PERFORMANCE OF CLUSTERING-BASED STOCK PORTFOLIOS – CASE: EXPLORATORY STUDY OF K-MEANS CLUSTERING FOR S&P500 IN 2010 – 2022 DATA USING COMBINATIONS OF SELECTED KEY FIGURES

Lappeenranta–Lahti University of Technology LUT

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Examiners: 1st Supervisor: Post-doctoral researcher Jyrki Savolainen

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ABSTRACT

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Performance of clustering-based stock portfolios – Case: exploratory study of k-means clustering for S&P500 in 2010-2022 data using combinations of selected key figures

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Keywords: Cluster analysis, K-means, Key figure, investing strategy

The purpose of this study is to use cluster analysis to determine whether there are combinations of common key figures that could have outperformed the S&P500 index within the studied timeframe. The data used are the stocks in the S&P500 index, their price data, and ratio values for the period 2010-2022. The methodology of the study is to make combinations of three ratios out of a total of eight ratios. The values corresponding to these ratios are grouped into five different clusters using the K-means method. For the analysis, the clusters with the highest and lowest midpoints are selected to form a "Growth Portfolio", composed of stocks with high ratios, and a "Value Portfolio", composed of stocks with low ratios. The total number of portfolios created using this method is 112. The average returns of the value and growth portfolios are compared, in absolute and risk-adjusted terms, with the returns of the S&P500 index and the returns of the randomly selected portfolios. In addition, a more detailed analysis will look at the best performing individual portfolios.

Based on the results, four growth portfolios performed best. These four portfolios were generated by clustering EV/EBIT, P/CF & EV/EBITDA; EV/EBIT, P/CF & P/E; EV/EBITDA, P/CF & P/B and EV/EBIT, P/CF & P/S. These four portfolios outperformed the random portfolios in absolute terms and had a higher Sharpe ratio than the S&P500 index. The average annual return on these ratios was at least 16.36% and the Sharpe ratio at least 3.70, in comparison with 9.82% and 3.36 for the S&P500 index respectively. The research done was an exploratory study. Based on the results, only some of the portfolios formed outperformed the S&P500 index, so in general no conclusions can be drawn about the superiority of this method compared to the S&P500 index.

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Klusterointiin perustuvien osakeportfolioiden suorituskyky - Tapaustutkimus: K-means-klusterointia koskeva kokeellinen tutkimus S&P500 aineistosta käyttäen valittujen tunnuslukujen yhdistelmiä vuosina 2010–2022

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Tämän tutkimuksen tarkoituksena on selvittää klusterianalyysin avulla, onko olemassa yleisten tunnuslukujen yhdistelmiä, joiden perusteella ylituottoa voidaan saavuttaa S&P500-indeksiin verrattuna. Datana käytetään S&P500-indeksiin kuuluvia osakkeita, niiden hintatietoja sekä tunnuslukujen arvoja vuosilta 2010–2022. Tutkimuksen metodina on tehdä kolmen tunnusluvun yhdistelmiä yhteensä kahdeksasta tunnusluvusta. Näitä suhdelukuja vastaavat arvot ryhmitellään viiteen eri klusteriin K-means -menetelmällä. Analyysiin valitaan klusterit, joiden keskipisteet ovat korkeimmat ja matalimmat, ja muodostetaan "Kasvuportfolio", joka on muodostettu korkeiden tunnuslukujen osakkeista, ja "Arvoportfolio", joka koostuu matalien tunnuslukujen osakkeista. Tällä menetelmällä luotuja salkkuja on yhteensä 112. Arvo- ja kasvuportfolioiden keskimääräisiä tuottoja verrataan absoluuttisesti ja riskikorjatusti S&P500-indeksin tuottoihin ja satunnaisesti muodostettujen portfolioiden tuottoihin. Lisäksi lähemmässä tarkastelussa perehdytään parhaiten tuottaneisiin yksittäisiin portfolioihin.

Tulosten perusteella parhaiten suoriutui neljä kasvuportfoliota. Nämä portfoliot muodostettiin klusteroimalla tunnuslukuryhmiä EV/EBIT, P/CF & EV/EBITDA; EV/EBIT, P/CF & P/E; EV/EBITDA, P/CF & P/B sekä EV/EBIT, P/CF & P/S. Nämä neljä portfoliota menestyivät absoluuttisesti paremmin kuin satunnaisportfoliot, ja niiden Sharpen luku oli korkeampi kuin S&P500. Näiden tunnuslukujen keskimääräinen vuosituotto oli vähintään 16,36 % ja Sharpen luku vähintään 3,70, kun S&P500-indeksin luvut olivat 9,82 % ja 3,36. Tutkimus tehtiin kokeilevana tutkimuksena. Tulosten perusteella vain osa salkuista ylitti S&P500, joten johtopäätöksiä portfolioiden yleisestä menestyksestä ei voida tehdä.

SYMBOLS AND ABBREVIATIONS

S_i	Sharpe ratio
D/E	Debt-To-Equity ratio
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
EV	Enterprise Value
G/S	Growth-in-Sales ratio
P/B	Price-to-Book ratio
P/CF	Price-to-Cashflow ratio
P/E	Price-to-Earnings ratio
ROIC	Return on Invested Capital
WACC	Weighted Average Cost of Capital

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1. INTRODUCTION

The return available from the stock market has attracted investors since the beginning of the stock market. Historically, stocks have outperformed other investments significantly. Investing in an index is safer compared to direct stocks due to the lower risk and lower volatility. Despite this, throughout history, investors have tried to use their returns to beat index investments.

With stock investments, attempts have been made to beat the index in several different ways, one of the most typical of which is to buy inexpensively valued stocks. The subject of this study is to investigate which combinations of key figures are such that it is possible to find systematic excess returns. In addition, this study explores the possibility of automating this stock selection process by looking at the historical performance of stocks. Beating the index in the long term is considered extremely difficult because only a small number of different companies make up a large part of the indices' returns. The S&P500 is a group of the 500 largest publicly traded companies in the United States. Since the 500 largest companies are always quoted in the index, the winning stocks continue in the index, while the losers drop out. This makes it difficult to compete with the stock index.

In this study, an analysis is made based on the indicators of the S&P500 companies and the aim is to explore possible combinations of stock-specific performance indicators that would enable excess returns. Companies are clustered using the most typical indicators and specific clusters are picked as investment portfolios. The returns of the stocks in the clusters are compared to the S&P500 index. In this way, the purpose is to look for key figure -based clusters that could generate excess returns for their owners. The subject of this research is to find out with the help of cluster analysis whether it is possible to form groups in the stocks of the S&P500 index that systematically generate excess returns concerning the benchmark index. The groups are formed by cluster analysis based on the valuation coefficients of the companies.

1.1. Background and Motivation

The motivation of the research is to find a combination of key figures of individual stocks, based on which it would be possible to systematically make an excess return on the stocks of companies in the S&P500 index. General stock-related key figures are for instance valuation ratios, efficiency ratios and leverage ratios. These measure a stock at some level, such as price or the ability to generate additional capital. The purpose is to study possible benefits of a cluster analysis to see whether it is possible to form clusters by combining different key figures that would perform better than the reference index. The purpose is to test the most common valuation coefficients and performance metrics.

