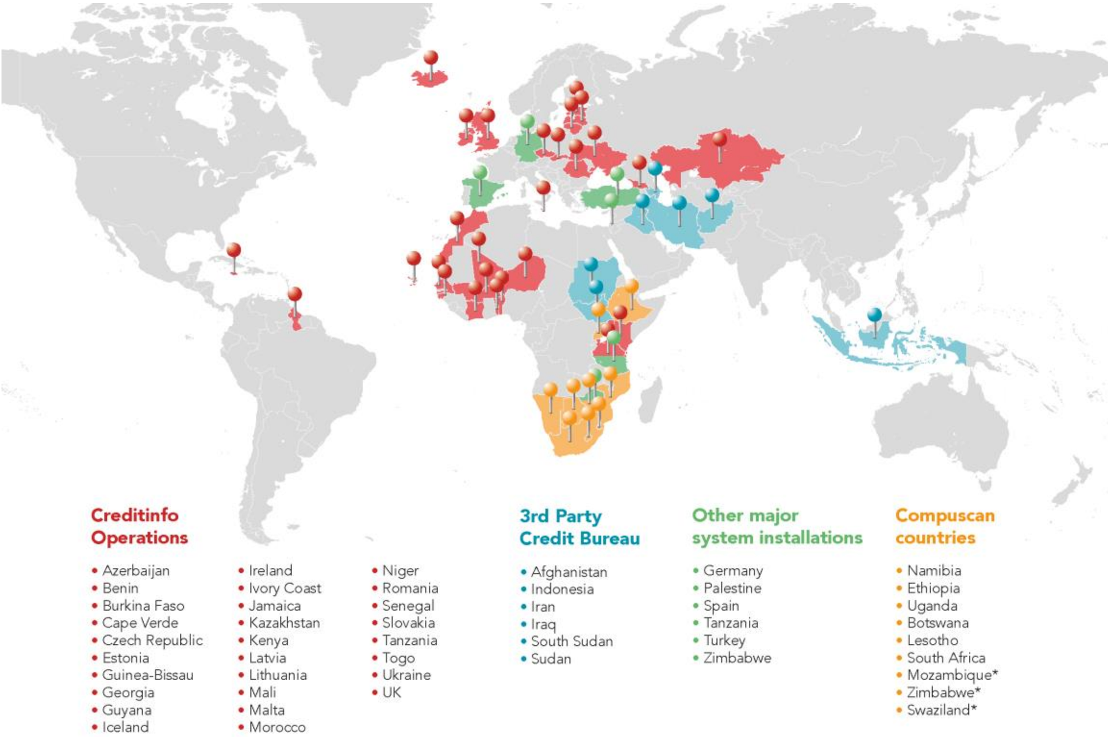
Creditinfo Default Score for B2B lending in Lithuania

Model Overview



This document is the proprietary and confidential information of Creditinfo Group and UAB Creditinfo Lietuva and all intellectual property rights arising in relation thereto are vested in Creditinfo Group and UAB Creditinfo Lietuva. This document is intended for use by the authorised recipient for its internal business purposes only and shall not be copied or reproduced in any way or disclosed to any third party. Creditinfo Group and UAB Creditinfo Lietuva shall take all such steps as it considers necessary to protect its rights in the event of any unauthorised use.

April 19th, 2024

Contents

About Creditinfo

Creditinfo began its operation in 1997 in Iceland by introducing online access to negative trade payment information and shortly after started to collect information from public data sources including financial statements, collaterals, and registry of enterprises information. Today, Creditinfo Iceland operates one of the most extensive commercial information and consumer credit databases known within the credit bureau industry. They currently offer five different credit scoring models and other value-added products. Their "Strongest in Iceland" program generates annual media attention.

Using this experience, Creditinfo started to expand its operations internationally in 2002 and today operates, maintains subsidiaries, or provides credit management services in over 30 countries.

The software and services subsidiary, Creditinfo, is located in Prague, Czech Republic. The company has more than 400 employees and provides software, analytical products, and general risk management consultancy services to all of Creditinfo's credit bureaus as well as various financial institutions across Creditinfo's geographic footprint.

Creditinfo has been particularly successful working in developing markets or developed, but fragmented, markets. As a result, the company has developed long-term relationships with many clients in Central and Eastern Europe.

Furthermore, we have an international team of skilled experts who have been involved in credit management projects in numerous countries and are always assigned according to customer requirements and their necessary qualifications.

Creditinfo has built up a strong Analytics competence centre developing statistically based credit risk models for credit bureaus and individual lenders across the globe, always with a primary view to mitigating credit risk for our customers and enabling better decision-making.

All predictive models are useful only in a combination with efficient credit strategies and policies. Therefore, Creditinfo offers a variety of consultancy services to help our partners incorporate predictive models into their operations. We design workflows suitable for specific credit products, determine appropriate credit limits, define business rules and make sure that a suit of monitoring reports is in place to provide transparency, support efficient decision-making and make sure that power of predictive models does not deteriorate. More recently, we have started using data from social media and various other 'non-traditional' data sources to target the 'thin-file' and 'unbanked' population. With experience of developing roughly 140 predictive models in over 50 countries Creditinfo has created various models for assessing the components of expected losses and scoring models for regulated institutions (incl. Credit Registers or Central Banks). Creditinfo score models a focused on of mitigating credit risk for our customers and enabling better decision-making.

Creditinfo iteratively builds up its score to become the universally accepted benchmark of risk in markets where it operates.

Introduction

The purpose of this document is to provide basic information about Creditinfo Lithuania Corporate Credit Risk (CIL Company) Score.

Score was developed by Creditinfo Decision Analytics team who has extensive experience in risk modelling for Creditinfo credit bureaus and their clients in 30+ countries.

Creditinfo Lithuania Company Score includes a broad range of predictive characteristics that capture the specifics of Lithuanian credit information environment (general and negative credit data), lenders' data disclosure requirements to credit bureaus, and publicly available information from Tax inspectorate and the State Enterprise Centre of Registers (SECR).

Creditinfo Lithuania introduced its first Company credit scoring model more than a decade ago, with at least by-early validations. The most recent model development took place in mid-2023, incorporating the newest data available.

CIL Company Default score stands at GINI 72 percent.

Important note! *Gini number above was calculated excluding companies already in default as of observation date. When applied to portfolios that include defaulted and non-defaulted companies Gini increases accordingly*.

Creditinfo Lithuania Corporate Credit Risk Score model should be used for credit risk assessment of companies. When applying or testing model on target portfolios lenders should pay particular attention to any differences in outcome definitions (definition of default).

What is a Scorecard?

Scorecard is a statistical model that predicts behaviour of a company (Subject) in the future based on information available at present.

Scorecard uses mathematical formulas to transform all the relevant information of the scored Subject into one number – credit score, which predicts Subject's risk in future. The higher is the score, the lower is probability that Subject will default on his or her payments (higher score implies better quality).

CIL Company Score is usually a component of credit assessment process. The usage of CIL Company Score replaces longer processes of manual reviews of the report. These kinds of scores are useful for decisioning, policy ruling, pricing and other credit risk evaluation related activities.

CIL Company Score provides accurate risk assessment of companies based on the information available in the CIL database at the moment of inquiry.

1.1 Benefits of scorecard

To credit providers CIL Company Score helps to improve the quality and speed of lending decisions using best industry standards and practices.

Companies benefit from easier access to credit on better terms and conditions. This, in turn, contributes to the growth of the economy.

Table 1 presents direct and indirect benefits of using CIL Company Score.

