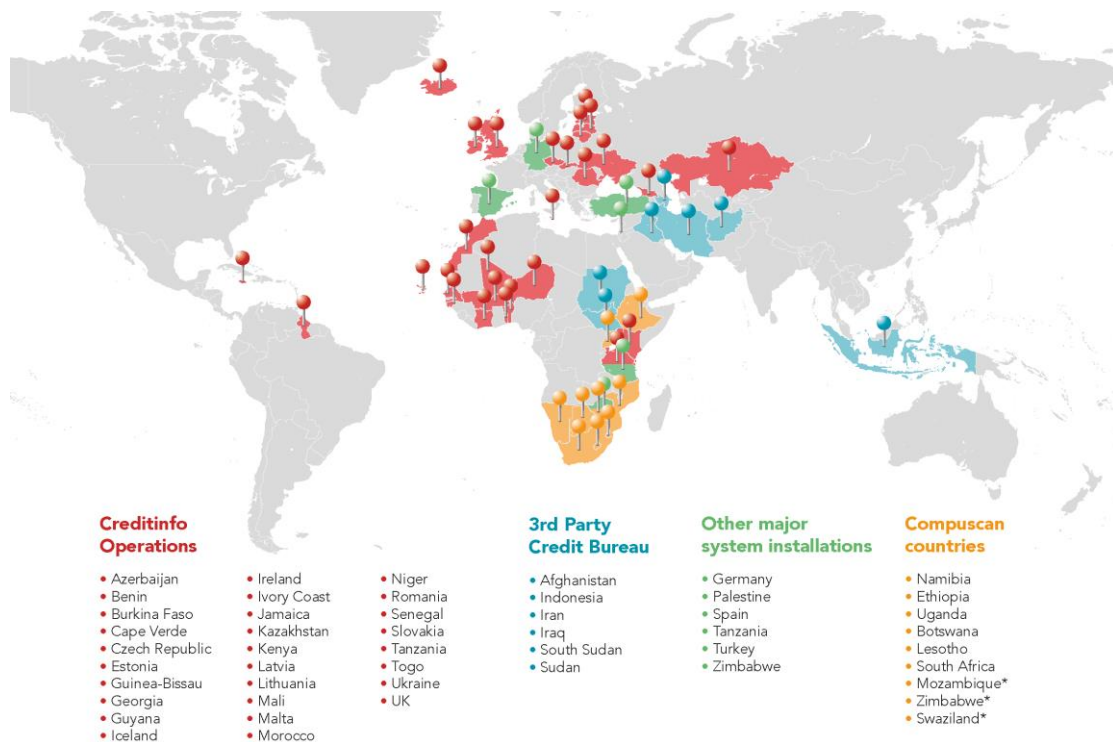


Creditinfo Bankruptcy Score for B2B lending in Lithuania

Model Overview



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April 19th, 2024

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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 Bankruptcy (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 Financial Default score has a Gini of 83.

Important note! *Gini number above was calculated excluding companies already bankrupted or in bankruptcy proceedings as of observation date.*

Creditinfo Lithuania Corporate Bankruptcy Score model can 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 or bankruptcy).

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) or in case of bankruptcy definition - bankrupts.

CIL Company Score is usually a component of the 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 decision-making, 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 using a scorecard

To credit providers CIL Company Score helps to improve the quality and speed of lending decisions using the 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
<ul style="list-style-type: none"> • <u>Reduced Costs</u> <ul style="list-style-type: none"> ➢ Scoring quickly sorts applicants by risk saving time • <u>Higher Volumes</u> <ul style="list-style-type: none"> ➢ Automated process leads to faster response leads to improved customer experience leads to growth in applications • <u>Faster Speed</u> <ul style="list-style-type: none"> ➢ Score is immediately available • <u>24/7 Availability</u> <ul style="list-style-type: none"> ➢ Score is calculated at the moment of inquiry 24 hours a day 7 days per week • <u>Increased Loyalty</u> <ul style="list-style-type: none"> ➢ Risk based pricing strengthens customer loyalty • <u>Objectiveness</u> <ul style="list-style-type: none"> ➢ Score is not biased by subjective considerations of credit reviewers 	<ul style="list-style-type: none"> • <u>Consistency</u> <ul style="list-style-type: none"> ➢ Subjects with similar information receive similar probability of bankruptcy (PB) estimate • <u>Risk and loss planning</u> <ul style="list-style-type: none"> ➢ Predicted probability of bankruptcy can be included into product pricing and business plan • <u>Consistency of processing information</u> <ul style="list-style-type: none"> ➢ Scorecard uses same data in the same way • <u>More transparency</u> <ul style="list-style-type: none"> ➢ 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 into 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 Number of currently opened contracts	0	15
		1	20
		2	10
		3	0
		4 +	-20
2	NMaxPDD12M Number of maximum past due days last 12 months	Missing	1
		< 5	4
		5 - 29	-5
		30 - 59	-15
		60 - 89	-25
	90 +	-35	
3	MLast30PDD Number of months since the last time borrower was 30 past due days and more	Missing	1
		[0,7)	-20
		[7,13)	-15
		[13,25)	-12
		[25, 37)	-10
		[37,61)	-8

Individual has 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.