The idea for the topic has come from the fact that in previous studies it has been found that there are value anomalies in the studies (Pätäri and Leivo, 2009; Yan and Zhao, 2011; Kim and Ha, 2012). Value anomalies refer to the fact that low-valued companies have outperformed the benchmark index, especially when measured by P/B and P/CF indicators (Cohen, Gompers and Vuolteenaho, 2002; Jokipii and Vähämaa, 2006). There are also several observations about the better performance of a low P/E ratio (Fama and French, 1998). However, little research based on valuation coefficients has been done using cluster analysis, even though cluster analysis itself is a decades-old unsupervised learning algorithm. In addition, the current research efforts made are done with small datasets (El, Guennoun and Hamza, 2012; Akhtar and Rashid, 2015) and not in the US markets which are considered as the most efficient. The goal is to test several key figure combinations and then create a working model that would have achieved excess returns among the world's largest companies within the period of 2010-2022. In addition, the way to find a way to get an excess return on the stock market is always essential information for both private investors and institutional investors. Returns will be examined both in absolute and risk-adjusted terms.

The research will be conducted around three theoretical themes. The theoretical framework of the study will be as follows: investing based on key figures, searching for anomalies in the stock market and using cluster analysis in stock selection. The theoretical framework is presented in figure 1:

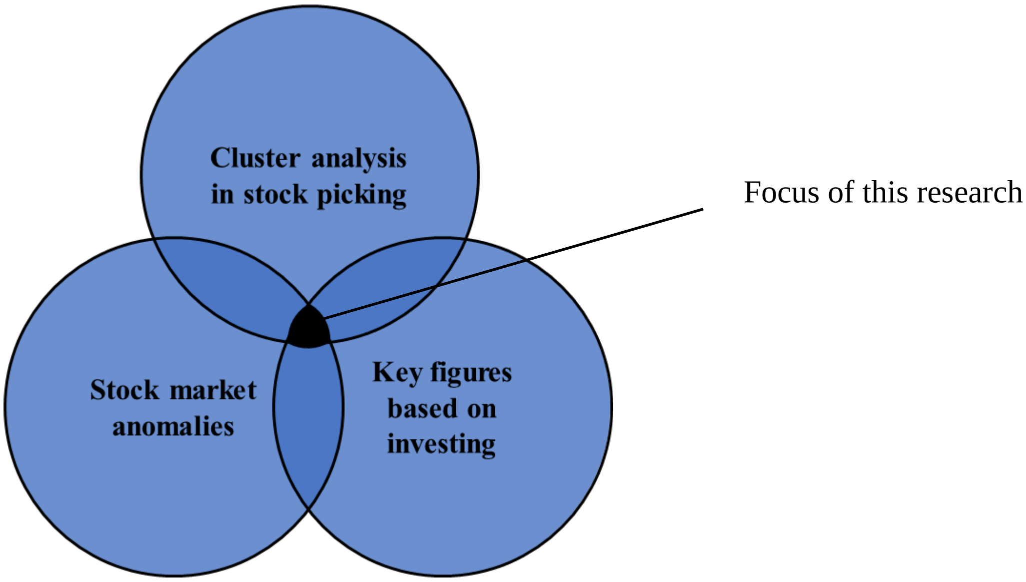

Figure 1. Theoretical framework

In figure 1 is presented the theoretical framework. It coincides with the intersection of Stock market anomalies, Cluster analysis in stock pricing and Key figures based on investing. It gets influenced by all three, which is why this study starts by exploring key figures-based cluster analysis and investigates whether anomalies can be found in the stocks of the S&P500 index in 2010-2022.

1.2. Research questions

The purpose of the study is to examine combinations of different common key figures. The aim is to see if there are combinations of these key figures that can be clustered to identify portfolios that generate excess returns. The first and second research question is therefore formulated as follows:

RQ1: Within the period of 2010-2022, would it have been possible to beat the S&P 500 return index by clustering the index companies by their selected key figures to form stock portfolios?

RQ2: Which of the key figure combinations would have made the best performing portfolios?

Another interesting topic is how well the portfolios perform compared to randomly drawn portfolios. It is essential to know whether the better performing portfolios are statistically significantly better in terms of returns than the randomly selected portfolios. The third research question is therefore posed as follows:

RQ3: If clustering based on ratios has been able to generate excess returns, are the results statistically significant compared to randomly selected portfolios?

1.3. Hypothesis

The assumption is that portfolios based on similar ratios, such as EV/EBITDA, EV/EBIT, P/E and P/B, will perform well if they represent similar companies. It should also be stressed that value portfolios created by these ratios would perform well, based on previous research on value anomalies in general. Previous studies emphasize the past good performance of Value Portfolios when portfolios are constructed based on the most conventional ratios, i.e., P/E, P/B and P/CF (Chan et al. 1991; Yan and Zhao 2011). On the other hand, clusters created with the highest coefficients may perform excellently, and clustering using the k-means method has previously been found that companies with high P/S and P/B ratios have also performed well (Akhtar and Rashid, 2015). Portfolios based on these ratios have been found to outperform the index (Pätäri and Leivo, 2009; Athanassakos and Chair, 2010). Correspondingly, however, a high ROIC is generally thought to be a key figure that creates shareholder value for stocks (McKinsey & Company, 2015, 131). In contrast, the leverage ratio is not highly regarded, as its low level may indicate a particularly profitable business, or in turn, heavy investments in growth, which justifies the inclusion of the leverage ratio. These general ratios can be examined with great interest in this case.

1.4. Data and methodology

The data is based on stocks in the S&P500 index, their daily price data for 2010-2022 and the most common investor-related key figures. The key figures used in this study are EV/EBITDA (Enterprise Value/Earnings Before Interest, Taxes, Depreciation & Amortisation), EV/EBIT (Enterprise Value/Earnings Before Interest & Taxes), P/E (Price/Earnings), P/B (Price/Book Value), P/CF (Price/Cash Flow), P/S (Price/Sales), D/E (Debt/Equity) and ROIC (Return on Invested Capital).

The methodology used is the K-means clustering algorithm for each combination of the three key figures. The key figures are divided into groups of three so that each combination is processed. Once the groups are in place, the corresponding key figures are clustered into a portfolio of high values, the "Growth Portfolio", and a portfolio of low values, the "Value Portfolio". In total, 112 portfolios will be created. The performance of these 112 portfolios is examined in absolute terms compared to each other and compared to the S&P500 index. They are also compared to portfolios that are randomly selected in order to see whether the performance of the portfolios that perform well is due to chance or whether they are statistically significant. Finally, the performance of the portfolios is also risk-adjusted in terms of the Sharpe ratio.

