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Operational Capability Analytics – A Data Envelopment Analysis on firm's fundamental data

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Abstract— There are various approaches to assess a firm's financial performance. Typically, financial ratios or metrics on supply chain performance are calculated and evaluated to assess a firm's financial performance. Problems often arise when firms from different industries, sizes and countries are evaluated because of the underlying linearity assumption in benchmarking comparisons. To overcome these difficulties we suggest to measure financial performance differently, which we call Operational Capability Analytics. We define the operational capability as the potential to translate firm's assets etc. efficiently into revenue, earnings etc.. We can show that the resulting efficiency score is highly correlated with a firm's financial performance represented by classical financial performance indicators. In this paper, the Banker, Charnes & Cooper (1984) (BCC) and Charnes, Cooper & Rhodes (1978) (CCR) Data Envelopment Analysis (DEA) models are used to calculate this operational capability. We use multiple input and output factors from the balance sheet, income and cash flow statement. The advantage of our non-parametric approach is that we can calculate the financial performance of different firms without knowing a priori the relationship between the input and output variables and their corresponding weights. We are able to show that our methodology can assess a firm's financial performance by deploying a correlation analysis to other performance indicator. As well, we establish a relationship to the stock market. An equity portfolio based on best performing firms calculated by our Operational Capability Analytics shows much better returns than portfolios composed by the worst firms. The yields are even better in the long run. Therefore, our conclusion is that operational capabilities pay off over a mid-term time horizon (> 1y). The market acknowledges the performance of the best operating firms. Our results can have useful implications for investment management. The BCC DEA model in general was the more valuable one in comparison with the CCR DEA model in this study. In the discussion, we show the limitations of our studies and how they can be solved and further developments.

Keywords—*DEA; Data Envelopment Analysis; Firm Performance; Operational Capability; Financial Performance; Fundamental Analysis; Portfolio Selection*

I. INTRODUCTION

The main objective of this paper is to find a methodology to measure a firm's financial performance. Normally you use classical financial ratios for liquidity, profitability, leverage and asset utilization (see [1] for further information) to assess a firm's financial situation respectively performance. These ratios assume a linear relationship between the variables. This is often not the case as in[2]because of economies of scale for example. Furthermore, it is often only possible to compare firms within the same industry and countries. This paper tries to overcome these difficulties by using the non-parametric DEA, which can evaluatevarious firms based onmultiple input and output variables. It is crucial to find the best variables for calculating a firm's operational capability, which reflects a firm's financial performance. More details about this connection will follow in section 3.DEA establishes a best-practice relationship between input and output parameters. The best firms specify the efficient frontier against which the other inefficient firms will beevaluated. In this paper, we want to test if DEA is applicable to resolve our main objectives and can be used as a method for measuring a firm's financial performance.

Further, we want to select equity portfolios in the stock market based on our performance evaluation results and compare the best firms of our evaluation against the worst. Due to the efficient market hypothesis it should not be possible to generate abnormal returns with any given investment strategy over a long time horizon. On the other hand, unique insights and analytics like assessing the operational efficiency should be rewarded (see[1] for further details) and could lead to higher returns.

In section II we will present former scientific papers, which worked on similar ideas like ours.

In section III will be an overview over fundamental analysis, DEA, our Operational Capability Analytics (OCA) method and the data collection.

Subsequently the results will be shared in section IV. As a last point we will draw our main conclusions and we will give an outlook to future research in section V.

II. LITERATURE REVIEW

During the past decades, many academic papers applied DEA to fundamental analysis. Some of themtried to overcome the problems of the typical financial ratios, others wanted to test the usability of DEA in the context of fundamental analysis and firm performance analysis. One of the first papers in this domain is from [3] who analyzed 47 pharmaceutical firms based on the constituent parts of return on capital employed. Thus, the selected variables were equity and average debt as inputs and tax, interest payments and earnings available for shareholders as outputs. Reference [3] used an input orientated BCC model for his assessment. The author is convinced that DEA is a very good tool for analyzing a firm, but is also aware of data quality problems.

Reference [4] evaluated 44 US computer manufactures based on variables from the income statement and balance sheet. His purpose was to analyze the computer industry in detail. He selected COGS, Capex, R&D, SG&A, number of employees and PP&E as inputs and revenue, EBT and market capitalization as outputs. The CCR input orientated model and the Malmquist Index were used as DEA methods. The authors do not completely explain their choice of variables.

A very interesting contribution to our domain was by [5]. In this paper, the author assessed the Fortune 500 firms based on the Fortune indicators. The benchmarking was done in a two stage procedure which is shown in Fig. 1. The first stage assesses the profitability of the given firms and the second stage the marketability. An interesting result is that the best firms in terms of profitability are not compulsory the best firms in terms of marketability. The author used the BCC and CCR model and showed that the BCC model is the better one for the given data because of the underlying variable returns-to-scale property.

