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THE USE OF DATA ENVELOPMENT ANALYSIS AS EQUITY PORTFOLIO SELECTION CRITERION IN THE FINNISH STOCK MARKET

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ABSTRACT

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This thesis examines the application of data envelopment analysis as an equity portfolio selection criterion in the Finnish stock market during period 2001-2011. A sample of publicly traded firms in the Helsinki Stock Exchange is examined in this thesis. The sample covers the majority of the publicly traded firms in the Helsinki Stock Exchange. Data envelopment analysis is used to determine the efficiency of firms using a set of input and output financial parameters. The set of financial parameters consist of asset utilization, liquidity, capital structure, growth, valuation and profitability measures. The firms are divided into artificial industry categories, because of the industry-specific nature of the input and output parameters. Comparable portfolios are formed inside the industry category according to the efficiency scores given by the DEA and the performance of the portfolios is evaluated with several measures.

The empirical evidence of this thesis suggests that with certain limitations, data envelopment analysis can successfully be used as portfolio selection criterion in the Finnish stock market when the portfolios are rebalanced at annual frequency according to the efficiency scores given by the data envelopment analysis. However, when the portfolios were rebalanced every two or three years, the results are mixed and inconclusive.

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Tutkielma tarkastelee Data envelopment analysis –menetelmän käyttöä osakeportfolion muodostamisessa Suomen osakemarkkinoilla aikavälillä 2001-2011. Tutkimuksessa on käytetty otosta Helsingin pörssiin listatuista julkisista osakeyhtiöistä ja otos kattaa suurimman osan listatuista yhtiöistä edellämainitulta aikaväliltä. Data envelopment analysis –menetelmää käytetään määrittämään yritysten tehokkuus panos/tuotos –asetelman perusteella. Tutkielmassa käytetyt panokset ja tuotokset ovat yritysten tilinpäätöksistä saatavaa informaatiota ja ne kattavat pääomien käytön tehokkuuden, likviditeetin, pääomarakenteen, kasvun, arvostuksen ja kannattavuuden. Koska panokset ja tuotokset riippuvat pitkälti yritysten toimialasta, vertailukelpoisuuden vuoksi yritykset ovat jaettu keinotekoisiin toimialaluokkiin. Yritykset ovat jaettu osakeportfolioihin omissa toimialaluokissaan tehokkuusluvun perusteella ja osakeportfolioiden menestystä on mitattu erilaisin menetelmin.

Tutkielman empiirisen osuuden perusteella data envelopment analysis –menetelmää voidaan soveltaa menestyksellisesti osakeportfolion muodostamisessa Suomen osakemarkkinoilla kun portfolion päivitysväli tehokkuuslukujen avulla on yksi vuosi. Tulosten perusteella tehokas osakeportfolio ei pärjännyt verrokkiosakeportfolioille kahden ja kolmen vuoden päivitysväleillä.

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1 Introduction

The importance of fundamental accounting information is essential in investment decision. Many scholars have employed accounting information as portfolio selection criteria (Ou and Penman, 1989; Piotroski, 2000; Bird et al., 2001; Chen and Zhang, 2007; Alexakis et al., 2010). The empirical evidence shows that using accounting information as portfolio selection criterion can create added value for investor.

Recently, data envelopment analysis (DEA) has been used as a tool to separate the winner stocks from loser stocks (Powers and McMullen, 2002; Edirisinghe and Zhang, 2007, 2008, 2010; Chen, 2008; Pätäri et al., 2010, 2012; Frijns et al. 2012). Data envelopment analysis is a linear programming based efficiency evaluation method developed by Charnes et al. (1978) and later modified by Banker et al. (1984).

The studies by Edirisinghe and Zhang (2007, 2008, 2010) have acted as an inspiration for this paper, as this paper employs rather similar input/output pattern that is used in their studies, respectively. However, the methodology is bit different and this paper focuses on the Finnish stock market. The goal of this paper is to find out is the DEA capable of separating the winner stocks from loser stocks in the Finnish stock market during period 2001-2011. To the author’s knowledge, such study as this has not been conducted before using data from the Finnish stock market. The research gap greatly motivates this paper.

The data envelopment analysis assumes that decision making units (DMUs), in this case firms, are efficient if they use minimal inputs to create maximum outputs. The input parameters in this paper are related to asset utilization, liquidity and capital structure measures. The output parameters are related to growth, valuation and profitability measures. In this context, the DEA approach classifies firms as efficient when they utilize assets effectively, are financially healthy, experience growth, are relatively moderately valuated and are profitable.

The basic idea is to divide the sample firms into a set of equity portfolios according to the DEA efficiency score and evaluate the portfolios performance with different risk-return metrics. The performance of portfolios is evaluated with average annual return, average annual volatility, Sharpe ratio, Jensen's alpha and beta. Stacked time series of monthly returns are used to calculate the risk and return measures. Statistical tests are carried on with Sharpe ratios and Jensen's alphas to determine statistically significant risk-adjusted returns.

The impact of holding period length is tested via rebalancing the portfolios with different frequencies. It is essential to perform such robustness checks, because the inputs and outputs change over time and this has a direct effect to efficiency scores and to stock returns. The holding periods are 1-year, 2- and 3-years in total length.

The research questions of this thesis are as follows:

1. Is the DEA approach employed in this thesis capable of separating the winner stocks from loser stocks in the Finnish Stock Market?
2. What is the optimal holding period for the DEA-portfolios?

The limitations of this study have to be considered when interpreting the results. First of all, the biggest problem is the small sample size as the Finnish stock market is rather tiny when it comes to the number of the publicly listed firms. The number of sample firms in 2001 is 112 and in 2011 it is 91. Another reason to small sample size is that data of small firms simply was not available at any public sources. To increase the validity of DEA approach, the sample firms were divided into three artificial industry categories that consist of technology, consumer goods and services, and industrial goods and services. The firms were divided into these categories rather roughly according to the main business segment of each firm. This maneuver was conducted, because many of the financial parameters used in this study are industry-specific and there would be no sense to treat, for instance, technology firms similar as industrial goods and services firms. However, Dyson et al. (2001)

recommend that the sample size should be at least twice as large as the sum of the inputs and outputs. This can cause the DEA model to lose its discriminatory power and it has to be taken into account when interpreting the final results, as the principle is partially violated in this study.

The second limitation is the DEA application used in this study. It uses the inputs separately with all the outputs included. This results as several input based efficiency scores. The average of these efficiency scores is calculated to determine the average efficiency score that is used to create the equity portfolios. This approach is used, because it provided a smaller number of efficient DMUs and hence allowed the use of multiple equity portfolios. Furthermore, the DEA approach seemed to provide the efficient DMUs in relation to the market sentiment. When the market was booming, the number of efficient DMUs relatively increased and conversely.

The third limitation is related to the testing of the holding periods. As the total examination period is 11 years long, the last year is not included in the two year holding period. Similarly, the two last years are not included when testing the three years holding period. This implies that the different holding periods cannot be compared to each other straightforward.

The last limitation is the most minor, but still important one. The DEA method is rather new in the academic field of finance. Hence, there are not many related studies. This study contributes to the scarce DEA literature, as there are only a handful of papers studying the applicability of DEA as portfolio selection criteria. This limits the interpretation of the results, as there are only few studies to compare the results with.

The structure of this thesis is as follows: The literature review and theoretical background discusses about the fundamental analysis and related studies. Also, sample of the DEA-related studies are examined in that section. Moreover, the background of the financial parameters used as inputs and outputs is introduced. Finally, a brief insight to the market environment during period 2001-2011 is carried on in order to characterize the underlying market sentiment.

The data and methodology section provides information of the empirical process, the descriptive statistics of the financial parameters and a deep briefing of the DEA approach. Furthermore, the portfolio performance evaluation methods are explained in this section. The fourth section presents the final results. The risk and return measures of one, two and three year holding periods are presented in the results section. Final discussion of the results and further research is conducted in the conclusions section.

2 Literature review and theoretical background

The structure of this section is as follows: the first part examines the fundamental analysis and studies related to using accounting information to select investment worthy stocks. The second part focuses on the scarce literature of DEA as portfolio selection criteria. In the third part, the nature of the financial parameters used in this study is revealed. The final part is a brief insight to the market environment during period 2001-2012.

2.1 Fundamental analysis and related studies

Fama (1970) proposed the efficient market hypothesis (EMH). The theory states that if financial markets are informationally efficient the average risk-adjusted market return cannot be consistently beaten if the all the information is publicly available to all market participants. In other words, in an efficient market the security prices reflect all available information to investors. Even the insider information is publicly available to investors in efficient market. Two weaker market efficiency forms are included in the EMH. The first one is semi-strong market efficiency and the second one is weak market efficiency. In the semi-strong market efficiency all the publicly available information is included in the securities prices. The weak form only assumes historical information to be included in security prices.

Malkiel (2003) carried out criticism to the efficient market hypothesis. The efficient market hypothesis implied that fundamental or technical analysis would not help an investor to earn returns that exceed the average market return. In this sense, stocks worthwhile investing could be selected randomly, for instance, via throwing darts in order to select a feasible investment portfolio. Furthermore, the EMH is related to the idea of “random walk”, where security prices float randomly and the security price tomorrow will not be affected by the stock price changes today. Hence, according to this theory, the securities price changes are unpredictable and completely random.

Malkiel (2003) points out that as long there are stock markets, there will be less rational market participants. As a consequence, irrational behavior in stock market can lead to pricing irregularities that can stand over time. Grossman and Stiglitz (1980) argued that it is impossible to maintain informationally efficient markets, for if markets are perfectly efficient, there would be no reward in gathering information and as a consequence there would be no rational reasons to trade and eventually markets would collapse.

Moreover, if the markets are imperfect, there is an incentive for investors to gather information, if the reward is to earn abnormal returns. However, the market inefficiencies must be identified before implementing a trading strategy that is based on these anomalies. There are vast amount of literature considering different investment strategies that can provide abnormal returns. Perhaps the most known strategy is the idea of value investing first presented by Graham and Dodd (1934). They proposed a general model that suggested investing to relatively undervalued stocks from perspective of valuation multiples.

Typically, valuation multiples consist of following ratio's: price to book, price to cash flow, price to earnings, price to earnings to growth, price to sales, dividend yield and enterprise value multiples. These valuation ratios and their relation to stock returns are comprehensively studied and there are empirical evidence supporting the stock pricing anomalies related to these valuation ratios. For instance, Leivo (2012) studied the existing literature related to pricing anomalies in his dissertation and he found that earnings yield, cash flow to price, EBITDA to enterprise value, book to price, dividend yield, sales to price and composite measures can successfully be used as basis of value investing strategies with certain limitations.

Relative valuation of stocks using valuation multiples is common method to separate winner stocks from loser stocks. However, the valuation ratios do not take into account some of the basic fundamentals of a firm, such as the effectiveness in asset utilization, financial health or capital structure. In this context, the fundamental analysis of the firm is appropriate as the valuation multiples show only the other side of the coin.