1.5. Limitations

The data source used in this study is Refinitiv Eikon, where all the data used in this study comes from. The data used are annual stock-specific key figures, their price data, S&P500 index price data and the daily US 1 year treasury yield. The single biggest limitation of the study is that the data cannot be extensively validated. In this case, it is therefore necessary to rely on Refinitiv Eikon as a data source. In addition, no guarantees can be made about stock mergers or split adjustments. Another potential problem with the data is that the S&P 500 index can be updated every day the stock market is open. This leads to the fact that companies can enter or leave the index daily, and the companies belonging to the same clusters do not necessarily remain the same from the beginning to the end of each review year. This is not considered in the study, but the portfolios are created by clustering based on the first trading day of the year. Clusters do not consider business transactions either. The data also contains empty values, in other words, the data is not completely uniform for all key figures. However, since there are relatively few missing values, this should not limit the quality of the study very much, but it is good to take it into account. Regarding EV/EBIT, EV/EBITDA, P/B and ROIC figures, the data also contains some negative values. However, negative values are preserved in the data as they have come from Refinitiv Eikon.

Another limitation related to the study is related to the clustering methods. K-means is a simple and efficient way to create clusters, but it also has the problem that it is sensitive to outliers. Other clustering methods are not considered in this study. There is no broad point of comparison for the results of the study because not much previous research has been done with clustering and stock performance. Especially with S&P500 stocks, no research has been done by testing several combinations of different key figures in clustering.

1.6. Structure of the study

The first chapter of the study introduces the topic of the study, the background of the study, and the motivation and formulates the research questions. In addition, it introduces the theoretical framework and presents the limitations of the study, which can negatively affect the conduct of the study. The second chapter introduces the theories used in the study. The theory part includes the clustering method used in this study, the key figures used and the figures that can be used to measure the risk-adjusted return, Sharpe ratio. The third chapter deals with the literature review and introduces what has been previously studied with the corresponding topic, what kind of methods have been used to do it, and what kind of results have been found. The topics deal with clustering related to the performance of stocks and anomalies related to the valuation of stocks in general. The fourth chapter presents the data used as material, describes the modifications made to it, and then presents the research methodology. The fifth chapter presents the results obtained from the study. The sixth chapter discusses the conclusions and makes a summary. Finally, further research questions are discussed, and research questions are answered.

2. THEORY

This chapter provides a general introduction to theoretical concepts, such as the key figures used in the study, as well as clustering and the clustering method used. In addition, this section introduces the Sharpe ratio, which can be used to study risk-adjusted returns and stock market anomalies.

2.1. Market prices indicators

In this study, key figures based on the market price will be used, which will be covered superficially in this section. These ratios are EV/EBITDA, EV/EBIT, P/E, P/B, P/CF, P/S, D/E, and ROIC. In addition, the derivation of EV due to its important role in other key figures will be discussed first. The key figures are discussed for the sake of clarity to distinguish between key figures that are similarly composed.

2.1.1. EV

Enterprise Value (EV) tells the company's debt-free value. Enterprise Value is in several key figures as a second component, for example, EV/EBITDA or EV/EBIT. Unlike purely equity-based key figures, EV-based key figures also take creditors into account. Equity-based key figures consider only the shareholders' share of the company and the income belonging to the shareholders. EV indicates the value at which it would theoretically be possible to buy the company off the stock market or even buy it debt-free on the open market. (Fields, 2003) Mathematically, EV could be described as follows:

$$EV = MC + Total\ Debt - C \tag{1}$$

where MC describes Market Capitalization (Number of Shares multiplied by their market price), Total debt (short and long liabilities) and C describes cash assets and income proportional to them.

2.1.2. EV/EBITDA

The EV/EBITDA indicator considers the previously determined Enterprise Value, in addition to which it considers EBITDA. EBITDA stands for Earnings Before Interest, Taxes, Depreciation and Amortization. It describes the daily operating income of a company, which is the result of operating a daily business after deducting operating expenses such as employee costs, rental costs and the cost of goods sold from turnover. The ratio in question tells how many years the company would make an EBITDA equal to its Enterprise Value if the EBITDA remained unchanged. EV/EBITDA is typically higher than average for faster-growing companies and correspondingly lower for slower-growing companies. Since the cyclicality of depreciation and amortization can have a significant impact on the company's business, a key figure based on EBITDA can be very useful in determining the company's value. (Hitchner 2003, 204)

2.1.3. EV/EBIT

EV/EBIT figure considers company value, but unlike EV/EBITDA, it also considers depreciation and amortization. EBIT comes from the words Earnings Before Interest and Taxes. EBIT is almost the same as EBITDA, but it also considers depreciation and amortisation. These are accounting values, however, and therefore do not directly reflect the profitability of the company's day-to-day operations. EBIT is more accurate than EBITDA in showing the proportion of the company's earnings that is subject to taxes and interest before the money reaches shareholders. This number, therefore, tells the number of years in which the company would make EBIT equal to its debt-free value. Both the EV/EBIT and EV/EBITDA figures are key figures that are used to determine the company's value before mergers and acquisitions, as they take the company's debts into account, unlike, for example, the P/E figure. The rule applies to all these key figures, according to which these numbers are higher than average for companies seeking growth and lower than average for companies in a mature stage. For all these key figures, it should be considered that they can be either reported or possibly adjusted for non-recurring items. (Hitchner, 2017) However, the reported figures are used by default.

2.1.4. P/E

However, in contrast to the ratios discussed earlier, P/E does not consider the creditors' share, but this figure is of interest only to the company's shareholders. The P/E figure tells how many years the company would make a net profit equal to its market value if the result would remain unchanged. The number can be calculated on a rolling basis from the reported last twelve-month period or the results of the previous calendar year. By default, the result of the previous financial year is used. The company price is calculated by multiplying the number of companies' shares by the price of one stock. Earnings, on the other hand, mean the company's net income. These can be calculated either per share or at the company level. (Bodie, Kane and Marcus, 2014)

2.1.5. P/B

P/E is probably the most well-known indicator in stock valuation. Another indicator based on the stocks market value is the P/B ratio. It describes the relationship between the equity price and the book value. Like the P/E ratio, it can be calculated either on a per-share level or a company level, with the help of which the same value can be obtained. The P/B ratio tells you how many times its market value is to the equity according to its balance sheet. (Bodie, Kane and Marcus, 2014) In capital-light industries, it has typically been high, and correspondingly in sectors that tie up a lot of capital, such as basic industry, the P/B figure is usually low. Because of this, it can be assumed that during the last decades, the P/B ratio of the S&P 500 index has been increasing as software companies increase their market value.