Reference [6]consider 29 firms in the energy sector in their calculations. The input and output variables are deduced from the DuPont Formula. They take total assets, equity and costs as input variables and revenue as an output variable. The results show that a financial DEA score is better for assessing a firms financial performance than simple financial ratios.

This was a quick overview about some possible solutions to measure a firm's financial performance. There are other papers which did related research like [7], [8], [9] etc..

Reference [10] used DEA for portfolio selection. In the first step, the author calculated a firm's efficiency (or financial performance) with the input variables average equity, average asset and sales cost and with the output variables revenues, operating profit and net income. Taiwanese firm data was used and the CCR and BCC models were implemented. The author showed superior returns for portfolios based on the DEA results and suggests testing the results in other markets.

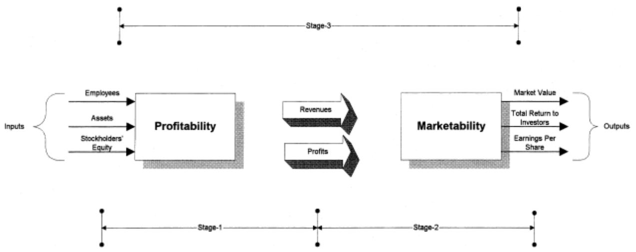

Figure 1: Input-output systems for Fortune 500 firms by Zhu (2000).

Reference [11] used DEA for equity portfolio selection. Three different DEA models, the CCR, super-efficiency and cross-efficiency model calculate the score.
They use stock price, enterprise value-per-share as input parameters, and book value-per-share, dividend-per-share and EBITDA-per-share as output parameters. In addition, they use a second model with a momentum indicator as an added output parameter. In a third model they use only stock price as an input parameter and the fourth one is similar to the third one but the earnings-per-share is substituted for EBITDA-per-share. All portfolios selected on the four different input-output-models significantly outperform the market portfolio and bottom portfolio. Their results show that DEA methods are applicable for portfolio selection.
In our literature review, we have shown that there are different DEA solutions for using a firm's fundamental data.Furthermore, other authors proved the applicability of DEA as a portfolio selection method. Some authors selected the input and output features based on the available data others started with causal dependency like in the DuPont formula.
We could identify a research gap in the applicability of DEA in fundamental analysis for different industries and countries. As well, we will present an input-output-model based on causal reasoning. Besides that, only few authors tried to validate their results with a correlation analysis to other performance indicators. In addition, our equity portfolios shall show if financial excellence pays off at the stock market.

III. DATA AND METHODOLOGY

In the following section, we will give an overview of fundamental analysis and data envelopment analysis. Succeeding we will design our own input-output-model for assessing a firm's operational capability. In the concluding subsection, we will introduce the data set.

A. Fundamental Analysis

Fundamental analysis is used for analyzing a firms expectations to determine a proper stock price (see [1]) based on a firm's fundamental data. Reference [12] shows that you can get abnormal returns by using fundamental signals. They concluded that the strongest indicators of on-year-ahead earnings are signals of relative changes in inventories, capital expenditures and effective tax rates. In general, fundamental analysis is based on the underlying assumption that every security has an intrinsic value, which depends on the earning potential of the security (see [13]). With the help of fundamental data from the balance sheet, cash flow and income statement and other sources, an analyst should be able to predict if the actual price of the security is above or below its intrinsic value. In the following subsections, we will use fundamental data to assess a firm's financial performance.

B. Data Envelopment Analysis

The DEA is a non-parametric performance or efficiency evaluation method based on linear programming. It was first introduced by [14] as a method to compare the efficiencies of different non-profit organizations (or so-called decision making units (DMUs)) and expanded over the years. In this paper, we use the original CCR model with constant returns-to-scale and a model based on a variable returns-to-scale assumption called the BCC model. These models are used as a ranking method for the firms in our data frame. DEA calculates a best-practice frontier function against which all the firms are evaluated.

1) The Charnes, Cooper & Rhodes model

The so-called CCR model from [14] is the original DEA model. The idea is to calculate for every Decision Making Unit (DMU) an efficiency score based on m inputs and s outputs. Reference [14] formulated this efficiency score in precise from as

$$\max \theta_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \qquad (1)$$

subject to:

$$\frac{\sum_{i=1}^{m} v_i x_{ij}}{\sum_{r=1}^{s} u_r y_{rj}} \geq 1; j = 1, \dots, n$$
$$v_i, u_r \geq 0$$

where v_i and u_r are the input respectively the output weights assigned to the m inputs and s outputs. θ_0 is the efficiencyscore of DMU 0 under evaluation. It is possible to solve this optimization problem in form of a fractional programming model (1) by using Charnes and Copper's transformation (see [15]). The converted linear programming model can be written as (see [16]):