Fundamental analysis is a tool to evaluate a firm whether or not it is a good investment target. The analysis is conducted by concentrating into the firm’s basic fundamental factors such as sales, earnings, growth, assets, debt, management, products and the market environment. The aim of the fundamental analysis is to forecast the price movement of a security in future. These forecasts can be used to form a suitable equity portfolio. In contrast, technical analysis studies the market prices as it assumes that all the available information is already in the security’s price. The nature of technical analysis is focused in short term, as fundamental analysis focuses in the long term development of securities price movements.

Ou and Penman (1989) provide evidence in their study that financial statements capture fundamentals that are not reflected in the stock prices. They use a comprehensive set of financial statement variables from years 1973-1983 as predictors of future earnings. Sophisticated statistical methods were used to gather the financial statement descriptors that predict the future earnings. These financial statement descriptors included financial health, asset utilization, leverage, profitability and growth measures.

These measures were combined to form a single financial statement measure that represents the above-mentioned perspectives. According to the measure, either long or short position is taken to that corresponding stock. The performance is evaluated via portfolio analysis using two year holding period. After controlling the size effect, the overall return with their method is close to seven percent. Bird et al. (2001) followed the concept by Ou and Penman (1989) and they used similar methods based on financial statement information. However, their results were rather mixed and in general, the results implied that the models did not provide a basis for a profitable investment strategy.

Piotroski (2000) studied the enhancement of B/P-based strategy with using accounting information. Piotroski calculated the F-score for individual firms annually according to financial statement composite variables. The F-score includes measures from the firm's profitability, financial health and operating efficiency. Hence, it is an aggregate measure of the firm's overall condition. The F-score was tested among a portfolio of high B/P firms and the results indicated that the mean return increased 7.5 percent annually by selecting financially strong high B/P firms. Furthermore, Piotroski (2000) carried a long/short strategy using the F-score and B/P to take long position with winner stocks and sell short loser stocks. The investment strategy provided an annual return of 23 percent during period 1976-1996.

Chen and Zhang (2007) created an accounting information based model to explain cross-sectional stock returns. They derive stock returns as a function of earnings yield, equity capital investment, changes in profitability, growth opportunities and discount rates. Their empirical results imply that the best explanatory power for stock returns is among the cash-flow related factors. Overall, the model explains approximately 20 percent of the cross-sectional return variation.

Alexakis et al. (2010) studied the application of accounting information to predict stock returns in Athens stock exchange during period 1993-2006. They used profitability, asset utilization, leverage, valuation and liquidity measures as accounting information. Alexakis et al. (2010) formed a panel data regression model to find causalities between the variables and stock returns. The results show that their model was capable to significantly predict the cross-section of stock returns. The firms were divided into winner and loser portfolios according the estimated parameters. The winner portfolios clearly outperform the loser portfolios and a long/short strategy where winners are bought and losers sold provided higher than average return.

2.2 Data envelopment analysis as portfolio selection criterion

Edirisinghe and Zhang (2007, 2008, 2010) have studied intensively the relationship of firm’s relative financial strength and stock returns. This paper follows the DEA theme introduced by Edirisinghe and Zhang (2007, 2008, 2010), respectively. According to the authors, their studies complement the approach of fundamental analysis.

The goal of the paper by Edirisinghe and Zhang (2007) is to create a measurable relative financial strength indicator (RFSI) that is highly correlated with stock price performance. They assume that the current stock price reflects all the available information regarding to the particular stock as stated in the efficient market hypothesis (Fama, 1970). However, the future stock price development expectation is dependent on the business and financial strength of the firm. The factor that takes into account the relative strength of a firm can be used to form equity portfolios.

Edirisinghe and Zhang (2007) use a generalized data envelopment analysis approach to determine the input/output universe. In other words, every financial ratio related to asset utilization, financial health, leverage, valuation, growth and profitability are used as parameters that can be either input or output or not used as all. The goal of RFSI is to have a maximum correlation with the stock returns. To determine the maximum correlations and the correct input/output parameters, they employ scientific procedures to find the optimal parameters to be used as inputs or outputs.

In their next study, Edirisinghe and Zhang (2008) employ the same RFSI-ideology with some differences compared to the earlier study. They use pre-specified optimal input/output models and compare the DEA-models to the residual-income-based valuation (RIV) model (Ali, Hwang, Trombley, 2003), that is used to predict the future cash flows of a firm. The sample consists of US firms from different industries from 1996 to 2002 using quarterly data. The relative financial scores from the DEA are then used to measure the correlation with lagged rates of return for stock portfolios.

The third paper by Edirisinghe and Zhang (2010) studies again the challenges related to the correct input/output selection in the RFSI-model. They present a new methodology, which employs different approaches. The goal is to use a reward variable, in this case stock return that is observed exogenous to the operation of the firm to select endogenously the input and output variables using partial or expert knowledge. After the first step, a two stage iterative optimization model is used which shows the gains of possibly violating the partial or expert information in order to decide an optimal endogenous performance evaluation of the firms for the maximum correlation with the reward metric that is stock return, respectively. They use a sample of 800 publicly traded US firms using quarterly data.

All the studies by Edirisinghe and Zhang (2007, 2008, 2010) employ the concept of relative financial strength indicator and the use of data envelopment analysis as a tool to form this indicator. In order to test the RFSI, they form equity portfolios according to the efficiency scores given by the DEA-models. The results of their three studies examined in this thesis clearly indicate the superiority of their DEA-approaches when taking into account the performance of the efficient DEA portfolios.

The purpose of study by Chen (2008) is to employ data envelopment analysis to create equity portfolios and to compare the actualized returns to market index in order to study whether or not DEA-based portfolios generate superior returns. The paper employs the firm size as controlling variable.

Chen (2008) uses data from Taiwan stock exchange during period 2004 to 2007 and the firms consist of cement, food, plastics, textiles, electronics and machinery, paper and pulp, construction and banking and insurance industries. Stocks and portfolios are picked and formed according to the size and DEA models. The firm size was determined by market equity and the firms were divided into small or big regarding to the average market equity.

Chen (2008) employed both CCR and BCC models to study firm efficiencies. He used average equity, average asset, and sales cost as input factors. Output factors were revenue, operating profit and net income. His results indicate that the portfolios created with BCC model beat the market 68 out of 96 cases. The CCR model portfolios beat the market in 67 out of 96 times. However, the portfolios that were classified as small firm portfolios did not perform as well as other portfolios and as a result, firm size according to Chen (2008) should not be used as a selection criteria in this context. Furthermore, statistically tested with t-tests and Sharpe ratio, the DEA portfolios returns significantly outperformed the industry average returns. Chen (2008) recommends DEA approach as useful tool in creating superior risk-adjusted equity portfolios.

A study by Pätäri, Leivo and Honkapuro (2010) focuses on the application of data envelopment analysis in the Finnish stock market as a value portfolio selection criterion. The data is from the Helsinki Stock Exchange and it consists of non-financial firms from the main list during period 1993 to 2007. Also delisted firms are taken into account from the perspective of survivorship bias.

Pätäri et al. (2010) use three different DEA models to form portfolios. The DEA applications employed are the variable returns to scale, the super efficiency and the scale efficiency model. The input variable is stock price and outputs are earnings per share, dividend per share and book value per share. The portfolios are formed based on the efficiency scores the stocks received in different DEA-approaches. Risk-adjusted performance metrics and average return is used to evaluate the performance of each portfolio. Also the impact of holding period length is taken into account in this study.

The results imply that portfolio selection criterion can be enhanced by using DEA-approach. DEA value portfolios were clearly better in terms of all performance metrics compared to glamour portfolio and the market portfolio when examining holding periods shorter than three years. Hence, the annual reformation of the portfolios in context of this study is not necessary. Furthermore, the results by Pätäri et al. (2010) suggest of using a longer holding period than one year, especially during bullish periods.

Another study by Pätäri, Leivo and Honkapuro (2012) studies the process of using DEA to form equity portfolios. The data is from the Helsinki stock Exchange and it consists of the main list firms from a period of 1994 to 2010. The firms are non-financial and in order to avoid survivorship bias, also the delisted firms are included in the study. The sample size ranges from 56 firms to 113, although the highest firm count is from year 2008, 126 firms.

The DEA models employed in their study are the constant returns to scale, the super-efficiency and cross-efficiency models. Pätäri and al. (2012) use four different input and output combinations with the DEA methods noted in the previous paraphrase. The first combination employs the stock price and enterprise value (EVPS) per share as input variables and book value per share (BPS), dividend per share (DPS) and EBITDA per share (EBITDAPS) as output variables. The second combination employs a momentum factor in the output variables as the input variables are equal. The third combination is the same than the previous one, but the stock price is the only input parameter. The fourth combination is a modification of the previous one, as the EPS is replaced with EBITDAEPS. The efficiency scores are recalculated at annual frequency on the portfolio rebalancing date.

The stocks examined are divided into three-quantile portfolios according to their efficiency score. The performance measurement of portfolios is conducted via examining the absolute returns and risk-adjusted performance measures. The empirical evidence shows that the DEA top-quintile portfolios significantly outperform the glamour and market portfolios.

Powers and McMullen (2002) study the application of DEA in selecting the efficient stocks among 185 largest market cap stocks. They use one, three, five and ten year returns and Earnings per share as outputs in their study. Inputs are price to earnings ratio, five year beta and sigma that stands for three year standard deviation of returns. The returns and EPS are categorized as outputs, because high values in these outputs are desirable in an investor’s perspective. Price to earnings and the risk factors are classified as inputs, due to investors wish that these values are as low as possible.

Before the analysis, the variables are standardized in order to weight the inputs and outputs properly. Powers and McMullen (2002) are concerned, because a particular stock could have feasible returns, but in the same time it could be very volatile. Without weighting, a particular stock could be classified as efficient and the results could be biased. They employ a pairwise weighting restriction that states that any variable can be considered no more than five times as important as other variables. The function of this method is to have all variables included, but still restricting some of the strongest variables of receiving too high weight in the analysis.

The results were that 14 out of 185 firms were efficient and 4 of the firms were almost near-efficient. They state that the DEA is capable of selecting the efficient stocks among the sample. Their contribution in the results section was also that these four inefficient firms could be turned into efficient by reducing the inputs used and augmenting the outputs. Moreover, via using a DEA-model the user can measure, how much improvement is needed to turn inefficient firms into efficient.

Frijns, Margaritis and Psillaki (2012) investigated the application of DEA as investment strategy. They used a sample of publicly traded U.S. firms from period 1988-2007. As inputs they used net property, plant and equipment, total long term debt, total assets, book value of equity, capital expenditure, costs of goods sold and selling, general and administrative costs. The output factors are the total sales and market value of equity at the end of each year. Portfolios were constructed of the sample firms according the efficiency scores from DEA and the performance of the portfolios was measured by controlling the risk factor. The significant results recommend a long-short strategy, where the long position is taken on the efficient firms and short position is taken on the inefficient firms. The cross sectional regression results between the efficiency of the firm and stock returns also support the DEA-results by Frijns et al. (2012).