Direct benefits	Indirect benefits
• Reduced Costs ➢ Scoring quickly sorts applicants by risk saving time • Higher Volumes ➢ Automated process leads to faster response; improved customer experience and growth in applications • Faster Speed ➢ Score is immediately available • 24/7 Availability ➢ Score is calculated at the moment of inquiry 24 hours a day 7 days per week • Increased Loyalty ➢ Risk based pricing strengthens customer loyalty • Objectiveness ➢ Score is not biased by subjective considerations of credit reviewers	• Consistency ➢ Subjects with similar information receive similar probability of default (PD) estimate • Risk and loss planning ➢ Predicted probability of default can be included into product pricing and business plan • Consistency of processing information ➢ Scorecard uses same data in the same way • More transparency ➢ Score ensures clear risk assessment process and transparency of decision making process to regulators

1.2 How is the Score Calculated?

Score calculation algorithm is based on a statistical model that incorporates information contained in the credit report. All information is divided in categories such as payment history, high level of indebtedness, length of credit history, etc.

Each category has characteristics (attributes) with values allocated based on the statistical analysis. Values of each attribute are grouped into ranges/groups. Total score is calculated by adding to model constant the sum of points given to each attribute.

To illustrate the process a very simplified example of a scorecard with 3 variables (based on individual score) and a constant is provided below.

Order	Variable	Attribute	Points
0	Constant	Constant	530
1	NActiveContrCurr	0	15
	Number of currently opened contracts	1	20
		2	10
		3	0
		4 +	-20
2	NMaxPDD12M	Missing	1
	Number of maximum past due days last 12 months	< 5	4
		5 - 29	-5
		30 - 59	-15
		60 - 89	-25
		90 +	-35
3	MLast30PDD	Missing	1
	Number of months since the last time borrower was 30 past due days and more	[0,7)	-20
		[7,13)	-15
		[13,25)	-12
		[25, 37)	-10
		[37,61)	-8

Individual has a one loan and was 3 months ago overdue 35 days. He does not have other loan.

Total score is calculated as *530 + (20 + -15 +-20)* = 515 points.

CONFIDENTIAL

1.3 CIL Company Score report

CIL Company Score results for both Default and Bankruptcy ratings are available as report (web or pdf) or xml via API in two languages – Lithuanian and English. The output (depending on report type) usually consists of several elements:

- CIL Company Score
- Probability of default (PD)
- Risk Grade (class)
- Reason codes (factors)
- 6 months history showing score trends

CIL Company Score and Probability of Default (PD)

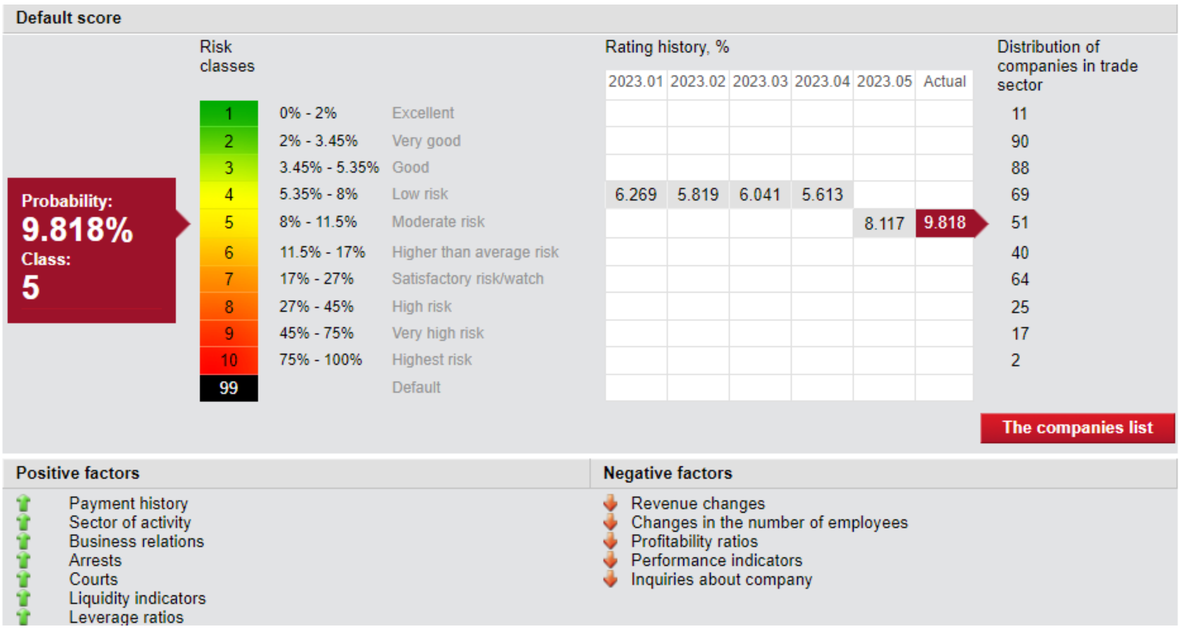
Based on the information of the last two years a prediction is made regarding a company's behavior in the next 12 months.

For exact definition of the event predicted see default definition in next section.

Risk grade with description

Risk grades are values determined by the value of score falling into a specified interval. The risk grades are meant to ease the interpretation of the score and probability of default. The 1st is the lowest risk, the 10th is the highest risk, 99 stands for the default event.

Below is an example of the professional report displaying Default ratings. The probability of Default risk classes ranges are exemplary.



Default score

Probability: 9.818%
Class: 5

Risk classes			Rating history, % 2023.01	2023.02	2023.03	2023.04	2023.05	Actual	Distribution of companies in trade sector
1	0% - 2%	Excellent							11
2	2% - 3.45%	Very good							90
3	3.45% - 5.35%	Good							88
4	5.35% - 8%	Low risk	6.269	5.819	6.041	5.613			69
5	8% - 11.5%	Moderate risk					8.117	9.818	51
6	11.5% - 17%	Higher than average risk							40
7	17% - 27%	Satisfactory risk/watch							64
8	27% - 45%	High risk							25
9	45% - 75%	Very high risk							17
10	75% - 100%	Highest risk							2
99		Default							

The companies list

Positive factors	Negative factors
Payment history	Revenue changes
Sector of activity	Changes in the number of employees
Business relations	Profitability ratios
Arrests	Performance indicators
Courts	Inquiries about company
Liquidity indicators	
Leverage ratios	

Reason codes

Reason codes are provided to help users (both lenders and the subject if he has requested his own credit report) to understand main reasons why the score is low or highlight information relevant to the risk assessment.

Reason code also provides explanation if score is not calculated (for example score is not calculated for companies in active insolvency/under bankruptcy).

Summary

Default rating	B class (The company is under bankruptcy)
Bankruptcy rating	B class (The company is under bankruptcy)

Company Score history

Score history for the last 6 months is provided in CIL report and Scoring report to provide additional information on trends in risk profile of the subject.

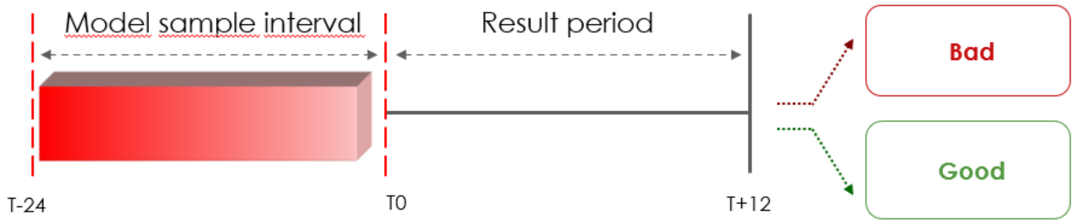
Score history serves financial education purpose, also helping companies to understand how their financial behavior changes their risk profile.