$$\max \theta_0 = \sum_{r=1}^{s} u_r y_{r0} \tag{4}$$

subject to:

$$\sum_{j=1}^{m} v_j x_{j0} = 1$$

$$\sum_{r=1}^{s} u_r y_{ri} \leq \sum_{j=1}^{m} v_j x_{ji}, \forall \text{ i } \in \{1, \dots, \text{n}\}$$

$$\text{v}_j \geq 0, \forall \text{ j } \in \{1, \dots, \text{m}\}$$

$$\mu_r \geq 0, \forall r \in \{1, \dots, s\}$$

A DMU is called CCR efficient if its optimal solution is $\theta^* = 1$ otherwise it is called CCR inefficient. Solving this kind of problem is still not perfectly possible under all circumstances. The model is transformed to a dual linear programming model with an input or output orientation. The dual problem can be written in input orientation as (see [16]):

$$\min_{\theta,\lambda} \theta \tag{3}$$

subject to:

$$\theta x_0 - X\lambda \geq 0$$
$$Y\lambda \geq y_0$$
$$\lambda \geq 0$$

Input orientation means that within the linear optimization the inputs are minimized. Output orientation is directly the opposite, the inputs are hold fix and the outputs are maximized.

2) The Banker, Charnes & Cooper model

Reference [17] extended the CCR model (1) so that the constant returns-to-scale assumption was replaced with a variable returns-to-scale assumption. The extended BCC model is named by their acronym. It can be written asdual linear programming model with input orientation:

$$\min_{\theta,\lambda} \theta$$

subject to:

$$\theta x_0 - X\lambda \geq 0$$

$$Y\lambda \geq y_0$$

$$\lambda \geq 0$$

$$e\lambda = 1$$

The additional constraint $e\lambda = 1$ changes the convexity assumption so that variable returns-to-scale can be assumed.

Supplementary we use the super-efficiency model to discriminate between DEA efficient firms, for more details see [18].

C. Operational Capability Analytics

The purpose of this paper is to develop a methodology to evaluate a firm's financial performance. In order to achieve the target we suggest calculating the operational capability of a firm. We suppose that a firm has capabilities to transform its assets (inputs) into outputs like revenue, earnings, cash flow etc. Normally the production function of each firm is unknown so we use the non-parametric DEA approach to calculate an efficient frontier function. The basic idea of the operational capability analytics (OCA) is shown in Fig. 2.A firm uses inputs like assets, equity, employees etc. and transforms them into outputs like sales, earnings etc. In this model, a firm can minimize its inputs with fixed outputs or it can maximize its outputs with fixed inputs. Therefore, our suggested Operational Capabilities Analytics identifies an efficient firm when it is using a minimum of inputs at fixed outputs or produces a maximum of outputs with fixed inputs. These are the two general possibilities of assessing the firms' operational capabilities.

Regularly it is difficult to compare firms from different industries, sizes and countries. To overcome these difficulties we use DEA to analyze the firm's operational capability. DEA can combine inputs and outputs without knowing a-priori the relationships between the variables and the corresponding weights. In this paper, we chose the input orientated CCR and BCC models for evaluating our Input-Output-Model. The models were introduced in subsection 2. B. We chose the input orientation because of the dataset's characteristics.

Choosing the correct input and output features is critical for every DEA. Reference [18] suggest only including variables, which make practical sense for the setting under investigation. Reference [20] emphasizethat raw data and ratios should not be mixed when it is possible. Reference [21] recommend toonly using variables, which can be clearly identified as inputs and outputs and not as a mixture.

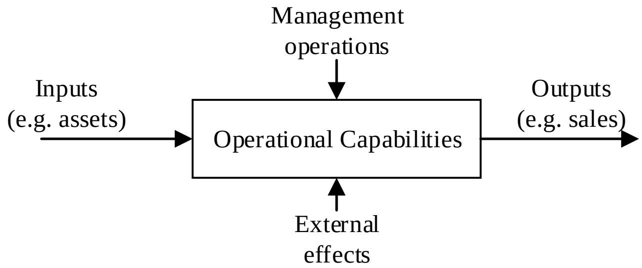

Fig. 2: System overview of a firm's inputs and outputs. Own presentation based on Bogetoft and Otto (2011, p.14).