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/bankruptcy (PD)
- Risk Grade (class)
- Reason codes (factors)
- 6 months history showing score trends

CIL Company Score and Probability of Bankruptcy

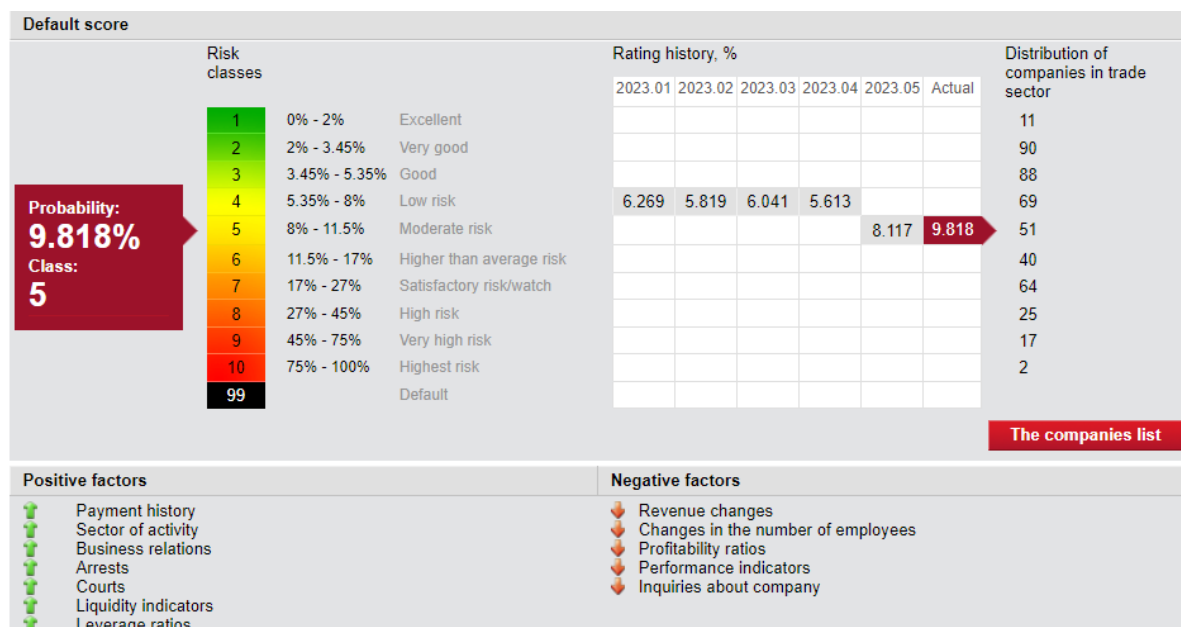
Based on the information of the last two years a prediction is made regarding a company's behavior in the next 12 months.

For the exact definition of the event predicted see bankruptcy 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 bankruptcy. The 1st is the lowest risk, the 10th is the highest risk, 99 stands for the bankruptcy event.

Below is an example of the professional report displaying Default ratings. The probability of Default risk classes ranges are exemplary. Same structure is used to display Bankruptcy risk, too.



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.

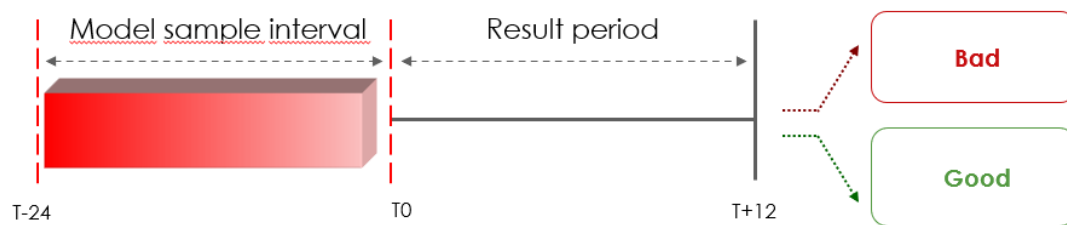
Score history serves financial education purpose, also helping companies to understand how their financial behavior changes their risk profile.

Bankruptcy Score at a Glance

Metric	Description
Model type	Statistical. Logistic regression.
Data used	Credit bureau data subject to limitations of information reciprocity groups.
Segmentation	Bankruptcy scorecard – specifically designed for Lithuanian market.
Exclusions	Not applicable to: <ol style="list-style-type: none"> 1) Individuals 2) Not scorable legal entities 3) Not scorable activity sectors
Business rules	Companies that are currently in bankruptcy or have severe negative status are allocated with the lowest possible score.
Performance characteristics	
Source of development and validation data	<p>Data sample included all active companies with no active bankruptcy procedures or no severe negative status at 3 points in time:</p> <ol style="list-style-type: none"> 1) 2019-01-01 83 214 observations 2) 2020-01-01 87 670 observations 3) 2021-01-01 88 068 observations <p>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 bankruptcy levels the same in both train and test samples.</p> <p>Covid period is not excluded under the assumption that the future is likely a mix of pre-pandemic and pandemic periods.</p>
Bankruptcy definition	<ul style="list-style-type: none"> - Company status changed into 'Bankrupting' (first stage of the bankruptcy) in the next 12 months after scoring or - New court process for bankruptcy

Metric	Description
	Good: all others
Gini (excluding bads as of observation) development	0.83

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 Bankruptcy

Definition of Bankruptcy is unified for all types of companies. Bankruptcy event is fixed when one of the following conditions is satisfied:

- **Company status changed into 'Bankrupting' (first stage of the bankruptcy) or**
- **New court process for bankruptcy**

in the next 12 months after the scoring date.

