trade-off curve in Graph 1 illustrates the effectiveness of the Failure Score by identifying the failure captured within population groups. At approximately 20% of the population, the Failure Score scores identified approximately 78% of the “Bads”. This means that if a business focused on the worst scoring 20% of their portfolio using the Failure Score, they would capture 78% of the “Bads” in that group.

The trade-off curve in Graph 1 illustrates the effectiveness of the Failure Score.



Scorecards are developed assuming that the relationships observed between past business characteristics and subsequent performance will hold true on future businesses. Because of this assumption, development statistics should be viewed as estimates, and not precise forecasts, of future performance at a given score.

SCORE PERFORMANCE MONITORING

Informa is committed to provide the highest quality risk assessment of businesses in Spain. In that sense, regular performance monitoring of the scorecards and back-testing exercises are used to ensure the maintenance of high performance standards of the scores in discriminating the failure risk of businesses in Spain. Whenever required, adjustments and recalibration are applied to keep up the performance of scores.

RELATIONSHIP BETWEEN THE FAILURE SCORE AND THE PROJECTED FAILURE RATES

A Risk Class is designed as a high-level segmentation tool defined into 4 classes. A Risk Class is statistically determined by the similarity of risk within the classes in contrast to other classes. Cases with the lowest Failure Risk fall in Class 1, whereas cases with the highest risk are in Class 4. Risk Class 3 is close to the national average.

Table 3 contains the national average failure rate of firms (with and without financials) by Failure Risk Class.

Table 3: National average failure rate of firms by Risk Class

FAILURE RISK CLASS	% OF DUN & BRADSTREET FILE REPRESENTED	PROJECTED BAD RATE WITHIN RISK CLASS	PROJECTED CUMULATIVE % OF FAILURES ELIMINATED
1	17.78%	0.12%	98.79%
2	32.72%	0.34%	92.77%
3	33.04%	1.05%	73.73%
4	16.46%	8.19%	0.00%

APPENDIX A

SELECTED ELEMENTS USED IN THE MODEL

Following is a list of some of the predictors used in the Failure Score Model:

Demographic Information and Activity Signs

VARIABLE	IMPACT ON MODEL
Sector of activity	Some sectors of activity have a higher exposure to economic crises than others, and so their business risk and risk of failure is also greater.
Legal form	Some legal forms are related to higher risk than others, especially when this information is combined with the type of shareholders.
Region	Different regions have different levels of risk which are reflected in the failure model
Age of company	Recently launched businesses are related to a very low risk of failure, as the underlying problems that normally lead to the failure of the business may not have emerged yet. Also, in general, more established businesses have greater stability, and hence their risk is reduced.
Age of balance sheet (whenever available)	The more outdated is the financial information of a firm, the fewer are the signs that it is actively trading; thus, the greater are the signs of the risk of an incoming situation of failure.
Number of employees	Businesses with heavy structures of human resources, i.e., higher weight of fixed costs, tend to have a higher risk of failure when compared to lighter structures.

Payment Information

VARIABLE	IMPACT ON MODEL
Recent Paydex®	Good payments on the most recent month indicates a lower level of risk.
Negative Data	The lack of historical negative data against a business is a strong indicator of low likelihood of closure within 12 months with unpaid debts.
Age, type and value of negative data	The higher the value of legal demands related to payment disputes and the more recent they are, the higher is the risk of failure. The risk also varies depending on the type of legal demands (e.g., Tax debts).

APPENDIX B

PROJECTED PERFORMANCE TABLES

The following Summary and Detailed Projected Performance Tables are based on a representative sample and actual performance may vary based on individual customer portfolios.

SUMMARY PROJECTED PERFORMANCE TABLES

CUMULATIVE FAILURE SCORE PERFORMANCE						
RISK CLASS	RAW SCORE RANGE	1-100 SCORE RANGE (APPROX.)	% OF BUSINESSES (APPROX.)	FAILURE RATE	% OF FAILURES ELIMINATED	GOOD-BAD RATIO
1	1542 - 1999	90 - 100	17.78%	0.12%	98.79%	805
2	1459 - 1999	57 - 100	50.51%	0.26%	92.77%	381
3	1377 - 1999	17 - 100	83.54%	0.57%	73.73%	173
4	1001 - 1999	1 - 100	100.00%	1.83%	0.00%	54