In addition, a variable should be contributing to the objectives of the analysis.In our OCA input-output-model we choose the DuPont formula given in [22] as a starting point for variable selection:

$$\text{ROE} = \frac{\text{assets}}{\text{equity}} \times \frac{\text{sales}}{\text{assets}} \times \frac{\text{after} - \text{tax interest} + \text{net income}}{\text{sales}} \times \frac{\text{net income}}{\text{after} - \text{tax interest} + \text{net income}}$$

In the next step we breakdown assets to current assets and fixed assets. Cash & marketable securities (CMS), accounts receivable (AR) and inventories (INV) are part of the current assets. We take property, plant & equipment (PPE) as an instrumental variable for the fixed assets. Continuing this approach we breakdown net income to sales minus cost of goods sold (COGS), Selling, general, and administrative expenses (SGA), Depreciation (DA) etc..
In addition to the Du Pont Formula, we add variables from the cash flow statement (see [23]). The free cash flow is defined as:

$$\text{Free Cash Flow} = \text{Operating Cash Flow} - \text{Capex}$$

We pick Free Cash Flow (FCF) as an output variable and Capex as an input variable. As working capital is part of the operating cash flow we add accounts payable (AP) as an input variables. Other variables of the cash flow statement are already included through the other resources. All our variables are listed in Tab. 1. In order to control for size effects we include the number of employees as an input variable.
In the following steps we will show the collected data and will calculate the firm's operational capabilities with our OCA methodology. Succeeding we will analyze the OCA results and compare them to other indicators. The aim is to show that the OCA score is a validated method for assessing firm performance.

TABLE 1: List of input and output variables.

Variables	
Inputs	***Outputs***
INV, CMS, AR, AP, SGA, COGS, Capex, DA, PPE, Equity, Employees	Sales, EBIT, FCF

D. Data collection and sample creation

The data was retrieved from Bloomberg and we collected the needed data for every firm in Western Europe with a market capitalization higher than 100 mio. Euros at the end of the year 2015. The financial and insurance industry were excluded from our dataset because of the different capital structure. For the 2.060 identified firms we had complete datasets of 447 firms in 2015, 428 in 2014, 415 in 2013, 412 in 2012 and 399 in 2011 for all variables. We also had to control for non-negative Inputs. Using negative inputs is not possible with our chosen DEA models with input orientation.

IV. Results

In the following sections, we will share our results.

A. Results from different sample years

The results of the BCC DEA model are shown in Fig. 3 and were calculated with the linear programing method given in formula (3). As you can see, there are many efficient firms each year. A firm is said to be efficient at 100 score points. For this reason, we calculated the super-efficiency (score from 100 to 1000) for ranking bcc-efficient firms.The results are relatively stable over the five years period. The OCA Scores calculated by the CCR model are shown in Fig. 4were calculated with the linear programing method given in formula (4). In comparison to the BCC results, there are less efficient firms now. This is due to the more discriminating power of the CCR model (see [20]). The BCC efficient frontier is more closely to the data therefore you get more firms, which are efficient.

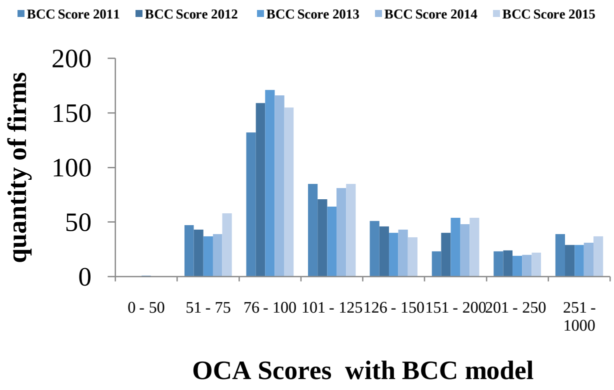

Fig. 3: OCA Scores with the BCC model.

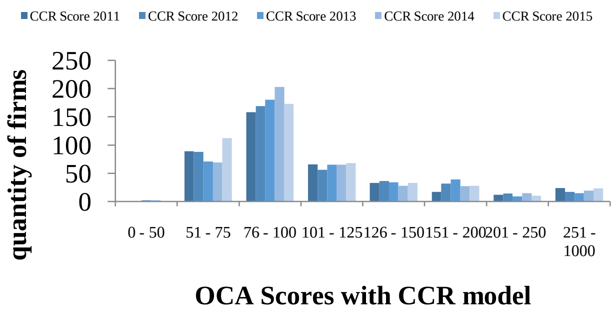

Fig. 4: OCA Scores with CCR model.

TABLE 2: This table shows the spearman correlation between the CCR, BCC Scores and the selected financial ratios. *, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively. A two-tailed test was used.

