Valuatum Platform

Efficient tools for Credit Risk Analysis

valuatum
Financial Analysis SOLUTIONS

Valuatum platform overview

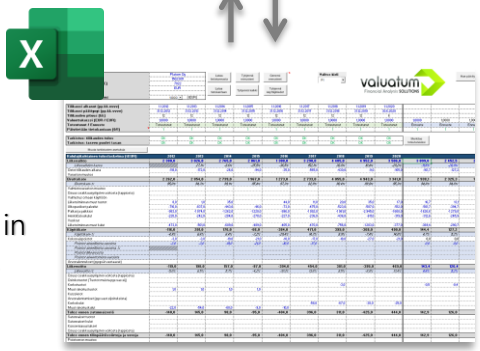
- Automatic bankruptcy risk forecasts and credit risk reports
- Access to historical financial statements, provided by external data providers, integrated in the system.
- Our service can be mass-customized quite effortlessly
- Standardized data enables comparisons
- Visual and verbal explanations for the given credit rating
- Our system supports multiple languages, including Finnish, English, Swedish, and Danish, with the flexibility to easily add new languages as needed.

External data providers

creditsafe schufa BÜRGEL Creditreform asiakastieto dun & bradstreet

REST API integration

Valuatum database

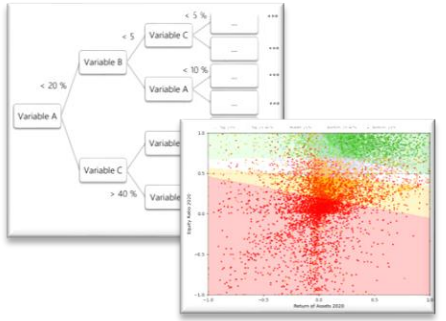


The system can be used both in Excel and via a web-interface.

Customizable platform offering company-specific information based on customer's needs

View how any company is compared to its peers

Bankruptcy and default risk measures are calculated with the help of machine learning



Generate fully customizable automated credit reports and loan proposals based on company financials

Benefits of our product

Our AI-based credit risk rating product offers **three** key benefits for users

1. Accuracy

Our credit risk model gives **more accurate** credit ratings and recognizes bankrupt companies 50-60 % better than traditional models commonly used by loan institutes. See more on next three slides.

2. Efficiency

Our platform **increases efficiency** by utilizing AI and machine learning models. Our credit ratings are calculated with machine learning model and with AI all items in financial statements are adjusted automatically. Generative AI is also used for giving automatic explanations for credit risk rating decisions. Furthermore, with AI it is possible to read financial statements of companies to get numbers easily and quickly to our system. All these reduce manual work.

3. Enhanced customer experience

Loan institutions using our platform can **provide superior customer experience**, as the credit applicants can get an answer in a matter of seconds. Alongside the initial credit decision, customers get insights about the possible credit amount or why they are not granted with loan and what should they do to improve their possibilities to get an approved application. Credit applicants can also be given an access to download both credit risk and valuation reports immediately when applying for a loan.

Why our model is superior?

There are two key reasons for our model performance:

1) Dynamic variable weights

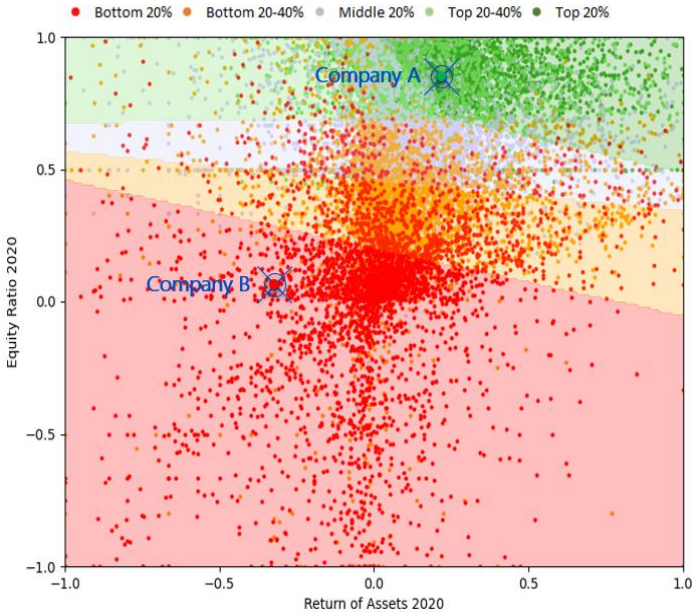
Machine learning models can produce company-specific risk estimates by dynamically adjusting the importance of different variables. This flexibility allows the model to accurately assess credit risk by considering each company's specific strengths and weaknesses.

In contrast, traditional regression models assign the same importance (i.e., weight) to variables for every company they assess. For instance, a typical regression formula might look like this: *X = -0.112 * Equity ratio + -0.162 * ROA + -0.054 * Quick ratio + … + 0.124*. This 'one-size-fits-all' approach often fails to capture the variation in individual companies. See example below.

Example: Company A has a very good solvency and profitability. Company B on the other hand has very poor solvency and it is unprofitable. When assessing their credit risk, these companies should have different weights for the explanatory variables like liquidity.

Here, Company A doesn't need to have good liquidity since it is able to fund itself through its operations or by loaning money. On the contrary, Company B is losing money and can't raise loans. The most important feature it has is its liquidity.

It can be clearly seen that varying weights are necessary for succesful credit risk assessment. Logistic regression has constant weights and thus it is unable to account for these firm-specific characteristics. Machine learning algorithms on the other hand can recognize that the significance of liquidity becomes larger with unprofitable companies and will adjust its credit ratings accordingly.



The image above represents a random sample of Finnish companies arranged by their profitability (x-axis) and solvency (y-axis). The color of each dot indicates the creditworthiness of the company, with red representing companies with highest credit risk, and dark green representing companies with lowest risk.

2) Number of model variables

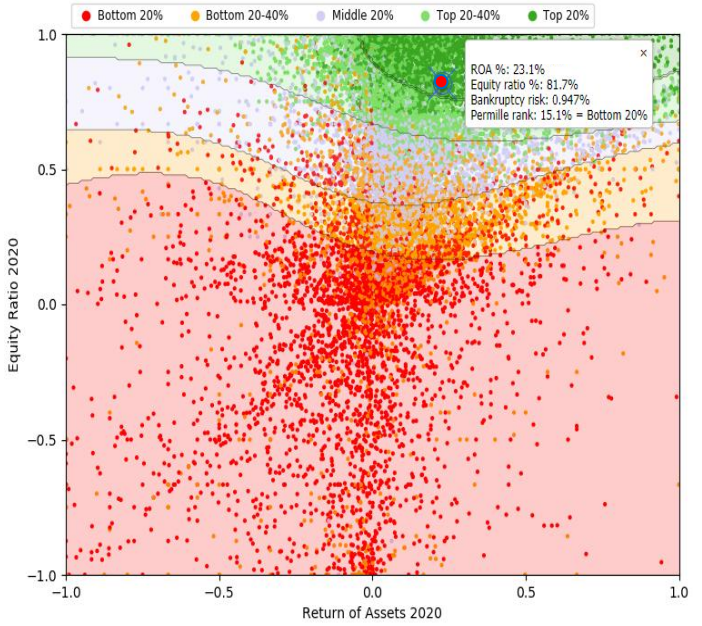
Machine learning models support the use of a **considerably larger number of variables than traditional models** without losing predictability. For example, our AI model includes around 30 explanatory variables, in order to capture all necessary variables that can affect a company's credit risk.

In contrast, traditional regression models struggle when faced with a large number of variables. Increasing the number of variables often leads to unstable predictions and overfitting. To avoid this, traditional models typically rely on just a few key variables, but this approach can result in removing important factors. See example below.

Example: Company has an excellent profitability and a high equity ratio, along with other key variables like liquidity. A traditional logistic regression model, which only considers these main variables, would likely assess that the company is highly creditworthy.

However, a machine learning model can evaluate a broader range of variables. It might notice that the company's sales receivables per net sales have been rising significantly in the last couple of years. This could indicate that a part of the receivables may not be collected, posing a risk to the company's figures.

If this is the case, the actual profitability and solvency of the company can be significantly lower than it would seem at a first glance. Our AI model can automatically take this into account in its assessment. Traditional models need a credit risk expert to manually adjust the profitability and solvency figures to account for possible non-receivable items beforehand.



Model performance comparison with steps (1/3)

1) Initial situation

Our comparison starts with the financial data from all approx. 200 000 Finnish companies

200 000 Finnish companies

2) Risk calculation

We first calculate the bankruptcy risks of all 200 000 companies using both our AI model and a logistic regression model.

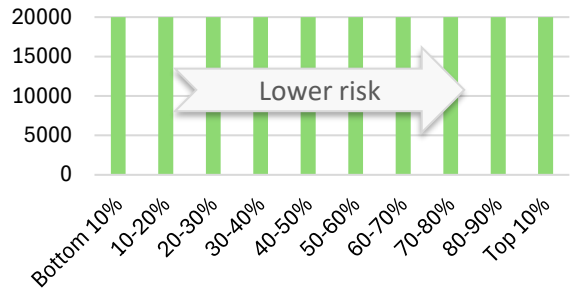
Valuatum AI model

Log. Reg. Risk model

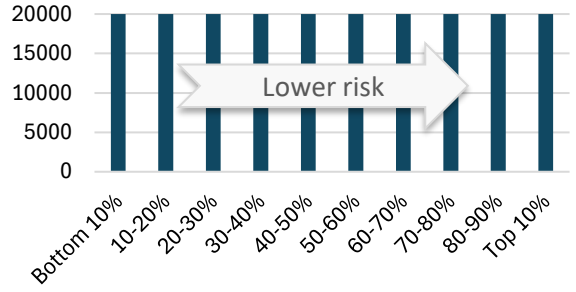
3) Company distribution

We distribute the companies into ten equally weighted groups (10% of companies in each group) ranging from 'Bottom 10%' to 'Top 10%' based on their assessed risk.

Companies by Valuatum's credit rating deciles



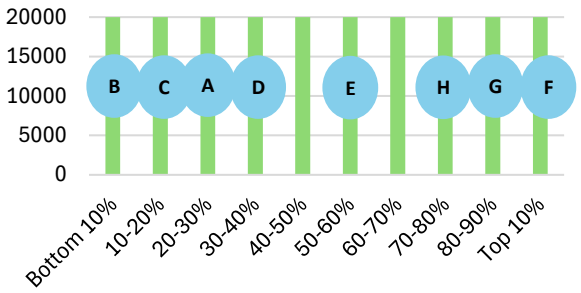
Companies by log.reg.'s credit rating deciles



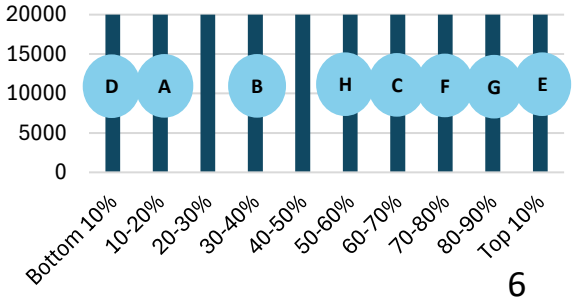
4) Different distributions

While every group includes 10% of companies, note that the models might categorize the companies in different deciles, which we can not see from the graph. We have demonstrated this with eight exemplary companies.

Companies by Valuatum's credit rating deciles



Companies by log.reg.'s credit rating deciles



Model performance comparison with steps (2/3)

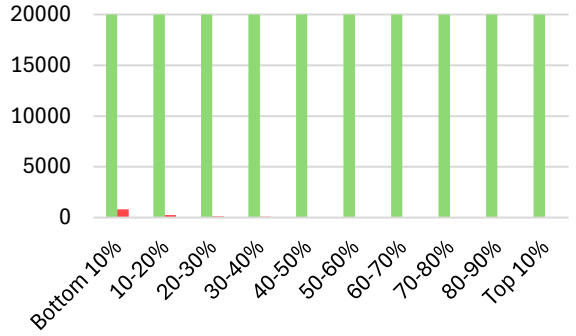
5) Bankrupties in 2024

To compare the accuracies of the model predictions, we separated all companies that went bankrupt in 2024

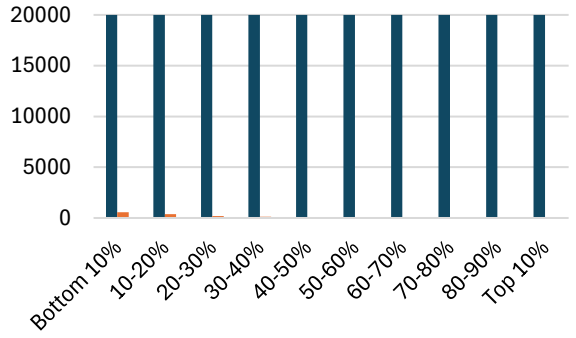
6) Bankruptcies in the distribution

We then checked how they were categorized by the models based on the 2022 financial data

Companies by Valuatum's credit rating deciles



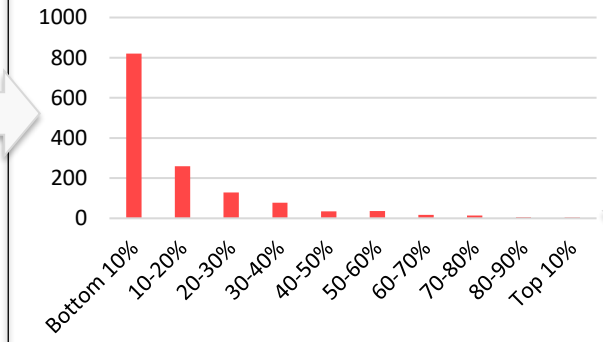
Companies by log.reg.'s credit rating deciles



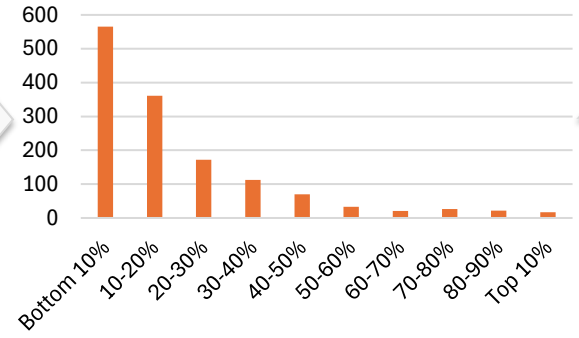
7) Bankruptcies by risk deciles

To get a better sense of the differences, we removed all non-bankrupt companies from the comparison.

Bankruptcies by Valuatum's credit rating deciles



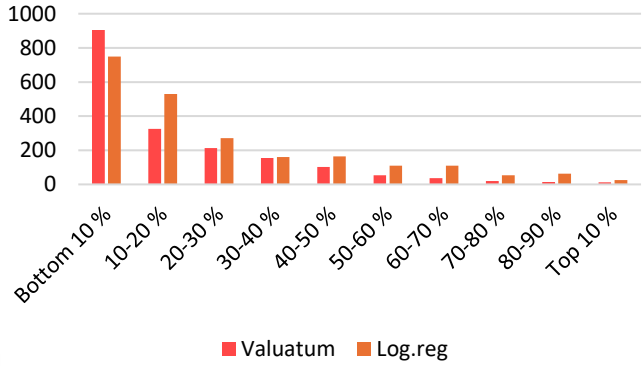
Bankruptcies by log.reg.'s credit rating deciles



8) Bankruptcy comparison

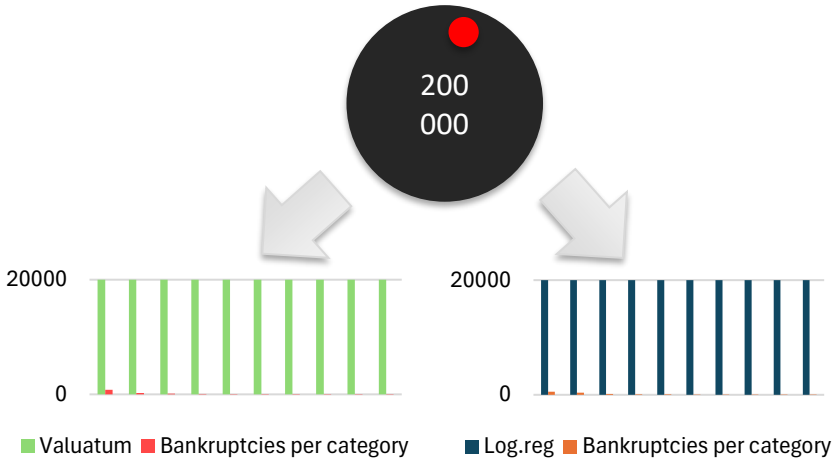
Finally, we combined them into a single graph. As expected, more companies went bankrupt in the higher risk percentiles, while fewer companies in the lower risk percentiles faced bankruptcy. We also notice differences between our AI-based model and the logistic regression model. In the next slide, we'll show how this can be translated into potential savings for the lender.