Default Score at a Glance

Metric	Description
Model type	Statistical. Logistic regression.
Data used	Credit bureau data subject to limitations of information reciprocity groups.
Segmentation	Negative scorecard – specifically designed for Lithuanian market.
Exclusions	Not applicable to: 1) Individuals 2) Not scorable legal entities 3) Not scorable activity sectors
Business rules	Companies that are currently in default or have severe negative status are allocated with the lowest possible score.
Performance characteristics	
Source of development and validation data	Data sample included all active companies with no active defaults or no severe negative status at 3 points in time: 1) 2019-01-01 49 312 observations 2) 2020-01-01 51 768 observations 3) 2021-01-01 52 231 observations Data was split at 70%/30% ratio, 70% used to train the model and 30% used for testing. The data was split randomly to keep default levels the same in both train and test samples. Covid period is not excluded under the assumption that the future is likely a mix of pre-pandemic and pandemic periods.
Default definition	Bad: Days Past Due (DPD) >=90 and Past Due Amount (PDA) >= 500 EUR, Good: all others
Gini (excluding bads as of observation) development	0.72

Figure below shows Model's observation and outcome periods.

Here:



- T0 - Score date
- T-24 - Score date minus 24 months (observation period)
- T+12 – Score date plus 12 months (outcome period)

Further information on score development methodology is provided in section 'Scoring Development Methodology'.

Definition of Default

Definition of Default is unified for all types of companies:

90 days past due and 500EUR payment incident in the next 12 months after scoring.

Model variables and their weights

Creditinfo has unique database, which could be used to compose variables containing wide range of information to predict credit risk. The table below displays variable groups that entered the model:

No	Variable Groups	Weight, %
1	Age and activity sector	42.5
2	Debt history	19.9
3	Finance	18.7
4	Inquiries	15.9
5	Other negative information	3.0

Table 1

1.4 Age and activity sector

Younger companies tend to have higher credit risk due to inexperience in the market and smaller monetary buffer. Company's activity sector is also a crucial indicator of credit risk as some sectors have proved to be riskier than others historically.

1.5 Debt history

Debt history includes historical payment incident information as well as currently open small overdue amounts. Missed payment information is relevant for 2 years since closing of the debt.

1.6 Finance

Yearly financial report data reflecting company's obligations level and efficiency. Higher obligations level usually indicates higher risk of bankruptcy.

1.7 Inquiries

Inquiry information from financial institutions, telecommunications and debt collectors proved to be significant in defining credit risk. Important indicator is significant increase or decrease from the average count of inquirers comparing last 6 months to last 3 months.

1.8 Other negative information

Other negative information about the company: frequent director changes, arrests, legal actions against the company and bailiff notifications to pay.

Risk Grades

Risk grades are Creditinfo solution to ease the interpretation of the PD values as well as provide ranking order for scored companies. The grades are from class 1 to 10, 1 being the best group, 10 – the worst. Additional classes 0 and 99 mean accordingly not rated companies and companies with default event already in place.

Risk grades are further explained below:

Grade	**PD range**	Description EN	Description LT
1	0.00 % - 0.08 %	Flawless	Nepriekaištinga būklė
2	0.08 % - 0.17 %	Excellent	Puiki būklė
3	0.17 % - 0.33 %	Very good	Labai gera būklė
4	0.33 % - 0.55 %	Good	Gera būklė
5	0.55 % - 1.08 %	Low risk	Žema rizika
6	1.08 % - 1.93 %	Average risk	Vidutinė rizika
7	1.93 % - 5.00 %	Higher than average risk	Aukštesnė nei vidutinė rizika
8	5.00 % - 8.00 %	Increased risk	Padidinta rizika
9	8.00 % - 10.00 %	High risk	Aukšta rizika
10	10.00 % - 100.00 %	The highest risk	Aukščiausia rizika
0	-	Not rated	Nereitinguojama įmonė
99	-	Default	Įvykis įvykęs

CONFIDENTIAL

Class 0 and 99

Apart from classifying companies by their PD values into different risk groups, exceptional classes 0 and 99 involve companies that do not have PD assigned due to various causes. Below subchapters explain reasons why companies can fall into one of these classes.

1.9 Class 0

Class 0 holds companies that are not suitable for rating calculations for the following reasons, listed in the following table:

Table 2. Class 0 reasons

Class	Subclass	Description	Comments
0	L0	The company is listed. Recommended for expert evaluation	Listed companies need expert-based evaluation as their provided financial reports are not standard and cannot be automatically uploaded into data bases
0	T0	The legal form of the company does not meet the criteria for the rating calculation	
0	A0	The company's activities do not meet the criteria for the rating calculation	
0	M0	Subsidiary company	
0	C0	The company provides consolidated financial statements only. Recommended for expert evaluation	

Legal entity types that are not-rated and belong to class 0 are listed in the table below.

Table 3. Not-rated legal entities

Company type in English	Company type in Lithuanian
Public institution	Viešoji įstaiga
Community	Bendrija
Budget institution	Biudžetinė įstaiga
Trade union	Profesinė sąjunga ir susivienijimas
Gardeners Society	Sodininkų bendrija
Charity and Sponsorship Fund	Labdaros ir paramos fondas

Traditional Lithuanian Religious Congregation or Community	Tradicinė religinė bendruomentė ar bendrija
Representative office of the Foreign Enterprise	Užsienio juridinio asmens ar kitos organizacijos atstovybė
Branch of the Foreign Enterprise	Užsienio juridinio asmens ar kiotos organizacijos filialas
Others	Kita

Activity sectors - NACE2 codes – that are not-rated are listed in the table below:

Table 4. Not-rated economic activities

NACE2 code	Description in English	Description in Lithuanian
640000	Financial intermediation, except insurance and pension funding	Finansinių paslaugų veikla, išskyrus draudimą ir pensijų lėšų kaupimą
641000	Monetary intermediation	Piniginis tarpininkavimas
641900	Other monetary intermediation	Kitas piniginis tarpininkavimas
641920	Credit granting credit institutions	Piniginių kreditinių įstaigų veikla
642000	Activities of holding companies	Kontroliuojančiųjų bendrovių veikla
643000	Trusts, funds and similar financial entities	Trestų, fondų ir panašių finansinių institucijų veikla
649100	Financial leasing	Finansinė išperkamoji nuoma
649200	Other credit granting	Kitas kredito teikimas
649900	Other financial intermediation n.e.c.	Kita, niekur kitur nepriskirta, finansinių paslaugų veikla, išskyrus draudimą ir pensijų lėšų kaupimą
650000	Insurance, reinsurance and pension funding, except compulsory social security	Draudimo, perdraudimo ir pensijų lėšų kaupimo, išskyrus privalomąjį socialinį draudimą, veikla
651000	Insurance	Draudimas
651100	Life insurance	Gyvybės draudimas
651200	Non-life insurance	Ne gyvybės draudimas
651210	Travel insurance	Kelionių draudimas
652000	Reinsurance	Perdraudimas
653000	Pension funding	Pensijų lėšų kaupimas
660000	Other financial activities	Pagalbinė finansinių paslaugų ir draudimo veikla

661000	Activities auxiliary to financial intermediation, except insurance and pension funding	Pagalbinė finansinių paslaugų, išskyrus draudimą ir pensijų lėšų kaupimą, veikla
661100	Administration of financial markets	Finansų rinkos valdymas
661200	Security and commodity contracts dealing activities	Vertybinių popierių ir prekių sutarčių sudarymo tarpininkavimas
661900	Other activities auxiliary to financial intermediation	Kita pagalbinė finansinių paslaugų, išskyrus draudimą ir pensijų lėšų kaupimą, veikla
662000	Activities auxiliary to insurance and pension funding	Pagalbinė draudimo ir pensijų lėšų kaupimo veikla
663000	Fund management activities	Fondų valdymo veikla
701000	Activities of head offices	Pagrindinių buveinių veikla