	CCR Score	BCC Score	ROE	ROA	PM	CR	QR	CTR	CF/Capex	Z	CCC
CCR 2011	1,00	0,83***	0,26***	0,23***	0,11*	-0,16***	-0,17***	-0,18***	0,26***	0,20***	-0,28***
BCC 2011	0,83***	1,00	0,24***	0,21***	0,11*	-0,14***	-0,21***	-0,20***	0,20***	0,16***	-0,33***
CCR 2012	1,00	0,84***	0,34***	0,33***	0,22***	-0,17***	-0,20***	-0,22***	0,27***	0,24***	-0,23***
BCC 2012	0,84***	1,00***	0,29***	0,28***	0,18***	-0,18***	-0,24***	-0,23***	0,26***	0,21***	-0,24***
CCR 2013	1,00	0,89***	0,28***	0,26***	0,17***	-0,21***	-0,20***	-0,24***	0,32***	0,25***	-0,28***
BCC 2013	0,89***	1,00***	0,22***	0,20***	0,13**	-0,19***	-0,24***	-0,24***	0,26***	0,17***	-0,28***
CCR 2014	1,00	0,85***	0,26***	0,23***	0,11*	-0,19***	-0,22***	-0,25***	0,28***	0,29***	-0,29***
BCC 2014	0,85***	1,00***	0,23***	0,19***	0,11*	-0,14***	-0,25***	-0,22***	0,22***	0,19***	-0,29***
CCR 2015	1,00	0,85***	0,27***	0,23***	0,12**	-0,18***	-0,21***	-0,24***	0,25***	0,27***	-0,30***
BCC 2015	0,85***	1,00***	0,21***	0,16***	0,09	-0,15***	-0,27***	-0,25***	0,15***	0,14***	-0,29***
CCR Ø	1,00	0,86	0,29	0,26	0,15	-0,18	-0,20	-0,23	0,28	0,25	-0,27***
CCR SD		0,02	0,04	0,05	0,05	0,02	0,02	0,03	0,03	0,03	0,03***
BCC Ø	0,85	1,00	0,24	0,21	0,12	-0,16	-0,24	-0,23	0,22	0,18	-0,28***
CCR SD	0,02	0,00	0,03	0,04	0,04	0,02	0,02	0,02	0,05	0,03	0,03***

On the other hand, the BCC model fits better to the variable returns-to-scale property of the datasets. The relatively stable score distributions over the five years tells us that our model is not sensitive to different data sets. As well, many of the best-benchmarked firms are the best ones in the following period.In conclusion, we suggest the hypotheses that a high efficiency score is positive correlated with other financial performance measures and that an efficient firm has a high probability to be efficient in the following period.

B. Verfication by correlation analysis

In this subsection, we want to verify our results by a correlation analysis. This should answer our hypothesis that a firm with a high OCA Score is also positive correlated to other financial performance indicators. Therefore, we choose several measures like Return on Equity (ROE), Return on Assets (ROA), Profit Margin (PM), Cash Ratio (CR), Quick Ratio (QR), Current Ratio (CTR), CF/Capex, Altman Z-Score (Z), and Cash Conversion Cycle (CCC).As it can be seen in Fig. 3 and Fig. 4, the OCA Scores are not normally distributed so hence we choose the Spearman's rank order correlation. The correlation results are listed in Tab. 2. In addition, the Spearman correlation is not so sensitive to outliers in comparison to the pearson correlation. Our OCA Scores show a very strong correlation between each other. The score is slightly more positive correlated with the ROE than the ROA. That could be due to the fact, that equity is included as an input variable and the total assets are divided into different Components in our model. We interpret these correlations as positive for our score. If a firm has a high score it should also has a higher ROE and ROA than other firms, this is consistent with our results. Further, we have a weaker positive correlation between the scores and the PM. This positive correlation was also expectable. When we look at the liquidity ratios, we see negative correlations. The reason could be that it is not preferable for a firm to hold to much cash and other marketable securities. The CTR is highly connected to the Working Capital, if it is lower the Working Capital is lower and this can preferable in some cases (see [24]for more details). Our last correlation is between our scores and the CCC. This is a negative one and this was expected. Reference [25] documented a negative relationship between CCC and corporate profitability. With this subsection, we verified and validated our score. The BCC and CCR model show more or less similar results in our correlation analysis. We conclude that the OCA Score provides a measurement of a firm's financial performance.

Following we want to test our second hypothesis if a firm with a high OCA score will tend to have a high OCA Score in the following period. In Tab. 3, the correlations of the OCA Scores calculated by the CCR model are listed. Evidently, the scores are positive correlated to the scores of the following years. For the CCR model we can accept our hypothesis.

In Tab 4. the correlations between the OCA Scores based on the BCC model are listed. We can note that the correlations are slightly higher for the BCC model than for the CCR model. In conclusion it is recognizable that our OCA Score of year t is positive correlated with year t+1. That means a company with a high OCA Score will have in general a higher score in the following year.

C. Portfolio selection and stock market performance

Based on the results of subsection A and B we want to select equity portfolios to show of that operational capabilities are also rewarded by the stock market. At first, the relationship between the OCA Scores and market data of the firms will be analyzed. As a starting point we look for classical value and growth indicators.