2.1.6. P/CF

If the investor had a cash flow statement, income statement, and balance sheet at his disposal in connection with the company's financial statements, and he could only use one, he would choose the cash flow statement. The cash flow statement talks about the company the money that goes out of the company's coffers and that comes in. It tells the actual movement of money before investments are considered. The cash flow should be at least large enough to cover both loan repayments and investment needs. As a key figure, P/CF tells how many years the company would generate cash flow equal to its market value. The figure obtained assumes that the cash flow would remain constant. However, cash flow can vary a lot between different accounting periods. (Bodie, Kane and Marcus, 2014)

2.1.7. P/S

Like the P/B figure, the P/S also varies a lot between industries. P/S tells how many times its market value is to its annual turnover if the turnover were to remain constant. In high-margin industries, such as those operating on the Software as a Service model, the P/S ratio is typically high, while in low-margin industries, the figure is low. Large differences within the same industry are often explained by large differences in profitability. A high P/S figure gives an image of the market's expectations for the company's high growth rate and good profitability. Correspondingly, a low number gives a picture of the market's expectations for the company either for low profitability or slow growth. (Bodie, Kane and Marcus, 2014) However, in most cases, the price-to-sales multiplier is not particularly useful because of the different levels of profitability but can be useful in industries where profits are negative or highly volatile (Koller, Goedhart and Wessels, 2015 373).

2.1.8. D/E

The D/E key figure refers to the number of times the firm's equity (E) could be acquired by the firm's debt (D). However, the E of this key figure refers to a different value than the P/E key figure. This key figure refers to Equity, which is the book value of equity attributable to shareholders and reported on the balance sheet of the firm. In general, the debt-to-equity ratio can be expressed in terms of total debt, long-term debt, or interest-bearing debt. The method of calculation does not always indicate what form of debt is meant. Often the current portion of long-term debt is often excluded in the calculation of the long-term version. However, a problem with using financial ratios based on book value in financial risk analysis is that there is a strong correlation between book value and market value in the value of a stock. (Drake and Fabozzi, 2010) In this study, values provided by Refinitiv Eikon were used, which consider the total debt of the shares.

2.1.9. ROIC

ROIC is an efficiency indicator that measures a company's ability to generate value for investors. ROIC describes how well a company can generate a proverbial return on invested capital. The ratio can range widely between companies and industries, so there is no clear rule for the values it should be assigned. The key point with this key figure is that the return should be higher than the WACC, regardless of the company, to generate shareholder value (Koller, Goedhart and Wessels, 2015, 131). In mathematical terms, net operating profit is divided by invested capital. This number can be calculated using many different methods, but this study uses a formula that is formulated as follows:

$$ROIC = \frac{Net\ Operating\ Profit - Adjusted\ Taxes}{Invested\ Capital} \tag{2}$$

This formula is taken as given by Refinitiv Eikon, and no further position is taken on the correctness of the formula.

2.2. Cluster analysis

The purpose of cluster analysis is to form clusters of data points based on uniform characteristics using a particular mathematical algorithm. Clustering is a data processing technique that uses an unsupervised learning process to find and classify hidden uniform features. In this chapter, the K-means method used in this study to form clusters is presented. It also presents the data normalization method to compare variables. The standardization method is used to put the different variables on the same scale as each other so that clustering can be done consistently.

2.2.1. K-means

K-means is perhaps the most used and well-known clustering method. K-means is one method for non-hierarchical clustering of data, and it aims to divide the existing data in the form of one or more clusters (Hruschka and Ebecken, 2003).

The K-means algorithm is to divide *M* points in *N* dimensions into *K* number of clusters in such a way that the sum of squares within the cluster is minimized (Hartigan and Wong, 1979). K-means is an unsupervised clustering algorithm. All data points used in clustering are used as testing data, based on which the clusters are built. The K-means algorithm takes as input the number of centroids used in clustering. The number of clusters can therefore be a user-defined parameter of the algorithm, or it can be determined automatically (Kubat, 2017). Each centroid defines its cluster. Clustering starts from a situation where K number of centroids are randomly drawn into the vector space.

K-means, the most essential steps are the determination step and the minimization step. In the determination step, each data point is determined to belong to a certain cluster according to its Euclidean distance. In the minimization phase, on the other hand, the centroids are moved to the point where the sum of squares of the distance of the data points assigned to it is minimized. Minimization ends the algorithm cycle. The configuration phase starts again and continues with minimization. Determination and minimization are repeated until the sum of the squares of the centroids of the clusters can no longer be reduced and the clusters get their final shape. (Skansi, 2018)

In mathematical representation, the K-means algorithm is presented by Syakur, Khotimah, Rochman & Satoto according to (Syakur *et al.*, 2018):

1. Determine the number K of clusters and the maximum number of iterations.
2. Perform the initialization process K midpoint cluster and then the equation of centroid count feature
3. Connect all observations to the nearest cluster. Euclidean distance spacing measurements based on the formula 3

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2} \tag{3}$$

4. Reallocate data to each cluster based on a distance-by-distance comparison relative to the clusters' midpoints

$$a_{ij} \begin{cases} 1 & d = min\{D(x_i, c_i\} \\ 0 & otherwise \end{cases} \quad (4)$$

5. Recalculate the cluster midpoint position. a_{ij} is the value of member point x_i to the centres of the group c_1 d is the shortest distance from the data x_i to the group K after being compared, and c_1 s the centre of the group to 1. The objective function used by this method is based on the distance and the value of the data membership in the group.

$$J = \sum_{i=1}^{n} \sum_{l=1}^{k} a_{ic} D(x_i, c_1)^2 \quad (5)$$

n is the amount of data, k is the number of groups, a_{i1} is the membership value of the data point x_i to the c_1 group followed a has a value of 0 or 1. If the data is an anngota of a group, the value a_{i1}= 1. If not, the value a_{i1}= 0.

6. If there is a change in the cluster midpoint position or number of iterations lower amount than the maximum number of iterations, return to step 3. If not, then return the clustering result.

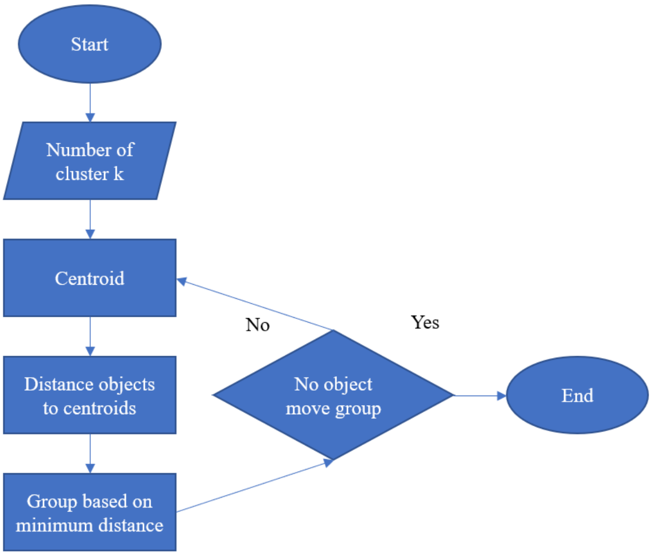

Figure 2. K-means clustering process, adapted from Majumdar, Manole & Nalty (2022)

The chart provided in figure 2 describes in a simplified way how the K-means clustering process works. For a more detailed discussion of the use of the K-means algorithm, its generation, the number of optimal clusters and applications, see for example Jain (2008).