FAILURE SCORE PERFORMANCE WITHIN RANGE				
RAW SCORE RANGE	1-100 SCORE RANGE (APPROX.)	% WITHIN RANGE (APPROX.)	FAILURE RATE	% OF FAILURES IDENTIFIED
1542 - 1999	90 - 100	17.78%	0.12%	1.21%
1459 - 1541	57 - 89	32.72%	0.34%	6.02%
1377 - 1458	17 - 56	33.04%	1.05%	19.04%
1001 - 1376	1 - 16	16.46%	8.19%	73.73%

EXPLANATIONS

CUMULATIVE FAILURE SCORE PERFORMANCE

- **% of Businesses:** To set an approval rate, select the appropriate “Score 1 - 100” range that yields the desired approval rate. For example, to develop a credit policy that approves a projected 83.54% of all customers requires accepting businesses scoring at or above 1377 (or 17 - 100 in the “Score 1 - 100”). Businesses scoring below the cutoff score 1377 are reviewed, declined, etc.

- **Failure Rate:** The failure rate represents those businesses that score between the lowest value in the score range (or Score 1 - 100) and 1999 (or 100 Score 1 - 100). For example, the failure rate for a credit policy which approves all businesses with a score at or above 1377 (or 17 - 100 in the “Score 1 - 100”) is expected to be 0.57%.

- **% of Failures Eliminated:** The percentage of total failed businesses that score between 1001 and the cutoff point for the approval rate. For example, approving businesses with a score at or above 1377 (or 17 - 100 in the “Score 1 - 100”) is expected to eliminate 73.73% of the “Bad” businesses.

- **Good-Bad Ratio (Odds):** The ratio of “Good” businesses to “Bad” businesses among those businesses that score between the lowest value in the score range and 1999 (or 100 Score 1 - 100). For example, a credit policy that approves all businesses scoring at or above 1377 (or 17 - 100 in the “Score 1 - 100”) should result in a portfolio with 173 “Good” businesses for every “Bad” business in the portfolio.

FAILURE SCORE PERFORMANCE WITHIN RANGE

- **Failure Rate within Range:** The failure rate for those businesses that score within the score range. For example, the failure rate for businesses scoring between 1001 - 1376 (or 1 - 16 in the "Score 1 - 100") is expected to be 8.19%.
- **% Of Failures Identified:** The percentage of total failed businesses within the score range. For example, 73.73% of failed businesses are expected to score between 1001 - 1376 (or 1 - 16 in the "Score 1 - 100").

DETAILED PROJECTED PERFORMANCE TABLE

CUMULATIVE FAILURE SCORE PERFORMANCE						FAILURE SCORE PERFORMANCE WITHIN RANGE			
RAW SCORE RANGE	1-100 SCORE RANGE (APPROX.)	% OF BUSINESSES (APPROX.)	FAILURE RATE	% OF FAILURES ELIMINATED	GOOD-BAD RATIO	ROW SCORE RANGE	1-100 SCORE RANGE (APPROX.)	FAILURE RATE	% OF FAILURES IDENTIFIED
1570 - 1999	96 - 100	5%	0.11%	99.36%	916	1570 - 1999	96 - 100	0.11%	0.64%
1546 - 1999	91 - 100	10%	0.12%	98.89%	820	1546 - 1569	91 - 95	0.14%	0.47%
1528 - 1999	86 - 100	15%	0.13%	98.42%	769	1528 - 1545	86 - 90	0.15%	0.47%
1513 - 1999	81 - 100	20%	0.15%	97.69%	654	1513 - 1527	81 - 85	0.25%	0.73%
1500 - 1999	76 - 100	25%	0.17%	94.94%	583	1500 - 1512	76 - 80	0.27%	0.75%
1489 - 1999	71 - 100	30%	0.20%	96.04%	509	1489 - 1499	71 - 75	0.38%	0.90%
1478 - 1999	66 - 100	35%	0.22%	95.03%	460	1478 - 1488	66 - 70	0.37%	1.01%
1467 - 1999	61 - 100	40%	0.24%	93.75%	410	1467 - 1477	61 - 65	0.47%	1.28%
1458 - 1999	56 - 100	45%	0.26%	92.63%	377	1458 - 1466	56 - 60	0.51%	1.12%
1448 - 1999	51 - 100	50%	0.29%	91.04%	341	1448 - 1457	51 - 55	0.57%	1.59%
1438 - 1999	46 - 100	55%	0.32%	89.50%	315	1438 - 1447	46 - 50	0.62%	1.54%
1429 - 1999	41 - 100	60%	0.35%	87.73%	286	1429 - 1437	41 - 45	0.86%	1.77%
1419 - 1999	36 - 100	65%	0.38%	85.63%	260	1419 - 1428	36 - 40	0.90%	2.10%
1409 - 1999	31 - 100	70%	0.42%	83.15%	235	1409 - 1418	31 - 35	1.15%	2.48%
1399 - 1999	26 - 100	75%	0.47%	80.49%	212	1399 - 1408	26 - 30	1.41%	2.66%
1388 - 1999	21 - 100	80%	0.52%	77.08%	190	1388 - 1398	21 - 25	1.55%	3.41%
1374 - 1999	16 - 100	85%	0.59%	72.75%	168	1374 - 1387	16 - 20	1.85%	4.33%
1357 - 1999	11 - 100	90%	0.68%	67.20%	147	1357 - 1373	11 - 15	2.34%	5.55%
1328 - 1999	6 - 100	95%	0.84%	52.27%	118	1328 - 1356	6 - 10	4.07%	9.93%
1001 - 1999	1 - 100	100%	1.83%	0.00%	54	1001 - 1327	1 - 5	15.10%	57.27%