The previous DEA-based studies by Edirisinghe and Zhang (2007, 2008, 2010), Chen (2008), Pätäri, Leivo and Honkapuro (2010, 2012), Powers and McMullen (2002) and Frijns, Margaritis and Psillaki (2012) imply that data envelopment analysis can be used to separate the DEA-efficient firms from inefficient firms. Their results show that the risk-adjusted returns of DEA-efficient portfolios are clearly superior when compared to market portfolio or reference portfolios. In this context, it is interesting to test the applicability of DEA in the Finnish stock market using accounting information as inputs and outputs.

2.3 The background of the financial parameters

In this section, the parameters used as inputs and outputs in this thesis are examined and they can be detected from Table 1. Furthermore, the relationship of the input and output variables and stock returns is studied via findings in the existing literature. The discussion in this part is straightforward as the discussion starts from the first input group, asset utilization and ends to the last output group, profitability.

The input parameters are receivables turnover, inventory turnover, asset turnover, current and quick ratio, debt to equity, leverage and solvency ratios 1 and 2. The output parameters are sales growth, EPS growth, earnings yield, book to price, return on equity, return on assets, net profit margin and earnings per share.

Table 1
The financial parameters used as inputs and outputs.

Input/Output	Financial parameter	Perspective
Input	Receivables turnover	Asset utilization
Input	Inventory turnover	Asset utilization
Input	Asset turnover	Asset utilization
Input	Current ratio	Liquidity
Input	Quick ratio	Liquidity
Input	Debt to Equity	Capital structure
Input	Leverage	Capital structure
Input	Solvency 1	Capital structure
Input	Solvency 2	Capital structure
Output	Sales growth	Growth
Output	EPS growth	Growth
Output	Earnings yield	Valuation
Output	Book to price	Valuation
Output	Return on Equity	Profitability
Output	Return on Assets	Profitability
Output	Net profit margin	Profitability
Output	Earnings per share	Profitability

2.3.1 Asset utilization

Receivables turnover measures operating performance of a firm and it also gives a view of firm’s credit policy and cash flow. Typically, the time window is accounting period, one year, and the measure states how much a firm can convert its credit sales into cash in this time period. Firms pursuit for high turnover ratio, in sense of effectiveness in collecting credit sales and wish that their customers pay their accounts in time. High ratio indicates that the firm’s credit and collection policies are efficient.

$$Receivables\ turnover = \frac{Sales_{t=0}}{Accounts\ receivables_{t=0}} \tag{1}$$

Chen and Shimerda (1981) studied the relation of financial ratios and firm failure. Receivables turnover ratio was included in their study and the results provided a link between bankruptcy and low receivables turnover ratio. Moreover, Michalski (2008) found in his study that accounts receivables management is rather complex issue. Liberal credit policies can result extra burden to the firm in terms of additional costs generated by bad credit and risky customers. On the other hand, Michalski (2008) defends the loose credit policy, because it could have a positive effect to sales income. However, it is the interest of the creditor to keep the level of risk as low as possible in order to avoid credit defaults from its customers.

There clearly are reasons to keep the receivables turnover ratio as high as possible. Loose credit policies might result as a bankruptcy, if the firm cannot convert enough receivables into cash. Liberal credit policies can also create additional costs in terms of financial distress if the stakeholders realize that the firm has difficulties collecting its receivables.

Inventory turnover ratio provides information of how many times over a period the inventory of a firm is sold and replaced. The key rule is to compare this ratio to the industry averages or to the ratios of the firms in the same industry, because depending on the industry, the values may vary a lot. Low ratio indicates that the firm has problems selling its inventories and due to that, it is generating excess inventory. However, the high ratio value usually signals that the firm has no trouble selling its inventories. Also if the firm is selling perishable goods, like food, it tends to have high ratio value. Moreover, if the firm is not selling its deteriorating goods fast enough, it usually generates losses in terms of worthless inventories.

$$Inventory\ turnover = \frac{Sales_{t=0}}{Inventory_{t=0}} \quad (2)$$

Choudhary and Tripathi (2012) studied the relation of inventory turnover and financial performance on retail industry in India. From viewpoint of financial performance, it is crucial to manage inventory successfully. The retailers in the study planned their inventory levels within their strategic positioning and sales forecasting. The difference between actual and forecasted sales has to be taken into account when maintaining the inventory level. Hence, the firm can avoid the above-described problems that could lead into poor financial performance. Moreover, their study showed that most of the firms had a negative relation between inventory days and financial performance. Chen and Shimerda (1981) found also a link between poor inventory management and firm failure. In this sense, there are managerial implications related to inventory turnover. It is beneficial to the firm to keep the amount of capital tied to the inventory as optimal as possible in order to keep the ratio value high.

Asset turnover indicates the amount of sales generated divided by assets. The higher the turnover, the better is the asset turnover. Firms with little or few assets possess a high ratio value and usually have a high profit margin, because there are little asset-related costs. Hence, firms with lot of assets usually have lower asset turnover ratio, but the profit margins are lower due to the asset related costs known as depreciations. This ratio should be compared among the firms within the same industry for reliable results.

$$Asset\ turnover = \frac{Sales_{t=0}}{Assets_{t=0}} \tag{3}$$

Jansen, Ramnath and Yohn (2012) studied the importance of asset turnover and profit margin in earnings management. Their study revealed that the simultaneous increase in the profit margin and decrease in the asset turnover seemed to indicate positive earnings management and vice versa. Fairfield and Yohn (2001) found that investors and analysts should concentrate on changes in asset turnover and profit margin in order to improve forecasts of firms' future profitability. In this sense, there appears to be a clear relation between firm profitability and asset turnover.

2.3.2 Liquidity

Current ratio is widely distinguished key ratio to measure the firm's liquidity and ability to pay its short term liabilities with its short term assets. It is a broader measure than the quick ratio, because it takes into account the firm's inventory. A general rule is that if the ratio value is lower than one, the firm cannot meet its liabilities at that point of time, and thus problems can occur. In this sense, current ratio is a proper ratio to measure the short-term financial health of a particular firm.

$$Current\ ratio = \frac{Total\ Current\ Assets_{t=0}}{Total\ Current\ Liabilities_{t=0}} \tag{4}$$

As well as current ratio, quick ratio represents the firm's short term liquidity. The ratio measures the ability to pay the firm's short term liabilities with cash and equivalents, marketable securities and accounts receivables. Quick ratio is also known as acid test. The definition is that if quick ratio is more than one, the firm can meet its short term liabilities.

$$Quick\ ratio = \frac{(Total\ Current\ Assets - inventory)_{t=0}}{Total\ Current\ Liabilities_{t=0}} \tag{5}$$

Lemke (1970) studied the relationship of liquidity, particularly current ratio and financial performance. He states that there is a level for current ratio, where the firms should aim to maintain it. The stakeholders of the firm monitor the current ratio and make their conclusions about the firm’s ability to pay its liabilities greatly based on the liquidity measures such as current ratio. However, current ratio is only a cross-section of the current state of the firms liquidity and hence, it is not a perfect measure for the firm’s liquidity.

2.3.3 Capital structure

The Debt to Equity ratio has been calculated by dividing the total long term debt by stockholders equity. The ratio indicates the firm’s financial leverage as terms of interest-bearing long term debt. High debt to equity ratio usually signals that firm is using heavy leverage to carry on its business. Leverage is good as long as the firm can pay its interest costs with its income financing. However, if the firm cannot meet its liabilities through income financing, the firm might face financial distress. In other words, there are benefits using leverage in generating earnings, but as the leverage grows, the financial risk also increases. In the worst case scenario, if the firm cannot pay its debt, it could lead to bankruptcy. Typically, depending on the business risk, firms in certain industry use certain amount of leverage in relation to their business risk.

$$Debt\ to\ Equity = \frac{Long\ term\ debt_{t=0}}{Shareholders\ equity_{t=0}} \tag{6}$$

Modigliani and Miller (1958, 1963) proposed the capital structure irrelevance principle, which states that in an efficient market in the absence of agency costs, bankruptcy costs, taxes and asymmetric information the firm value is not affected by the financial structure of the firm. However, in the presence of imperfect market conditions, the capital structure seems to have an impact to the market values of firms.

According to Li (2013) there are well-known capital structure theories, such as the static tradeoff theory, where firms compare their tax benefits of debt against costs related with financial distress and firm failure. The pecking order theory states that firms have a hierarchy when selecting their source of financing. First, firms prefer internal financing, then debt and as a last resort, equity. The market timing theory hypothesizes that firms take benefit when the market conditions are optimal for issuing more debt at a relatively cheap cost.

Leverage ratio used in this paper is calculated through dividing total assets by shareholders equity. The ratio indicates the relationship of the total assets to the amount owned by shareholders. Again, the ratio is very much dependent on the industry of the firm. For reasonable comparison, this ratio should be compared amongst the firms within the same industry. High ratio signals high leverage and substantial debt portion in the balance sheet. However, the high leverage ratio is acceptable, if the interest costs generated by the debt do not exceed the firm's capabilities to pay its debts.

$$Leverage\ ratio = \frac{Total\ assets_{t=0}}{Shareholders\ equity_{t=0}} \tag{7}$$

George and Hwang (2010) studied the relation of stock returns and leverage. They form two puzzles related to leverage and stock returns. The first puzzle states that financial distress risk measures can forecast the default risk of individual firm and, on average the measures are larger during economic downturn. However, the risk and return should be positively correlated according to economic theories, but in this case the evidence shows that stock returns are lower for firms with higher distress. The second puzzle is related to the study by Penman, Richardson and Tuna (2007), in which they state that stock returns are negatively related to leverage. George and Hwang (2010) disclose that the two puzzles are clearly irrational, and they are evidence of market mispricing.

The results of study by George and Hwang (2010) indicate that firms with low (high) leverage suffer more (less) in financial distress. Firms consistently manage their capital structure in order to avoid the financial distress costs. The differences in leverage are also priced in the stock and the differences capture the exposure to financial distress costs. In addition, Martikainen (1993) studied the relation of financial ratios and stock returns in Finnish stock market and he found that operating and financial leverage is the main factor explaining stock returns in the period 1976-1986. The results of the study by Opler and Titman (1994) support the negative relationship between leverage and firm performance, as they found that during industry downturns highly levered firms are more prone to lose market share. As a consequence, the firms operate with lower profitability than their competitors.