2.3. Z-score normalizing

Z -score normalizing refers to a method in which the data is modified in such a way that each measured variable is placed on the same scale. These variables must have their numerical value and a sufficiently large sample size in common. The purpose of the Z -score is to tell how many standard deviations away from the average of the sample the observation is for each variable. When the different variables are normalized to the same scale, they are mutually measurable, and different variables can be clustered together without the clusters being distorted due to the differences in the scale of the variables. The Z-value can therefore have both negative and positive values.

Z - score is defined mathematically as follows:

$$z = \frac{x - \mu}{\sigma} \tag{6}$$

where x describes the absolute initial value of the sample observation, μdescribes the sample mean, and σ describes the sample standard deviation. (Singh and Singh, 2022)

2.4. Sharpe ratio

Sharpe ratio can be used to compare the risk-adjusted returns of stocks. Sharpe ratio aims to expand the risk-return measure so that portfolio volatility can be considered. The Sharpe ratio, therefore, reflects how much the portfolio has produced about the risk it carries. The goal of investors is to invest either with the index with the same risk, but with higher returns, or to reach the same return as the index, but with less risk. The goal is to get the best possible risk-adjusted return. According to the mathematical definition, Sharpe's number follows the following formula (1966):

$$S_i = \frac{E[r_i - r_f]}{\sigma_i} = \frac{E[r_i - r_f]}{\sqrt{Var[r_i - r_f]}} \tag{7}$$

where $r_i$describes the return of the stock portfolio, $r_f$is the return of the risk-free benchmark index and $\sigma_i$describes the volatility of the portfolio.

A positive Sharpe number indicates profitable risk-taking, and a negative one indicates unprofitable risk-taking. In this study, the S&P500 index will be used as a reference index, which is considered a risk-free option here. Risk-adjusted return indicator Sharpe's ratio is based on five assumptions regarding stock trading (Jensen, 1968).

1. All shareholders want to avoid risk and want to maximize returns.
2. All investors have the same decision horizons and the same assumptions about investment opportunities.
3. All investors can choose their portfolios based on return expectations and return variability.
4. Taxes and transaction costs are zero.
5. All shares can be divided into parts without limit.

2.5. Anomalies of stocks valuations

Anomalies are recurring events in the stock market that have made it possible to make excess returns. It has not always been possible to explain these events, although one can be sure of their recurrence. Such anomalies are, for example, the January phenomenon, where stocks have been found to perform well on average and excess returns based on outperforming stocks with low key figures. This section discusses anomalies based on key figures.

There have been several anomaly observations related to identification numbers. Yan and Zhao (2011) made observations related to both key figures and quarterly earnings releases. They used the closing prices of stock prices from 1984–2008 as data, in addition to which they studied the reactions of stock prices to earnings announcements. They divided the stocks used into quintiles based on stock price valuations. E/P, C/P and S/G (Growth in

Sales) ratios were used as valuation metrics. They found that value stocks outperformed growth stocks after good interim reports. In addition to this, the findings revealed that value stocks move both positively and negatively less than growth stocks. Value stocks were found to be more stable than growth stocks and perform better, especially in the long term. (Yan and Zhao, 2011)

For a long time, the traditional view regarding the returns on stocks has been that excess returns can be made based on their valuation coefficients. In addition to this, however, it has been noticed that the mood of investors plays a significant role in determining prices, especially for small companies (Kim and Ha, 2012). Kim and Ha (2012), who conducted research on the Korean stock market from 1994 to 2008, found that investor sentiment significantly affects the returns of investment portfolios made up of value stocks. Their results suggested that investor sentiment systematically affects the stocks of Korean companies with small sizes, low prices, and low market value (Kim and Ha, 2012). Similar results were obtained by Banz (1981) after studying the 1926–1975 stock returns on the New York Stock Exchange. He found that small companies had significantly higher risk-adjusted returns compared to large and medium-sized companies. This phenomenon has been explained by the high value of the E/P ratio, although at the same time, it can be stated that the E/P ratio and the size of the company largely influence each other (Reinganum, 1981). Looking at the E/P ratio, Chan, Hamao and Lakonishok (1991) achieved almost statistically significant research results in the Japanese stock market from 1971–1988. On the other hand, according to them, B/P and CF/P, especially for small companies, were even more significant ratios for the excess return on stock prices. Also, Fama and French (1992) found that stocks perform best when undervalued with a B/P ratio.

Stocks with both expected and realized profitability higher than the benchmarks could be seen to have been lower risk in the US stock market from 1979-1993 (Haugen and Baker, 1996). Similar results on profitability were obtained by Cohen, Gompers and Vuolteenaho (2002) after studying cash flow-based news. They found that stocks made excess returns from 1983 to 1993 when stocks underreacted to positive cash flow news (Cohen, Gompers and Vuolteenaho, 2002). The cash flow-based anomaly has been studied extensively on a general level. The anomaly of positive free cash flow, the low level of multiples based on it, and the low leverage ratio have also been found in the Finnish stock market in 1992-2002 (Jokipii and Vähämaa, 2006). On the other hand, Jokipii and Vähämaa observed the success of such stocks with companies with large market capitalization, although excess returns with high E/P and B/P ratios have been observed more widely among small companies (Reinganum, 1981; Chan, Hamao and Lakonishok, 1991; Fama and French, 1992; Jokipii and Vähämaa, 2006).

Value and growth investing have been compared to each other many times. Lakonishok, Shleifer and Vishny (1994) compared investment strategies in the US stock market from 1963-1990 using E/P, CF/P, B/M and S/G (Growth in Sales) ratios. Growth stocks were noticed to significantly underperform value stocks, especially when measured by the CF/P ratio. Companies with low CF/P ratios had a better annual return (20.1%) than companies with high ratios (5.6%), and in addition, value stocks had significantly lower (Lakonishok, Shleifer and Vishny, 1994) volatility. The same comparison was made by Dhatt, Kim and Mukherji (2004) when doing research based on B/P, E/P, CF/P, S/P and the company's market value. They built a total of 11 different combinations based on these key figures and found that a low P/S ratio provides the highest excess return, while a low P/CF provides the best risk/return ratio. Pätäri and Leivo (2009)also came to similar conclusions when they studied the Finnish stock market. They found that when stocks were sorted by valuation multiples EBITDA/EV, CF/P, D/P, B/P, S/P, the value portfolio generated excess returns that were not achievable with growth portfolios or market portfolios (Pätäri and Leivo, 2009).

Fama and French (1998) studied the success of value stocks on the largest stock exchanges from 1975 to 1995. They found that the P/CF anomaly works in 12 out of 13 stock markets, and with the other indicators used, value stocks were found to produce better than growth stocks. These indicators were E/P, B/P and D/P. (Fama and French, 1998) Athanassakos and Chair (2010) also study the returns of value portfolios between 1985 and 2006 for companies in the S&P500 index. They found that portfolios based on low P/E and P/B ratios had significantly better returns than the rest of the market. The value premium was observed to be particularly strong for stocks in the NASDAQ index, and they found it to be significantly stronger than in previous studies (Athanassakos and Chair, 2010).