CONFIDENTIAL

1.10 Class 99

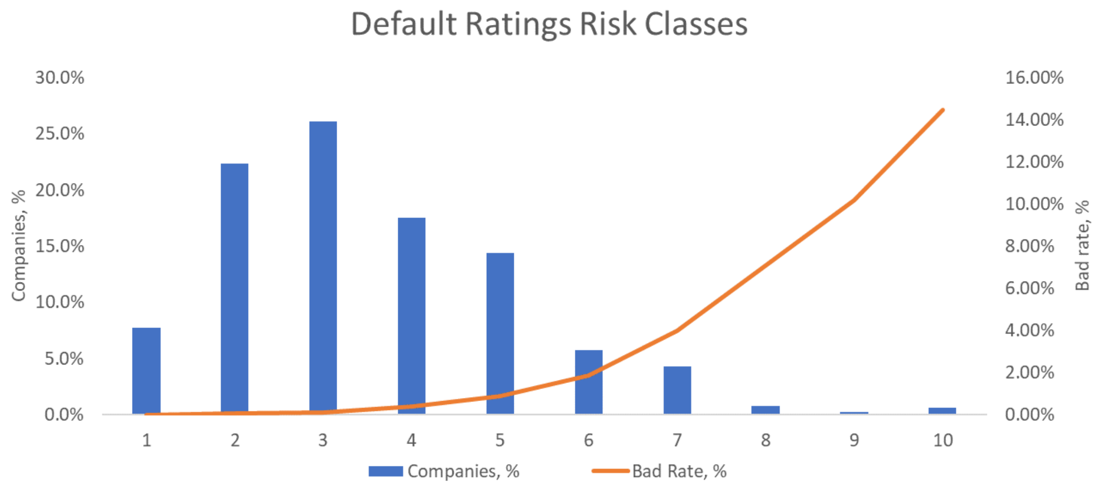
Class 99 includes companies with severe negative status:

Table 5. Class 99 reasons

Class	Subclass	Description	Comments
99	B1	The company is declared bankrupt	In court for bankruptcy
99	B2	The company is under bankruptcy	Bankruptcy proceedings
99	B3	The company is bankrupt	
99	R	The company is being restructured	
99	L	The company is under liquidation	
99	IS	The company is deregistered	
99	F0	The company does not comply with laws regulating financial statement delivery	4 months after closing financial year, legal entities that are obliged to conduct financial reports have to submit them to the Center of Registry
99	BB	Registered in the court hearing the criminal case	
99	S0	The company is under economic sanctions	
99	99	Predicted event has already occurred	Active default 500EUR+ & 90dpd
99	D0	The company has no employees	Only for legal entities that are obliged to have at least 1 employee

Risk class distributions

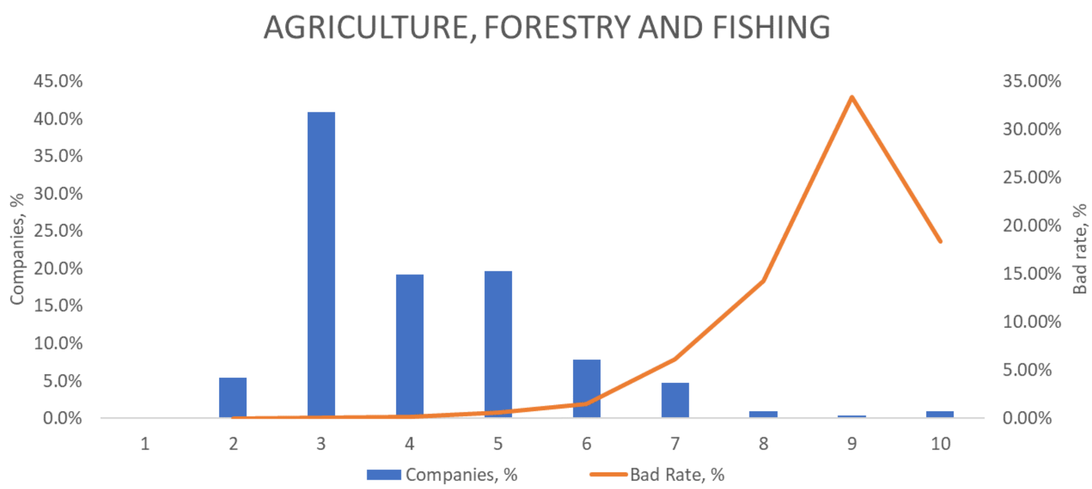
The graph below shows Default ratings class % distribution of companies – total modelling sample population.



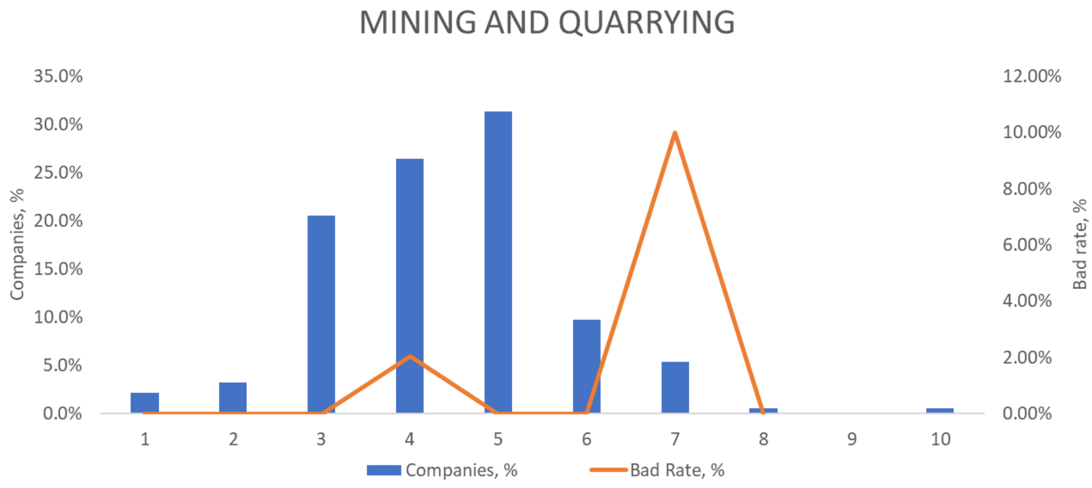
1.11 Risk classes distribution by activity sector

Below graphs show risk grade distribution by different activity sector groups. NACE 2 code letter level grouping is displayed.

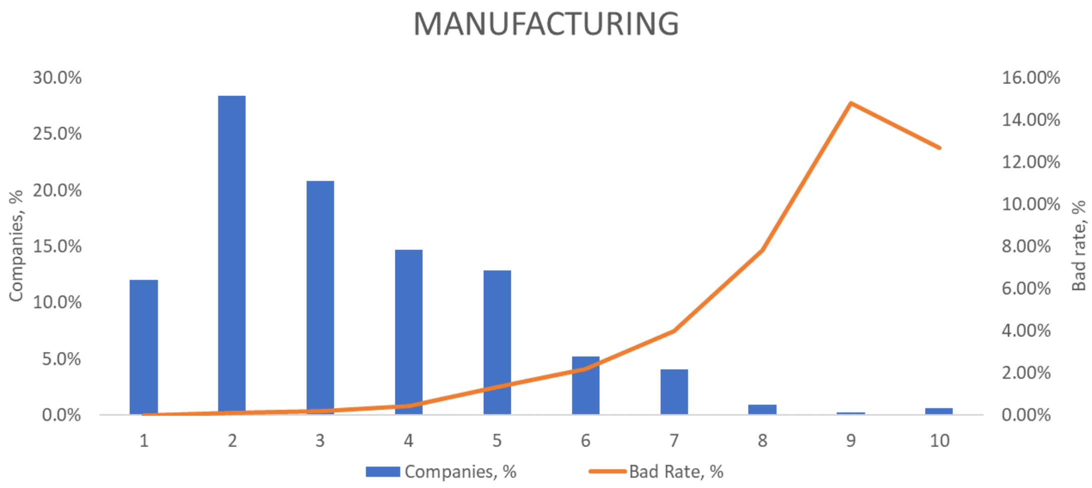
1.11.1 Group A:



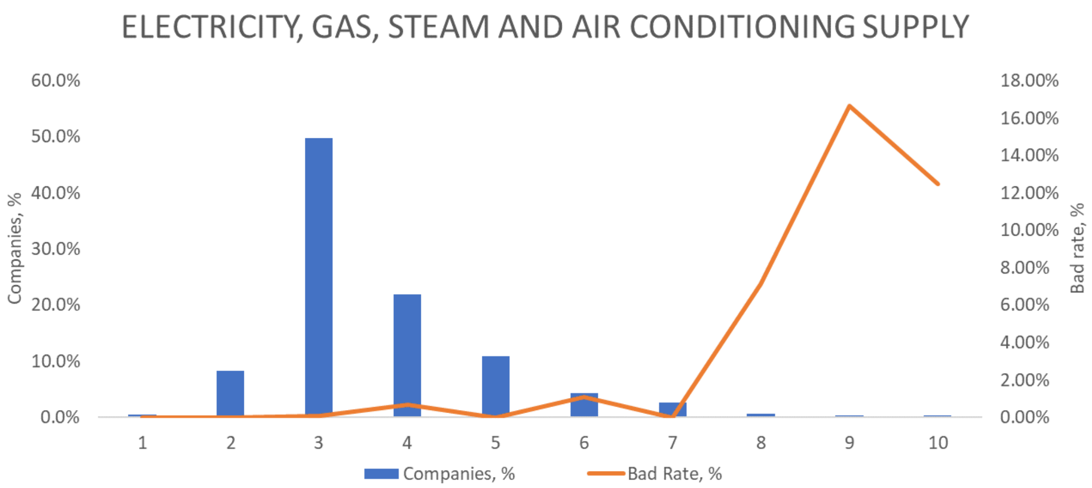
1.11.2 Group B:


MINING AND QUARRYING
35.0%
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
Companies, %
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
Bad rate, %
1
2
3
4
5
6
7
8
9
10
Companies, %
Bad Rate, %

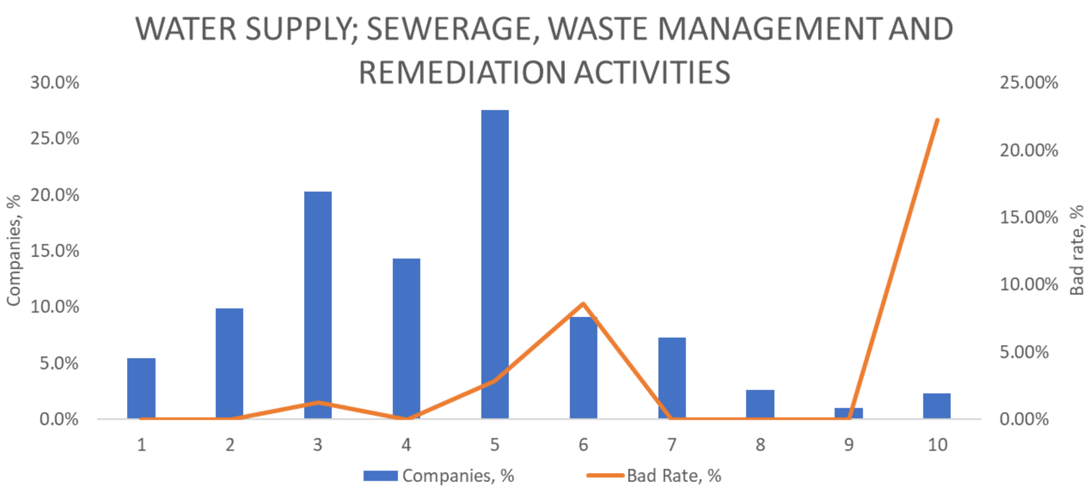
1.11.3 Group C:


MANUFACTURING
30.0%
25.0%
20.0%
15.0%
10.0%
5.0%
0.0%
Companies, %
16.00%
14.00%
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
Bad rate, %
1
2
3
4
5
6
7
8
9
10
Companies, %
Bad Rate, %

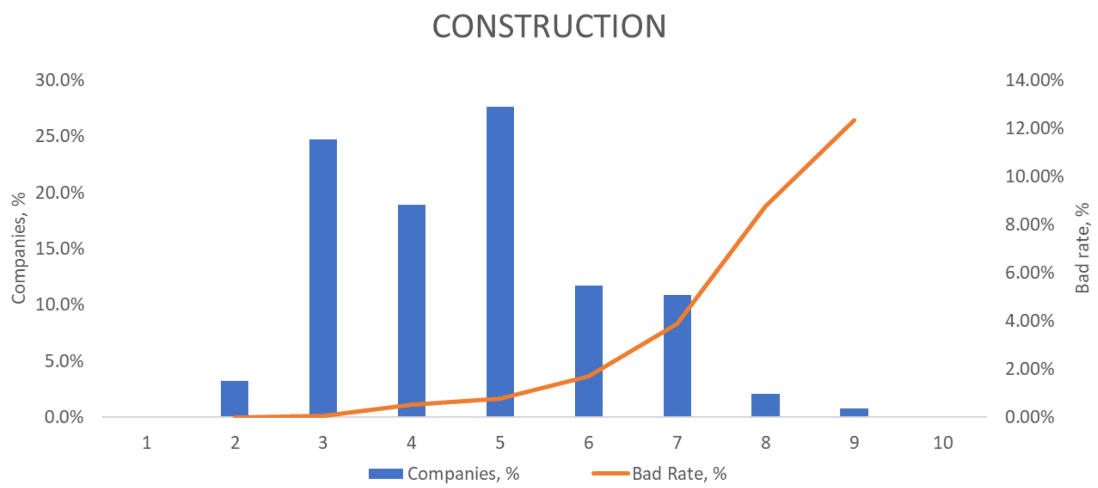
1.11.4 Group D:



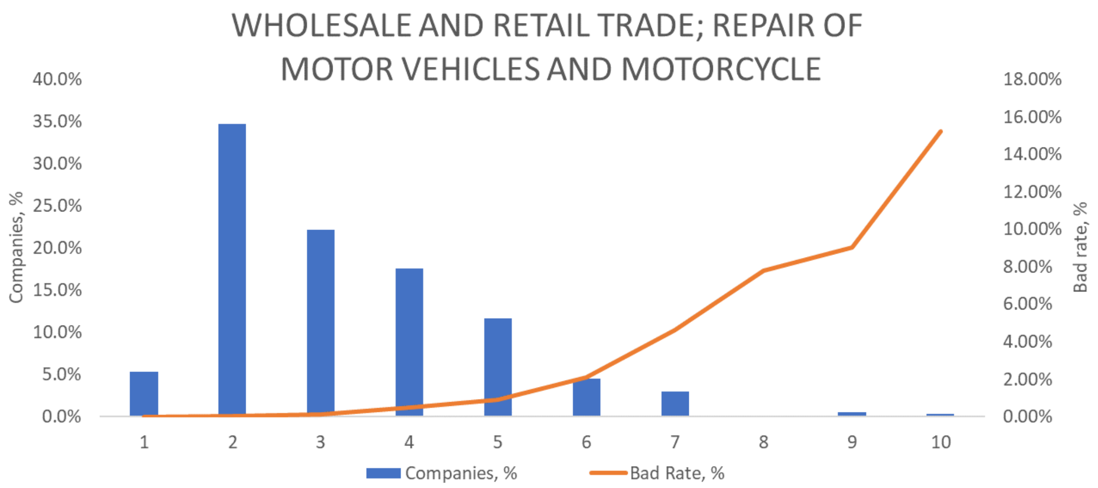
1.11.5 Group E:



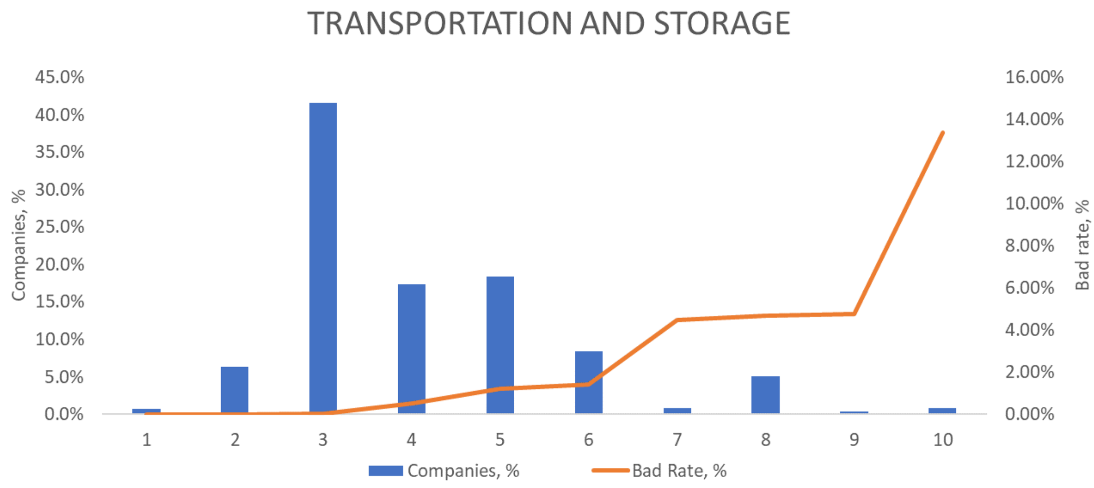
1.11.6 Group F:



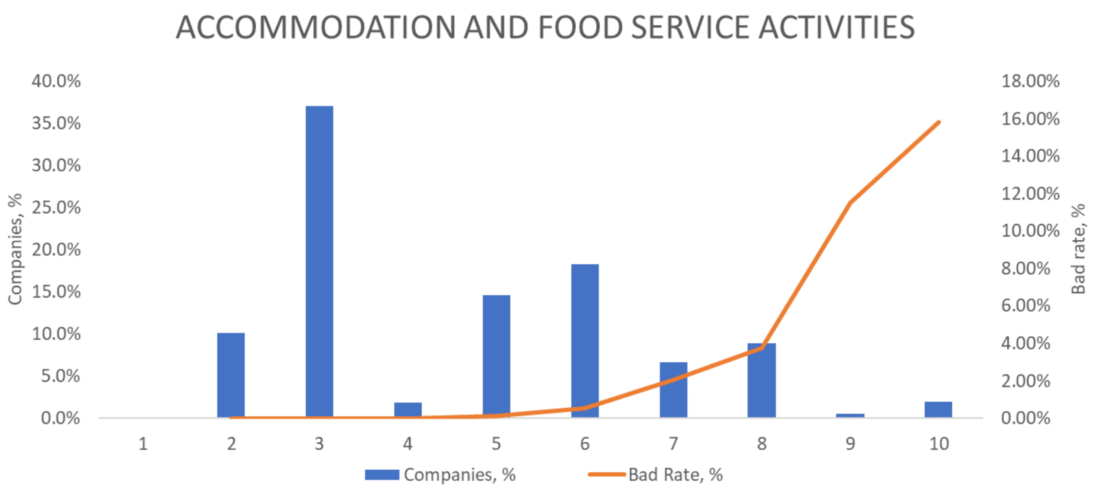
1.11.7 Group G:



1.11.8 Group H:

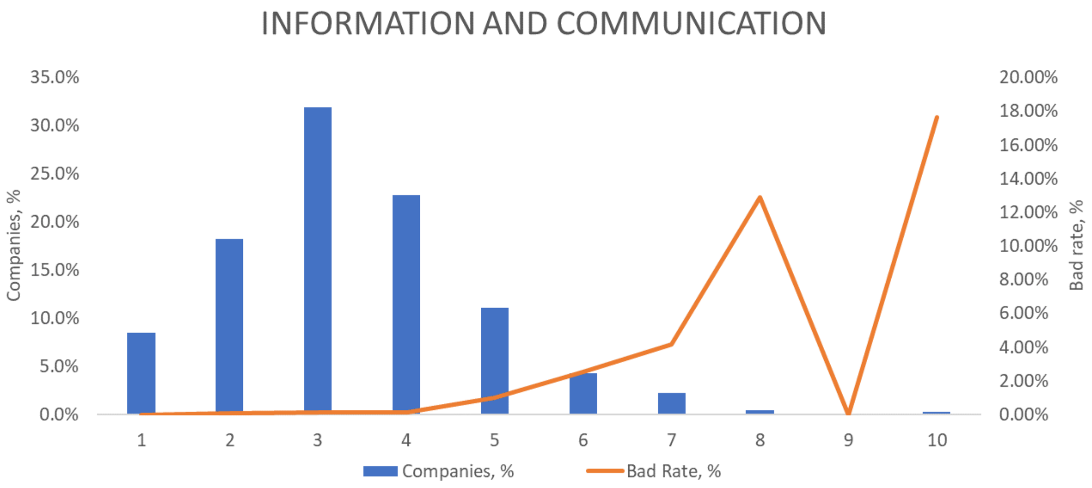


1.11.9 Group I:



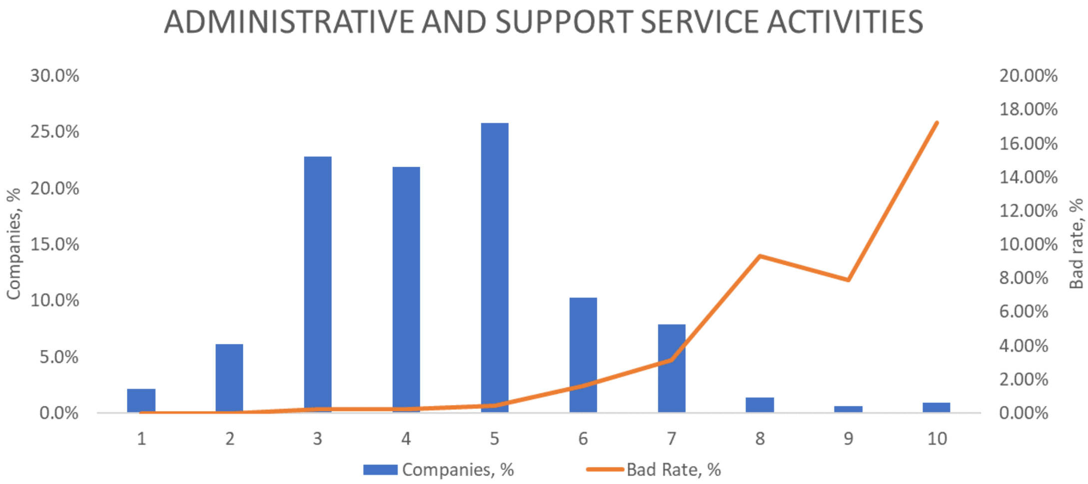
CONFIDENTIAL

1.11.10 Group J:

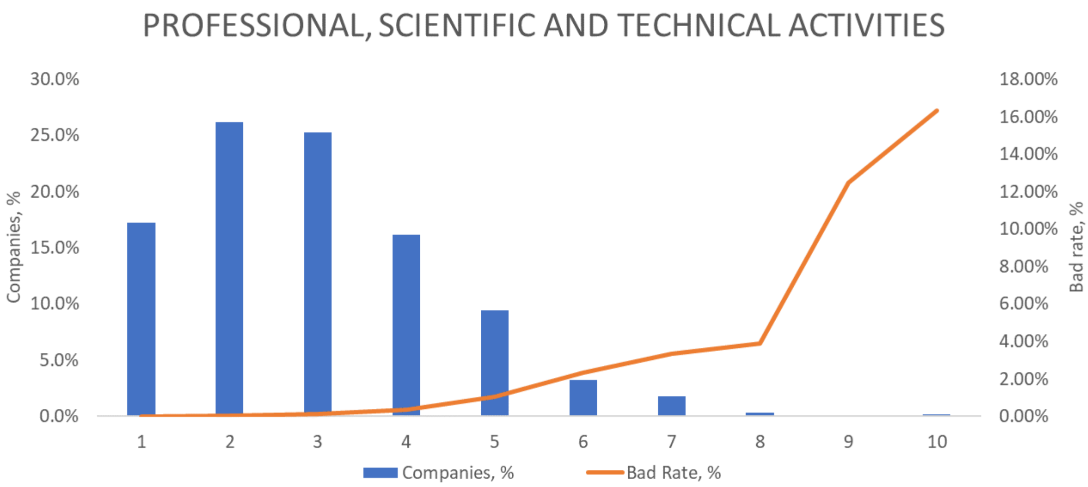


1.11.11 Group L:

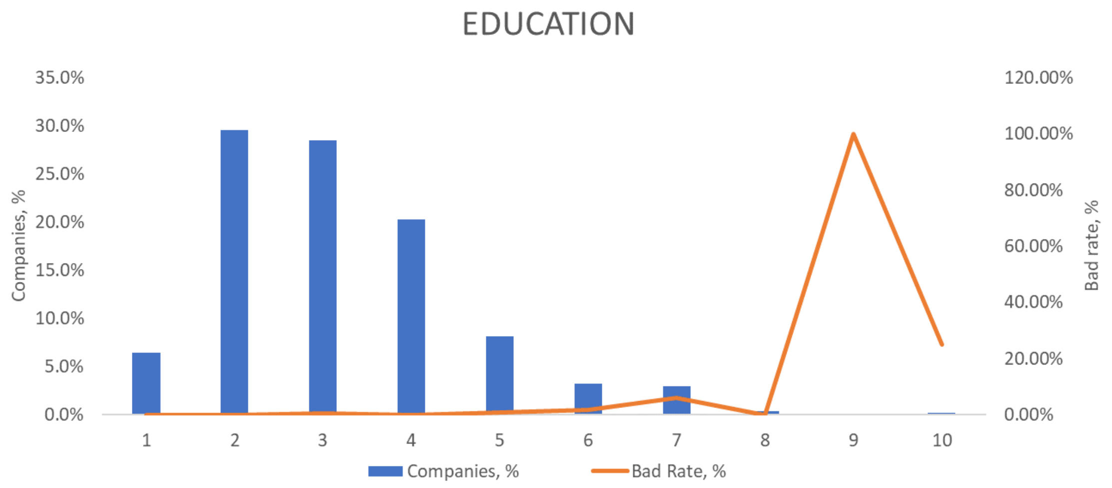
1.11.12 Group M



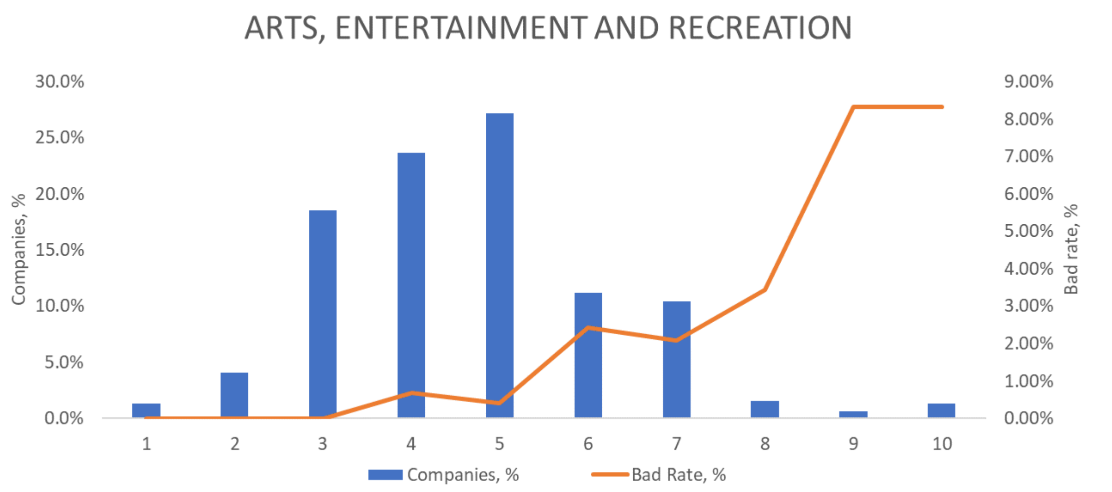
1.11.13 Group N:



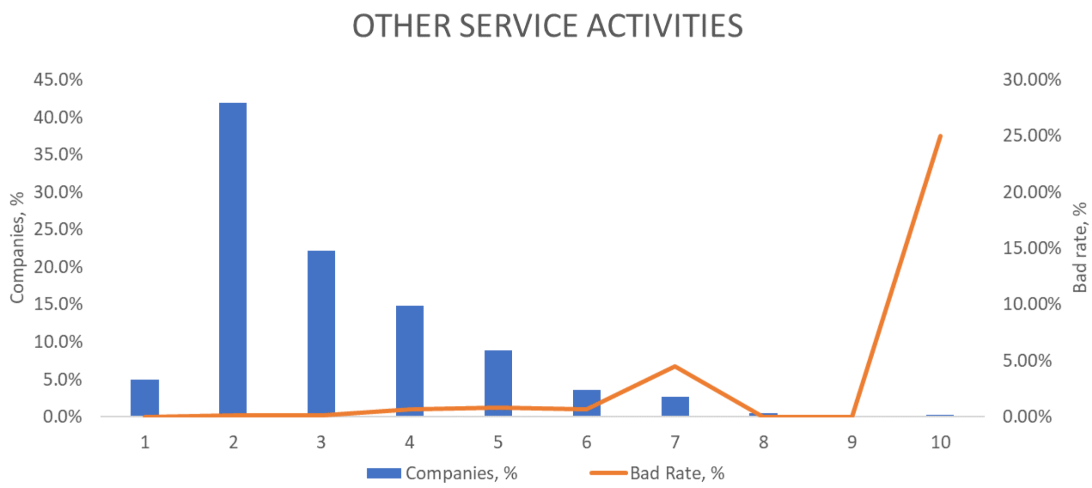
1.11.14 Group P:



1.11.15 Group R:



1.11.16 Group S:



CONFIDENTIAL

Reason Codes

Reason codes explain indicators that influence the score of the company the most. They can be both positive and negative.

Table 6: List of reason codes

Reason code description EN	**Priežastys**
Sector of activity	Veiklos sektorius
Age	Amžius
Arrests	Areštai
Bailiff notification	Antstolių raginimai
Sodra Debts	Skolos Sodrai
Inquiry	Užklausos iš išieškojimo agentūrų
Courts	Teismai
Director change	Direktoriaus pasikeitimai
Payment history	Mokėjimų istorija
Performance indicators	Efektyvumo rodikliai
Financial liability indicators	Finansinių įipareigojimų rodikliai

CONFIDENTIAL

Appendix 1. Score Development Methodology

Subsequent chapters describe main steps of scorecard development process applied to the score. Creditinfo has accumulated significant experience in credit risk modelling and adheres to standard methodology in line with best practice.

1.12 Data

As a first step we computed a number of different variables using data contained in the database, including information on demographics, debt information, inquiries, data from public sources.

Sample selected included all active subjects having no severe negative status at 3 points in time. Typically, we select samples that contain at least 100 thousand observations. In this case it was around 150 thousand observations.

The selection of the observation window is driven predominantly by the necessity to have a stable bad rate throughout the time interval. Furthermore, the observation window should be sufficiently large to protect against possible bias in model due to seasonality.