Solvency ratio 1 is calculated by dividing total liabilities which includes short- and long term liabilities by total assets. This ratio measures the financial risk associated with a particular firm.

$$Solvency\ ratio\ 1 = \frac{Total\ liabilities_{t=0}}{Total\ assets_{t=0}} \tag{8}$$

Solvency ratio 2 is calculated by dividing total liabilities by shareholders equity. It describes the equity and debt that has been used to finance the firm’s assets. The ratio measures the financial risk associated with a particular firm.

$$Solvency\ ratio\ 2 = \frac{Total\ liabilities_{t=0}}{Shareholders\ equity_{t=0}} \tag{9}$$

2.3.4 Growth

The sales growth is calculated by dividing the sales in year one by sales in year zero minus one. The sales growth rate is used to measure how fast the particular business is growing. Investors and analysts are interested in growth trends, where sales have been growing for a certain period. If all the cost factors remain the same, the growth in sales should promote the net income growth.

$$Sales\ growth = \left(\frac{Sales_{t=1}}{Sales_{t=0}}\right) - 1 \tag{10}$$

The annual EPS growth rate is calculated by dividing the EPS in year one by EPS in year zero minus one. This ratio represents the growth in earnings per share in one year period. All things being equal, stocks with higher EPS growth rates attract investors more than stocks with lower or negative EPS growth rates. However, the dilution effect has to be taken account when observing this ratio, (e.g. seasoned equity offerings lead to stock dilution).

$$EPS\ growth = \left(\frac{EPS_{t=1}}{EPS_{t=0}}\right) - 1 \tag{11}$$

Capon, Farley and Hoenig (1990) studied the relation between various factors and financial performance. According to their observations, high growth situations are desirable, because in most cases it leads to increased profitability. They also stated that having a large market share is a good thing, but it does not always lead to profitability. Li (2011) studied stocks from the U.S. stock markets from perspective of value vs. growth stocks. He found that growth stocks react more positively on favorable market conditions than value stocks. However, growth stocks react more intensively to negative market conditions than value stocks. This claim receives support from study by Chan and Lakonishok (2004). They comment that value stocks keep their value better than growth stocks in economic downturns. Moreover, according to their study, growth stocks are not riskier than value stocks, but still for some reason growth stocks react more intensively to market turbulence.

Jegadeesh and Livnat (2006) studied the impact of firms' revenue surprises to stock returns. They found that simultaneous earnings and sales growth surprises lead to more persistent earnings growth than just sales growth surprises. Furthermore, after controlling the earnings surprises impact, the surprises in sales growth provided significant abnormal returns. However, for large firms, the abnormal returns did not persist in the post-announcement period. Skinner and Sloan (2002) studied the growth stock puzzle in their paper. Their finding was that investors have overoptimistic expectations about the future earnings of growth stocks. They state that investors extrapolate the current earnings into a too long period in the future and this can lead to a pricing bubble.

2.3.5 Valuation

The earnings yield is calculated trough dividing the earnings per share from the latest annual report by the stock price from the last trading day in April. In other words, it is the inverse of price to earnings ratio, but the earnings yield is more suitable for this study because of the methodological reasons. The earnings yield indicates the return in terms of percentage for the amount of money being invested to the particular stock. The earnings yield is useful ratio, because it is comparable with other securities, such as bonds or other asset classes.

$$Earnings\ yield = \frac{E_{t=0}}{P_{t=0}} \tag{12}$$

Basu (1983) studied the relationship between earnings yield and firm size using the returns of the stocks of NYSE firms. Stocks with high E/P ratio tend to provide higher risk-adjusted returns on average than stocks with low E/P ratio. Moreover, the results of his study are significant regardless of the firm size. Davis (1994) studied the relationship of valuation ratios and realized stock returns using NYSE firms during the period 1940-1963 and he found a significant positive relation between E/P ratios and realized stock returns. Hence, investors prefer stocks with high E/P ratios, because historically the returns have proven to be higher, even if the returns are risk-adjusted.

The book to price ratio is calculated by dividing the book value of the firm by the stock price of the firm using the stock price of the last trading day in April. The book value of the firm is obtained from the latest annual report. The book to price ratio is the reciprocal of price to book ratio and in different sources it is also called the book to market ratio. In this case, if the ratio is lower than one, then the firm is valued more than its book value and vice versa. If the firm is undervalued in terms of B/P ratio, it can signal that the firm is experiencing difficult times.

$$Book\ to\ price = \frac{B_{t=0}}{P_{t=0}} \tag{13}$$

Piotroski (2000) studied the relation of book to market values and returns of firms during period 1976-1996. He found that firms with good financial health and high B/P ratio generated the highest returns in average. Also Fama and French (1992) discovered similar results, as they found that the B/P ratio had the best explanatory power on expected returns in the U.S. markets during the period 1963-1990.

Leivo, Pätäri and Kilpiä (2009) studied the application of using different valuation ratios to create equity portfolios in the Finnish stock market during period 1991-2006. Their study show that E/P and B/P anomaly also existed in the Finnish stock market as stocks with high E/P and B/P values generated substantial risk-adjusted abnormal returns during the examination period.

2.3.6 Profitability

Return on equity (ROE) is calculated by dividing the net income by shareholder’s equity. ROE is a classical measure of profitability. It measures how much profit a firm earns with the shareholders money invested. High ROE indicates that a firm is able to generate profits for the shareholders. ROE usually varies between industries and in order to compare firms reliably, only the firms in the same industry should be taken into account in analysis. ROE gives a rather good picture about the firm’s profitability when using average from past five to ten years.

$$Return\ on\ equity = \frac{Net\ income_{t=0}}{Shareholder's\ equity_{t=0}} \tag{14}$$

Return on assets (ROA) is calculated by dividing net income by total assets. The ratio indicates how much net income the firm is able to generate in relation to its total assets. It describes how efficient the firm management uses its assets to make profits. The fewer assets are used to generate net income, the better it is for the firm. Firms in different industries carry different amount of assets in balance sheet and in order to use this ratio effectively, firms within the same business should be used in comparison.

$$Return\ on\ assets = \frac{Net\ income_{t=0}}{Total\ assets_{t=0}} \tag{15}$$

Net profit margin (NPM) is calculated by dividing the net income by sales. The ratio shows how much a firm can generate profits as a portion of its sales. Typically, net profit margin depends on the industry a particular firm is operating. The ratio can be used to compare firms in similar industry and usually a high profit margin compared to the other firms in the industry signals a proper control of the firm's costs.

$$Net\ profit\ margin = \frac{Net\ income_{t=0}}{Sales_{t=0}} \tag{16}$$

Earnings per share (EPS) is calculated by dividing net income by average outstanding shares. The ratio measures the firms profit divided into each outstanding share of common stock. EPS is also used to calculate the E/P ratio. It is considered as valuable ratio when determining a stock's price. Investors are willing to pay more from the stock of a firm if the firm is generating relatively high earnings per share.

$$Earnings\ per\ share = \frac{Net\ income_{t=0}}{Average\ Outstanding\ shares_{t=0}} \tag{17}$$

Pastor and Veronesi (2003) studied profitability and stock valuation. Their concern was how to valuate stocks with unknown future profitability. According their results, firm's price to book ratio as well as idiosyncratic return volatility increases when the future profitability of the firm is unknown or difficult to measure. Moreover, their data show that the profitability of firms in major U.S. stock exchanges has become more volatile over the past decades. Pastor and Veronesi claim, that the collapse of entry barriers allow more firms to enter a particular industry and because of this, the profitability of incumbent firms could become more volatile.

Vuolteenaho (2002) states that the volatile cash flows and expected future profitability news cause the stock return volatility. However, predominantly cash flows drive the firm-level stock returns. In contrast, Baker and Wurgler (2006) claim that investor sentiment has its impact on future stock returns. They state that when the sentiment is estimated to be high, optimists and speculators become interested of investing to such stocks that arbitrageurs avoid during that period. Frankel and Lee (1998) found evidence that analysts seem to be over-optimistic with firms that have higher estimated earnings growth and higher estimated ROEs compared to the current values. In this sense, the stock return of a particular firms is greatly driven by future earnings forecasts, but as Pastor and Veronesi (2003) claim, the future profitability of firms has become more volatile over time. According to the authors, it is difficult to estimate the future profitability of a firm. Moreover, the future profitability of a firm seems to greatly dictate the future stock returns of the particular firm.

2.4 The market environment

A brief analysis of the time period 2001-2011 is conducted in this section. Below, the figure 1 represents the development of the Helsinki Stock Exchange general index during the examination period. As Finland is an export-based economy, the international economic events usually have their impact on the Finnish stock market. Peavler (2013) has listed some of the most important economy related events during the last decade. In the end of 1990’s investors saw a huge potential in online and information business, and as a result, a speculative price bubble was born.

Unfortunately, the bubble burst in early 2000’s and asset prices fell dramatically.

Soon after the collapse of technology bubble, the 9/11 terrorist attacks in New York shook the whole world. Year 2001 was also famous for the Enron scandal, where the firm was caught from using creative accounting. As result, Enron defaulted and shareholders lost more than $60 billion. The scandal partially led to the passage of Sarbanes-Oxley act in 2002, which forced the publicly listed firms to tighten their policies in disclosure and accounting. In 2003, the U.S. president George W. Bush launched the campaign against terrorism by starting a war in Afganistan and Irak. This war had significant impact on oil prices all over the world.

During the decade, the economic growth of the BRIC countries was recognized. The BRIC countries include Brazil, Russia, India and China, respectively. Also, the emerging markets raised their status as investment targets. The year 2005 was catastrophic in U.S. history, because the hurricanes Katrina and Rita hit the U.S. coast with disastrous consequences. The effect on oil price was significant.

Elliot (2011) describes the key stages of global financial crisis. The phenomena called sub-prime mortgage loans in USA made the housing markets boom. This was a consequence of loose credit policies, because almost anyone was qualified for sub-prime mortgage loan. In the end of 2007, it was obvious that low income families and individuals could never afford to pay back their loans, and as a result they defaulted on their loans.

The credit rating agencies and investment banks were also involved in creating the housing bubble. They packaged the sub-prime mortgage loans and sold them forward to international investors, as credit rating agencies rated the financial instruments as investment-worthy. The crisis escalated when Lehman Brothers bankrupted in September 2008. Stock prices in all over the world fell dramatically after bankruptcy of Lehman Brothers.

As consequence of credit crunch launched by the default of Lehman Brothers, central banks dropped interest rates near to zero and announced massive stimulus packages. The crisis seemed to ease in 2009, after vast recovery policies. During the same year the G20 summit was held, in order to let the world leaders to discuss of the solutions to overcome the financial crisis. However, the crisis continued 2010 in Europe as Greece was considered insolvent. The economical focus changed rapidly from solvency of banks to solvency of countries.

The European central bank (2013) was later on concerned about the solvency of some particular European countries. Six months passed from the beginning of Greece-episode as Ireland requested for aid in its financial problems in November 2010. Portugal requested also for aid in spring 2011. It was obvious that the problems were much deeper in the foundations of eurozone and as a consequence, major actions were conducted in order to reinforce the European economic situation. The financial markets suffered especially in Europe, because of the economic uncertainty relating to the solvency of European banks and countries.