3. LITERATURE REVIEW

In this section, previous studies are discussed stock key figures and clustering in stock research in general. The literature review was conducted by searching Google Scholar and the LUT University Primo service for research articles. The search terms used were "Stock market cluster analysis", "K-means stock market", "K-means predicting stock markets", "Cluster analysis". In addition, the corresponding words related to stock market prediction by clustering were used separately as search terms. Materials were selected on the basis of their relevance to the research to be carried out and to ensure that they were cited as much as possible. Studies with fewer than 10 citations were excluded.

3.1. Use of cluster analysis in stock market

Nanda, Mahanty, and Tiwari (2010) clustered stocks from the Indian Stock Exchange of 2007 and created clustering portfolios using K-means, fuzzy C-means, and SOM neural network methods. They used P/E, P/B, P/CEPS (Price to Cash Earnings Per Share), EV/EBITDA and Market cap/Sales. They analysed the returns of a total of 106 stocks. They propose that the results could be applied to asset management, algorithmic trading, and technical information processing for investors in financial markets. They found that out of the tested set of clustering algorithms the K-means method to create tighter clusters compared to the other methods.

El, Guennoun, and Hamza (2012), in turn, used the K-means method to study the optimization of equity portfolios by minimizing their risk. They first used the K-means clustering algorithm to classify stocks, followed by the dynamic optimization algorithm MinVaRMaxVaL. They found this method-based portfolio to be satisfactory based on simulations as it resulted in better performance compared to the initial portfolio. They used Moroccan stock prices for 2008–2010 as data consisting of 48 stocks.

In contrast, the K-means and Fuzzy K-means clustering methods were compared by examining the banking and energy sectors clustered by Al-Augby, Majewski, Majewski, and Nermend (2014). In their study, they found the clustering methods to be independent of each other concluding to recommend the Fuzzy K-means method as it was found to be more flexible than the traditional K-means method. They used the Gulf Cooperation Council stock markets of the banking and energy sectors, with 86 stocks in the banking sector and 19 stocks in the energy sector in October-December 2012 as their data set.

In 2016, Bini and Mathew (2016) studied stock market forecasting by comparing different clustering techniques and then regressing the clustering results. They used the Indian stock market with 1,232 stocks for January 2015 as their data set. They used open, close, high, low previous close and average price for clustering and classification. They studied K-means, EM (Expectation Maximization), Hierarchical technique, and DBSCAN (Density-Based Spatial Clustering of Applications with Noise) as clustering methods and they observed that K-means and EM were the best methods.

Cheong, Kim, Byun, Oh and Kim (2017) attempted to predict Korean stock markets between January 2007 and January 2014 by developing a portfolio optimization strategy based on clustering. Their proposed model was based on the Generic Algorithm method and obtained significant results in terms of both return and risk as measured by Sharpe ratio. They found in their research that investor behaviours can be used to generate investment strategies.

Zuhroh, Rofik, and Echchabi (2021) investigated the impact of macroeconomic factors on Indonesian listed stocks from 2016 to 2019. They used the k-means method as a clustering method and dynamic panel data regression after clustering. As data, they used the monthly prices of 28 listed stocks. They found that clustering revealed unique characteristics and opportunities for return optimization. They found also that stock prices, which are highly correlated with interest rates, exchange rates and inflation, are the most suitable for long-term investments. In contrast, the moderately correlated cluster performed better in the short term.

Shin and Sohn (2004) investigated three clustering methods, namely K-means, self-organizing map, and fuzzy K-means to find properly graded stock market brokerage commission rates based on the 3-month long total trades of two different transaction modes, representative assisted and online trading system. They used customer data from 1999, with a total number of observations of 3,000 customers. They found fuzzy K-means to be the best approach for segmenting customers of both trading modes.

K-means and K-medoid methods were studied on Indonesian stock market data for 2018–2020 by Medellu and Nugraha (2021). They investigated the characteristics of clustering and found that the K-means method can generate better clusters concerning the K-medoid one. The K-means method has also been used by Lee, Lin, Kao, and Chen (2010) to study the prediction of short-term stock movements after a financial review. Using stocks of S&P500 companies from 1995-2008, they found that the HRK method they created performs better than the SVM. They used the train-test method, with 20,884 observations in their training data and 5,371 observations in their test data.

Renugadevi, Ezhilarasie, Sujatha, and Umamakeswari (2016) seek to minimize risk in the Indian stock market. In their study, they considered 22 trading days and used Hierarchical Agglomerative Clustering (HAC) first and then K-means clustering as methods. They observed that K-means clustering selects a better cluster center as the sample size is reduced.

Aslam, Bhuiyan, and Zhang (2023) also studied stock returns as a criterion for selecting portfolios based on clustering. They applied the 2010-2021 Malaysian stock market as their data and the K-means method as their clustering method. The total number of observations in the data they used was 695. They selected the clusters that had higher risk-adjusted returns in terms of Sharpe ratio for portfolio selection. As a result, they found a strategy that had the potential to achieve higher risk-adjusted returns for investors.

In contrast, Wu, Wang, and Wu (2022) used the K-means method as part of the strategy they created to improve returns and reduce risk in stock portfolios. They select the appropriate stocks for portfolios and calculate the right weights for them. For the data, they used trading data from 2001 to 2020 on the Chinese stock market, which included a range of trading-related figures. It covered 400 stocks, each with daily data on stock codes, opening prices, closing prices, the highest prices, the lowest prices, trading volumes and trading amounts. They were able to predict stock market trends and thus outperform.

The relationship between ratios and stock price performance has been studied by (Akhtar and Rashid 2015), who examined the valuation of stock prices in terms of the key figures P/E, P/B, P/CF as well as P/S. They used Pakistani stock price data from 2004 to 2011 as a dataset. These ratios were found to have the highest explanatory power together compared to separately. In addition, they found that investors can earn higher returns by investing in stocks with high P/B and P/S ratios.

The performance of the K-means and K-medoid methods was also compared by Herman, Zsiko, and Zenyves (2022) when they examined the success of combinations of ROS, ROA, and ROE ratios. They used stock price data of Romanian and Hungarian food retail companies as data. As data they had 690 Romanian stocks and 211 Hungarian stocks. Their results suggest that the method chosen to group stocks can affect the financial performance of firms: the K-means method produces a larger set of different groups and the results obtained after grouping are broader, while the K-medoid method has a significantly more balanced group distribution and results.

3.2. Summary of the literature review

Previous studies on clustering and stock prices have examined several different aspects. Stock price returns have been studied by clustering returns on ratios in several studies (Nanda, Mahanty and Tiwari, 2010; Akhtar and Rashid, 2015; Herman, Zsido and Fenyves, 2022; Aslam, Bhuiyan and Zhang, 2023). In addition, stock price prediction has been done over shorter time horizons by predicting stock prices using clustering of trading parameters (Shin and Sohn, 2004; Wu, Wang and Wu, 2022). The time periods and the size of the datasets have varied significantly. Several studies have used observation sets of tens of stocks as data sets (El, Guennoun and Hamza, 2012; Zuhroh, Rofik and Echchabi, 2021), some hundreds (Nanda, Mahanty and Tiwari, 2010; Al-Augby *et al.*, 2014; Herman, Zsido and Fenyves, 2022; Wu, Wang and Wu, 2022; Aslam, Bhuiyan and Zhang, 2023) and some in the thousands (Shin and Sohn, 2004; Lee *et al.*, 2010; Bini and Mathew, 2016). Portfolio rotation has been performed in long data sets on an annual basis (Nanda, Mahanty and Tiwari, 2010; Aslam, Bhuiyan and Zhang, 2023) or in shorter cycles such as daily, weekly, monthly or every three months (Nanda, Mahanty and Tiwari, 2010).

