

# Firm scores and future performance predictions

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This version: October 2020

## Sample

The firm sample for which scores are calculated comprises all Danish firms of type joint stock (A/S) and limited partnerships (ApS and I/S).

## Score types

We make currently available four different scores, all being categorized on ten-point scales:

1. CREDIT DEFAULT RISK SCORE: A measure of future bankruptcy probability. A low score indicates low statistical probability of bankruptcy in the future, while a high score indicates relatively higher risk of bankruptcy.
2. RETURN ON ASSETS SCORE: A measure of the probability of generating high return on assets (accounting profits over total assets) in the future. Model estimates are based on 'high' return on assets being defined as return on assets of and above 20 percent. A low score indicates low statistical probability of achieving high return on assets in the future, while a high score indicates high statistical probability of achieving high return on assets.
3. EMPLOYMENT GROWTH SCORE. The business authority supplies number of employees information in a set of employment size categories. The EMPLOYMENT GROWTH SCORE is an estimate of the probability of increasing employment size by two categories over a given time horizon. A low score indicates low statistical probability of achieving high employment growth, while a high measure indicates a higher statistical probability of achieving high employment growth. There is a substantial number of firms that do not report employment size, and for these the EMPLOYMENT GROWTH SCORE is set to the lowest measure 1.
4. INNOVATION SCORE. This score is somewhat different from the other scores. It does not look into the future, but describes the statistical propensity of given firms of having participated in a Danish public innovation support scheme. The score is, thus, a measure of expected interest in innovation support, presumably correlated with innovation activity as such or at least innovation ambition.

## Accessibility

Scores are either

1. shipped to clients as csv-formatted lists of firms with their corresponding credit scores.
2. made accessible as single firm look-up on our website.

3. made accessible as (json-encoded) lists for web-integration by an API on our website.

Scores are updated at least four times per year, or updated on demand. The website offers 'outdated' scores for illustration purposes. Potential clients interested in up-to-date information are very much welcome to taking contact with us. Pricing is contingent on number of firms, number of annual updates, number of expected copies at client side, and other factors.

List of firms can be grouped in different dimensions, like industries, size classes, geographical regions and firm age. We supply, for illustration purpose, lists for each of the 98 Danish municipalities, and separate lists for start-ups, defined as firms started in the preceding calendar month<sup>1</sup>.

## Scores are statistical estimates

Scores are based on relatively detailed firm level data and new combinations of putting these data into work. We use data back in time and statistics to learn about the relationships between variables and outcomes, and use what we have learned to make estimates about the future. These estimates are summarized in our scores. A score for a given firm is purely statistical and indicates the expected outcome or outcome probability based on the experience of other firms with similar characteristics.

Data for the scores is from public information such as financial accounts, the relationships database (stakeholders, managers, boards, auditors), and the Danish CVR-register. The latter adds a set of variables like industry, firm status (normal, under bankruptcy, etc.), firm names, and business purpose statements to our models. All data are made available by the Danish Business Authority's open data initiatives.

Scores are based on performance evaluations over a three-year period. We always employ the most recent three-year period (currently 2017-2020) to 'train' our algorithms and to generate the most recent scores.

## Precision evaluation (status September 2020)

An obvious question is, of course, how useful the scores are for prediction-making. We can evaluate the predictive power of earlier scores back in time, and compare how well or badly these scores were to predict actual outcomes.

This is what we do below: demonstrate the accuracy of scores of previous years in terms of foreseeing outcomes up to now.

It is these evaluations that we consider being a competitive edge of our scores: Measures of how good or bad earlier scores performed should be of interest for the decision of any potential customer to purchase credit rating scores or any other score that claims being able to predict the future. No-one would buy a racing car without asking for its top speed, yet it appears as if many credit scores out on the market are sold without giving even the slightest idea of their relevance for prediction by relating earlier scores back in time to subsequent observed outcomes.

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<sup>11</sup> If sample size of these start-ups being below 50 in given municipalities, in the preceding three calendar months.

For the evaluation of our scores, we use our scores one year back in time, and measure the precision of these ratings for bankruptcy prediction on the actual developments between one year back in time and present time.<sup>2</sup>

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<sup>2</sup> Important parts of the public data go back in time until 2015. In the future, it will become possible to employ longer time series for both learning from the data and for the assessments of prediction precision of the scores. As an option to enable you doing your own performance evaluations, we supply 'outdated' scores to our clients on request.

Latest precision accuracy evaluation is on a training sample from 01-09-2016 to 01-09-2019. Scores for evaluation purposes are based on this sample and compiled for 01-09-2019. The prediction accuracy of these scores is evaluated by comparison to performance in the subsequent year, i.e., from 2019-09-01 to 2020-09-01. We summarize as follows.

### CREDIT DEFAULT RISK SCORE – predictive accuracy

Results for our credit risk measure under the above-described evaluation scheme are summarized in TABLE 1.

**TABLE 1: Credit scores: Testsample 2019-2020: rankings & factual observations**

<b>N bankruptcies between 01-09-2019 and 01-09-2020</b>						
Credit scores based on training sample 2016-2019	N bankrupt	N not bankrupt	Share of all bankruptcies	Share of all bankruptcies at and above score	Share bankruptcies in score	
1	14	25,125	0%	100%	0.1%	
2	25	27,059	1%	100%	0.1%	
3	50	27,345	1%	99%	0.2%	
4	86	27,442	3%	97%	0.3%	
5	115	27,498	3%	95%	0.4%	
6	220	27,418	7%	91%	0.8%	
7	336	27,513	10%	85%	1.2%	
8	475	27,567	14%	75%	1.7%	
9	694	27,463	21%	61%	2.5%	
10	1,359	26,788	40%	40%	4.8%	
Total	3,374	271,218		(true positives)		

For credit scores on basis of the information in the test sample (2016-2019), it is found that more than 90 percent of all bankruptcies in the following year are in the top-5 categories of the scores. Bankruptcy shares increase from virtually zero for low scores to 4.9 percent for the highest score. The ROC-AUC statistic for this credit score evaluation is 0.79.