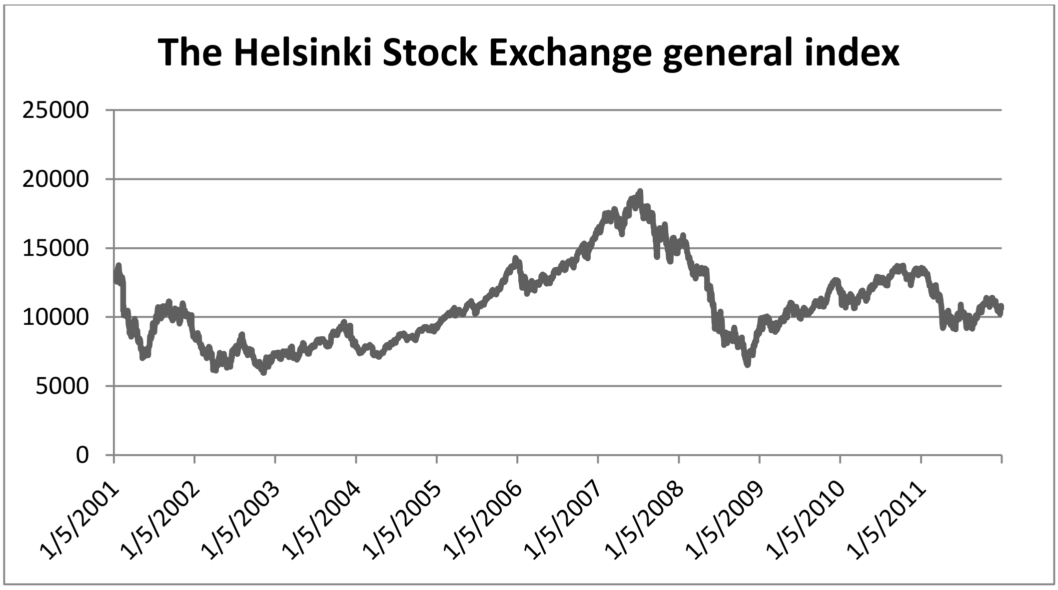

Figure 1. The Helsinki Stock Exchange general index 2001-2012. Source: Bank of Finland (2013).

3 Data and Methodology

This paper examines a sample of firms from the Helsinki Stock Exchange during years 2001-2011. The sample contains also delisted firms during the period to avoid the survivorship bias. If a particular firm had two stock series listed in the stock exchange, the more liquid stock series is preferred in this study. Adjustments for capitalization issues, dividends and splits are conducted in the stock return data. The firm-specific data in this paper has mostly been collected using DATASTREAM–database. The data that was not available in DATASTREAM has been complemented with data from annual reports. The firms with missing values were dropped out of the sample. The amount of firms in the sample is 112 in year 2001 and 91 in year 2011. The BCC-model of data envelopment analysis has been tested with MATLAB-program.

The sample firms are divided into three artificial industry categories consisting of technology (TECH), consumer goods and services (CGS) and industrial goods and services (IGS). This categorization is done, because the financial parameters used in this thesis require more or less that the firms are compared within their own industry. This maneuver increases the validity of this thesis, for the sake of different firm and industry characteristics. However, because the Helsinki Stock Exchange is rather small stock exchange in terms of number of publicly traded firms, the artificial industry categories are rather roughly formed by using the main business sectors of the firms when categorizing them. The performance evaluation is done by dividing the firms among the industry categories into long equity portfolios according to the efficiency score given by the data envelopment analysis. The TECH firms are divided into decile portfolios, CGS firms are divided into tercile portfolios and lastly, the IGS firms are divided into quintile portfolios.

Time series of monthly stock returns, market returns and Finland interbank fixing three-month risk-free rate are used to analyze the performance of the equity portfolios. The portfolios are formed in the first trading day of

May according to the efficiency score given by DEA. All the annual report data of the sample firms should be available to investors by the end of April and hence it is natural to form the portfolios in the beginning of May. The holding periods used in this paper are 1-, 2- and 3-years forward from the portfolio formation date. Depending on the holding period length, the efficiency scores are recalculated to match the holding periods (i.e. for 2-year holding period the efficiency scores are recalculated every second year, and so on). Portfolios are equally weighted between the stocks. If a firm is being delisted during the holding period, the money invested to that particular stock is distributed equally among the remaining stocks in the portfolio in the beginning of next month’s first trading day.

The performance of the portfolios is measured in terms of average annual return, annual volatility, Sharpe (1966) ratio, Jensen’s (1968) alpha and Beta. The statistical significance of Sharpe ratio and Jensen's alpha and the differences between the portfolios are examined with Opdyke (2007) test and Welch’s t-test. The performance of portfolios is also compared to the market performance in order to characterize the underlying market conditions. The performance metrics are described later in this section.

3.1 Descriptive statistics

The descriptive statistics of averaged financial ratios during the period 2001-2011 are shown in Table 2. The financial ratios are presented separately between the artificial industries categories used in this thesis. The focus is on the median values of the financial ratios, because the kurtosis and skewness of the ratios is notable and hence the examination of the mean values is not appropriate. The data has not been standardized, because it is not necessary with the DEA-approach employed in this thesis. However, it has an effect to descriptive statistics as the statistics show that many parameters have so-called outlier observations. The earnings per share (EPS) is not included in Table 2, because EPS is incomparable due to its nature that is fully dependent on the outstanding shares of a firm.

The asset utilization efficiencies depend greatly on the industry of the firm. Roughly the TECH category is the most efficient in collecting receivables. In inventory turnover, the IGS firms are the most efficient. However, the inventory turnover ratio is more or less biased, because the sample firms also consist of service-based firms that usually carry very small inventory. The asset turnover is slowest among the CGS firms whereas among IGS firms it is the fastest. The liquidity measures current ratio and quick ratio signal that technology firms have the best financial health among publicly listed Finnish firms. Furthermore, the IGS firms have second best liquidity and the CGS firms have the lowest liquidity in terms of median values of current ratio and quick ratio.

What comes to capital structure measures, the IGS firms use the most leverage and TECH firms are the least levered in terms of debt to equity, leverage, solvency ratio 1 and solvency ratio 2. However, these industries cannot be compared straightforward as the business and financial risk of the firms are substantially different.

The sales have grown among every industry category during the examination period. The median value of sales growth ranges from 4 to 6 percent, as it is the highest among the TECH firms. The earnings yield is highest among the CGS firms and lowest on average among the technology firms according to the median values. The IGS firms are the most moderately valued according to the median value of book to price ratio, but the CGS firms are rather close to the IGS firms. Obviously, the technology firms have the lowest book the price ratios on average. The median profitability ratios show that the CGS firms have been the most profitable during the time period. The median values of ROE, ROA and NPM are clearly higher among CGS firms compared to TECH and IGS firms.

Table 2

Descriptive statistics of the financial parameters.

	REC TO	INV TO	ASS TO	CR	QR	D/E	LEV	SOLV 1
TECH								
Mean	4,46	199,13	1,16	2,23	1,92	0,19	1,98	0,51
St. Error	0,38	153,92	0,1	0,31	0,29	0,09	0,24	0,12
Median	4,58	7,42	1,23	1,95	1,66	0,05	1,76	0,42
St. Dev	1,55	637,46	0,39	1,25	1,19	0,37	0,97	0,47
Kurt.	-0,03	13,86	0,28	3,12	3,25	4,95	5,91	5,15
Skew.	-0,31	3,65	-0,52	1,49	1,51	2,05	1,68	1,52
Min	1,46	0	0,4	0,65	0,42	0	1,04	0,17
Max	7,05	2632,84	1,8	5,71	5,27	1,4	5,06	2,12
CGS								
Mean	12,34	24,75	1,29	1,84	1,25	0,39	2,23	0,5
St. Error	3,44	8,73	0,12	0,41	0,33	0,06	0,13	0,03
Median	8,31	8,91	1,16	1,24	0,83	0,31	2,12	0,52
St. Dev	19,54	49,81	0,67	2,39	1,92	0,35	0,73	0,15
Kurt.	16,1	15,15	3,3	15,24	16,6	2,27	2,09	0,69
Skew.	3,43	3,53	1,23	3,23	3,4	1,27	1,09	-0,38
Min	0,43	1,6	0,25	0,42	0,26	0	1,18	0,14
Max	111,51	263,02	3,45	13,82	11,25	1,48	4,43	0,81
IGS								
Mean	6,94	32,95	1,39	1,76	1,15	0,62	3,13	0,58
St. Error	0,61	22,79	0,08	0,24	0,22	0,13	0,46	0,02
Median	5,99	5,5	1,36	1,46	0,85	0,43	2,53	0,59
St. Dev	4,38	163,03	0,57	1,73	1,61	0,92	3,26	0,15
Kurt.	18,06	37,09	1,57	11,58	13,63	17,58	17,66	0,21
Skew.	3,44	5,82	0,7	2,33	2,88	3,55	3,54	-0,41
Min	2,55	0	0,24	0,46	0,29	0	1,26	0,2
Max	30,38	1147,62	3,23	11,9	11,2	5,77	22,66	0,89

	SOLV 2	S GR	EPS GR	E/P	B/P	ROE	ROA	NPM
TECH								
Mean	1,03	0,06	0,2	-0,04	0,5	-2,47	0,28	-12,33
St. Error	0,26	0,05	1,13	0,05	0,11	10,97	6,79	15,82
Median	0,77	0,06	-0,18	0,03	0,44	8,48	5,85	3,84
St. Dev	1,05	0,22	4,74	0,21	0,46	44,56	27,52	63,69
Kurt.	6,42	2,5	6,01	5,08	1,41	6,65	7,74	8,6
Skew.	2,13	0,16	-0,51	-1,93	0,19	-2,27	-1,86	-2,6
Min	0,21	-0,38	-8,14	-0,72	-0,37	-149,12	-82,97	-239,74
Max	4,42	0,53	13,64	0,14	1,37	37,95	35,07	22,72
CGS								
Mean	1,22	0,07	0,39	0,06	0,61	12,22	7,65	6,5
St. Error	0,13	0,04	0,95	0,02	0,08	4,62	1,79	1,66
Median	1,11	0,04	-0,05	0,06	0,51	11,71	6,56	4,82
St. Dev	0,77	0,26	5,66	0,1	0,45	26,7	10,18	9,43
Kurt.	3,55	9,34	14,39	8,47	2	11,35	7,77	5,71
Skew.	1,29	0,93	0,17	-0,44	1,35	-0,06	0,35	0,98
Min	0,18	-0,39	-9,72	-0,24	0,07	-74,55	-18,24	-11,42
Max	3,76	1,08	26,47	0,34	1,95	85,67	39,68	38
IGS								
Mean	2,05	0,11	0,03	0,01	0,97	3,9	4,19	-6,87
St. Error	0,41	0,06	0,62	0,04	0,32	4,66	1,42	10,46
Median	1,49	0,05	-0,19	0,05	0,52	11,27	5,66	3,41
St. Dev	2,89	0,45	4,32	0,3	2,3	33,12	10,14	75,3
Kurt.	17,73	20,36	20,57	18,17	30,19	10,04	5,39	18,84
Skew.	3,54	2,91	1,83	-2,42	5,19	-2,2	-1,34	-2,79
Min	0,26	-0,58	-10,75	-1,24	0,05	-143,33	-35,29	-518,16
Max	19,07	2,67	21,45	0,84	15,15	66,8	28	28,24

The table 2 presents the descriptive statistics of the averaged financial parameters from period 2001-2011. The values are presented separately for each artificial industry category, beginning from TECH firms and ending to IGS firms. St. Error denotes standard error, St. Dev stands for standard deviation, Kurt. denotes the kurtosis of the parameter and the Skew. stands for the skewness of the parameter. Min presents the minimum value of the parameter and Max presents the maximum value of the parameter, respectively.