Research approaches have largely been history-oriented (Shin and Sohn, 2004; Nanda, Mahanty and Tiwari, 2010; Al-Augby *et al.*, 2014), but have also included predictive models using train-test datasets to make forecasts (Lee *et al.*, 2010). A recurring finding has been that almost always, learning a model from history and using it to predict the future yields better results compared to a benchmark index. On the other hand, it has been found that it is possible to find a portfolio that repeatedly outperforms using a variety of methods. In the past, K-means has been well suited to creating portfolios that outperform the benchmark index. K-means and K-medoid methods have been compared in several studies (Medellu and Nugraha, 2021; Herman, Zsido and Fenyves, 2022), and K-means has been found to be better suited as a clustering method for finding outperformance. In the literature, k-means clustering has also performed well in other studies compared to the benchmark index, which is why it is also chosen as the clustering method used in this study.

Table 1. Use of cluster analysis in stock market literature review

Author(s)	Published	Country	Methods	Data set size	Research questions	Results
Aslam, Bhuiyan ja Zhang	2023	Malesia	K-means	695	Is it possible to create an excess return-generating strategy by clustering stocks?	It is possible to risk adjust using the Sharpe ratio
Wu, Wang & Wu	2023	China	K-means, MV theory, t-SNE, DELM	400	Is it possible to automatically adjust stock positions based on a continuous trend and thus generate excess returns?	Market downtrends and uptrends can be predicted, allowing for excess returns
Herman, Zsiko & Zenyves	2022	Hungary & Romania	K-means & K-cendroid	690	What are the performance differences between clustered portfolios generated by K-means and k-cendroid?	K-means wider range of performance and more precise dispersion than K-medoid
Affonso, Mangela , Dias and Pinto	2021	U.S.	K-means, LSTM	-	Can clustering and neural networks be combined to predict stock prices?	The results are in the right direction, but no conclusions can be drawn.
Zuhroh , Rofik and Echchabi	2021	Indonesia	K-means	28	How do macroeconomic factors affect stock returns?	Stocks with the highest returns are the most resistant to changes in stock prices.
Medellu & Nugraha	2021		K-means, K-medoid	-	Which method creates better clusters?	K-means

Muangprathub, Intarasit, Boongasame and Phaphoom	2020	Thailand	K-means	-	Can SMA-PCR-N make an excess return compared to portfolios created on the basis of traditional SMA?	SMA-PRC-based clusters were better than SMA-based ones when using K - means clustering method
Cheong, Kim, Buyn , Oh and Kim	2017	South Korea	K-means, Genetic algorithms	-	Is it possible to make excess returns on the Korean stock market by clustering and optimizing stock weights?	Excess returns can be achieved by clustering investors into groups and then weighting the stocks Genetically using an algorithm.
Bini and Mathew	2016	India	K-means, Expectation Maximization, Hierarchical algorithm, DBSCAN	1,232	Which of the four different clustering methods is the best?	K - means and EM are the best methods
Akhtar and Rashid	2015	Pakistan	Regression analysis & K-means	-	How do clustered portfolios based on valuation multiples perform?	Clusters with high P/S and P/B ratios performed best
Al Augby , Majewski , Majewska , Nermend	2014	Bahrain, Saudi Arabia, Qatar, Oman and the United Arab Emirates	K-means, fuzzy c-means	105	Compare two different clustering methods in the banking sector of the stock market	The recommendation is to use fuzzy K -means
El, Guennon and Hamza	2012	Morocco	K -means, MinVaRMaxVaL	48	Can clustering reduce the risk of the stock portfolio and improve returns?	The risk could be reduced and the performance better when they were examined separately.
Nanda, Mahanty and Tiwari	2010	India	K-means, SOM, Fuzzy K-means	106	Can the risk be minimized without significantly reducing the return?	The risk can be reduced, the risk-adjusted return will increase

Lee, Lin, Kao, ja Chen	2010		HRK (Hierarchical agglomerative and Recursive K-means clustering), SVM	26,255	Does the HRK method they generate, and use perform better than the SVM in predicting stock prices after financial reports?	HRK performs better
Shin & Sohn	2004	3,000	K-means, fuzzy K-means self-organizing map	-	What is the most efficient way to segment stock market brokerage commissions to clients?	The best method for this is fuzzy K-means

Table 1 describes the studies covered in section 3.1 , their authors, used dataset, and the year of publication. The research questions and their answers are also presented.

4. DATA AND METHODOLOGY

This section discusses the data used in the research and the methodology applied to it. In addition, this section discusses the pre-processing of the data and presents the other characteristics of the data and its scope.

4.1. Data

In this study, the data used are the stocks of the S&P500 index for the period 2010-2022. The 13-year reference period used in this study has been chosen on the basis of the quality of the data available. At the beginning of each year under consideration, the price data of the stocks included in the index are collected from Refinitiv Eikon. In addition to the price data, Eikon was used to retrieve common key figures for these stocks, which are used in this study. The key figures used are EV/EBITDA, EV/EBIT, P/E, P/B, P/CF, P/S, D/E and ROIC. The key figures used are chosen for the choice of the research. The ratios used are also commonly used ratios that describe valuation ratios, the leverage ratio and capital generation capacity. In addition to the key figures and price data, daily price data of the S&P500 index at the closing price and daily data of US one year treasury yield are imported from Eikon to illustrate the risk-free return. For the first trading day of each year under consideration, the previously mentioned indicators are taken so that the clustering was done at the same point in time, repeatedly and continuously. This study does not consider trading costs and taxes that would in reality reduce realised profits. In addition, dividends in any form were not considered in this study. Dividends are therefore not received as a return on each portfolio and cannot therefore be reinvested.

Three files were downloaded from Refinitiv Eikon. One contained the stock indicators for each year of the S&P500 index separately for the first trading day of the year, their tickers and the annual figures for the stocks and indicators. The second file contained price data for the corresponding stocks as time series data daily, so that the stocks on the first trading day of each year were included for the whole of the following year. The third file contained the values of the S&P500 index for the whole period under review, the dates, and daily data of US one year treasury yield.

Data was retrieved from Refinitiv from Eikon with Microsoft Excel. Data was exported as a csv file to RStudio, where the research itself was conducted out. The data was processed using RStudio and code by Topi Issakainen. The data was exported on an annual level per file, where the data was read, clustering were done, and portfolio-specific returns were calculated. Risk-adjusted returns were calculated either in Microsoft Excel or RStudio.