Number of companies gone bankrupt by credit rating deciles in 2024

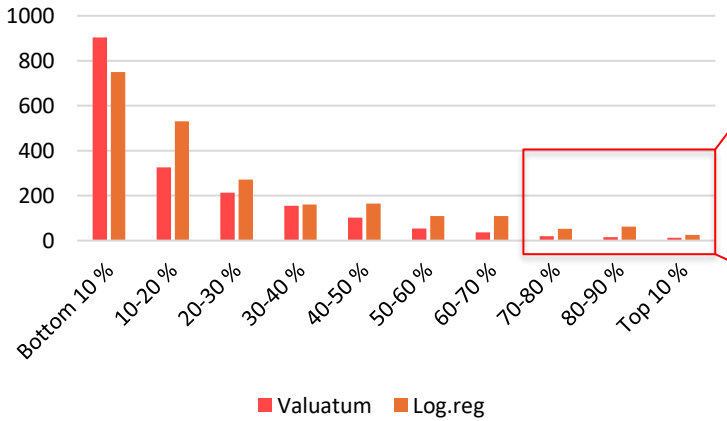


Model performance comparison with steps (3/3)

The route so far:

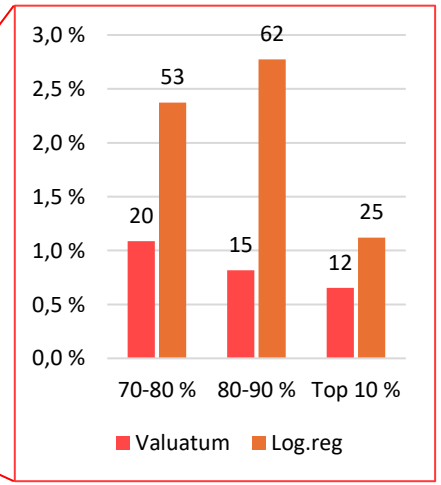


Number of companies gone bankrupt by credit rating deciles in 2024



The 'Top 30%' comparison

Since lenders usually lend to the most creditworthy companies, the large difference in predictive accuracy in the top companies directly affects potential financial losses. Below, we have zoomed in on the predictive differences of the 'Top 30%' companies.



Let's talk about this comparison in terms of potential savings

Assume, that a lender has issued 10 billion euros of credit to the most creditworthy 30% of companies using their logistic regression model. They recorded a credit loss of 25 million euros or 0.25% of issued credit when 140 companies that they granted loans to went bankrupt.

By using our AI model and the same threshold, only 47 companies that later went bankrupt would've received a loan.

Using our AI model would have saved the lender 66.4 % of the losses or 16.6 million euros.

Loan grant threshold	Bankrupt companies (Valuatum)	Bankrupt companies (Log.reg.)	Savings %
Top 30%	47	140	66.4 %
Top 20%	27	87	69.0 %
Top 10%	12	25	52.0 %

The figures are cumulative, e.g., 'Top 30%' includes the companies in 'Top 10%' and Top 20%'

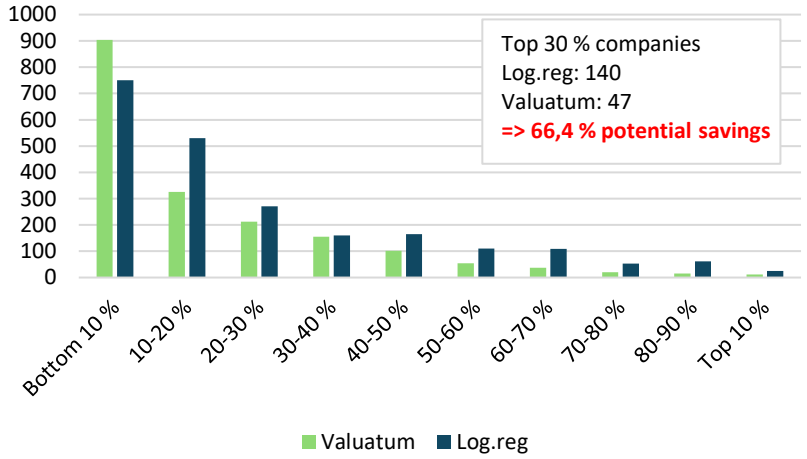
For further comparisons, see the following slides:

Slide: Valuatum vs Logistic Regression for bankruptcies between 2019 - 2024

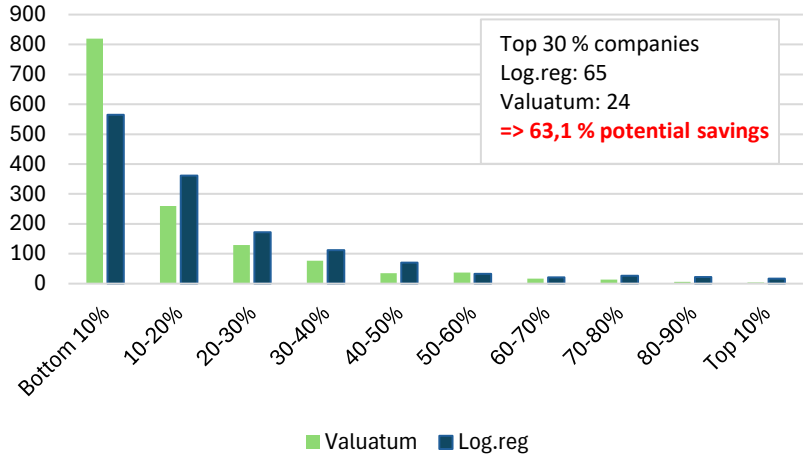
Slide: Valuatum vs Logistic Regression for small companies with limited data

Valuatum's AI-based model and logistic regression model comparison between 2019-2024

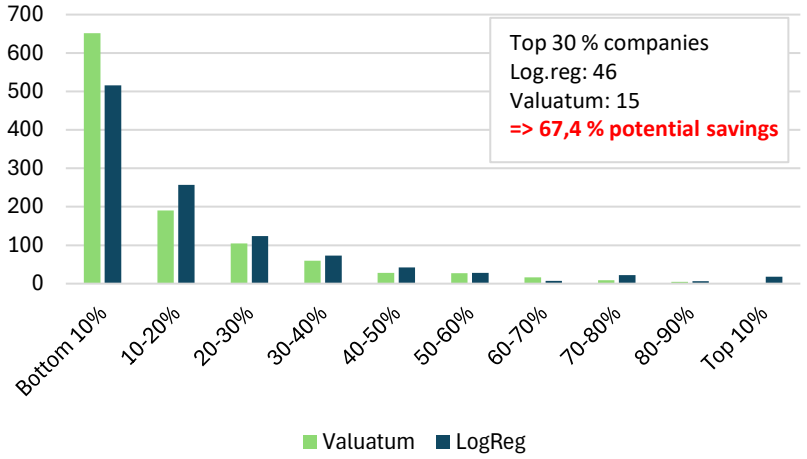
Number of companies gone bankrupt by credit rating deciles in 2024



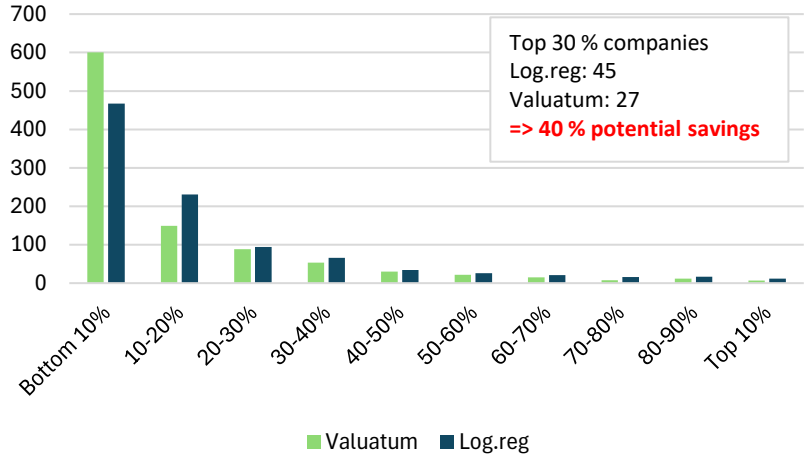
Number of companies gone bankrupt by credit rating deciles in 2023



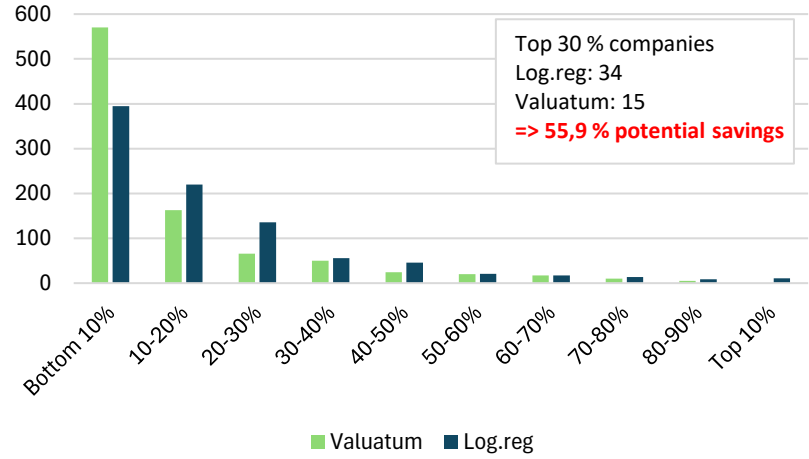
Number of companies gone bankrupt by credit rating deciles in 2022



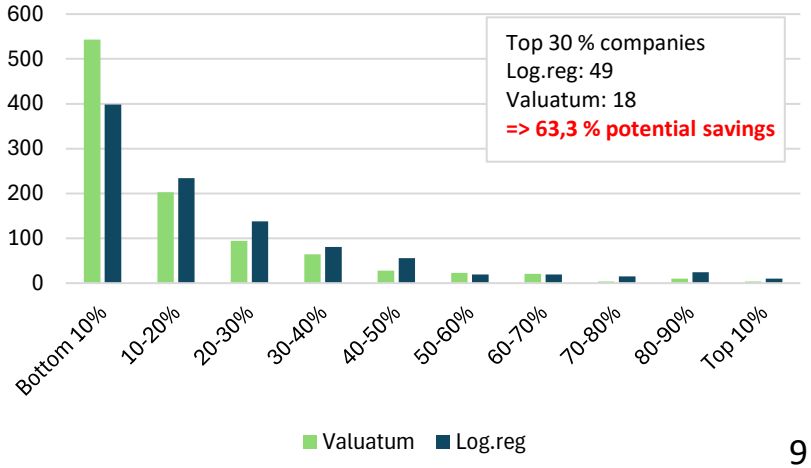
Number of companies gone bankrupt by credit rating deciles in 2021



Number of companies gone bankrupt by credit rating deciles in 2020



Number of companies gone bankrupt by credit rating deciles in 2019

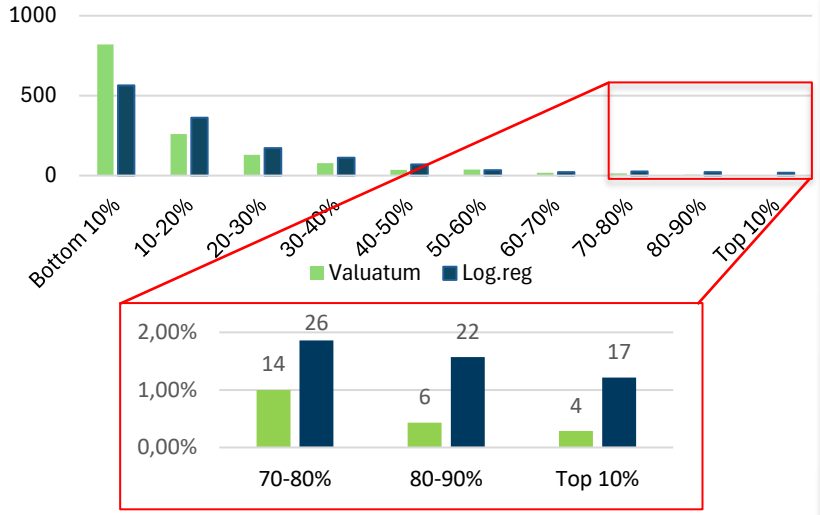


Valu vs. LogReg for small companies with limited data

The following comparisons are based on filtered results from the dataset shown on slide 7.

The calculated risks are based on the financial statements of 2022 for companies that went bankrupt in 2024.

Number of companies gone bankrupt by credit rating deciles in 2023

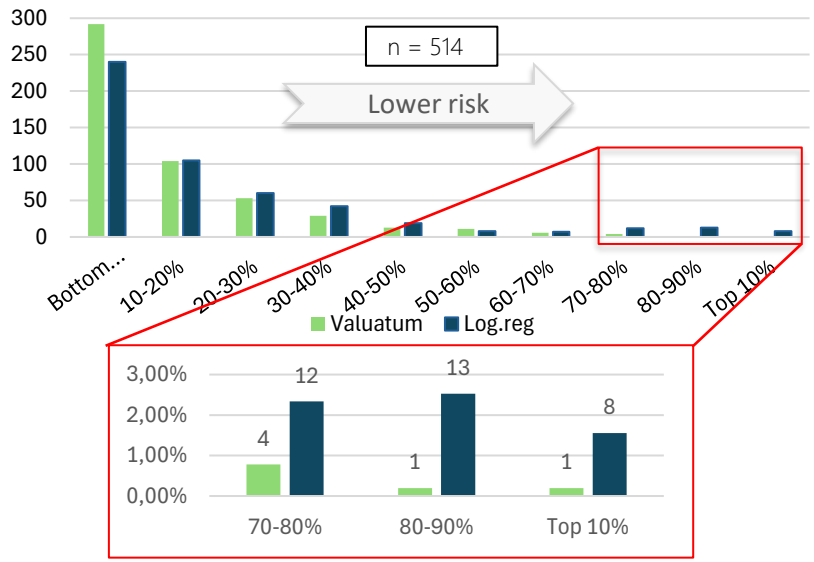


Loan grant threshold	Bankrupt companies (Valuatum)	Bankrupt companies (Log.reg.)	Savings %
Top 30%	24	65	63.1 %
Top 20%	10	39	74.4 %
Top 10%	4	17	76.5 %

The figures are cumulative, e.g., 'Top 30%' includes the companies in 'Top 10%' and Top 20%'

The results here are the same as represented in slide 9.