Table 3: Correlation between the CCR OCA Scores of the tested years. All correlations are significant at 1% level.

	2011	**2012**	**2013**	**2014**	**2015**
2011	1,00	0,88	0,75	0,74	0,69
2012	0,88	1,00	0,83	0,80	0,74
2013	0,75	0,83	1,00	0,91	0,85
2014	0,74	0,80	0,91	1,00	0,89
2015	0,69	0,74	0,85	0,89	1,00

Table 4: Correlation between the BCC OCA Scores of the tested years. All correlations are significant at 1% level.

	2011	**2012**	**2013**	**2014**	**2015**
2011	1,00	0,89	0,81	0,79	0,73
2012	0,89	1,00	0,88	0,86	0,79
2013	0,81	0,88	1,00	0,90	0,83
2014	0,79	0,86	0,90	1,00	0,90
2015	0,73	0,79	0,83	0,90	1,00

Table 5: This table shows the spearman correlation between the CCR, BCC Scores and the selected value key figures.*, **, and *** denotes significance at the 10%, 5%, and 1% level, respectively. A two-tailed test was used.

	3-YRG	**5-YRG**	**5-Y EBIDTA G**	**ROIC**	**ROIC / WACC**
CCR 2011	0,21***	0,13**	0,13**	0,29***	0,29***
BCC 2011	0,20***	0,12*	0,11*	0,27***	0,29***
CCR 2012	0,03	0,16***	0,16***	0,38***	0,40***
BCC 2012	-0,02	0,14**	0,13*	0,32***	0,37***
CCR 2013	0,17***	0,19***	0,17***	0,33***	0,35***
BCC 2013	0,10*	0,13**	0,10*	0,27***	0,30***
CCR 2014	0,21***	0,15***	0,04	0,29***	0,30***
BCC 2014	0,14***	0,08	0,01	0,25***	0,25***
CCR 2015	0,14***	0,17***	0,18***	0,29***	0,33***
BCC 2015	0,07	0,09*	0,12*	0,21***	0,24***
CCR Ø	0,15	0,16	0,14	0,32	0,34
CCR SD	0,07	0,02	0,06	0,04	0,04
BCC Ø	0,10	0,11	0,09	0,26	0,29
BCC SD	0,08	0,03	0,05	0,04	0,05

For [26] revenue growth (RG) and return on invested capital (ROIC) are the main value drivers. These two key figures determine how revenues are converted to cash flows. To sustain its value a firm has to exceed its weighted average cost of capital (WACC) with its future cash flows. Following this idea we take the ROIC/WACC ratio as another indicator for our correlation analysis. To consider M&A effects we look at the three and five year average revenue growth rates (3-YRG/5-YRG). In addition, we add the five year EBIDTA growth (5-YEBIDTAG) as an indicator. The relationship between the OCA Scores and indicators are shown in Tab. 5. In almost every year, the OCA Scores are positive and significant correlated to the 3-YRG and the 5-YRG. Therefore, firms which where benchmarked higher indicate in general a higher revenue growth. This is the first evidence, that the OCA Scores can be used for equity portfolio selection.

Similar to the revenue indicators the 5-YEBTIDAG is almost positive and significant correlated to our OCA Scorein every year. Furthermore, the ROIC and ROIC/WACC ratio show positive and significant correlations. Summarizing we can say, that the OCA Score should be a validated benchmark for portfolio selection.

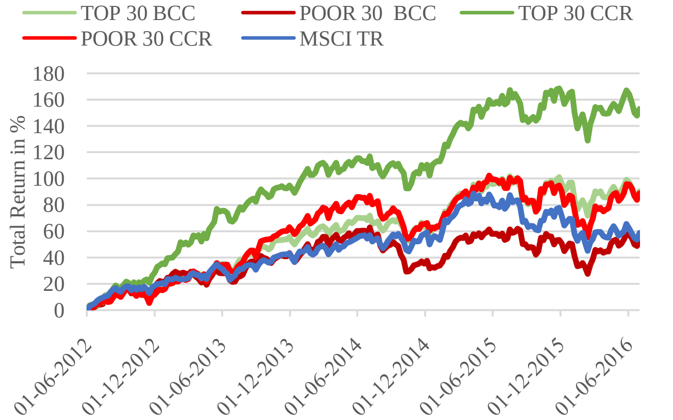

Figure 5: Portfolio comparison of the different rebalanced TOP and POOR portfolios. The portfolios were generated with Bloomberg.

The correlations for the BCC scores are slightly lower than for the CCR scores. This could be an indication for a better applicability of the CCR score for portfolio selection.