3.2 Data envelopment analysis and the BCC model

First, the basic CCR model is introduced to get familiar with the Data envelopment analysis (DEA). The CCR model was proposed by Charnes, Cooper and Rhodes in 1978 and the model is named after their first initials. Basically, DEA is a linear programming-based method for measuring the efficiency of a particular decision making unit (DMU) using certain input and output variables. A DMU is efficient when it is using a minimal input in order to generate a maximum output when compared to other DMUs.

DEA is an efficient tool when comparing the efficiencies of entities called DMUs. Multiple inputs and outputs can be employed in the model in order to rank the DMUs according to their efficiency score. DEA can be used in wide range of industries and it is rather simple, because of its non-parametric nature. It is not necessary to a priori define the relationships between input and output variables or the pre-assigned weights of the parameters.

DEA has been also used to study its implications in portfolio management. Different input and output variables in addition to different methods have been used in order to separate the winner stocks from loser stocks. For instance, Powers and McMullen (2002), Edirisinghe and Zhang (2007, 2008, 2010), Chen (2008), Pätäri, Leivo and Honkapuro (2010, 2012) have studied the implications of using DEA in portfolio management. The DEA-studies relating to portfolio management were examined profoundly in the literature review section. DEA is classified as a part of fundamental analysis, because it uses firm-specific data. However, the point is not to calculate an intrinsic value for a stock, but rather to classify stocks according their efficiency score.

The mathematic formulation of the basic CCR model is as follows (Charnes et al., 1978):

$$\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

$$\text{Subject to: } \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \; ; \; j = 1, \ldots, n$$

$$u_r, v_i > 0; \;\; r = 1, \ldots, s; \;\; i = 1, \ldots, m \tag{18}$$

where, h_0 = efficiency score of the DMU 0

y_{rj}, x_{ij} = The values of output *r* and input *i* of the DMU *j*

u_r, v_i = The weights of the similar outputs and inputs

s = The number of outputs

m = The number of inputs

The CCR model (Charnes et al., 1978) is input-oriented and presumes constant returns to scale (CRS). The model determines the weights of input and output variables in order to maximize the efficiency score of the particular DMU. However, the output and input weights are limited so that the efficiency score of a DMU never exceeds one. Furthermore, a DMU is efficient if the efficiency score is one and a DMU is inefficient if the efficiency score is between 0 to 0,99. The DMUs are ranked according to their efficiency score from one to zero.

Banker, Charnes and Cooper (1984) modified the original CCR model further and came up with a model that is known today as the BCC model, named after the authors of the model. The crucial difference between the CCR and the BCC model is that there is an extra parameter in the BCC model, the free variable u_0, as shown below. As the CCR model assumes constant returns to scale, the BCC model assumes variable returns to scale (VRS).

VRS model should be used if it is supposed that an increase in inputs does not result in a proportional change in the outputs. Constant returns to scale assume that an increase in inputs results as a proportionate increase in the output levels. In other words, if the input values are doubled, then the output values must be at least twice as much (Emrouznejad 2013).

The mathematic formulation of the BCC model is as follows (Banker et al., 1984):

$$\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0} - u_0}{\sum_{i=1}^{m} v_i x_{i0}}$$

$$\text{Subject to: } \frac{\sum_{r=1}^{s} u_r y_{rj} - u_0}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \ ; \ j = 1, \dots, n \qquad (19)$$

Before using the model, a number of tests were carried on to get conclusive foundations for portfolio formation. The first step was that the model was run as all the firms in the data were on the same list with their inputs and outputs. Clearly there were two major problems at this approach; the firms in different industries were not comparable with each other and the results provided too many efficient DMUs, as in some cases over 50 percent of the sample firms were efficient.

The solution to the first problem was to roughly divide the small sample of the Helsinki stock exchange firms into three above-mentioned different artificial industry categories. The limitations were that each industry category would have at least 15 firms in order to divide the firms according to their efficiency score to minimum of two portfolios. However, Banker et al. (1989) suggest as a rule of thumb that sample size used in DEA should be at least three times larger than the sum of inputs and outputs. Furthermore, Dyson et al. (2001) recommend that the sample size should be twice as large as the sum of the inputs and outputs. This can cause the DEA model to lose its discriminatory power and it has to be taken into account when interpreting the final results.

The second problem still existed, although the firms were now more comparable with each other. There were still too many efficient DMUs in the industry categories, as almost 50 percent of the firms had efficiency score of one. This problem was solved after numerous tests by running the BCC model using separately each input with all the outputs. In other words, single inputs are tested with multiple outputs. This method provided interesting results, as the number of efficient DMUs was radically decreased.

The next step was to calculate the average of the nine different efficiency scores resulted from the previously mentioned method for each firm. After calculating the average, the firms were ranked from efficient to inefficient according to the average efficiency score.

The mathematic formulation of the average efficiency score:

$$\overline{h_0} = \frac{1}{n}\sum_{i=1}^{n} h_i = \frac{(h_1 + \cdots + h_x)}{n} \qquad (20)$$

where,

h_i = The efficiency score of DMU

n = The number of observations

3.3 The performance measures

3.3.1 Sharpe ratio

William F. Sharpe (1966) developed the Sharpe ratio to measure risk-adjusted stock performance. The higher the portfolio’s Sharpe ratio the better is the risk-adjusted performance. Negative Sharpe ratio caused by negative excess return points out that the risk-free asset provides better return than the portfolio examined. Furthermore, negative excess returns can cause validity problems and in order to avoid such problems, modified Sharpe ratio by Israelsen (2005) is used in this thesis.

The modified Sharpe ratio formula is:

$$Sharpe\ ratio = \frac{R_i - R_f}{\sigma_i^{(ER/|ER|)}} \tag{21}$$

where,

R_i = The average monthly return of portfolio *i*

R_f = The average monthly risk free rate of return

σ_i = The standard deviation of the average excess returns of portfolio *i*

ER = The average excess returns of portfolio *i*

3.3.2 Jensen's alpha

Jensen's (1968) alpha measures the abnormal return of a portfolio over the expected return estimated by the capital asset pricing model (CAPM). The Jensen's alpha is used to measure the risk-adjusted return of a portfolio.

The Jensen's alpha formula is:

$$Jensen's\ alpha = R_i - [R_f + \beta_i(R_m - R_f)] \tag{22}$$

where,

R_i = The average return of portfolio *i*

R_f = The average risk free rate of return

β_i = The beta of portfolio *i*

R_m = The average market return

3.3.3 Volatility

Volatility is a statistical measure of the fluctuation of the portfolio's returns over time. High volatility measure indicates that the price of underlying security can change considerably over time. Low volatility is a sign of moderate price changes over short period of time. However, the price can move either direction over short period, but volatility still does not measure the direction of change in the asset's value.

The formula of annualized volatility:

$$Annualized\ volatility = \frac{\sigma_i}{\sqrt{T}} \tag{23}$$

where,

σ_i = The standard deviation of portfolio *i* in time period T

$\sqrt{T}$ = The trading days in time period *T*

3.3.4 Beta

Beta measures the systematic risk of a portfolio compared to the market index. Beta is calculated from the capital asset pricing model (CAPM) (Treynor 1961, Sharpe 1964, Lintner 1965), where beta is vital component in calculating the expected returns of an asset. Beta is calculated via regression analysis comparing the asset returns to market returns. If beta is greater than one, the underlying asset's returns fluctuate more volatile than the market's returns and vice versa.

Beta's formula is:

$$Beta = \frac{Cov(R_i, R_m)}{Var(R_m)} \tag{24}$$

where,

$Cov(R_i, R_m)$ = Covariance between portfolio return and market return

$Var(R_m)$ = Variance of market return

3.3.5 Statistical tests

The Sharpe ratios are tested with Opdyke (2007) test, which assumes that the data is not necessarily normally distributed and revises the formulae for the restricting variances of Lo (2002) and of Memmel (2003), respectively, which assume that the data is normally distributed. General stationary data, such as time series is also considered in the Opdyke (2007) test.

The skewness- and kurtosis-adjusted asymptotic variance of the difference between two comparable Sharpe ratios is formulated by Opdyke (2007) in the following formula:

$$Var_{diff} = 2 - SR_a \frac{\mu_{3a}}{\sigma_a^3} - SR_b \frac{\mu_{3b}}{\sigma_b^3} + SR_a \frac{\mu_{1b,2a}}{\sigma_b \sigma_a^2} + SR_b \frac{\mu_{1a,2b}}{\sigma_a \sigma_b^2} + \frac{{SR_a}^2}{4}\left[\frac{\mu_{4a}}{\sigma_a^4} - 1\right] + \frac{{SR_b}^2}{4}\left[\frac{\mu_{4b}}{\sigma_b^4} - 1\right] - 2\rho_{a,b} - SR_a SR_b \frac{1}{2}\left[\frac{\mu_{2a,2b} - \sigma_a^2\sigma_b^2}{\sigma_a^2\sigma_b^2}\right] = 2 - SR_a \frac{\mu_{3a}}{\sigma_a^3} - SR_b \frac{\mu_{3b}}{\sigma_b^3} + SR_a \frac{\mu_{1b,2a}}{\sigma_b \sigma_a^2} + SR_b \frac{\mu_{1a,2b}}{\sigma_a \sigma_b^2} + \frac{{SR_a}^2}{4}\left[\frac{\mu_{4a}}{\sigma_a^4} - 1\right] + \frac{{SR_b}^2}{4}\left[\frac{\mu_{4b}}{\sigma_b^4} - 1\right] - 2 * \left[\rho_{a,b} + \frac{SR_a SR_b}{4}\left[\frac{\mu_{2a,2b}}{\sigma_a^2\sigma_b^2} - 1\right]\right] \tag{25}$$

Parallel to Memmel (2003), the test statistic to compare the difference in Sharpe ratio between two portfolios *(i, j)* is calculated as follows:

$$Z = \frac{Sh_i - Sh_j}{\sqrt{V}} \tag{26}$$

In the formula Sh_i and Sh_j expresses the Sharpe ratios of portfolios *i* and *j* and *V* stands for the asymptotic variance that is calculated by dividing Var_{diff} (attained from equation 25) by the number of monthly observations. The Z-distribution with defined risk levels is used to evaluate the statistical significance of the calculated Z-statistic.