EXPLANATIONS

CUMULATIVE FAILURE SCORE PERFORMANCE

- **Approval Rate:** To use, select the appropriate projected score or Score 1 - 100 cutoff that yields the desired approval rate. Approved businesses are companies scoring between the lowest value in the score range (or Score 1 - 100) and 1999 (or 100 Score 1 - 100). For example, a credit policy that approves 73% of all businesses requires accepting businesses between 1409 - 1999 (or 31 - 100 in the “Score 1 - 100”). Businesses scoring below the cutoff (1001 - 1408) are reviewed, declined, etc.

- **Failure Rate:** Represents those businesses that score between the lowest value in the score range and 1999. For example, the failure rate for a credit policy which approves all businesses with a score at or above 1409 (or 31 - 100 in the “Score 1 - 100”) is expected to be 0.42%.

- **% of Failures Eliminated:** The percentage of total failed businesses that score between 1001 and the cutoff point for the approval rate. For example, approving businesses with a score at or above 1409 (31 - 100 in the “Score 1 - 100”) is expected to eliminate 83.15% of the “bad” businesses.

- **Good-Bad Ratio (Odds):** The ratio of “Good” businesses to “Bad” businesses among those businesses that score between the lowest value in the score range and 1999 (or 100 Score 1 - 100). For example, a credit policy which approves all businesses scoring at or above 1409 (or 31 - 100 in the “Score 1 - 100”) should result in a portfolio with 235 “Good” businesses for every “Bad” business in the portfolio.

FAILURE SCORE PERFORMANCE WITHIN RANGE:

- **Failure Rate:** The incidence of failure for those businesses that score within the score range. For example, the failure rate for companies scoring between 1399 - 1408 (or 26 - 30 in the “Score 1 - 100”) is expected to be 1.41%.

- **% of Failures Identified:** The percentage of total failed businesses within the score range. For example, 2.66% of all failed companies are expected to score between 1399 and 1408 (or 26 - 30 in the “Score 1 - 100”).

APPENDIX C

GLOSSARY OF SCORING TERMS

Following is a list of some Scoring Terms used in this document.

TERM	EXPLANATION
Informa Failure Score	Risk Score predicting likelihood of Failure
Raw Score	Score with a direct relationship to Probability of Failure. The Failure form of the raw score is a 4 digit score
Score 1 - 100	Lesser granularity of the Failure Score: Values range between 1 and 100, where 1 is the highest probability of failure
Risk Class	Lowest granularity of Failure Score; Segmentation of the Failure Score is done into 4 risk segments, where 1 denotes the lowest probability of failure
Scoreable Universe	Includes all records in the Data Cloud which meet criteria for score assignment. Examples of records excluded from the Scoreable Universe include Out of Business records, Foreign Companies etc.
Scored Universe	Includes all cases which have a score assigned
Observation Point	Date at which the data sample of active businesses is extracted and where data elements observed at that point in time are evaluated as potential predictors
Performance Window	Period where the data sample is monitored to classify businesses as GOOD and BAD
Failure BAD definition	List of Legal Events that define the targeted risk behavior
BAD	A business which meets the Bad definition, i.e., a business which has been subject to one or more of the legal events defined as failure.
GOOD	A business which does not have any information listed within the BAD definition, i.e. a business which has not been subject to any of the legal events defined as failure.
Out of Business	Businesses that are no longer trading