## Evaluation RETURN ON ASSETS SCORE

This score is based on the performance variable return on assets assuming a value of 0.2 (20 percent) or higher. The evaluation exercise is again based on a training sample 2016-2019 and a testing sample 2019-2020. TABLE 2 summarizes.

**TABLE 2: ROA>0.2: Testsample 2019-2020: rankings & factual observations**

<b>N ROA&gt;0.2 after 01-09-2019</b>						
ROA scores based on training sample 2016 until 01-09-2019	N		Share of all ROA>0.2	Share of all ROA 0.2 at and above score	Share ROA>0.2 in score	
	N ROA>0.2	ROA<0.2				
<b>1</b>	799	19,692	2%	100%	4.1%	
<b>2</b>	1,129	25,896	3%	98%	4.4%	
<b>3</b>	1,362	25,687	4%	94%	5.3%	
<b>4</b>	1,656	25,394	5%	90%	6.5%	
<b>5</b>	2,129	24,918	6%	85%	8.5%	
<b>6</b>	2,524	24,526	7%	79%	10.3%	
<b>7</b>	3,096	23,953	9%	72%	12.9%	
<b>8</b>	4,285	22,765	13%	62%	18.8%	
<b>9</b>	6,827	20,222	20%	50%	33.8%	
<b>10</b>	9,931	17,119	29%	29%	58.0%	
Total	33,738	230,172		(true positives)		

For scores on basis of the information in the test sample (2016-2019), it is found that approximately 80 percent of all firms with 20 percent return on assets and above are in the top-5 categories of the scores. High return on assets shares increase from approximately 4 percent for low scores to almost 60 percent for the highest score. The ROC-AUC statistic for this score is 0.73.

### EMPLOYMENT GROWTH SCORE – predictive accuracy

Results for the employment growth measure subject to the above-described evaluation scheme are summarized in TABLE 3. Note the evaluation is based on firms that report employment size only, ie. leaves out firms with missing employment information.

For these firms with employment information in the Business Authority’s data, it is found that 89 percent of the high growth events between 2019 and 2020 are in the top-3 employment score categories. The area under the receiver operating characteristic curve is 0.88.

**TABLE 3: High employment growth: Testsample 2019-2020: rankings & factual observations**  
**N high growth events between 01-09-2019 and 01-09-2020**

Credit scores based on training sample 2016-2019	N high employment growth	N not high employment growth	Share of all high empl. growth	Share of all high empl. growth at and above score	Share high empl growth in score
1	2	12,027	0%	100%	0.0%
2	10	12,020	1%	100%	0.1%
3	10	12,019	1%	99%	0.1%
4	9	12,021	1%	98%	0.1%
5	16	12,013	2%	97%	0.1%
6	17	12,013	2%	95%	0.1%
7	40	11,989	4%	94%	0.3%
8	47	11,983	5%	89%	0.4%
9	118	11,911	12%	85%	1.0%
10	720	11,310	73%	73%	6.0%
Total	989	119,306		(true positives)	

### INNOVATION SCORE – predictive accuracy

Results for the innovation measure are summarized in TABLE 4. Note the evaluation is based on a cross section of firms of September 2019.

**TABLE 4: Innovation support scheme participation: Cross section september 2019: rankings & factual observations**

Innovation scores based on training sample 2016-2019	N firms participated in previous five-year-period			Share of all having participated at and above score	Share having participated in score
	N having participated	N not having participated	Share of all having participated		
<b>1</b>	14	27,676	0%	100%	0.1%
<b>2</b>	30	27,660	0%	100%	0.1%
<b>3</b>	41	27,649	1%	99%	0.1%
<b>4</b>	44	27,646	1%	99%	0.2%
<b>5</b>	61	27,629	1%	98%	0.2%
<b>6</b>	94	27,597	1%	97%	0.3%
<b>7</b>	164	27,526	2%	96%	0.6%
<b>8</b>	358	27,332	5%	93%	1.3%
<b>9</b>	846	26,844	13%	88%	3.1%
<b>10</b>	4,912	22,779	75%	75%	17.7%
Total	6,564	270,338		(true positives)	

It is found that 88 percent of firms that have participated in any of the innovation schemes registered in the Danish Innovation Denmark are in the top-2 innovation score categories. In other words, the model relatively easily identifies firms prone to innovation activity.

## Summary

We are able to generate scores that are strongly related to future developments. We believe that we are one of very few suppliers (or maybe even the only supplier) of credit risk assessments that documents these relationships.

Our own stance on the scores is that they can qualify assessments of firm portfolios' future risk and return. For single firms, they can act as notifications for further investigation. Also, they can help screening and filtering of firm samples, for example by increasing the efficiency of identification of high potential firms. In sum, single firm assessments based on statistics, like our scores, need further investigation and qualification before making decisions. For firm portfolios, on the other hand, the statistical law of large numbers will quickly make our tools valuable for portfolio risk and return evaluations.

The strengths of the relationships between scores and actual later developments will be followed closely in the future, as longer time series of public data will become available. Currently, extending follow-up periods for evaluation at the cost of shortening the 'learning periods' of the training samples would compromise the precision of the scores.

At present, we will stick to the scores that are described in this note, and to the models behind these scores. However, we will add other scores on, e.g. equity growth or innovation potential in the, hopefully, near future, and keep on working on the improvement of our scores. Any comments or questions related to the scores, are, of course, greatly welcome and appreciated at any time.