For our portfolios, we take the 30 best (which we call TOP 30) and worst firms (which we call POOR 30) of our benchmark every year and compare the portfolios to the MSCI Europe Total Return Index. The portfolio will be adjusted every year on June 1st. The logic in that is, that the financial data is released each year between March and May for the preceding year. After the release of the financial data, we calculated our OCA Scores and used them for portfolio selection.

The total return of each rebalanced portfolio is shown in Fig. 5.

The TOP 30 CCR portfolio is obviously the best performing portfolio with a cumulated total return of 152.8% during the period under review.The second best portfolio is the TOP 30 BCC portfolio with a cumulated total return of 90.3%. Prominent is that the POOR 30 CCR portfolio (total return of 90.0%) is performing only slightly worse that the TOP 30 BCC portfolio. The POOR 30 BCC portfolio is performing worst over the given time period with a total return of 52.6%. To consolidate these results we can see, that our OCA Score based on the CCR model performs much better when considering the best firms. In contrast, the portfolio based on the POOR 30 BCC perform much worse than any other portfolio. We see this first portfolio tests as a starting point for further research. Obviously, you can get very well performing portfolios under the given circumstances.

When we look at firms over a long time horizon, in this case 4 years, the differences between high and low ranked firms are becoming larger (see Fig. 6). The total returns for investors of the different portfolios are listed in Tab. 6. That could be an evidence for our hypothesis that the stock market acknowledges financial excellence in the long run and the differences between the firms are even plainer after one year. To validate this hypothesis different periods and years must be considered in future work.

The target for the future would be to find better feature variables and frontier functions to discriminate better the well and poor performing firms.

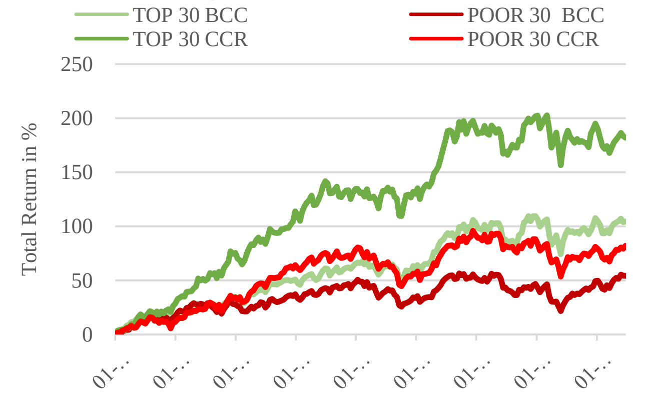

Figure 6: Portfolio comparison of the different TOP and POOR portfolios based on 2011 data. The portfolios were generated with Bloomberg.

Table 6: Total Return of the yearly adjusted portfolios and the long run portfolios based on 2011 data. The timeframe is 1st June 2012 to 1st Juli 2016.

	yearly adjusted Portfolio total return	long run portfolio (2011) total return
TOP 30 BCC	90,33%	96,49%
POOR 30 BCC	52,58%	45,59%
TOP 30 CCR	152,85%	174,13%
POOR 30 CCR	88,96%	70,97%
MSCI	58,80%	58,80%

The worst firms of our OCA Scores should perform much worse than the comparison index. On the positive side, we can show that a high financial performance pays off and is acknowledge by the market.

CONCLUSIONS

Using DEA, we showed that it is possible to assess a firm's financial performance with our OCA model. Our OCA score is consistently correlated to other financial performance indicators. Overall, we found a valid score, which can be used as an equity portfolio selection tool. The best ranked firms showed much higher returns than the worst ranked firms. In the long run this difference is becoming larger and larger. Operational capabilities pay off and are acknowledged by the market over a longer time horizon.

The CCR model generated the better results although the underlying data set has variable returns-to-scale properties. The reason for this could be in the more discriminant power of the CCR frontier. As we can see in Fig. 3 &4, there are many efficient firms and these firms can only be discriminated by the super-efficiency calculations. Normally less features lead to less efficient firms. Due to the less possibilities of reaching an efficiency value of 1, there are less efficient firms with less variables.

In future research, it would be great to investigate different variables and models. On the one hand decreasing numbers of variables could enhance the results. On the other hand, increasing numbers of firms could lead to better results.

Another future research domain would be to analyze a firm's slacks based on the OCA results. This could lead to managerial implications and could improve overall firm performance.

References

[1] Bodie, Zvi; Kane, Alex; Marcus, Alan J. (2011): “Investments and portfolio management.” 9. ed., global ed. New York, NY: McGraw-Hill/Irwin.

[2] Whittington, G. (1980), “SOME BASIC PROPERTIES OF ACCOUNTING RATIOS.” Journal of Business Finance & Accounting, 7: 219–232.