- Had less than 1 million euros in net sales in 2022
- Had less than four years of financial data before 2022



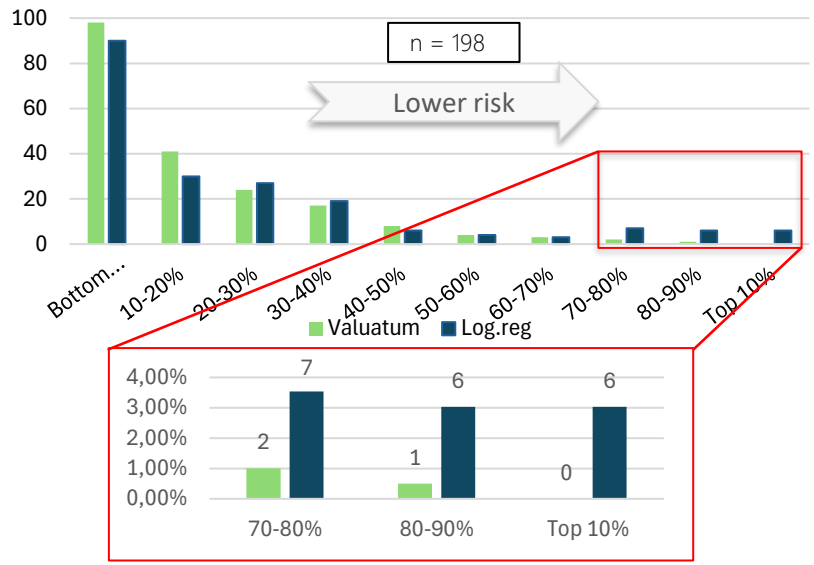
Loan grant threshold	Bankrupt companies (Valuatum)	Bankrupt companies (Log.reg.)	Savings %
Top 30%	6	33	81.8 %
Top 20%	2	21	90.5 %
Top 10%	1	8	87.5 %

The figures are cumulative, e.g., 'Top 30%' includes the companies in 'Top 10%' and Top 20%'

Results:

- Our AI model was clearly better amongst companies with shorter financial data and was able to categorize 81.8 % less bankrupt companies to the top 30 %
- This is a far better result than with the whole dataset, highlighting that our model is more than capable of determining accurate risks for companies with less than four years of financial data
- Other thresholds (Top 10% and Top 20%) showed similar behavior with a 11-16 percentage point difference increase compared to the whole dataset

- Had less than 1 million euros in net sales in 2022
- Had financial data only for 2022



Loan grant threshold	Bankrupt companies (Valuatum)	Bankrupt companies (Log.reg.)	Savings %
Top 30%	3	19	84.2 %
Top 20%	1	12	91.7 %
Top 10%	0	6	100.0 %

The figures are cumulative, e.g., 'Top 30%' includes the companies in 'Top 10%' and Top 20%'

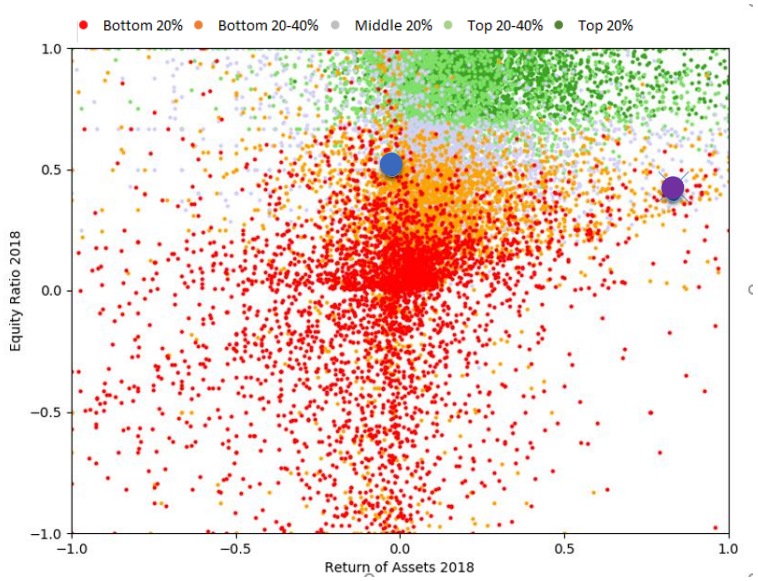
Results:

- Our AI model was clearly better amongst companies with shorter financial data and was able to categorize 84.2 % less bankrupt companies to the top 30 %
- This is a far better result than with the whole dataset, highlighting that our model is more than capable of determining accurate risks for companies with only one year of financial data
- Other thresholds (Top 10% and Top 20%) showed similar behavior and there were no bankrupt companies within top 10% at all

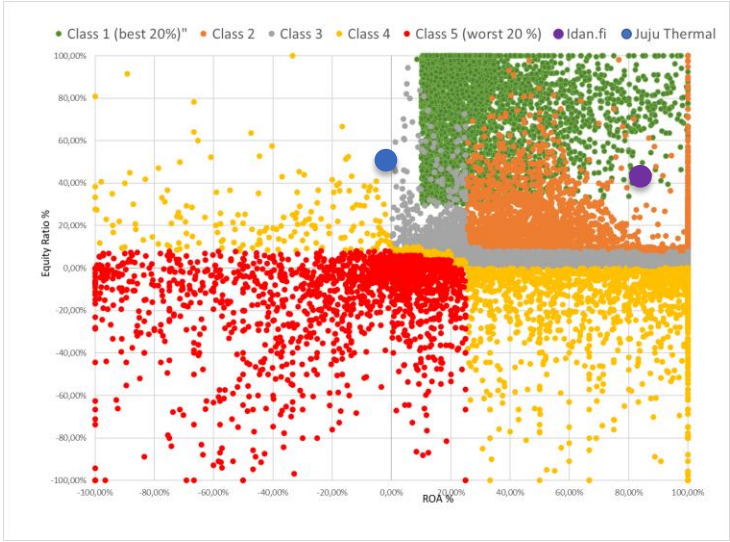
Model comparison

Key ratios	Jujo Thermal (mEUR)	Idan.fi (kEUR)
Net sales	112	1 046
Balance sheet (total)	56	583
Short-term receivables	24.8	541
Cash & cash equivalents	1.2	36
ROA %	-2.8 %	83.4 %
Equity ratio	52.5 %	43.6 %
Quick ratio	1.0	1.7
Log. reg. bankruptcy risk	**B (0.67 %)**	**A (0. 44 %)**
Log. Reg. percentile	**51 %**	**57%**
Valuatum bankruptcy risk	**C (3.59 %)**	**C (1.93 %)**
Valuatum percentile	**9 %**	**4 %**

Valuatum model



Logistic regression - based model



Explanation of the model comparison example:

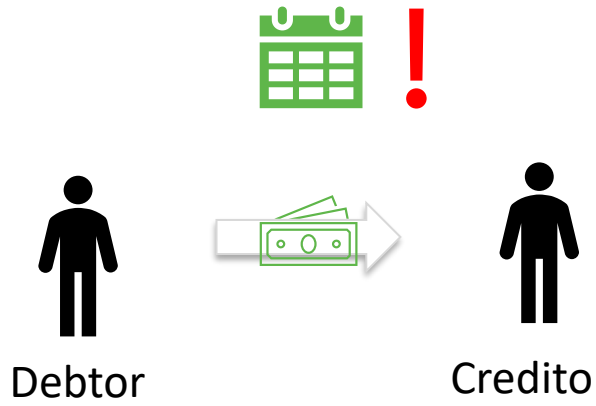
In these two cases, the calculated bankruptcy risks differ a lot between our model and the logistic regression model. Let's investigate the details.

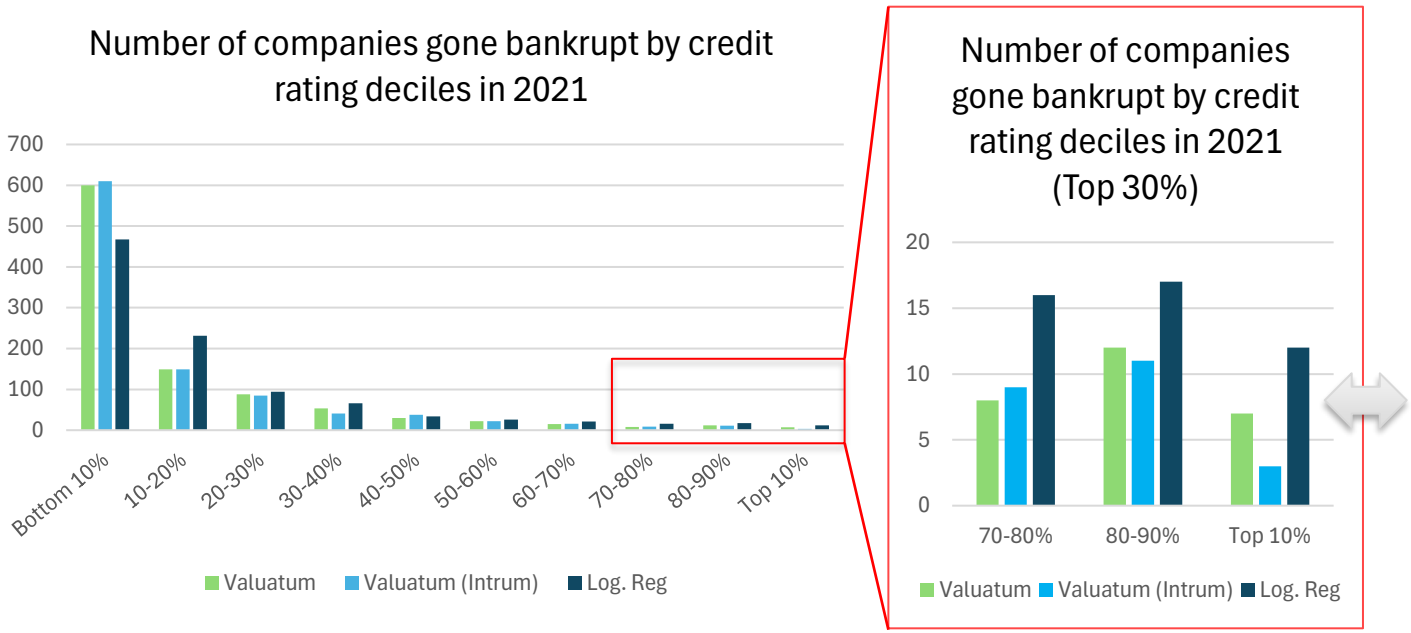
The financial situation of Idan.fi seems to be excellent based on ROA and equity ratio. Jujo is making a loss, but it still has a good equity ratio. However, if we take a closer look at the assets, logistic regression model misses something that the machine learning model notices immediately. A large amount of the balance sheet total (583kEUR & 56mEUR) consist of short-term receivables (541kEUR & 24.8mEUR). Moreover, the companies have very little cash on their balance sheet. The companies' own equity is quickly gone if some part of these receivables are not valid.

Our model acknowledges and includes above in the calculation of the bankruptcy risk as an increase in short-term receivables does often tell of some financial struggles. Models based on logistic regression do not notice this as an important warning signal since the weights for each variable are constant. This is where the logistic regression model fails. It doesn't factor in the short-term assets when calculating bankruptcy risk – even when it should.

Payment behavior data

- Information on how the company pays their bills (related to the due date)
  - Integrated into our machine learning model
  - Data provided by collection agencies etc.
- Possible shifts for worse (more payments overdue) usually indicates a weaker financial status -> higher credit risk
- The inclusion of payment data has improved the performance of our credit risk model in our tests according to statistical metrics**
  - ROC – AUC: 0.9066 -> 0.9110
  - PR – AUC: 0.1765 -> 0.1823
- The payment behavior data can further increase the accuracy of Valuatum's model, as the graph below shows. However, the difference between regular model and model including payment behavior data is not that significant.



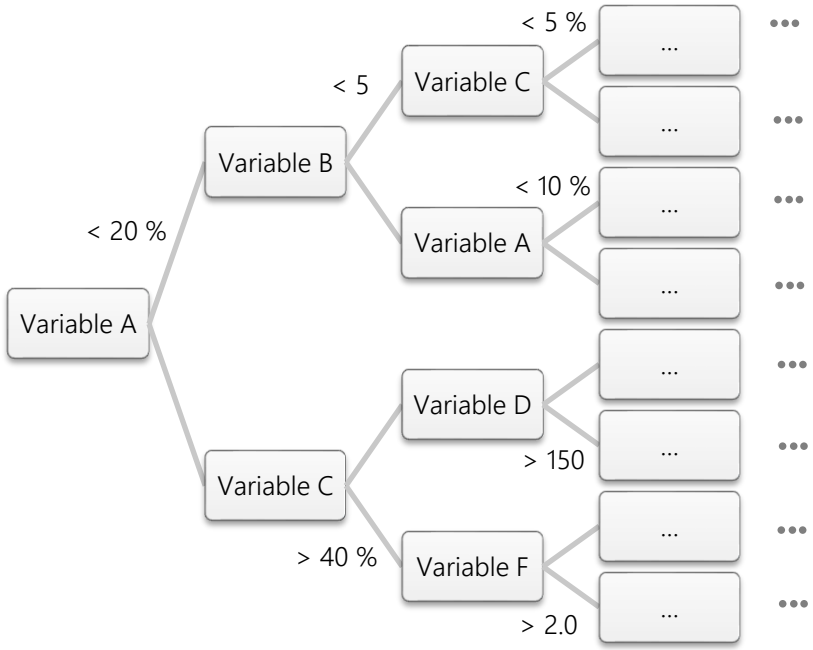


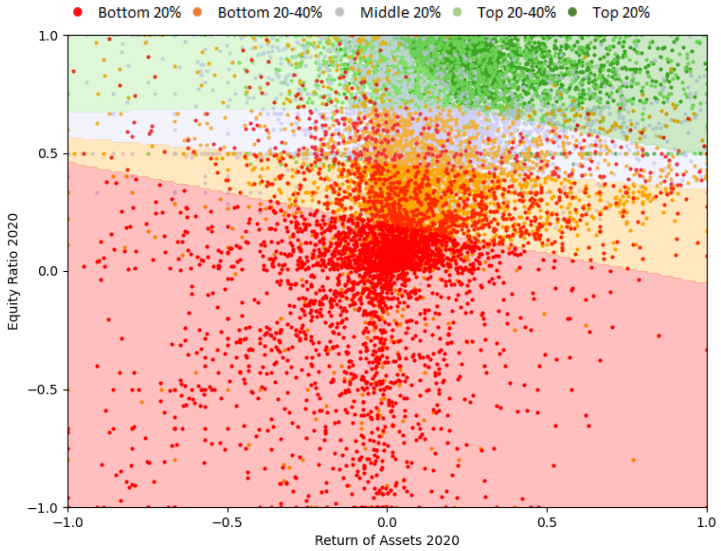
Loan grant threshold	Bankrupt companies (Valuatum)	Bankrupt companies (Valuatum+ Intrum)	Bankrupt companies (Log.Reg.)	Intrum savings % vs. Log.Reg	Intrum savings % vs. Valuatum
Top 30%	27	23	45	48.9 %	14.8 %
Top 20%	19	14	29	51.7 %	26.3 %
Top 10%	7	3	12	75.0 %	57.1%

** More information on these metrics and how to interpret them can be found from the following links: ROC-AUC curves & PR-AUC curves

XGBoost (eXtreme Gradient Boosting)

- We have utilized machine learning methods in the development of our bankruptcy risk model
  - Data with hundreds of thousands of data points from different companies is provided to the machine learning algorithm.
- The best results have been achieved with an algorithm called XGBoost
  - Well-suited for classification problems such as bankruptcy risk
  - Better and faster performance than other methods
- Our XGBoost model generates a decision tree with tens of thousands of nodes, each describing a unique combination of key figures and empirically assigning a characteristic probability of default





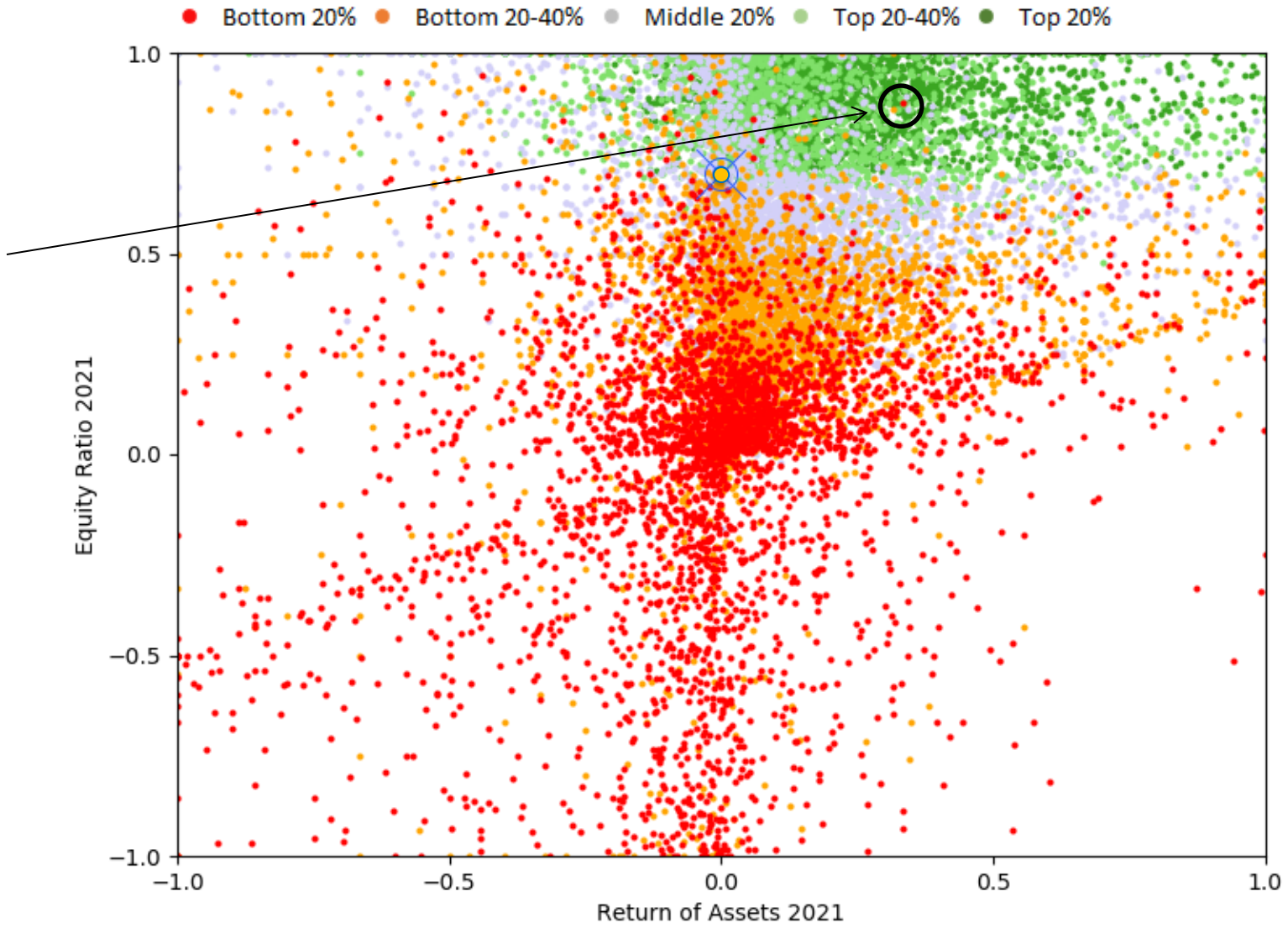
Groups of companies are very intertwined. Contours added to help visualize areas where most of the observations for each company group lie