The statistical significance of Jensen's alphas spreads between the DEA-portfolios is tested with the Welch's t-test. It is formulated as follows:

$$t = \frac{\alpha_i - \alpha_j}{\sqrt{SE_{\alpha i}^2 + SE_{\alpha j}^2}} \tag{27}$$

where,

α_* = The alpha of portfolio *

SE_{α_*} = The standard error of portfolio *

The degrees of freedom for the test statistic are calculated as follows:

$$v = \frac{\left(SE_{\alpha i}^2 + SE_{\alpha j}^2\right)^2}{\frac{SE_{\alpha i}^4}{v_i} + \frac{SE_{\alpha j}^4}{v_j}} \tag{28}$$

where,

v_i, v_j = the degrees of freedom determined by the number of monthly observations in samples *i* and *j (v = n - 1).*

4 Results

First, the results of the annually rebalanced (1-year holding period) DEA-portfolios of the three artificial industry categories are presented. Next, the results of the DEA-portfolios that are rebalanced every second year (2-year holding period) are presented and lastly, the results of the DEA-portfolios that are rebalanced every third year (3-year holding period) are presented. In order to clarify the results tables, a brief description is given. The upper row of Tables 3-5 presents average annual return, average annual volatility and Sharpe ratio. The Sharpe ratio is presented multiplied by ten to the power of 2 in order to simplify the results. The statistical significance of Sharpe ratios and Sharpe ratio differences are tested with

Opdyke's test (2007). The lower row of the table presents the market beta, the alphas and the alpha spreads. The statistical significance of the alphas and alpha spreads are tested with Welch's t-test. The portfolios are formed according to the DEA efficiency score. P1 is the DEA-efficient top portfolio, the Px with the greatest value is the most DEA-inefficient portfolio in the particular industry category and M stands for the market portfolio, respectively. The t=1 portfolios are rebalanced annually and the time period is from May 2001 to May 2012. The t=2 portfolios are rebalanced every second year and the time period is from May 2001 to May 2011. The t=3 portfolios are rebalanced every third year and the time period is from May 2001 to May 2010.

The overall results of annually rebalanced portfolios from Table 3 show that the DEA-approach employed in this thesis clearly separates the winner portfolios from the worst-performing portfolios. This can be detected especially from the performance of the top CGS portfolio and the top IGS portfolio, and as well from the top TECH portfolio. However, both of the TECH portfolios generated negative average annual returns, as the top portfolio generated an average annual return of -7.78% and the bottom portfolio generated an average annual return of -27.41%. In this sense, the top portfolio in the TECH category still provided better returns. The average annual return of the top CGS portfolio is the highest among the 1-year holding period portfolios (i.e. 19.81% p.a.) and the second highest average annual return is generated by the top IGS portfolio (i.e. 18.73% p.a.). The rest of the portfolios in CGS and IGS categories provided adequate average annual returns, but the difference between the top portfolio and the second portfolio in both categories is rather substantial. All the portfolios except the TECH portfolios outperformed the average market return which was -5.49% p.a. during the time period, respectively. The average annual volatility measures present that the TECH portfolios were the most volatile during the time period, as the annual volatility of the corresponding bottom portfolio is 36.73%. The annual volatilities of the rest of the portfolios are around 20%, as the annual market volatility during the time period is 26.22%. In general, the CGS portfolios had a slightly lower volatility than the IGS portfolios as the TECH portfolios had the highest annual volatility.

The Sharpe ratios indicate that the top CGS portfolio had the best Sharpe ratio and the top IGS portfolio had the second best Sharpe ratio as the both portfolios are statistically significant compared to the market portfolio at the 99% confidence level. The Sharpe ratio difference between the two TECH portfolios shows that the difference is not statistically significant. In the CGS category the difference between the top portfolio and the second portfolio is significant (at the 10% level) and the difference between the top and the bottom portfolio is very significant (at the 1% level). The Sharpe ratio difference between the top IGS portfolio and the bottom portfolio is very significant (at the 1% level) and the difference between the top portfolio and the second portfolio is significant (at the 10% level).

The market beta shows that the TECH portfolios had the highest betas among all the portfolios. On average, the CGS portfolios had slightly lower betas than the IGS portfolios. The beta of the top portfolio in the CGS category is lowest among the CGS portfolios. Conversely, the top portfolio and the P4 portfolio in the IGS category have the highest beta among the IGS portfolios. The alphas present that the performance of the top IGS portfolio is the best (i.e. 21.45%) among all the portfolios whereas the top portfolio in the CGS category has the second best alpha (i.e. 20.39%). Both of the alphas of the top portfolios are significant at a 99% confidence level. The alpha of the top TECH portfolio is slightly positive, which is rather odd when taking into account the average annual return of the corresponding portfolio, but after checking the data, it still remained positive. However, the above-mentioned alpha is not statistically significant. The alpha spread between portfolios is highest when compared the top IGS portfolio and the bottom portfolio as the spread is significant (at the 1% level). The spread between the top CGS portfolio and the bottom portfolio is also significant (at the 5% level). The alpha spread between the two TECH portfolios is rather substantial, as the spread is significant at 90% confidence level but as the performance of the both TECH portfolios is poor, this significance is somewhat meaningless.

Table 3
The performance of annually rebalanced TECH, CGS and IGS portfolios during the full time period (2001-2011).

T=1	Av. Annual return (%)	Av. Annual volatility (%)	SR x 10^{-2}	SR (sign.) Pi vs. M	SR diff. Pi vs. Pj	SR diff. (sign.)
TECH						
P1	-7,78	34,90	-0,036	(0.790)	P1 VS. P2	(0.109)
P2	-27,41	36,73	-0,250	(0.050)		
CGS						
P1	19,81	18,52	27,706	(0.000)	P1 VS. P2	(0.062)
P2	10,08	18,18	12,692	(0.034)	P1 VS. P3	(0.003)
P3	3,97	14,97	4,674	(0.167)	P2 VS. P3	(0.230)
IGS						
P1	18,73	21,45	21,664	(0.000)	P1 VS. P5	(0.005)
P2	9,11	21,13	10,786	(0.057)	P1 VS. P2	(0.079)
P3	4,94	19,84	6,193	(0.177)	P1 VS. P4	(0.009)
P4	4,86	21,34	6,355	(0.158)	P2 VS. P5	(0.092)
P5	-0,43	18,17	-0,004	(0.674)	P4 VS. P5	(0.308)
M	-5,49	26,22	-0,029			
	Beta	**Alpha**	**Alpha (sign.)**	**Alpha spread Pi vs. Pj**	**Alpha spread**	**Alpha spread (sign.)**
TECH						
P1	1,10	0,69 %	(0.905)	P1 VS. P2	18,68 %	(0.051)
P2	1,14	-17,99 %	(0.024)			
CGS						
P1	0,33	20,39 %	(0.000)	P1 VS. P2	8,30 %	(0.304)
P2	0,47	12,09 %	(0.029)	P1 VS. P3	15,74 %	(0.018)
P3	0,42	4,65 %	(0.211)	P2 VS. P3	7,44 %	(0.277)
IGS						
P1	0,58	21,97 %	(0.000)	P1 VS. P5	21,00 %	(0.008)
P2	0,53	12,31 %	(0.059)	P1 VS. P2	9,65 %	(0.300)
P3	0,47	7,05 %	(0.213)	P1 VS. P4	13,39 %	(0.143)
P4	0,58	8,57 %	(0.179)	P2 VS. P5	11,35 %	(0.175)
P5	0,44	0,96 %	(0.846)	P4 VS. P5	7,61 %	(0.354)

The overall results of the every second year rebalanced portfolios (Table 4) are mixed and the results present that the performance of the DEA-efficient portfolios in each category is not superior compared to the lower portfolios among the corresponding industry categories. The average annual returns of the both TECH portfolios refer to the poor performance during the time period, but nevertheless the top portfolio seemed to perform better than the bottom portfolio. The average annual return of the top portfolios in the CGS and the IGS categories is equal (i.e. 16.07% p.a.). However, the middle portfolio in the CGS category generated an average annual return of 18.93% p.a. and the P4 portfolio in the IGS category generated an average annual return of 17.89% p.a., which are greater compared to the average annual returns of the top portfolios in corresponding categories. All the portfolios except the TECH portfolios outperformed the market return during the time period. The average annual volatility is highest among the TECH portfolios and lowest among the CGS portfolios, as the market volatility is 25.85%.

The middle portfolio in the CGS category and the P4 portfolio in the IGS category have higher Sharpe ratio than the top portfolios in corresponding categories as all the above-mentioned portfolios are statistically significant (at the 5% level). The Sharpe ratios of TECH portfolios are negative and they are not statistically significant. Moreover, they are lower than the market Sharpe ratio. The Sharpe ratio differences are statistically significant between the middle and bottom portfolio in the CGS category (at 5% level) and the difference between the top and the second portfolio in the IGS category is significant (at the 5% level). The rest of Sharpe ratio differences are not significant.

The market betas are highest among the TECH portfolios as they are equal (i.e. 1.09) and the lowest betas are among the CGS portfolios. It is interesting that the both top portfolios in the CGS and the IGS categories have the highest beta among their categories. The alphas are clearly negative among the TECH portfolios and not statistically significant. The alphas of the top (i.e. 16.20%) and middle (i.e. 18.77%) portfolios in the CGS category and the top (i.e. 17.30%) and P4 (i.e. 18.84%) portfolios in the IGS category are statistically very significant (at 1% level). The both top portfolios in the CGS and IGS categories lose in comparison of the alphas to the middle CGS and P4 IGS portfolios. Only the spread between the middle and bottom portfolio in the CGS category is significant as the spread is significant (at 10% level).

Table 4
The performance of every second year rebalanced TECH, CGS and IGS portfolios during the time period (2001-2010).

T=2	Av. Annual return (%)	Av. Annual volatility (%)	SR x 10^{-2}	SR (sign.) Pi vs. M	SR diff. Pi vs. Pj	SR diff. (sign.)
TECH						
P1	-11,86	33,89	-0,073	(0.383)	P1 VS. P2	(0.620)
P2	-18,84	36,20	-0,144	(0.158)		
CGS						
P1	16,07	17,42	21,191	(0.012)	P1 VS. P2	(0.599)
P2	18,93	17,31	25,836	(0.001)	P1 VS. P3	(0.125)
P3	6,35	14,80	8,387	(0.159)	P2 VS. P3	(0.019)
IGS						
P1	16,07	19,96	19,280	(0.007)	P1 VS. P5	(0.391)
P2	6,49	20,38	7,853	(0.231)	P1 VS. P2	(0.050)
P3	9,44	19,04	11,592	(0.112)	P1 VS. P4	(0.771)
P4	17,89	20,51	21,340	(0.005)	P2 VS. P5	(0.634)
P5	8,49	17,00	11,678	(0.125)	P4 VS. P5	(0.283)
M	-3,53	25,85	-0,015			

	Beta	Alpha	Alpha (sign.)	Alpha spread Pi vs. Pj	Alpha spread	Alpha spread (sign.)
TECH						
P1	1,09	-5,74 %	(0.335)	P1 VS. P2	6,25 %	(0.498)
P2	1,09	-11,99 %	(0.113)			
CGS						
P1	0,39	16,20 %	(0.003)	P1 VS. P2	-2,57 %	(0.751)
P2	0,38	18,77 %	(0.000)	P1 VS. P3	10,33 %	(0.149)
P3	0,38	5,87 %	(0.159)	P2 VS. P3	12,90 %	(0.065)
IGS						
P1	0,54	17,30 %	(0.002)	P1 VS. P5	6,33 %	(0.230)
P2	0,53	8,51 %	(0.217)	P1 VS. P2	2,87 %	(0.350)
P3	0,45	10,40 %	(0.086)	P1 VS. P4	0,74 %	(0.863)
P4	0,47	18,84 %	(0.002)	P2 VS. P5	3,46 %	(0.941)
P5	0,30	7,88 %	(0.110)	P4 VS. P5	5,59 %	(0.184)

The overall results of every third year rebalanced portfolios (Table 5) show that the DEA-approach used is this thesis does not clearly separate the winner and loser portfolios. However, the top portfolios in TECH (i.e - 15.45% p.a.), CGS (i.e. 14.27% p.a.) and IGS (i.e. 13.09% p.a.) categories generated the best average annual return compared to the lower portfolios among the corresponding categories, but the differences in average annual return are very small. In this sense, the DEA-approach seems to have no discriminatory power when rebalancing the portfolios every third year. The average annual volatilities are highest among the TECH portfolios and lowest among the CGS portfolios. The top portfolio in CGS category has the highest volatility among the CGS portfolios and the top IGS portfolio has the fourth lowest volatility among the IGS portfolios. The annual market volatility during the time period was 26.58%.