Model variables and their weights

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

No	Variable Groups	Weight, %
1	Finance	43.2
2	Age and activity sector	23.7
3	Debt History	16.7
4	Other negative information	12.8
5	Debt Collection inquiries	3.7

Table 1

1.4 Finance

Yearly financial report data reflecting company's obligations level and efficiency. Higher obligations level usually indicates a higher risk of bankruptcy. Only 12 months financial statements.

1.5 Age and activity sector

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

1.6 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. Debts for tax institution SODRA are also a good indicator of risk and having higher tax debt has more negative impact on the company.

1.7 Other negative information

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

1.8 Debt Collection inquiries

Debt Collection agencies usually inquiry companies that are severely in debt. Debts issuers sell their debts to collection agencies for lower amount than past due amount, due to failure to collect debts themselves amicably. Therefore, having such an inquiry for a company is a good indicator of increased risk in both credit and bankruptcy.

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 % - 0.03 %	Flawless	Nepriekaištinga būklė
2	0.03 % - 0.08 %	Excellent	Puiki būklė
3	0.08 % - 0.16 %	Very good	Labai gera būklė
4	0.16 % - 0.22 %	Good	Gera būklė
5	0.22 % - 0.30 %	Low risk	Žema rizika
6	0.30 % - 0.57 %	Average risk	Vidutinė rizika
7	0.57 % - 1.53 %	Higher than average risk	Aukštesnė nei vidutinė rizika
8	1.53 % - 5.00 %	Increased risk	Padidinta rizika
9	5.00 % - 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

Classes 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 Table 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 bendruomenė ar bendrija
Representative office of the Foreign Enterprise	Užsienio juridinio asmens ar kitos organizacijos atstovybė
Branch of the Foreign Enterprise	Užsienio juridinio asmens ar kitos 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

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	D0	The company has no employees	Only for legal entities that are obliged to have at least 1 employee

Reason Codes descriptions

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
Business relations	Verslo sąsajos
Director change	Direktoriaus pasikeitimai
Payment history	Mokėjimų istorija
Equity indicators	Nuosavo kapitalo rodikliai
Profitability indicators	Pelningumo rodikliai
Liquidity indicators	Likvidumo rodikliai

Appendix 1. Score Development Methodology

Subsequent chapters describe the 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.

1.11 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.

1.12 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 the 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
- Not scorable companies, such as banks and insurance companies

Concise outcome definition is a key to 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.

1.13 Univariate Analysis

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

Each of the variables calculated in the 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 the next phase - modelling.

1.14 Modelling

We use an 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 bankruptcy 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.

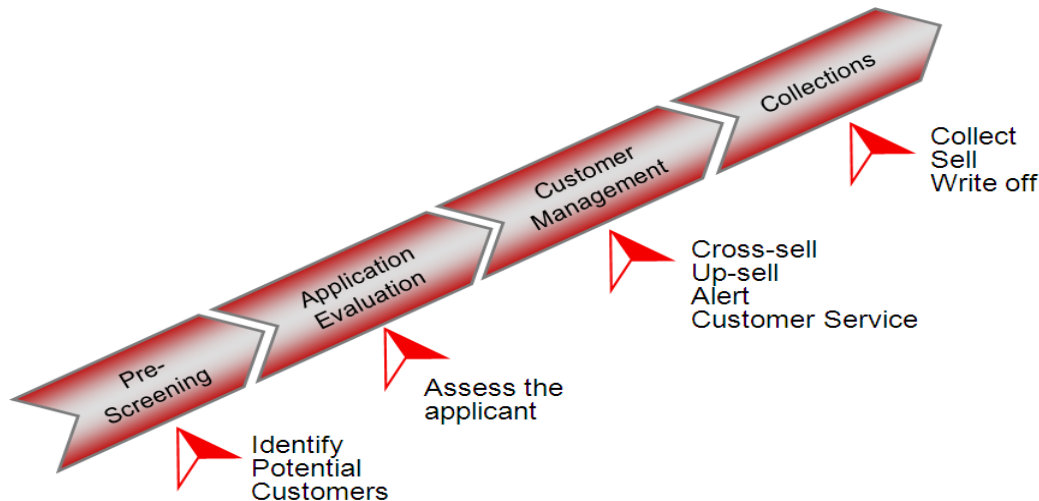
1.15 Finalization

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

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

Portfolio analysis

The Company score provides a 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.

PB (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.