-> visualizations can be utilized in automatic text generation (see slides 9 & 10)

Credit risk visualization

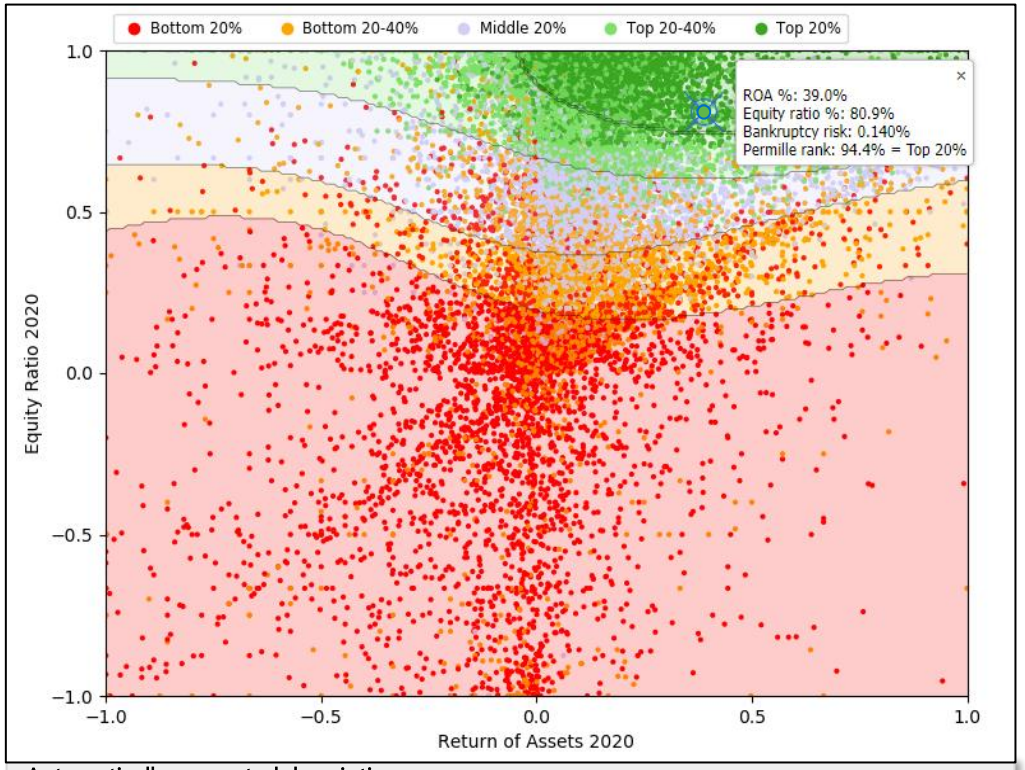
Example of an outlier/anomaly

- Visualization graphs can be used to find outliers in the data, e.g., high credit risk companies with ROA & Equity ratio similar to low credit risk companies
  - A “bad apple” -> high bankruptcy risk despite of being surrounded by top companies
- Allows for examination of these “bad apples” are located with the top 20-40%, when they belong in bottom 20%?
  - Most common reason for this is a weak balance sheet, e.g., high level of receivables in the balance sheet or low cash reserves
  - In our report, the reasons can be generated with automatic text (see next slides)



Example: visualization & automatic text (1/2)

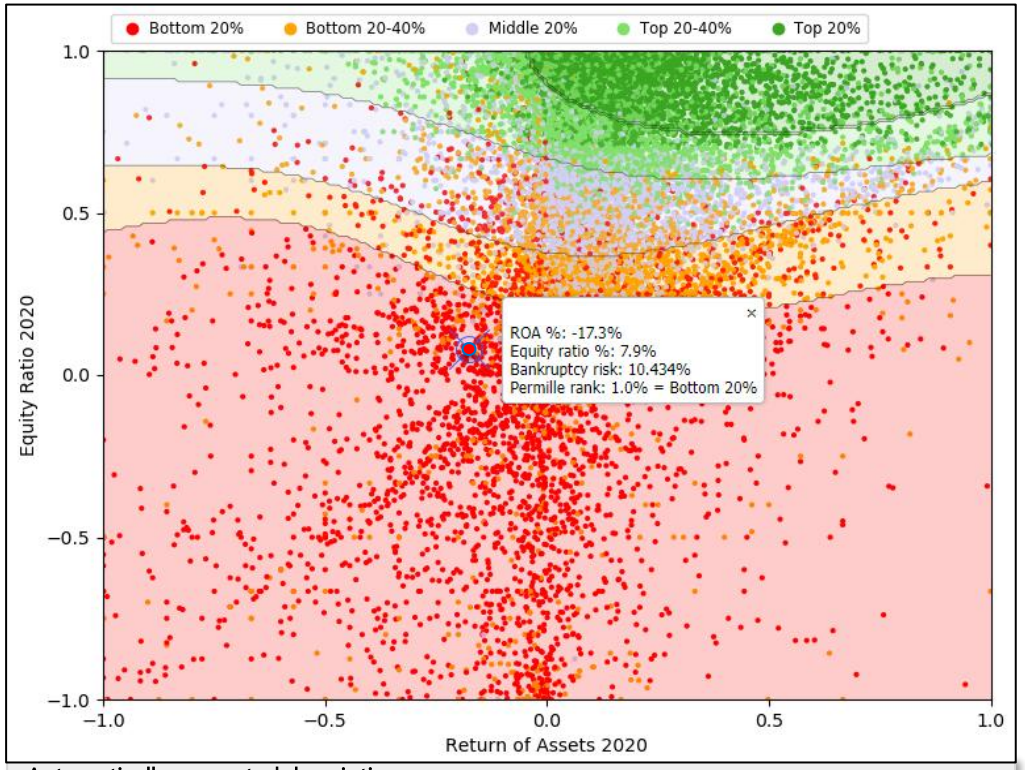
A) Good company in good area



Automatically generated description:

The company has been excellent in terms of profitability and solvency. For example, in 2020, the ROA-% of Company X was 39.0 % and the equity ratio was at 80.9 %. The net sales in 2020 were 1,020 kEUR which represents a growth of 11.5 % from the year before. Based on these factors and many others, our credit risk model has assessed that the company has a very low bankruptcy risk of 0.14 %, which corresponds to a credit rating of AA (excellent).

B) Bad company in bad area



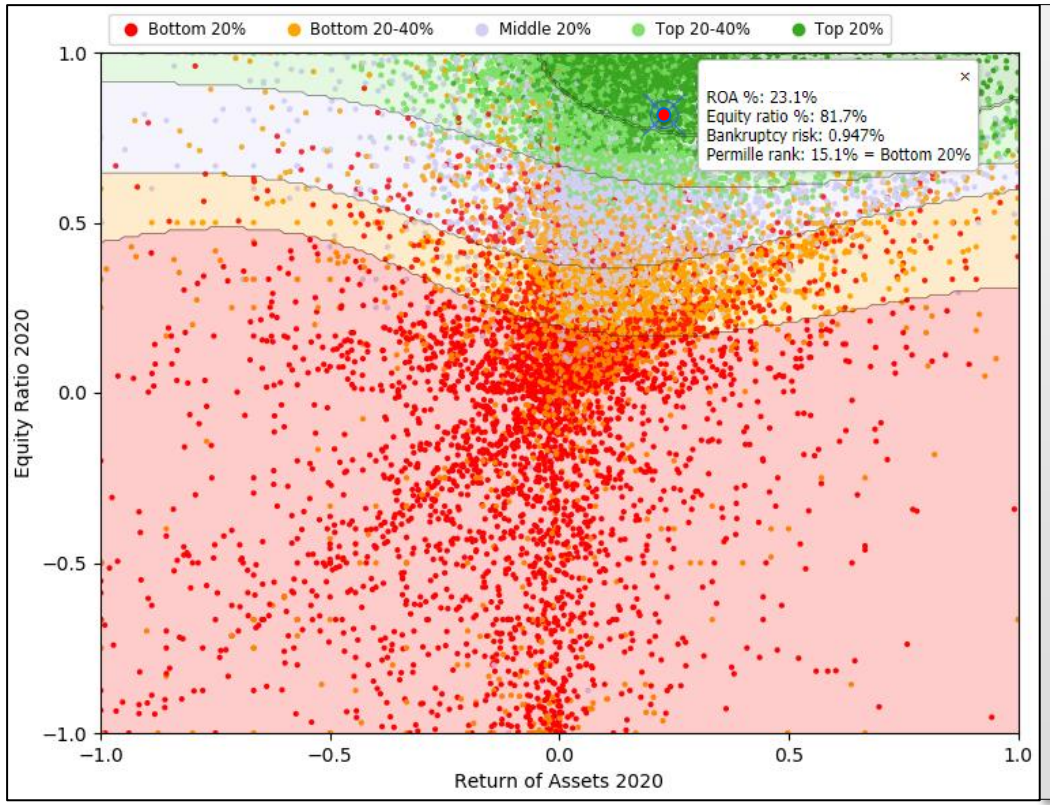
Automatically generated description:

The company has been very weak in terms of profitability and solvency. For example, in 2020, the ROA-% of Company X was -17.3 % and the equity ratio was 7.9 %. The net sales for 2020 were 2,275 kEUR which represents a decline of -13.9 % from the year before. Based on these factors and many others, our credit risk model has assessed that the company has a very high bankruptcy risk of 10.434 %, which corresponds to a credit rating of B&C (very poor).

Both cases are straightforward: bankruptcy risk estimate correlates with placement in the chart (ROA, Equity ratio)
However, sometimes the cases might not be as simple, and they might need further explanation (see next slide)

Example: visualization & automatic text (2/2)

C) Bad company in good area



Automatically generated enhanced description:

The company has very high profitability and solvency. For example, in 2020, the ROA-% of Company X was 23.1 % and the equity ratio was at 81.7 %. The net sales in 2020 were 845 kEUR which represents a growth of 13.1% from the year before. While the company has excellent figures in these aspects, the credit risk model has rated the company much lower than other companies with similar profitability and solidity. The higher credit risk is a result of the following weaknesses identified by the model:

1. *Increasing current loans receivable: From 2016 to 2020, current loans receivable grew from €22k to €186k, indicating that the company is lending out more money, which could result in bad debt if borrowers default.*

2. *Low cash and cash equivalents: The company has consistently low cash balances, with only €5k in cash at the end of 2020, which may make it difficult to cover short-term obligations or unexpected expenses.*

3. *High non-interest-bearing liabilities: In 2020, non-interest-bearing liabilities reached €68k, putting pressure on the company's liquidity and potentially increasing bankruptcy risk if they are unable to pay off these liabilities.*

Based on the above-mentioned factors, our credit risk model has assessed that the company has a high bankruptcy risk of 0.947 %, which corresponds to a credit rating of BAA (poor).

Generated by ChatGPT

When our XGBoost model identifies a bad apple – a company with high bankruptcy risk in a green zone - automatically generated description is supplemented with key reasons for high bankruptcy risk (can be generated with our own system or with ChatGPT via an API)

Performance evaluation

- All recent academic research that we have found has shown that machine learning (ML) models tend to outperform traditional regression-based methods in bankruptcy risk estimation *

- We have also conducted a study to compare our model to multiple benchmark models
  - Studied models include XGBoost, random forest model, artificial neural networks, an ensemble method and logistic regression
  - Results are also compared to the results obtained by Altman et al. (2014) **
  - A total of approximately 170 000 Finnish companies and 30 input variables were used in the training of the models
    - Half of data was used for the training set and half for the testing set

- Our XGBoost model outperforms all benchmark methods in our study.
  - For example, in ROC – AUC metric our model (0.9066 or 0.9110) beats the logistic regression model (0.895) and Altman's Z-score (0.894) with a clear margin

- The maximum value for ROC-AUC is 1.0. ***
  - ROC-AUC of 0.8 can be considered good, while values exceeding 0.9 are excellent. A random model has a ROC-AUC of 0.5.

	Our XGBoost model	Our model w/ payment behavior data	Random forest (RF)	Artificial neural network (ANN)	Ensemble method (RF & ANN)	Logistic regression	Altman et al. (2014)
ROC – AUC**	0.9066	0.9110	0.904	0.880	0.902	0.895	0.894

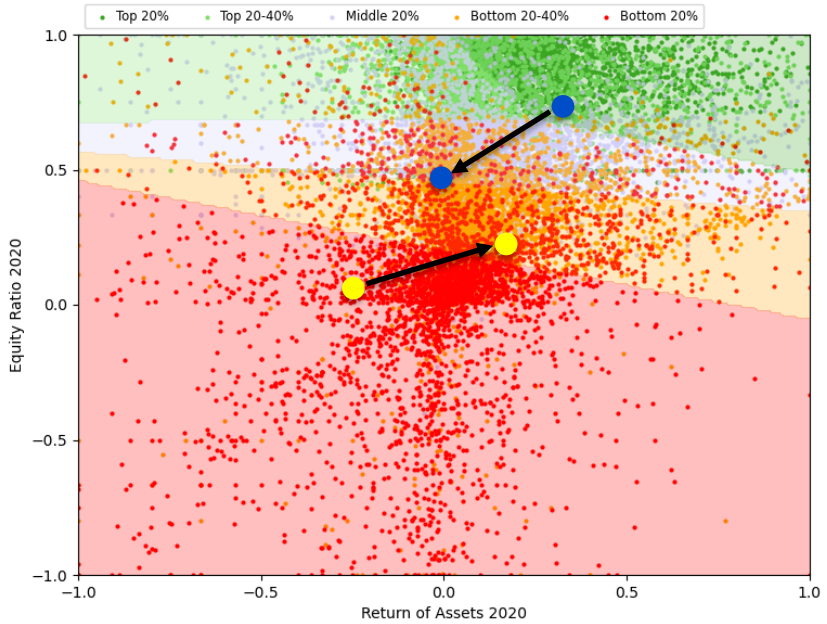
* See, e.g., Ciampi, Francesco & Gordini, Niccolò (2013) "Small Enterprise Default Prediction Modeling through Artificial Neural Networks: An Empirical Analysis of Italian Small Enterprises" & López Iturriaga, Félix J. & Sanz, Iván Pastor (2015) "Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks"

** Altman et. al. (2014), "Distressed Firm and Bankruptcy prediction in an international context: a review and empirical analysis of Altman's Z-Score Model", Available [online]: https://pdfs.semanticscholar.org/257c/b4227101b4da636e90b323736c68c0653a4f.pdf

*** More information on the metric and how to interpret it can be found from the following link: ROC-AUC curves

PSD2-data

- PSD2 is a directive to regulate payment services and the transparency of payment information by requiring banks to open payment infrastructure to third parties
- Implemented separately into the credit risk decision
- Can allow access to the account transaction information of a specific company from the past 12 months
  - The company in question must approve of their data being used
- Our machine learning based bankruptcy risk is adjusted by estimating new key figures with the PSD2 data and by comparing median risk of companies with similar figures



Effects of PSD2 implementation:

Blue company (class Top 20%):
PSD2 data shows declining net sales and significantly negative cash flows and therefore the credit risk is adjusted from "Top 20%" to class "Bottom 20-40%".

Yellow company (class Bottom 20%):
PSD2 data shows notable improvement in net sales and significantly positive cash flows and therefore the credit risk is adjusted from "Bottom 20%" to class "Bottom 20-40%".

PSD2-based adjustment in practice

Historical data from 2023 backwards → Forecast generation 2024 → PSD2-data → Change forecasted 2024 figures based on PSD2-data → Risk recalculation based on 2024 figures

Income statement	2022	2023
Net sales	130	129
…		
EBIT	15	10
…		
Net earnings	9	5

Balance sheet	2022	2023
Accounts receivable	17	16
…		
Cash	15	16
…		
Loan liabilities	23	29
…		
Accounts payable	12	15

Income statement	2024
Net sales	132
…	
EBIT	13
…	
Net earnings	9

Balance sheet	2024
Accounts receivable	17
…	
Cash	17
…	
Loan liabilities	30
…	
Accounts payable	15

Figures are forecasted using automated rules.
For example, account receivables are estimated using the weighted average of 'Account Receivables per Net sales' ratio which is ~13% historically.