Despite the fact that top portfolios in the CGS and IGS categories have the highest average annual returns, the middle CGS and P4 IGS portfolios have better Sharpe ratio than the top portfolios. The above-mentioned Sharpe ratios of the portfolios are statistically significant (at 5% level). The both TECH portfolios have a poor Sharpe ratio and the ratios are worse than the market Sharpe ratio. None of the Sharpe ratio differences between the portfolios are statistically significant.

Market betas show that the TECH portfolios have the highest betas among all of the 3-year holding period portfolios. The betas of the IGS portfolios are clearly higher than the betas of the CGS portfolios. The alphas present the poor performance of the TECH portfolios. Conversely to the Sharpe ratios, the top portfolios in the CGS (i.e. 15.10%) and the IGS (i.e. 14.89%) categories have the best risk-adjusted performance in terms of alphas. The alphas of CGS top and middle portfolios and the alphas of top IGS and P4 portfolios are statistically significant (at the 5% level). However, because the results are rather mixed, the alpha spreads are not substantial between the portfolios and as a result, none of the alpha spreads are statistically significant.

Table 5
The performance of every third year rebalanced TECH, CGS and IGS portfolios during the time period (2001-2009).

T=3	Av. Annual return (%)	Av. Annual volatility (%)	SR x 10^{-2}	SR (sign.) Pi vs. M	SR diff. Pi vs. Pj	SR diff. (sign.)
TECH						
P1	-15,45	36,40	-0,1087	(0.490)	P1 VS. P2	(0.991)
P2	-17,27	39,89	-0,125	(0.430)		
CGS						
P1	14,27	19,45	17,625	(0.029)	P1 VS. P2	(0.819)
P2	14,12	15,34	19,657	(0.008)	P1 VS. P3	(0.508)
P3	8,54	14,58	11,749	(0.059)	P2 VS. P3	(0.195)
IGS						
P1	13,09	17,24	15,654	(0.017)	P1 VS. P5	(0.838)
P2	8,73	20,56	9,872	(0.131)	P1 VS. P2	(0.280)
P3	10,53	18,91	12,557	(0.071)	P1 VS. P4	(0.954)
P4	13,04	19,62	16,066	(0.026)	P2 VS. P5	(0.601)
P5	9,41	15,35	13,956	(0.069)	P4 VS. P5	(0.801)
M	-5,07	26,58	-0,026			
	Beta	**Alpha**	**Alpha (sign.)**	**Alpha spread Pi vs. Pj**	**Alpha spread**	**Alpha spread (sign.)**
TECH						
P1	1,01	-7,42 %	(0.382)	P1 VS. P2	0,01 %	(0.999)
P2	1,20	-7,43 %	(0.343)			
CGS						
P1	0,37	15,10 %	(0.000)	P1 VS. P2	0,91 %	(0.916)
P2	0,37	14,19 %	(0.005)	P1 VS. P3	6,73 %	(0.407)
P3	0,36	8,36 %	(0.059)	P2 VS. P3	5,82 %	(0.403)
IGS						
P1	0,52	14,89 %	(0.011)	P1 VS. P5	6,33 %	(0.412)
P2	0,55	12,02 %	(0.127)	P1 VS. P2	2,87 %	(0.781)
P3	0,48	12,34 %	(0.053)	P1 VS. P4	0,74 %	(0.932)
P4	0,43	14,15 %	(0.019)	P2 VS. P5	3,46 %	(0.713)
P5	0,25	8,56 %	(0.063)	P4 VS. P5	5,59 %	(0.477)

After examining the results of all three different holding period lengths, it is clear that the best performance for the DEA-efficient portfolio is achieved with the 1-year holding period, where the portfolio is annually rebalanced according to the DEA-efficiency score. The statistical significance of the Sharpe ratio and alpha differences between the top and bottom portfolio in the CGS and the IGS categories clearly indicate the superior performance of the DEA-efficient portfolios. The performance of TECH portfolios is very poor in every holding period length and as a result, no conclusive remarks can be done, except for possibly using the results for purposes of considering a short position. However, because the time period is shorter using 2- and 3-year holding periods, the 1 year holding period results are not fully comparable with the longer holding periods. Moreover, the results of the 2- and 3-year holding periods seem to be rather mixed, because the DEA-efficient portfolio is not necessarily the best performing portfolio in terms of the risk-adjusted measures. Furthermore, the statistical significance in differences of Sharpe ratio and Jensen's alpha between the top and the bottom portfolio are not significant in any of portfolios in the 2- and 3-year holding periods.

It is interesting that the volatility and beta measures of the top portfolios are in some cases higher than the measures of the lower portfolios among the corresponding industry category. It seems that the top portfolio can be, in some cases, riskier (in terms of volatility and beta) compared to the lower portfolios, but despite the riskiness the top portfolio still generates notable returns. However, no conclusive remarks can be done, and the claim should be empirically tested. It is also interesting that the bottom portfolio in the IGS category has the lowest beta in every holding period when compared to the middle portfolios and the top portfolio. This could be explained with the low-liquidity effect that is consequence of the low trading volumes of these stocks in the particular bottom portfolio.

5 Conclusions

The previous studies in the literature review section show that different DEA-approaches have been successfully used as portfolio selection criterion in various stock markets. The motivation of this thesis is to test the applicability of data envelopment analysis as portfolio selection criterion in the Finnish stock market. A sample of publicly traded Finnish firms presenting different industries from time period 2001-2011 are examined in this study.

This paper employed several financial parameters as inputs and outputs. The inputs represent the asset utilization, liquidity and capital structure of a firm whereas the outputs represent the growth, valuation and profitability of a firm, respectively. A firm is classified DEA-efficient when it uses minimum inputs to generate maximum outputs. The sample of firms were divided into three artificial industry categories according their main business segment and the BCC-model was used to classify the firms among the industry categories as DEA-efficient or DEA-inefficient. The firms were then divided into portfolios along their efficiency score as the DEA-efficient firms were set to the top portfolio and the DEA-inefficient firms were set to the rest of the portfolios according to their efficiency score. Finally, the performance of the portfolios was examined using time-series of monthly returns with several measures in order to determine the risk-return characteristics of the portfolios.

The results of this thesis show that DEA as portfolio selection criterion works best when the DEA-efficient portfolio is rebalanced annually according to the efficiency scores received from the DEA. The significance of the results indicates the superior performance of the top portfolio in the customer goods and services- and industrial goods and services industry categories. The performance of the technology portfolios was poor in each holding period and hence, rather than taking a long position, a short position with these portfolios could have provided better results. However, when the portfolios are rebalanced every second and every third year according to the efficiency scores, the results are mixed as the risk-adjusted and absolute performance of the top portfolio is weaker when compared to the lower portfolios. In general, the DEA-approach of this thesis can successfully be used in the Finnish Stock Market as the optimal rebalancing frequency of the DEA-efficient portfolios is one year.

For further research, the DEA could be used to determine the performance of the DEA-efficient portfolio during bullish and bearish periods. More interesting would be to test the approach with larger sample, for instance, firms from the same industry worldwide or from a particular region, such as Europe or U.S. The input and output pattern could also be varied to find different efficiencies or new parameters could be included in the analysis. Moreover, different DEA-approaches, such as super-efficiency or cross-efficiency models would be interesting to test with similar or different foundations.

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Appendices

Appendix 1. The sample firms in artificial industry categories.

TECH	CGS	IGS
ALDATA SOLUTIONS	ALMA MEDIA	ASPO
BASWARE	AMER SPORTS	ASPOCOMP
COMPTEL	ATRIA	BIRKA LINE
DIGIA	BIOHIT	CENCORP
ELEKTROBIT	CHIPS	COMPONENTA
F-SECURE	ELISA	CRAMO
GEOSENTRIC	FINNAIR	DOVRE GROUP
IXONOS	FISKARS	EFORE
NOKIA	HACKMAN	EIMO
OKMETIC	HARTWALL	ELCOTEQ
SENTERA	HKSCAN	ELECSTER
SOLTEQ	HONKARAKENNE	ETTEPLAN
STONESOFT	ILKKA YHTYMA	EVIA
TECNOTREE	INSTRUMENTARIUM	EVOX RIFA
TEKLA	JANTON	EXEL COMPOSITES
TELESTE	KESKISUOMALAINEN	FINNLINES
TIETO	KESKO	FORTUM
WM-DATA	LANNEN TEHTAAT	GLASTON
YOMI	LASSILA & TIKANOJA	HUHTAMAKI
	MARIMEKKO	INCAP
	MARTELA	KEMIRA
	NOKIAN RENKAAT	KESLA
	OLVI	KONE
	ORION	KONECRANES
	POHJOIS-KARJALAN KRJ	LAROX
	PUUHARYHMA	LEMMINKAINEN
	RAISIO	METSO
	RAPALA	NURMINEN LOGISTICS
	RAUTAKIRJA	PARTEK
	SAGA FURS	PERLOS
	SANOMA	PKC GROUP
	SAUNALAHTI	PLANDENT
	SILJA	PONSSE
	SONERA	POYRY
	STOCKMANN	RAMIRENT
	SUOMEN SPAR	RAUTE
	TALENTUM	REVENIO
	TAMRO	ROCLA
	TIIMARI	SIEVI CAPITAL
	VIKING LINE	STROMSDAL

continued on next page.

CGS	IGS
TELIASONERA	SUOMINEN
TERVEYSTALO	TAKOMA
	TAMFELT
	TURVATIIMI
	UPONOR
	VAAHTO GROUP
	VACON
	VAISALA
	WARTSILA
	WULFF
	YIT
	YLEISELEKTRONIIKKA
	NESTE OIL
	KEMIRA GROWHOW
	SALCOMP
	CARGOTEC
	OUTOTEC
	POWERFLUTE
	SRV YHTIOT
	TIKKURILA