Scorecard development was divided into following four steps:

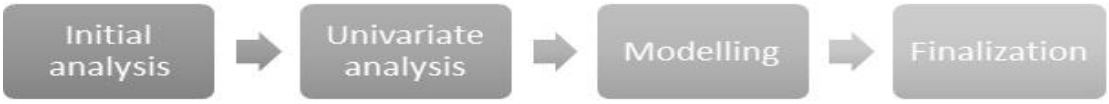


Figure 3

Brief description of each step is provided below.

1.13 Initial Analysis

The initial analysis phase involves data preparation and loading, plus a general review of the data set to be analysed. Certain observations should not be included into the scorecard development sample. This includes all subjects different from a population of customers for whom the model is designed. We exclude erroneous observations. More precisely, most exclusions are driven by the following reasons:

- Companies with severe negative status, such as bankrupting, in liquidation or restructuring
- Companies in active default
- Not scorable companies, such as banks and insurance companies

Concise outcome definition is a key of the scorecard development. It allows to identify dependencies between variable values and either good or bad payment behaviour.

Then we created validation samples. The purpose of using one or more validation samples is to test model on different groups of contracts **to protect against 'overfitting' the model to particular development sample**.

In out-of-sample testing, proportion of the original data set – 30% – was removed from the analysis and the model was built using the remaining 70% of the data. The proportion was made using stratified sampling. The model was then tested on the portion of the data which was held out of the original analysis.

1.14 Univariate Analysis

Next step is univariate analysis sometimes known as 'characteristic analysis. We investigated potential predictors of credit default in isolation applying outcome definition to historical data.

Each of the variables calculated in previous step were reviewed as a predictor of future delinquency. The goal was to identify the strongest and most stable variables which are then considered for inclusion into the model. Variables that are unstable, produce illogical results or show weak predictive quality were excluded at this stage.

Then variables were split into ranges or "bins" to:

- Increase sample counts within each range and maximize their predictive power;
- Reflect any previously discussed operational considerations;
- Smooth random disturbances while keeping bad rate trend and preserving predictive strength of the variable;

Weight of Evidence (WoE) coefficients were computed for each "bin" of each variable. WoE served as inputs to next phase - modelling.

1.15 Modelling

We use iterative approach in model development. Each iteration has following steps:

1. Variable Clustering. Clustering algorithms are applied on a correlation matrix constructed for all variables.
2. Clusters of variables that are correlated between each other were identified.
3. One or two variables from all main clusters that are representative of all variables from the same cluster were selected to reduce the total number of variables.
4. Finally, we construct the model. In the first iteration we use all variables selected despite the fact such model 'overfits' the data and performs badly on independent samples. This approach, however, allows to get a feeling of what a maximum Gini might be and serves as a benchmark during next iterations.
5. We then go back to the fields pre-selected through variable clustering, force them into the regression and simultaneously allow other variable candidates to enter the model through stepwise selection process.

Variables labelled as excluded are still tried out in various model specifications. This allows to maximize model performance and guarantees that we do not 'overlook' any important variables.

The scoring model was developed using Weight of Evidence (WoE) logistic regression to produce a ranking mechanism. This approach has several advantages:

- Estimated default probabilities lie between 0 and 1;
- Linearization of trends implies good statistical properties;
- Efficient operation with categorical variables;
- Bad rate is translated to the score via the use of WoE.

Missing fields may also provide valuable information on the subject. Therefore, when some parameters are not available, they were incorporated in the model as separate attributes.

The predictive power and the behaviour of the model was then tested repeatedly on the development sample, hold-out sample, out-of-time sample and recent data sample.

CONFIDENTIAL

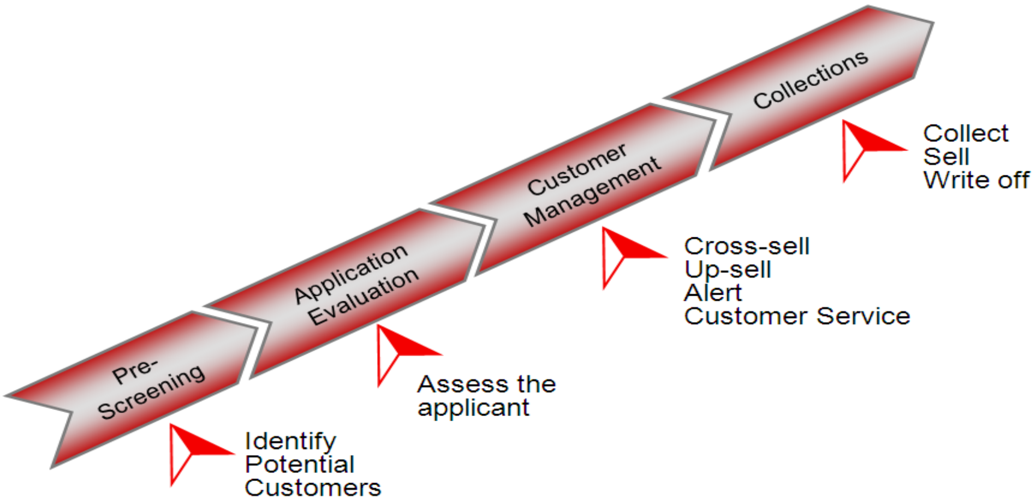
1.16 Finalization

The final stage involved validation of the model and calibration of the resulting scores.

Besides a statistics-based validation, we also employed a checklist of qualitative factors we consider to be important when validating a model.

Appendix 2. Use of credit score

CIL Company score can be used at each stage of the credit risk management decision cycle.



Automated Process

If an internal score already exists, the Company score can be combined with it to enhance quality of decisions. It can be incorporated in a matrix form or as a separate variable in the internal model.

Customer Management

Combined with the internal score the score improves customer service. For example, better customers are offered better credit terms.

Collections

The Company score helps to optimize collections process. If subject has bad debt with another financial institution this decreases expected recovery amount. The Company score monitoring helps to identify customers who require immediate action.

Portfolio analysis

The Company score provides universal measurement tool for comparing portfolio risk profile of single lender versus market or industry that can be used in reporting and strategic planning by executives, risk managers, marketing and sales.

Credit loss provisioning

If properly calibrated, the Company score can be applied in more accurate and reliable prediction of credit losses, either reflected in loss provisions or not.

Appendix 3. Process of retrospective testing and PD calibration

If user wants to test the Company score we suggest to use a sample from subscribers portfolio to calculate the score retrospectively, providing a historical date at which the companies should be scored. This is called **RETROSPECTIVE TEST**. By doing this user can measure the predictive power of the Score on **own customers portfolio** and is able to **quantify the benefit** in terms of minimising losses by using the Company score. Providing data for retrospective tests is one of Creditinfo Lietuva services.

NB! If subscriber is applying Creditinfo Lietuva information to decision-making processes this will result in the worst risk customers being declined already. This bias must be taken into account during retrospective testing because performance of declined customers will not be taken into account in the results and Gini calculated during retrospective tests.

PD (Probability of Default) CALIBRATION. There can be misalignments between the PD predicted by the Company score and risk measures used internally. The calibration tests the relation between the score and measures of risk used by particular lender, which can be different from the default definition. Here are some of the most common reasons for PD misalignment:

1. Specific customer target group – portfolio of credit provider is not a random selection out of the total Lithuanian business population, but it is specific due to the market positioning, distribution channels, regional structure, etc.

2. Customer level vs. facility level risk measurement – score alignment is conducted on customer level, while credit provider's risk measure is defined on facility level. The phenomenon of incomplete default (customer is defaulted only on part of his facilities) introduces differences in the level of risk measured by these two approaches.

3. Incomplete payment data – if lender does not report all payment defaults to Creditinfo Lietuva (as it should be) and so there is difference in raw data about who is good and who is bad.

Due to these reasons minor misalignments are legitimate, unavoidable, and can be accounted for. Nevertheless, even on the different scale, Creditinfo Lietuva score effectively ranks Subjects by risk.