PSD2 12-month -cash flows	
12-month Income:	182
12-month Expense:	168
➡ Net sales: (Income/1+(VAT%))	**146**
➡ EBIT: (Income-Expenses)	**14**
Cash balance at 12-month-end	**21**
Change in loan balance (Incoming – outgoing loan payments)	**19**

Income statement	2024
Net sales	**146**
…	
EBIT	**14**
…	
Net earnings	10

Balance sheet	2024
Accounts receivable	18
…	
Cash	**21**
…	
Loan liabilities	**48**
…	
Accounts payable	16

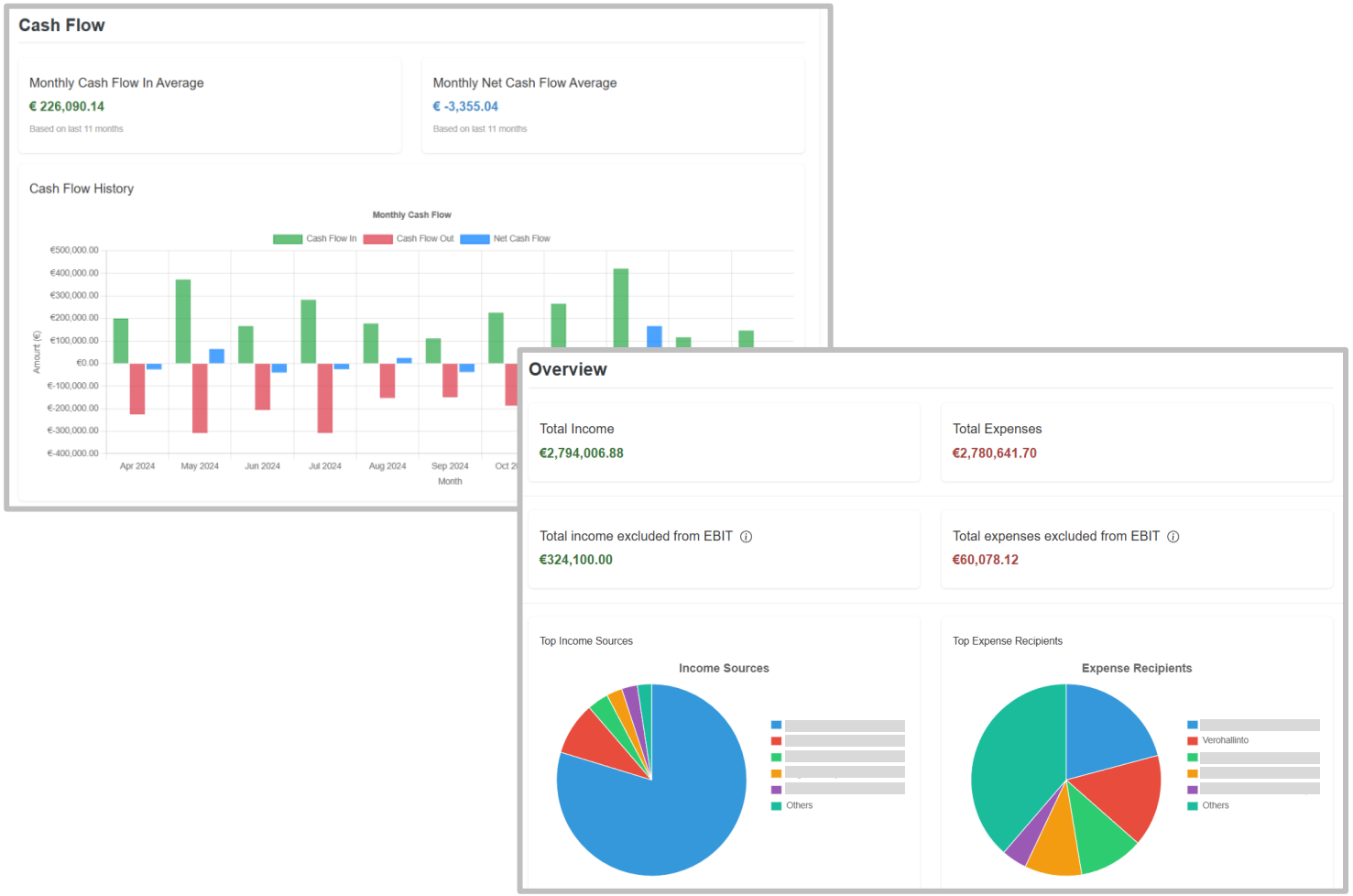
29 + 19 = 48

Other figures are adjusted to match the former ratios, for example account receivables are still ~13 % of net sales as previously (18/146).

	2024
Bankruptcy risk	0.456 %
Credit score	46
Credit rating	BBB
Credit limit	1.25
Loan price %	9.75%

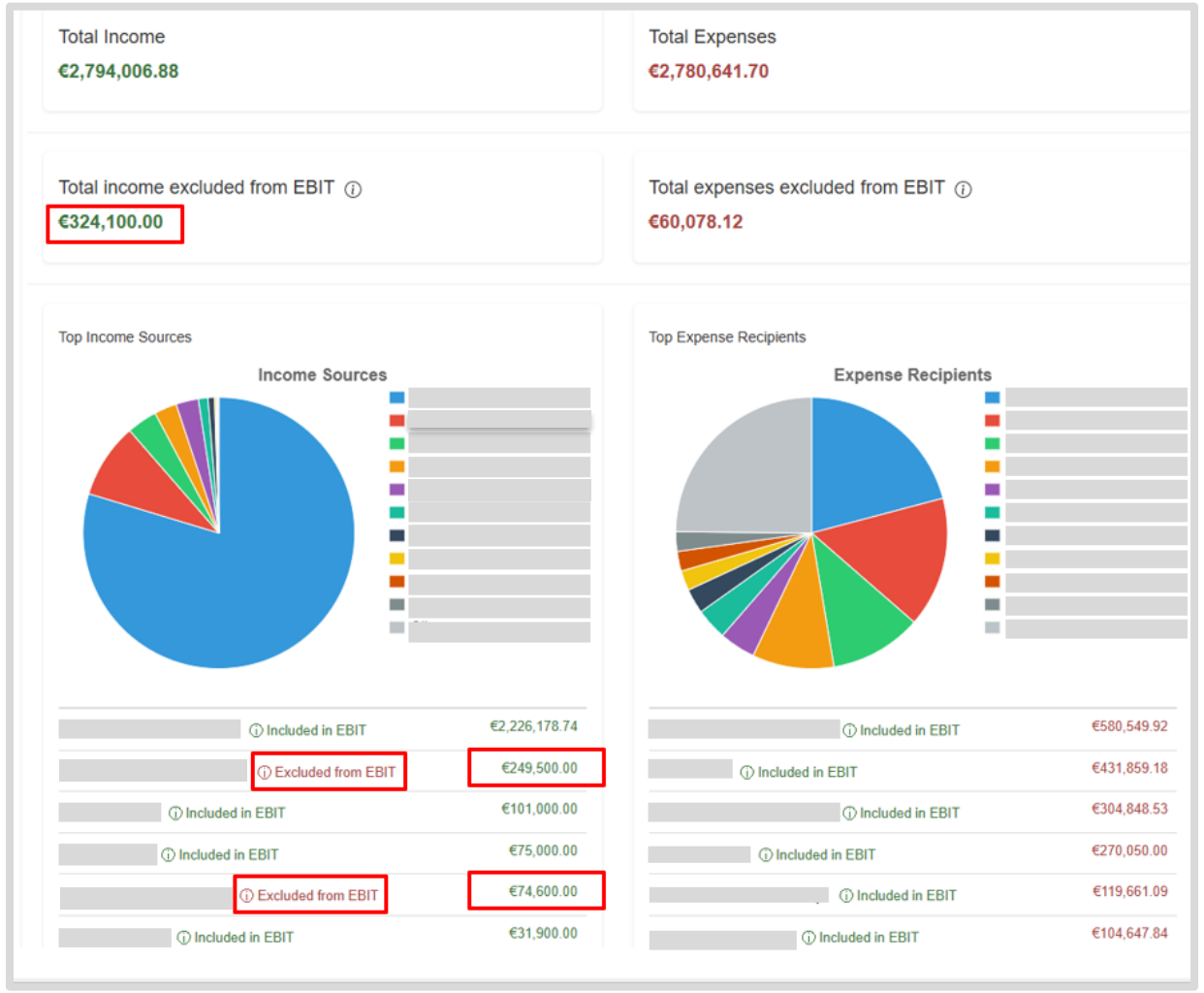
PSD2 visualization in Valuatum company portal (1/2)

- In Valuatum company portal, we can view PSD2-data visually and more thoroughly
- We can view the company's:
  - Incoming and outgoing monthly cash flows
  - Top income sources and expense recipients
  - All income and expense transactions



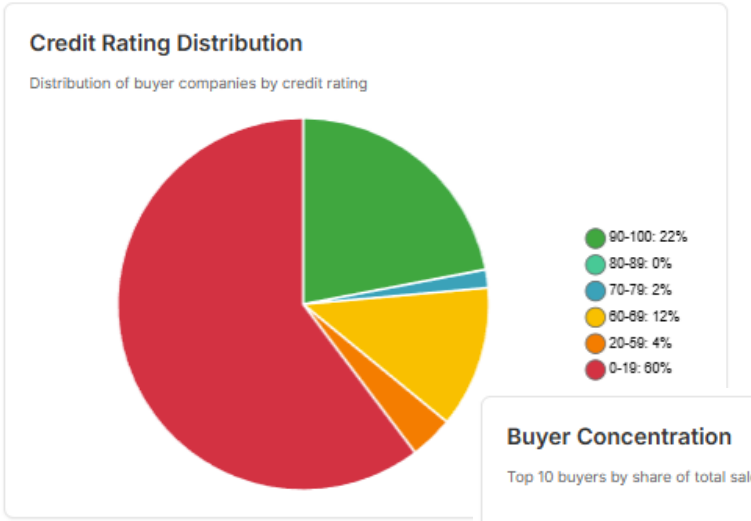
PSD2 visualization in Valuatum company portal (2/2)

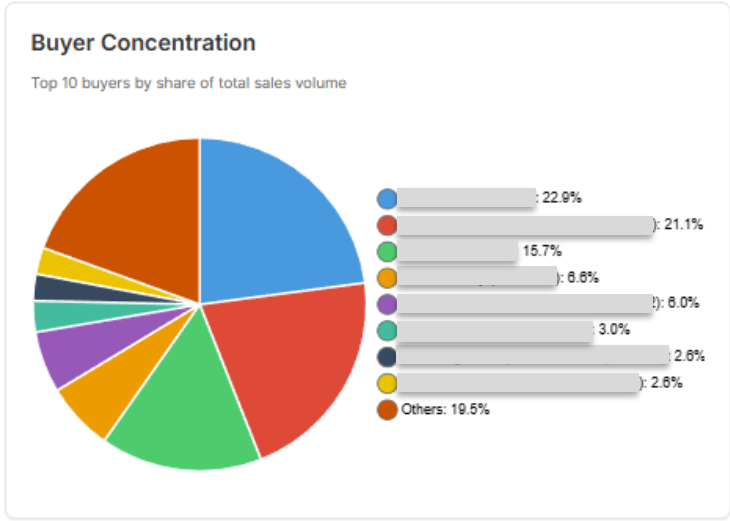
- In PSD2-visualization page, we can also view transactions and make adjustments to EBIT based on the transaction sender/recipient.
- In the adjacent picture we can see that the company has received payments from a pension insurance company and a credit institution. Based on our knowledge of the company these are not payments related to revenue, so we can exclude these from EBIT and therefore make more accurate forecasts.
- Excluding and including transactions can be done by clicking transaction, changing transaction category and saving changes.



Sales Ledger Analysis (1/2)

- Get a quick, high-level view of your entire factoring portfolio risk in just minutes
- It only takes a few moments and a few steps
- Receive a ready-made dashboard with key metrics, including:
  - Total Sales Volume
  - Average Payment Time
  - % of Overdue Invoices
  - Weighted Credit Score of Buyers
  - Concentration of Top Buyers



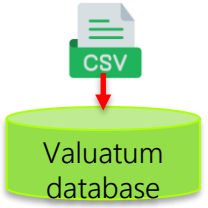


See more dashboard visuals on the next slide.

Step 1: Export data from your accounting system (e.g., Netvisor, Procountor, Talenom).

procountor
TALENOM
netvisor

Step 2: Upload a csv-file from your accounting system to our database



Step 3: Check out the dashboard

Sales Ledger Analysis (2/2)

Portfolio overview

Total Sales Volume **€7,710,318** 2903 invoices, 119 buyers	Invoice Size **€2,656** Avg. size | Largest: €51,712	Payment Behaviour **26 days** Avg. time to pay | Avg. term: 27 days	Overdue Sales **19.2%** Share of total sales overdue (more than 7 days)
Seller Credit Score **30** Bankruptcy Risk: 0.54%	Seller 12 Month PD **4.48%** 12-month probability of default	Buyers' Credit Score **70** Weighted avg. risk: 0.00%	Buyers' 12 Month PD **0.03%** Weighted avg. 12M PD of buyers
Credit Notes **10.9%** Share of total volume	Buyer Concentration **84.6%** Top 10 buyers | Largest: 22.9%	B2B Sales **7.7M € (100%)** B2C: €0	

Detailed buyer information

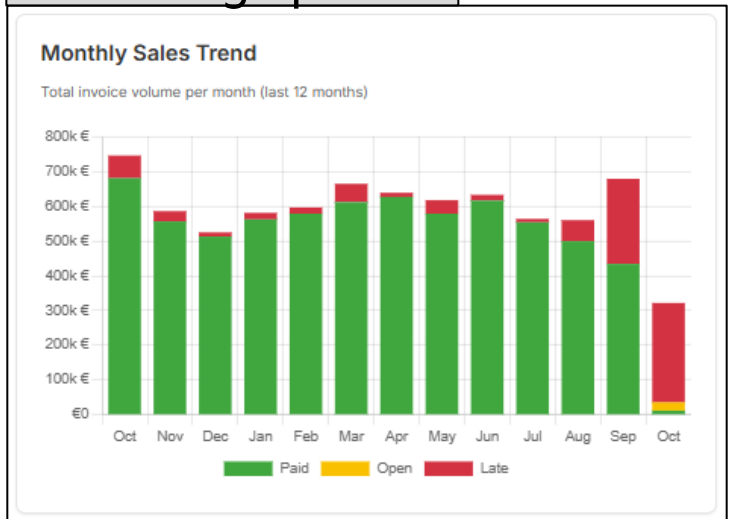
Buyer Portfolio Details

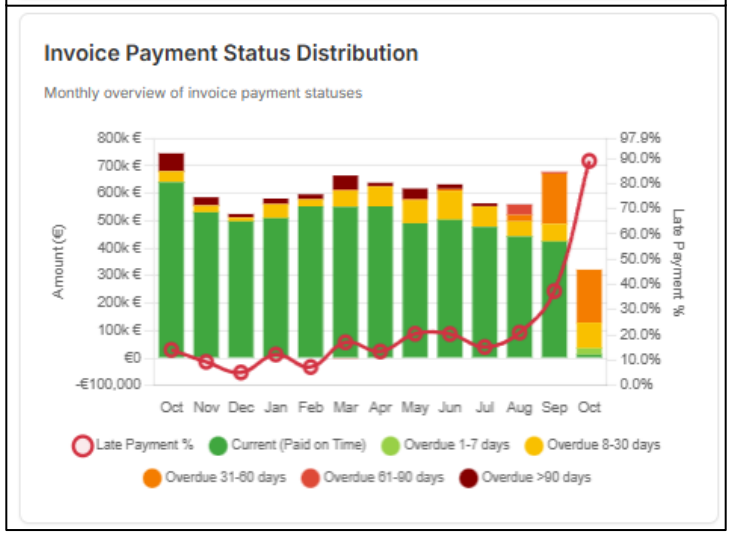
Detailed analysis of all buyers and their transaction patterns

Search companies... | 10 entries

Buyer	Total Purchases	Portfolio Share	Invoices	Avg. Size	12M PD	Credit Score	Avg. Delay
+ [redacted]	€1,767,673.96	22.93%	684	€2,584.32	-	-	+2 days
+ [redacted]	€1,625,933.41	21.09%	359	€4,529.06	-	-	-1 days
+ [redacted]	€1,211,109.35	15.71%	267	€4,535.99	0.01%	93	-14 days
+ [redacted]	€511,668.46	6.64%	65	€7,871.82	0.02%	66	0 days
+ [redacted]	€460,141.75	5.97%	130	€3,539.55	0.01%	94	+4 days
+ [redacted]	€232,989.16	3.02%	44	€5,295.21	0.05%	19	+3 days

More graphs

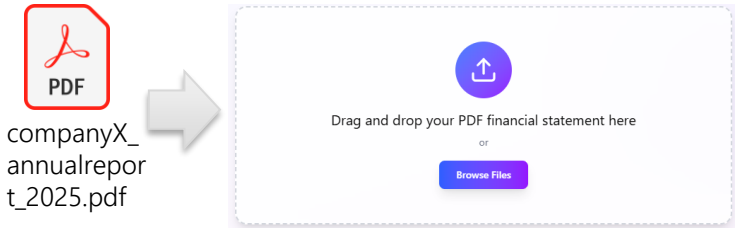




PDF Import Tool

- We have developed a PDF reading tool that accepts any company's PDF financial statement, processes it, and converts it into Valuatum's standardized financial statement format.
- The entire process takes only a few minutes.
- The tool currently achieves approximately 95% accuracy, and is still in beta with ongoing improvements to further enhance performance.
- Try it yourself for free with 1 credit via this website and receive a complimentary valuation and credit risk report.