[3] Smith, P. (1990): “Data envelopment analysis applied to financial statements.” In: Omega 18 (2), S. 131–138.

[4] Thore, Sten; Kozmetsky, George; Phillips, Fred (1994): “DEA of financial statements data. The U.S. computer industry.” In: J Prod Anal 5 (3), S. 229–248.

[5] Zhu, Joe (2000): “Multi-factor performance measure model with an application to Fortune 500 companies.” In: European Journal of Operational Research 123 (1), S. 105–124.

[6] Feroz, E. H.; Kim, S.; Raab, R. L. (2003): “Financial statement analysis. A data envelopment analysis approach”. In: J Oper Res Soc 54 (1), S. 48–58.

[7] Friedman, Lea; Sinuany-Stern, Zilla (1998): “Combining ranking scales and selecting variables in the DEA context. The case of industrial branches.” In: Computers & Operations Research 25 (9), S. 781–791.

[8] Lin, Weng-Cheng; Liu, Ching-Feng; Chu, Ching-Wu (2005): “Performance Efficiency Evaluation of the Taiwan's Shipping Industry: an Appliaction of Data Envelopment Anaylsis.” In: Proceedings of the Eastern Asia Society for Transportation Studies (5), S. 467–476.

[9] Chen, Tser- Yieth; Chen, Ling- hua (2007): “DEA performance evaluation based on BSC indicators incorporated.” In: Int J Productivity & Perf Mgmt 56 (4), S. 335–357.

[10] Chen, Yao; Iqbal Ali, Agha (2004): “DEA Malmquist productivity measure. New insights with an application to computer industry.” In: European Journal of Operational Research 159 (1), S. 239–249.

[11] Pätäri, Eero; Leivo, Timo; Honkapuro, Samuli (2012): “Enhancement of equity portfolio performance using data envelopment analysis.” In: European Journal of Operational Research 220 (3), S. 786–797.

[12] Abarbanell, Jeffery S.; Bushee, Brian J. (1998): “Abnormal Returns to a Fundamental Analysis Strategy.” In: The Accounting Review 73 (1), S. 19–45.

[13] Fama, Eugene F. (1995): “Random Walks in Stock Market Prices.” In: Financial Analysts Journal 51 (1), S. 75–80.

[14] Charnes, A.; Cooper, W. W.; Rhodes, E. (1978): “Measuring the efficiency of decision making units.” In: European Journal of Operational Research 2 (6), S. 429–444.

[15] Charnes, A. and Cooper, W. W. (1962): “Programming with linear fractional functionals.” Naval Research Logistics, 9: 181–186.

[16] Cooper, William W.; Ruiz, José L.; Sirvent, Inmaculada (2007): “Choosing weights from alternative optimal solutions of dual multiplier models in DEA.” In: European Journal of Operational Research 180 (1), S. 443–458.

[17] Banker, R. D.; Charnes, A.; Cooper, W. W. (1984): “Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis.” In: *Management Science* 30 (9), S. 1078–1092.

[18] Andersen, Per; Petersen, Niels Christian (1993): “A Procedure for Ranking Efficient Units in Data Envelopment Analysis.” In: Management Science 39 (10), S. 1261–1264.

[19] Cook, Wade D.; Tone, Kaoru; Zhu, Joe (2014): “Data envelopment analysis. Prior to choosing a model.” In: Omega 44, S. 1–4.

[20] Dyson, R. G.; Allen, R.; Camanho, A. S.; Podinovski, V. V.; Sarrico, C. S.; Shale, E. A. (2001): “Pitfalls and protocols in DEA.” In: European Journal of Operational Research 132 (2), S. 245–259.

[21] Golany, B.; Roll, Y. (1989): An application procedure for DEA. In: *Omega* 17 (3), S. 237–250.

[22] Brealey, Richard A.; Myers, Stewart C.; Allen, Franklin (2011): Principles of corporate finance. 10. ed., global ed. New York, NY: McGraw-Hill Irwin.

[23] Zülch, Henning; Hendler, Matthias (2015): “International financial reporting standards 2015.” Weinheim: WILEY.

[24] Aktas, Nihat; Croci, Ettore; Petmezas, Dimitris (2015): “Is working capital management value-enhancing? Evidence from firm performance and investments.” In: Journal of Corporate Finance 30, S. 98–113.

[25] Enqvist, Julius; Graham, Michael; Nikkinen, Jussi (2014): “The impact of working capital management on firm profitability in different business cycles. Evidence from Finland.” In: Research in International Business and Finance 32, S. 36–49.

[26] Koller, Tim; Copeland, Thomas E. (2011): “Valuation workbook. Step-by-step exercises and tests to help you master Valuation.” 5th ed. Hoboken, N.J: John Wiley & Sons Inc (Wiley Finance, v.496).