Step 1: Upload your PDF to our tool



Step 2: Data is extracted by AI and formatted correctly to fit our format

Liikevaihto 1000
Liiketoiminnan muut tuotot 200
Ostot tilikauden aikana -678
Metsävarojen käyvän arvon muutos 32
Liiketoiminnan muut kulut -245
Osuus osakkuusyritysten tuloksista 40
Suunnitelman mukaiset poistot -200
Liikevoitto 149
.....

NetSales 1000
OtherOperatingIncome 232
PurchasesDuringFiscalYear -678
OtherOperatingExpenses -245
ShareOfProfitsAssociates 40
DepreciationAccordingToPlan -200
OperatingIncome 149
.....

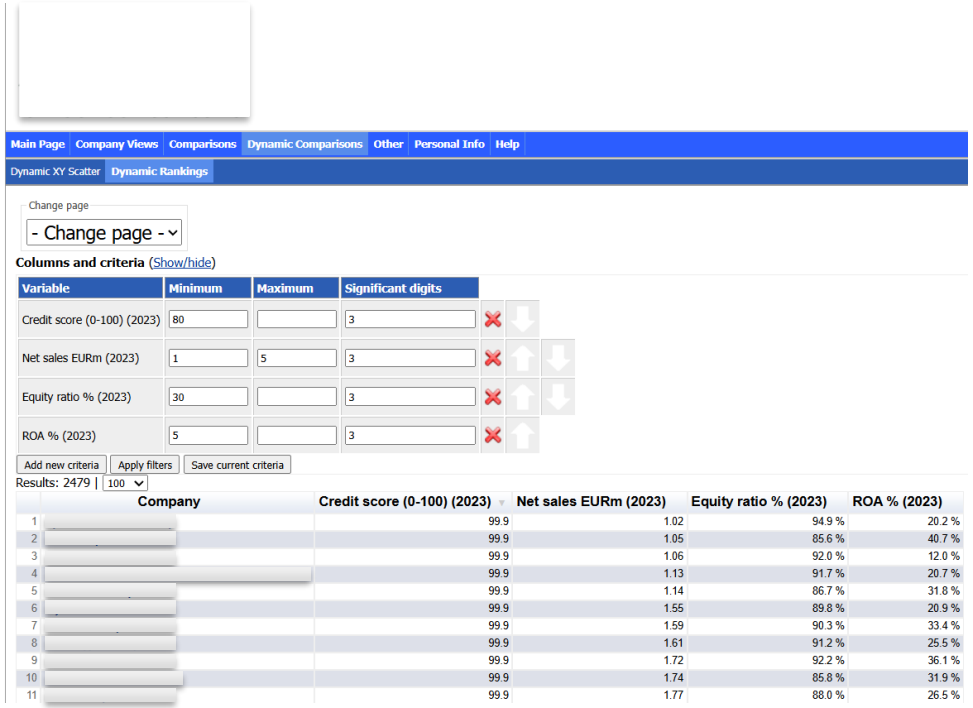
Step 3: Data is sent to our system

Income statement (EURk)	2024 2025/1
Net sales	**1,000**
Other operating income	232.0
Purchases during the financial year	-678.0
Other operating expenses	-245.0
Net income from associates	40.0
Total depreciation and amortization	-200.0
EBIT	**149.0**

Valuatum Dynamic Rankings

Dynamic Rankings –page is available in Valuatum company portal.

In Dynamic Rankings –page, we can create our own lists and comparisons of companies based on different criteria.



Criteria to rank companies:

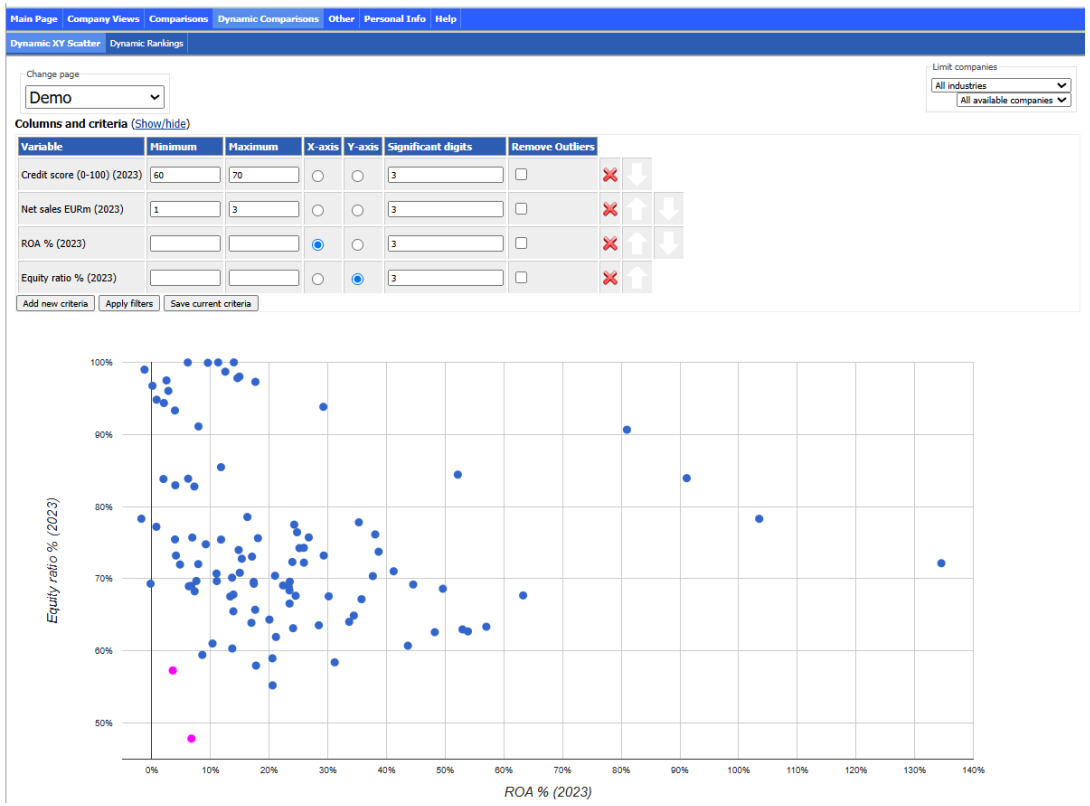
- Credit score
- Net sales
- Equity ratio
- ROA-%
- Bankruptcy risk
- Balance sheet total
- EBIT-%
- Net sales growth
- Industry
- etc.

- We can also create new criteria from existing parameters based on the user's needs

Comprehensive instructions: https://www.valuatum.com/support/credit-risk-manual/comparisons/

Valuatum Dynamic XY Scatter

Dynamic XY scatter has the same principles than Dynamic Rankings. In XY scatter we can view list of companies in one picture and detect best performers visually.



Criteria to rank companies:

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- Balance sheet total
- EBIT-%
- Net sales growth
- Industry
- etc.

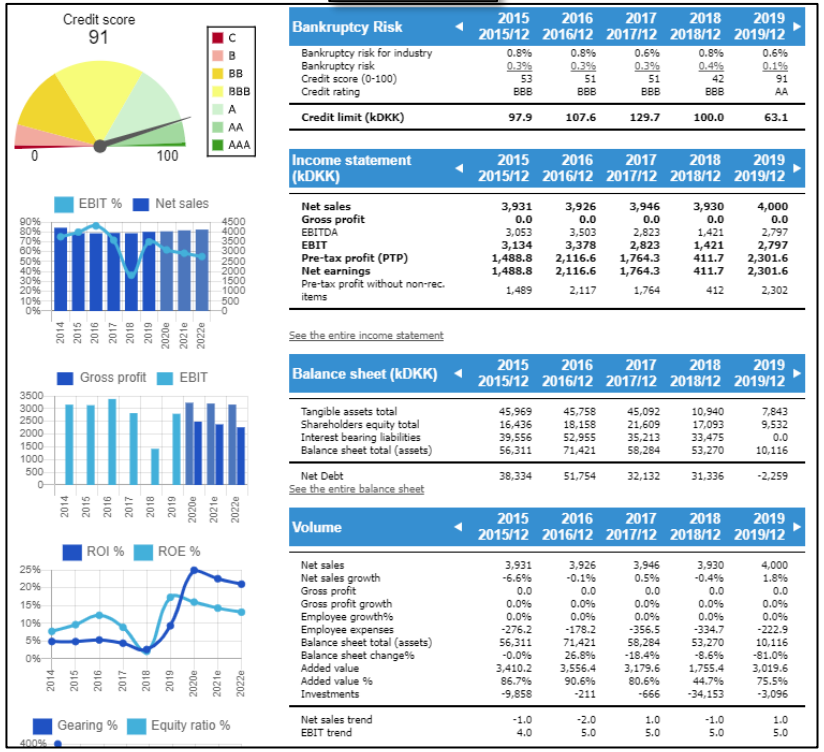
- We can also create new criteria from existing parameters based on the user's needs

Comprehensive instructions: https://www.valuatum.com/support/credit-risk-manual/comparisons/

Company Views

- Company Views is our web interface that gives a comprehensive outlook into the financial position of a company
- Layout of Company Views can be modified to fit customer needs
  - Select pages that you want (e.g., Financial statements, Cash flow statements, Valuation)
  - Choose which figures and graphs you want to display
- System is developed for financial statement analysis:
  - System can generate estimates automatically or user can make own estimates
  - User can create multiple scenarios for the company
  - User can also adjust historical figures
- Formulas for calculations can easily be checked by clicking the variable

Overview



Bankruptcy Risk	2015 2015/12	2016 2016/12	2017 2017/12	2018 2018/12	2019 2019/12
Bankruptcy risk for industry	0.8%	0.8%	0.6%	0.8%	0.6%
Bankruptcy risk	0.3%	0.3%	0.3%	0.4%	0.1%
Credit score (0-100)	53	51	51	42	91
Credit rating	BBB	BBB	BBB	BBB	AA
Credit limit (kDKK)	**97.9**	**107.6**	**129.7**	**100.0**	**63.1**

Income statement (kDKK)	2015 2015/12	2016 2016/12	2017 2017/12	2018 2018/12	2019 2019/12
Net sales	**3,931**	**3,926**	**3,946**	**3,930**	**4,000**
Gross profit	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
EBITDA	3,053	3,503	2,823	1,421	2,797
EBIT	**3,134**	**3,378**	**2,823**	**1,421**	**2,797**
Pre-tax profit (PTP)	**1,488.8**	**2,116.6**	**1,764.3**	**411.7**	**2,301.6**
Net earnings	**1,488.8**	**2,116.6**	**1,764.3**	**411.7**	**2,301.6**
Pre-tax profit without non-rec. items	1,489	2,117	1,764	412	2,302

See the entire income statement

Balance sheet (kDKK)	2015 2015/12	2016 2016/12	2017 2017/12	2018 2018/12	2019 2019/12
Tangible assets total	45,969	45,758	45,092	10,940	7,843
Shareholders equity total	16,436	18,158	21,609	17,093	9,532
Interest bearing liabilities	39,556	52,955	35,213	33,475	0.0
Balance sheet total (assets)	56,311	71,421	58,284	53,270	10,116
Net Debt	38,334	51,754	32,132	31,336	-2,259

See the entire balance sheet

Volume	2015 2015/12	2016 2016/12	2017 2017/12	2018 2018/12	2019 2019/12
Net sales	3,931	3,926	3,946	3,930	4,000
Net sales growth	-6.6%	-0.1%	0.5%	-0.4%	1.8%
Gross profit	0.0	0.0	0.0	0.0	0.0
Gross profit growth	0.0%	0.0%	0.0%	0.0%	0.0%
Employee growth%	0.0%	0.0%	0.0%	0.0%	0.0%
Employee expenses	-276.2	-178.2	-356.5	-334.7	-222.9
Balance sheet total (assets)	56,311	71,421	58,284	53,270	10,116
Balance sheet change%	-0.0%	26.8%	-18.4%	-8.6%	-81.0%
Added value	3,410.2	3,556.4	3,179.6	1,755.4	3,019.6
Added value %	86.7%	90.6%	80.6%	44.7%	75.5%
Investments	-9,858	-211	-666	-34,153	-3,096
Net sales trend	-1.0	-2.0	1.0	-1.0	1.0
EBIT trend	4.0	5.0	5.0	5.0	5.0

Financial statements

Income statement (kDKK)	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A
Fiscal year (months)	12	0	0	0	0
Net sales	**4,000**	**4,027**	**4,077**	**4,116**	**4,195**
Change in finished goods inventory	0.1	0.1	0.1	0.2	0.2
Manufacturing for enterprise's own use	0.0	0.0	0.0	0.0	0.0
Other operating income	0.0	0.0	0.0	0.0	0.0
External services	0.0	0.0	0.0	0.0	0.0
Administrative expenses	-222.9	-285.1	-314.0	-342.6	-375.4
Gross profit	**0.0**	**3,231**	**3,200**	**3,159**	**3,147**
Net Income from Associates	0.0	0.0	0.0	0.0	0.0
Wages and salaries	0.0	0.0	0.0	0.0	0.0
Other operating expenses	-580.4	-742.2	-817.5	-892.0	-977.3
Reduction in value of non-current assets	0.0	0.0	0.0	0.0	0.0
EBIT	**2,796.7**	**2,488.4**	**2,382.1**	**2,266.5**	**2,169.2**
Other financial income	0.0	0.0	0.0	0.0	0.0
Other financial expenses	-495.1	-495.1	-495.1	-495.1	-495.1
Pre tax profit less extra ordinaries	**2,301.6**	**1,993.4**	**1,887.0**	**1,771.4**	**1,674.1**
Pre-tax profit (PTP)	**2,301.6**	**1,993.4**	**1,887.0**	**1,771.4**	**1,674.1**
Income taxes	0.0	-398.7	-377.4	-354.3	-334.8
Net earnings	**2,301.6**	**1,594.7**	**1,509.6**	**1,417.1**	**1,339.3**

Assets (kDKK)	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A
Intangible assets total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Buildings	7,843.2	9,056.7	9,168.3	9,256.1	9,434.9
Tangible assets total	**7,843.2**	**9,056.7**	**9,168.3**	**9,256.1**	**9,434.9**
Other receivables	0.0	0.0	0.0	0.0	0.0
Investments total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Other stocks	0.0	0.0	0.0	0.0	0.0
Current assets total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Long term receivables total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Current trade debtors	0.0	0.0	0.0	0.0	0.0
Current other receivables	12.6	12.7	12.8	13.0	13.2
Prepayments and accrued income	1.4	1.4	1.5	1.5	1.5
Short term receivables total	**14.0**	**14.1**	**14.3**	**14.4**	**14.7**
Cash equivalents total	**0.0**	**0.0**	**0.0**	**0.0**	**0.0**
Cash and bank deposits	2,258.8	2,274.2	2,302.2	2,324.3	2,369.2
Cash (generated)	0.0	472.7	583.3	696.0	704.3
Balance sheet total (assets)	**10,116.0**	**11,817.7**	**12,068.2**	**12,290.7**	**12,523.0**

Equity and liabilities (kDKK)	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A
Share capital	76.4	76.4	76.4	76.4	76.4
Retained earnings	8,630.6	8,795.7	9,114.6	9,416.5	9,699.9
Profit of the financial year	825.1	1,594.7	1,509.6	1,417.1	1,339.3
Shareholders equity total	**9,532**	**10,467**	**10,701**	**10,910**	**11,116**
Appropriations total	**0**	**0**	**0**	**0**	**0**
Non-current loans from credit institutions (Estimate years generated)	0.0	0.0	0.0	0.0	0.0
Non-current liabilities total	**0**	**0**	**0**	**0**	**0**

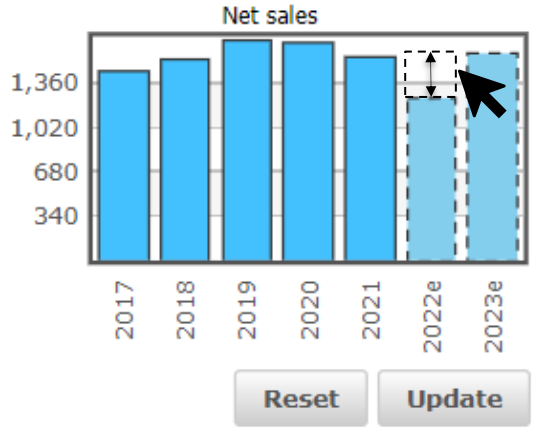
Valuation

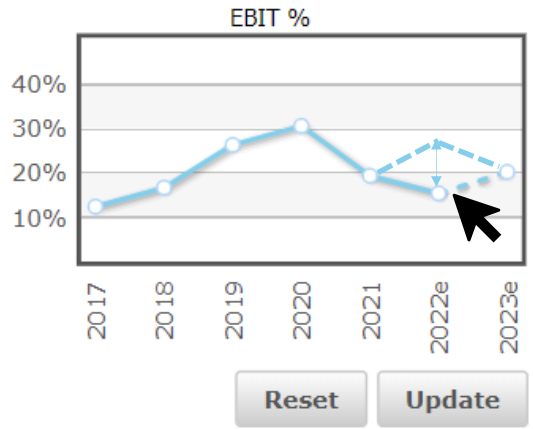
DCF Valuation (kDKK)	2018 2018/12	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A	2024e N/A	2025e N/A	2026e N/A	2027e N/A	2028e N/A	2029e N/A	TRM N/A
EBIT	1,421	2,797	2,488	2,382	2,266	2,169	2,080	1,992	1,898	1,797	1,688	1,571	1,619
+ Total depreciation	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
- Paid taxes	0.00	0.00	-399	-377	-354	-335	-317	-299	-281	-260	-239	-215	0.00
- Tax, fin. expenses	0.00	0.00	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	-99.0	0.00
+ Tax, fin. income	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
- Ch. in working cap.	-28,840	38,058	767	16.5	12.9	26.4	35.9	41.5	43.9	45.4	46.8	48.2	0.00
Operating cash flow	-27,420	40,855	2,758	1,922	1,826	1,762	1,700	1,635	1,562	1,483	1,397	1,305	0.00
+ Inc. in nib. l-t liab.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
- Gross capex	34,153	3,096	-1,213	-112	-87.7	-179	-243	-281	-297	-308	-317	-326	-336
Free oper. cash flow	6,733	43,952	1,545	1,810	1,738	1,583	1,457	1,354	1,265	1,176	1,081	979	0.0
+/- Other items	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Free cash flow	6,733	43,952	1,545	1,810	1,738	1,583	1,457	1,354	1,265	1,176	1,081	979	10,853
Discounted FCFF			1,931	2,016	1,724	1,398	1,146	948	789	653	534	431	4,780
Cum. disc. FCFF			**16,349**	**14,418**	**12,403**	**10,679**	**9,281**	**8,136**	**7,188**	**6,399**	**5,746**	**5,211**	**4,780**
- Int-bear. debt				0.00									
+ Cash at bank				2,747									
+ Market value of associated companies				0.00									
- Market value of minorities				0.00									
- Prev. year paid dividends				0.00									
Value of equity				**18,937**									
/ No of shares (m)				0.00									
Fair value DCF				**0.00**									

EVA Valuation (kDKK)	2018 2018/12	2019 2019/12	2020e N/A	2021e N/A	2022e N/A	2023e N/A	2024e N/A	2025e N/A	2026e N/A	2027e N/A	2028e N/A	2029e N/A	TRM N/A
EBIT	1,421	2,797	2,488	2,382	2,266	2,169	2,080	1,992	1,898	1,797	1,688	1,571	1,619
- Taxes on EBIT	0.00	0.00	-498	-476	-453	-434	-416	-398	-380	-359	-338	-314	0.00

Company Views: Estimates and Adjustments

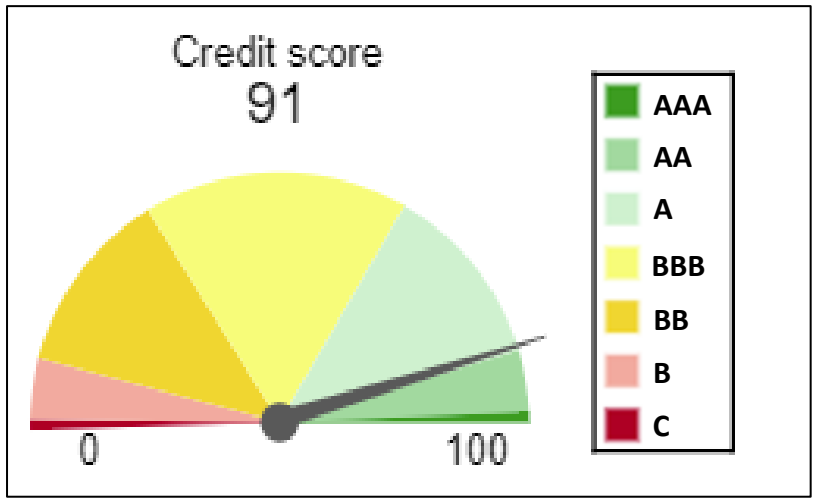
Income statement (EURm)	2017 N/A	2018 2018/12	2019 2019/12	2020e N/A
Fiscal year (months)	0	12	12	0
Net sales	9,116	9,071	9,382	9,518
Net sales growth	*7.5%*	*-0.5%*	*3.4%*	*1.4%*
Other operating income	0.0	22.0	22.8	23.1
Other operating income / Net sales	*0.0%*	*0.2%*	*0.2%*	*0.2%*
Purchases during the financial year	0.0	-3,614.4	-3,739.7	-3,799.1
Purchases during fiscal year / Net sales	*0.0%*	*-39.8%*	*-39.9%*	*-39.9%*
Wages and salaries	0.0	-2,818.4	-2,916.1	-2,962.4
Wages and salaries / Net sales	*0.0%*	*-31.1%*	*-31.1%*	*-31.1%*
Other operating expenses	-7,755.6	-1,498.6	-1,550.5	-1,575.2





- Adjustments to historical figures and estimates can be made on the web interface
- Adjustments can be made in two different ways:
  1. Changing the values in tables
  2. Dragging the bars or lines in charts (see the picture on the left!)
- After adjustments, the financial statements and key ratios are updated accordingly
- Estimates can be input either as absolute or relative values (e.g., net sales or net sales growth-%)
- Adjustments and estimates can also be easily edited in the Excel model

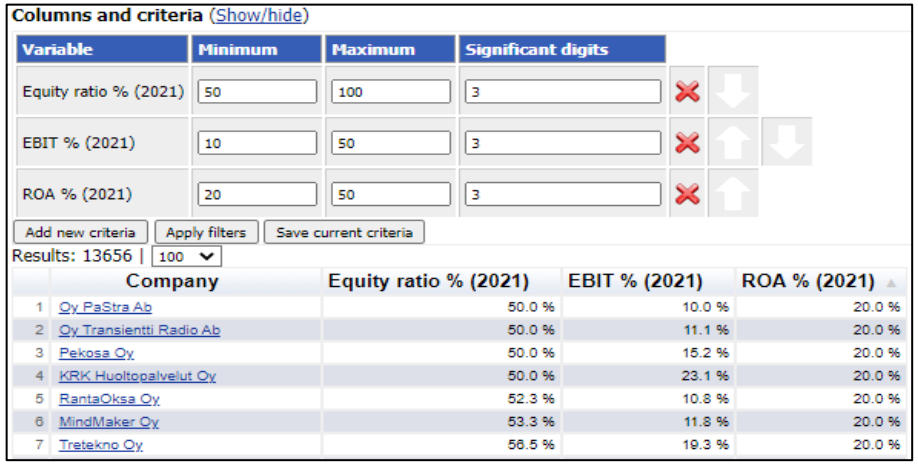
Bankruptcy Risk

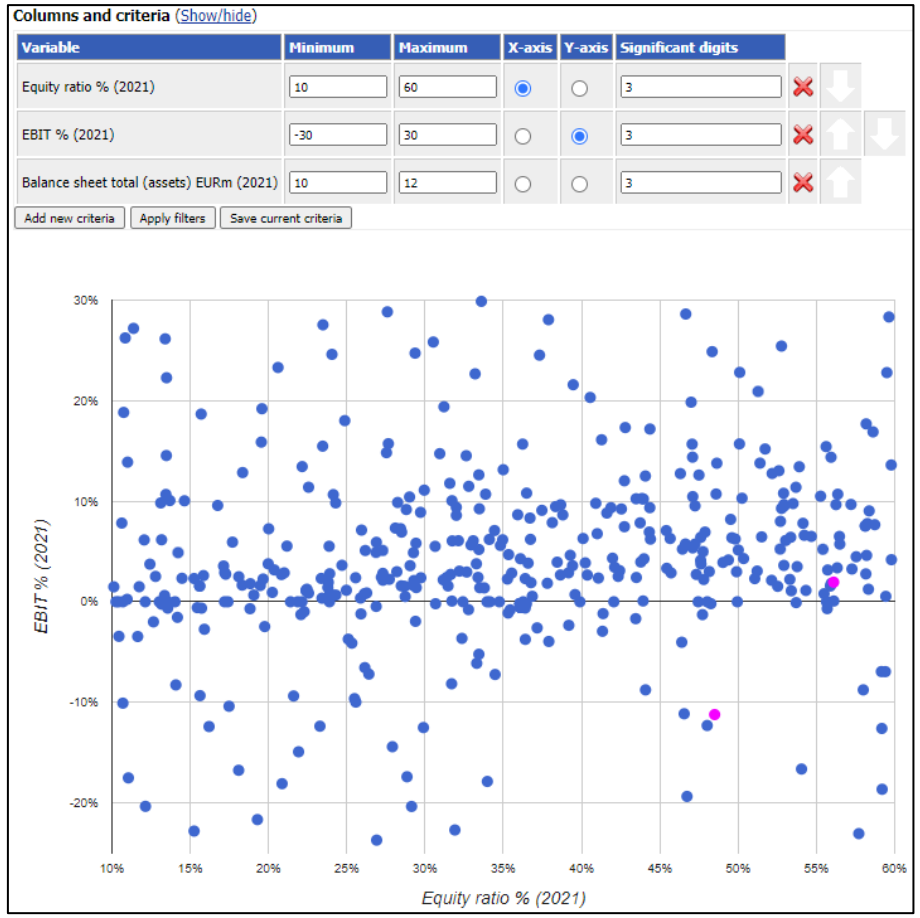


Bankruptcy Risk	2018 2019/6	2019 2020/6	2020 2021/6	2021 2022/6	2022 2023/6
Bankruptcy risk for industry (2 years)	1.05%	1.24%	0.81%	0.46%	0.56%
Bankruptcy risk -%	0.2091%	0.1841%	0.1756%	0.1770%	0.1705%
Risk rating AAA-B&C	A	A	A	A	A
Credit score (0-100)	76	82	87	86	91
Credit limit (kEUR)	14.6	21.9	27.1	30.0	34.0
Loan price (%)	7.4%	7.2%	7.2%	7.2%	6.9%

Comparisons: Lists and Scatters

- The user can either make comparisons in a scatter or list form.
- The comparison group can be narrowed to any industry or list of user's choice.

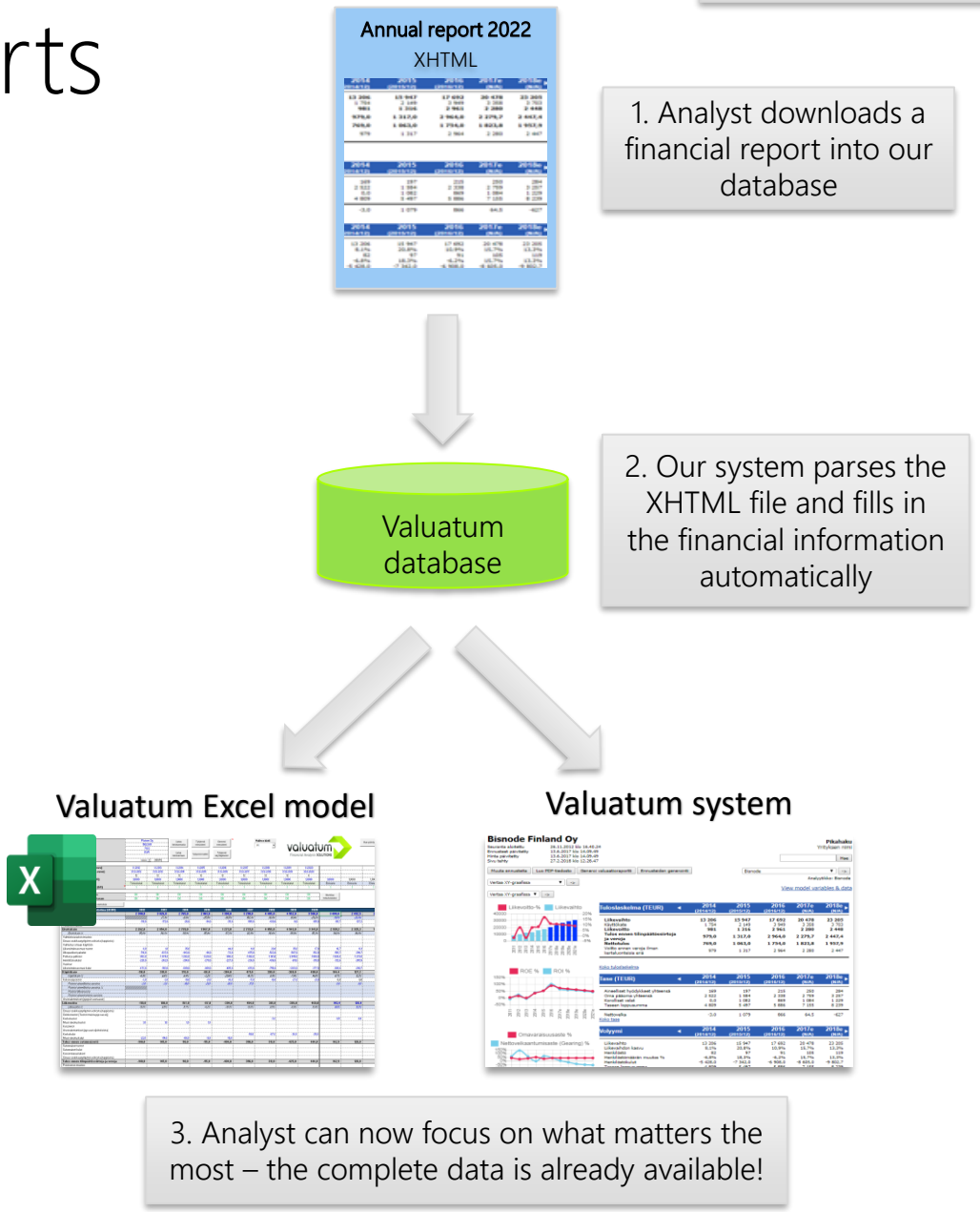




Automatic financial reports with XBRL

- XBRL is a standardized format that enables efficient exchange of financial information through digital means
- Possible to upload XHTML-type financial reports into our system which then automatically completes the financial statements for analysts
- Useful if data can't be automatically found from an external data provider. This can happen with e.g. foreign companies.

  -> financials can then be uploaded through XBRL



More information about our services

Overview of our credit risk services:
https://www.valuatum.com/credit-risk/

Our bankruptcy risk model (includes a technical white paper):
https://www.valuatum.com/credit-risk/bankruptcy-risk/

Our other methods for risk estimation:
https://www.valuatum.com/credit-risk/bankruptcy-risk/machine-learning-in-risk-estimation/

Example of how our system can be used in practice for credit risk assessment:
https://www.valuatum.com/credit-risk/credit-risk-in-practice/

Contact information

Customer support
contact@valuatum.com
+358 45 123 0308

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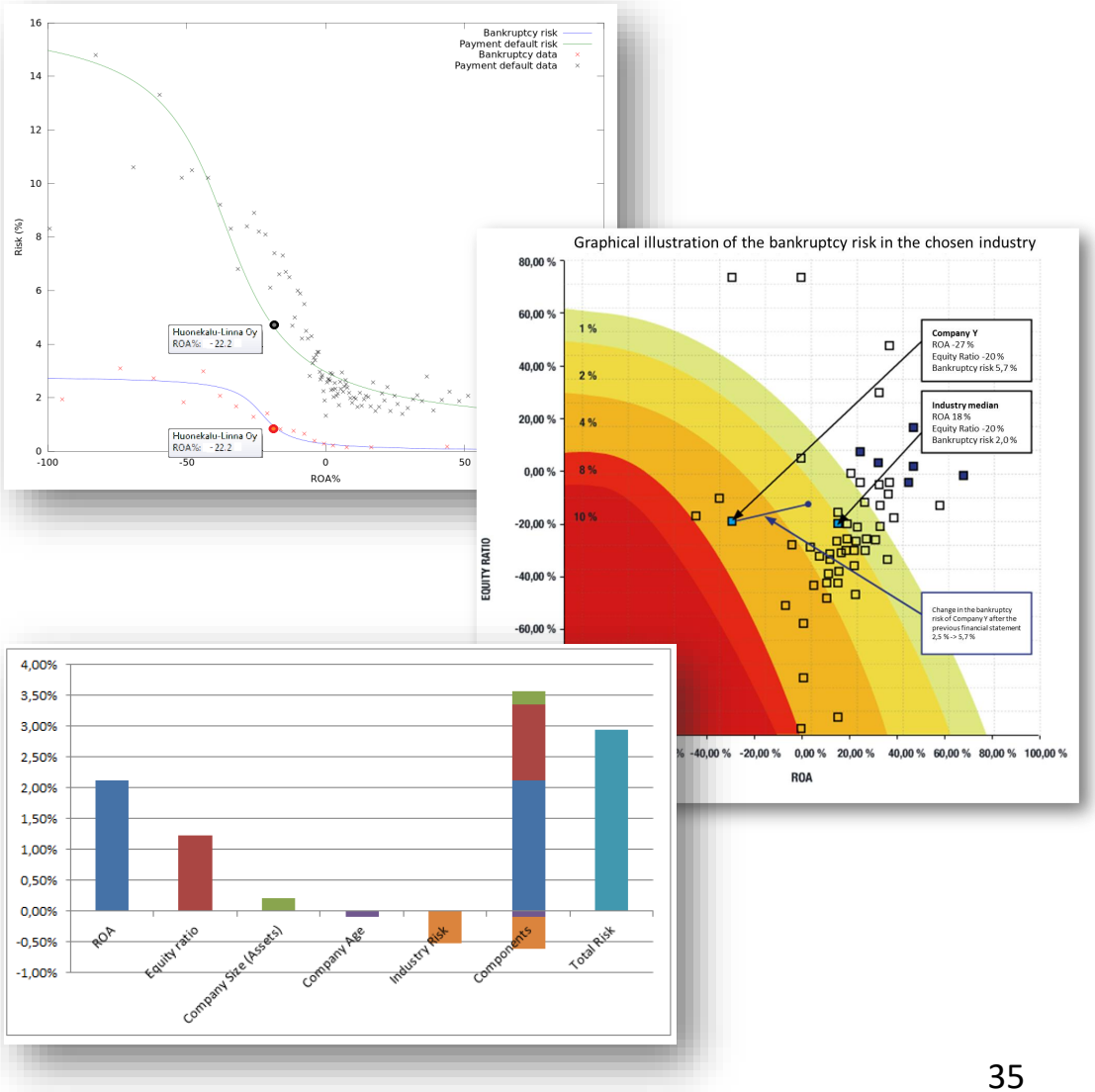
Financial Analysis SOLUTIONS

Additional Information

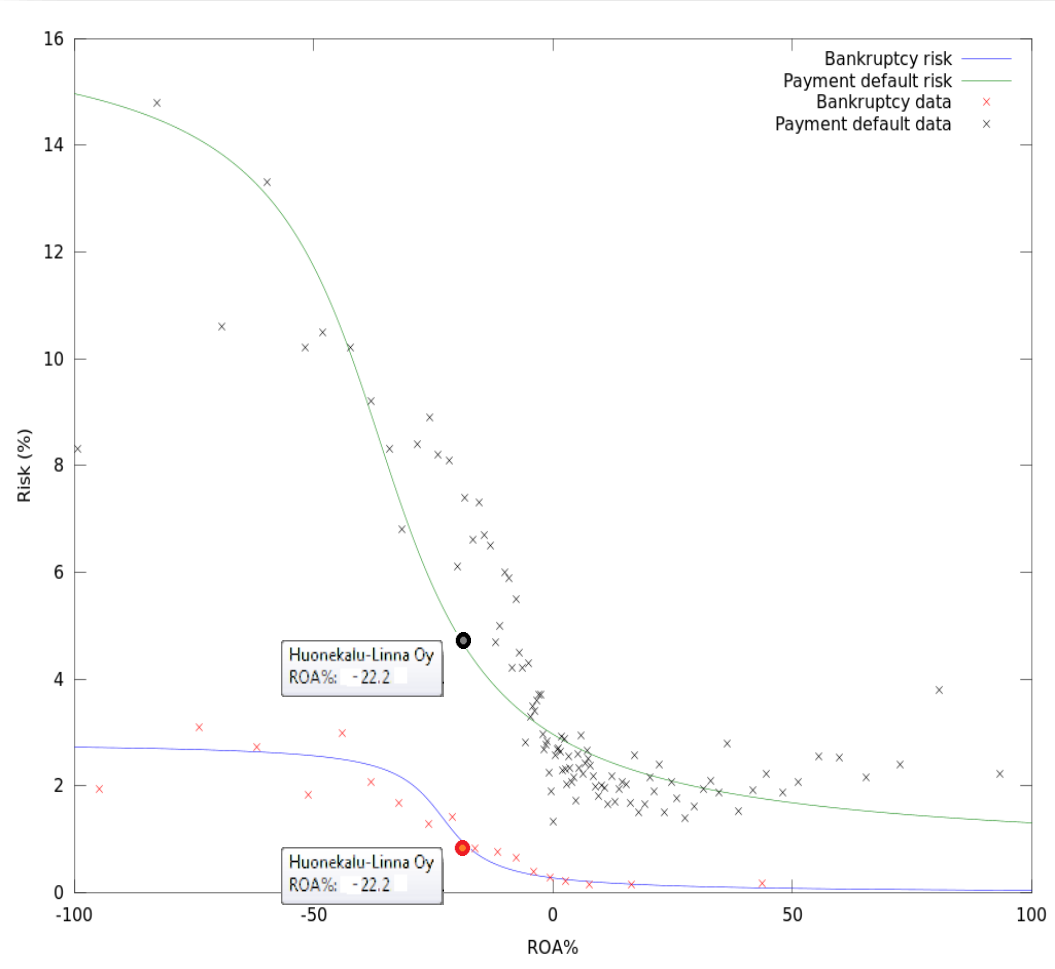
History of credit and default risk assessment

- Credit and bankruptcy risk predictions have usually been based on simple linear statistical models that use a few financial ratios such as ROA, Debt to Equity and Quick ratio
  - The Altman Z-score is a famous method that uses five explanatory variables to calculate the probability of bankruptcy
  - One of the most well-known methods is the logistic regression

- Logistic regression-based models remain one of the most widely used methods for bankruptcy risk prediction even today
  - Based on regression of defaults and several key figures
  - Often used because of its simplicity and efficiency
    - The decision of the model is also easy to interpret as the model coefficients provide the relative importance of the variables
  - Outputs a function 1/(1 + e^(-X)) that tells the probability of default, where X is a polynomial function. For example,
  - *X = -0.112 * Equity ratio + -0.081 * ROA + -0.054 * Quick ratio + … + 0.124 * IF(Industry A, 1, 0) + 0.056 * IF(Industry B, 1, 0) + … + -0.321 * IF(StDev(ROI) < 0.05, 1, 0) + 0.167 * IF(StDev(ROI) > 0.20, 1, 0) + … + IF(Net sales < 3 mEUR, (1 - (Net sales / 3)), 0) + IF(Net sales > 30 mEUR, log(Net sales) / log(30) - 1, 0) + …*

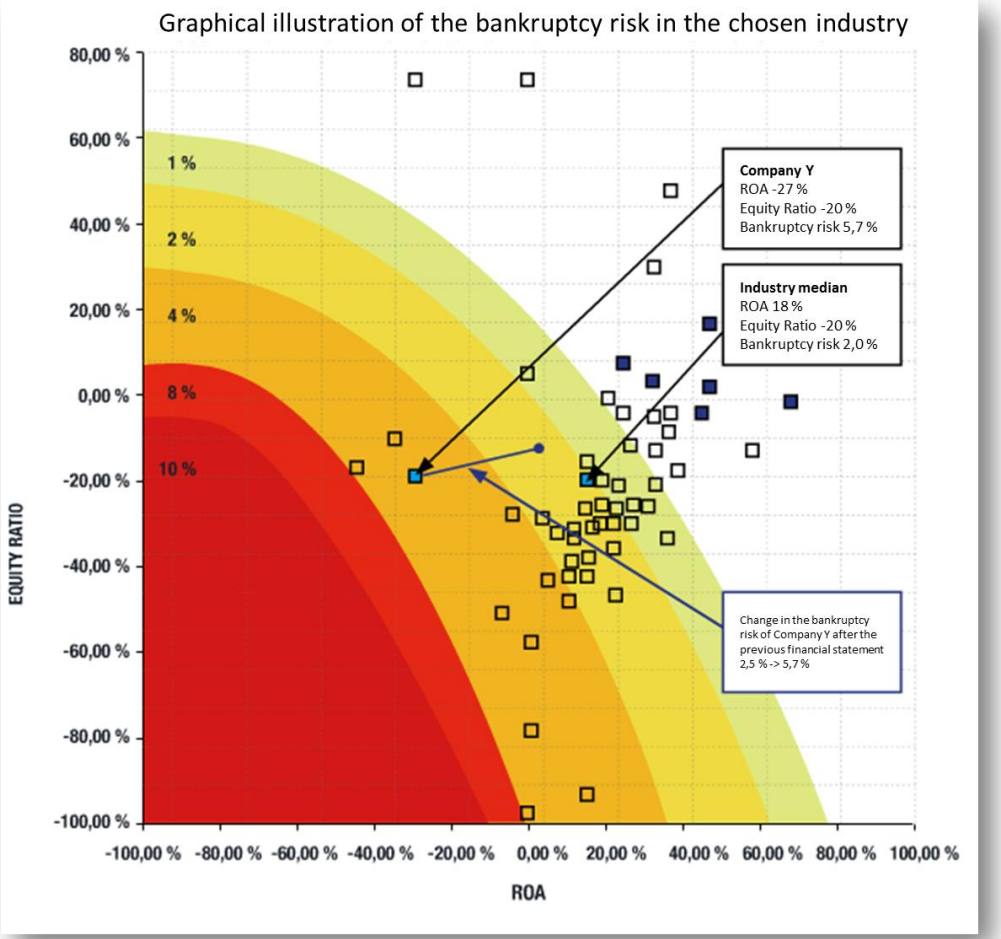


Credit and Default Risk: Single Variable



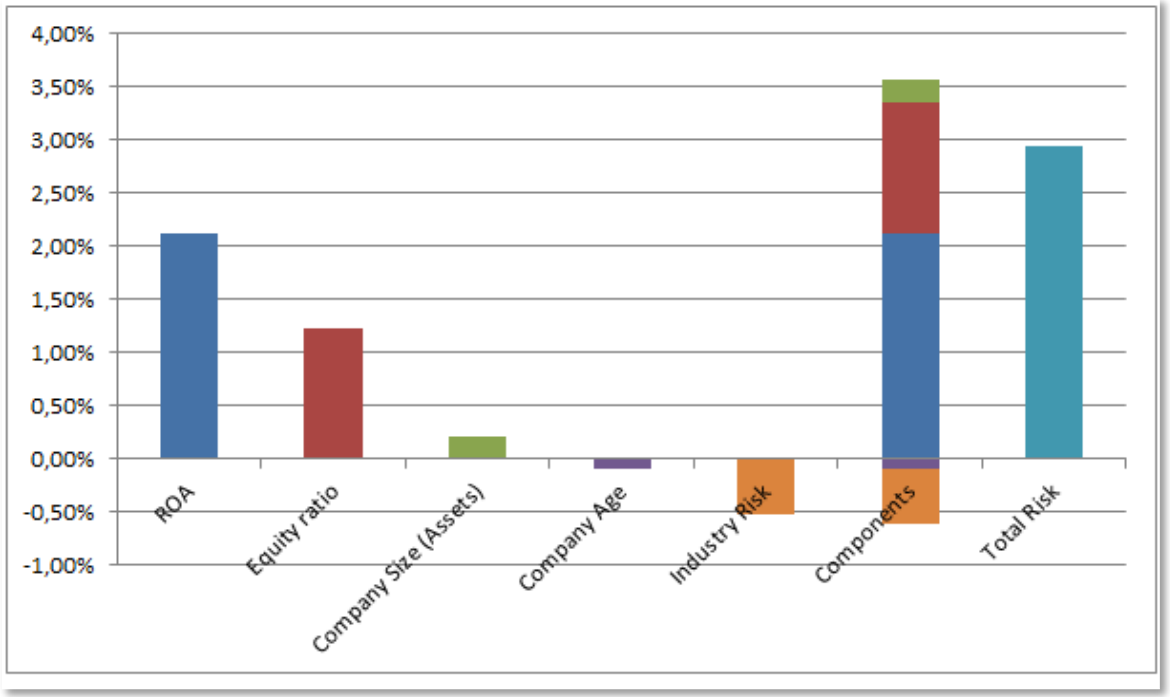
- What is the probability that a company will not be able to serve its debt e.g. in the next two years?
- The probablities are defined by observing the relationship between defaults and financial, e.g. profitability, variables with statistical methods.
- The graph illustrates the relationship of Return on Assets to defaults and financial distress within some 200 000 Finnish companies so that each dot represents approximately 4000 entities.

Credit and Default Risk: Two Variables



- Forecasting with one variable only gives a quite simple one-dimensional view.
- With a model using two variables, graphical representation is still possible and illustrates the possibility that another variable can compensate the high risk that a single variable could imply.
- The graph also shows how the default risk of a company has been developing during the years.

Credit and Bankruptcy Risk: Multivariable



In the diagram, bankruptcy risk is forecasted with five variables.

The variables are sorted from biggest contributor to risk to least contributing variable.

- Even though single and two variable models can offer a lot, the best prediction and illustration of financial distress is given by multivariable models, which take multiple aspects, e.g. profitability, profitability development, solvency, balance sheet quality, the age and size of a company, industry risk level etc., into account.
- Under our R&D at Valuatum we have empirically learned that examples of good predictive variables include but not limit to worsening profitability, stable profitability, increase in bad assets and rapid relative growth of accounts payable
- The component representation represents, which factors contribute to the default risk the most in the case of given company.

Accuracy of our XGBoost model

- Table on the right demonstrates how firms that have gone bankrupt were positioned according to the risk estimate made by ValuBooster model
  - Comparisons were done for companies available in our database (data from the years 2017-2018)
  - Companies have been sorted according to our bankruptcy risk scores and then divided into 10 equally large groups (Group 10 comprises of companies that have the highest 10 % of bankruptcy risk scores)

- In general, the results show that the higher the bankruptcy estimate given by the model was, the more bankruptcies happened

Not convinced?

- The same comparison can be done for any group of firms

- It is also possible to compare how the firms are ranked according to our metrics and yours
  - Provide us with the data (hundreds or thousands of previously rated potential clients) and we will generate, e.g., the probability of bankruptcy within the next two years based on the financial information available at the time of the original rating

2017			
Group number (sampled according to bankruptcy risk)	# of bankruptcies in the group	% of whole sample that have gone bankrupt	Highest bankruptcy risk in the group
1	6	< 0.01 %	0.0015
2	11	0.01 %	0.0016
3	19	0.01 %	0.0018
4	30	0.02 %	0.0023
5	26	0.01 %	0.0030
6	43	0.02 %	0.0039
7	71	0.04 %	0.0052
8	126	0.07 %	0.0081
9	253	0.14 %	0.0162
10	1054	0.57 %	0.6667
Total	**1640**	**0.89 %**	

2018			
Group number (sampled according to bankruptcy risk)	# of bankruptcies in the group	% of whole sample that have gone bankrupt	Highest bankruptcy risk in the group
1	2	< 0.01 %	0.0015
2	2	< 0.01 %	0.0016
3	13	0.01 %	0.0018
4	13	0.01 %	0.0023
5	7	0.00 %	0.0029
6	12	0.01 %	0.0038
7	23	0.01 %	0.0051
8	43	0.02 %	0.0080
9	93	0.05 %	0.0165
10	563	0.29 %	0.6858
Total	**771**	**0.39 %**	