It was worth noting that the ratios and stock price data were taken as they were provided and calculated by Refinitiv Eikon and cannot been guaranteed to be correct. Data was imported directly from Refinitiv Eikon, and its correctness cannot be fully guaranteed. There may have been differences between the different units, depending on the calculation methods used. The study did not consider the transaction costs that would occur in portfolio changes each year. The income from the stocks was considered when they were received from Eikon, and no opinion was taken on whether the stocks include splits, mergers of shares, stock dips caused by dividends or cancellations of own shares. Correspondingly, key figures for the stocks were processed as they were received from Refinitiv Eikon, and therefore no position was taken on negative cash flows, EBITDA, EBIT, Book Value or Earnings.

4.2. Data pre-processing

The data was pre-processed into a format in which it can be processed by R programming afterwards. The stock price data was imported from Refinitiv Eikon into an Excel file, where it was put into the same format and easily processed. Stocks may be removed from the index in the current years for several reasons. The most common reasons for such a procedure were that a company was delisted from the stock exchange, its public listing was terminated, it went bankrupt, or, for example, the market value decreased substantially or there was little trading, which causes it to be removed from the index. In such cases, the price of the stocks after the end of trading was recorded as the price at which they were traded at the last price at which they were included in the index. If, on the other hand, the key figures EBIT, EBITDA, Book value or Earnings were negative, they were set to zero, as Refinitiv Eikon did not have negative values available. Similarly, as with stocks, the US 1 year treasury yield was recorded as the previous day's value if it was not otherwise available. The number of trading days was the first 248 trading days of each year for each index stock, the S&P500 index and the US 1 year treasury yields respectively. 248 trading days were chosen for practical reasons, so that each year under consideration had the same number of trading days.

Most of the key figures applied function as such, as the assumption was that small values were positive and large values were negative due to the valuation multipliers. In contrast, ROIC ratio was treated by raising it to the exponent -1, so that the small values obtained were better and the large ones were worse. The clustering could subsequently consider clusters with low values as value clusters and clusters with high values as growth clusters. Other key figures were not treated in a similar way before clustering but were taken from Refinitiv Eikon without being treated.

Table 2 shows the number of observations in the unprocessed data for the period 2010-2022, along with the most common and frequent data figures for each key figure. The number of samples depends on the key figure, as not all key figures were available from Refinitiv Eikon. The outermost edges of the sample were very far apart, and the standard deviations were high, making it necessary to remove outliers. The most common features of the key figures are presented table 2:

Table 2. Unprocessed data from Refinitiv Eikon

	MAX	MIN	AVG	MEDIAN	STD	SAMPLE SIZE
EV/EBITDA	36 138.8	-14.91	21.19	11.13	454.23	6 369
EV/EBIT	6 164.1	-8.65	25.82	15.44	120.93	6 249
P/E	17 737.37	0.8	39.78	20.41	301.11	5 910
P/B	2 785 410	-10 036.90	437.85	2.70	34 731.59	6 432
P/CF	6224.39	0.04	20.00	12.72	137.16	6 121
P/S	54.35	0.05	3.22	2.10	3.50	6 426
D/E	42210	0.02	168.89	72.10	1 074.87	6 065
$ROIC^{-1}$	23.34	-247.05	0.09	0.09	3.27	5 908

Before clustering, the data should be normalized to remove outliers. The data was normalized by the z-score method using R programming. Once the data was normalized, outliers were removed by excluding all stock ratios that exceed 3 standard deviations from the mean for that ratio or, respectively, fall below 3 standard deviations. 3 sigmas have been chosen for the analysis to remove the largest outliers from the data. Statistically, values within three sigmas of the mean represent 99.7% of all observations under the assumption that the observations are normally distributed. This means that 0.3% of all observations for each key figure were selected as outliers. However, it should be noted that outliers for all ratios were not necessarily the individual ones, and overlaps between different ratios were possible. These stocks were not considered for clustering and outliers were eliminated. The purpose of this data cleaning was to make the data more consistent and homogeneous. The aim of more uniform data was to allow easier and more meaningful clustering results, so that the most distant centres of the clusters were not located so far apart. The normalisation of the data therefore aims to improve the quality of the clusters. Portfolio returns were expected to be steadier with larger clusters and less volatile than without data cleaning. The data were then re-standardized by z-score.

When only companies with values for all ratios and standard deviations below 3 standard deviations in either direction were included, 5 070 observations remain. The largest outliers and companies with no data cells were filtered out of the samples. The most typical ratios were shown below to illustrate the data used in the study. The study uses the accompanying data by re-normalizing it, so that the observations for each ratio become normally distributed. It should be noted that the observations include observations from 2010 to 2022 for the first trading day of each year for the stocks in the S&P500 index, and was therefore a large sample of indicators, so they may have varied significantly between years. The features of the key figures after pre-processing are shown in the table 3:

Table 3. Key figures after pre-processing

	MAX	MIN	AVG	MEDIAN	STD	SAMPLE SIZE
EV/EBITDA	540.81	-11.02	12.61	10.8	11.03	5 070
EV/EBIT	330.93	-6.83	18.72	14.86	16.08	5 070
P/E	553.33	0.8	27.02	19.7	32.70	5 070
P/B	856.45	-334.42	4.88	2.85	21.93	5 070
P/CF	403.29	0.04	14.05	12.24	10.80	5 070
P/S	13.71	0.07	2.81	2.02	2.44	5 070
D/E	3 380.93	0.02	122.53	71.39	231.39	5 070
$ROIC^{-1}$	8.36	-20.4	0.12	0.09	0.42	5 070

With these stocks, it was possible to create more stable clusters when the outliers were not influencing the cluster centres in their direction. Once the data was normalized and filtered out the outliers, clusters containing more observations can be expected, and thus the clusters will be of better quality. Some of the key figures do not include data for specific stocks, so because of this and the outliers, the initial data to be processed was decreased slightly. This would affect the clustering so that the max and min cluster centroids would be closer together compared to the unprocessed data. The annual numbers of stocks included in the study are shown in the table 4vbelow:

Table 4. Number of companies in S&P500 index & Companies without data or outliers

YEAR	NO OF COMPANIES IN S&P500	COMPANIES WITHOUT OUTLIERS OR DATA
2010	500	312
2011	499	369
2012	500	406
2013	500	398
2014	500	405
2015	502	421
2016	504	404
2017	506	402
2018	505	393
2019	505	410
2020	505	405
2021	505	358
2022	505	387
OVERALL	**6 536**	**5 070**

4.3. Methodology

This section presents the methodology used in the study. The methodology details the clustering process, portfolio returns and the random portfolio method for measuring the goodness of the results.

4.3.1. Clustering process

The purpose of this study was to investigate whether excess returns can be found in the S&P500 index when portfolios of stocks were created by clustering combinations of different ratios three at a time. The clusters with the lowest and highest cluster midpoint were selected as the stock portfolio. The lowest cluster was referred to here as the "Value portfolio" and the cluster with the highest midpoint was referred to as the "Growth portfolio". Figure 3 outlines the clustering process for this study:

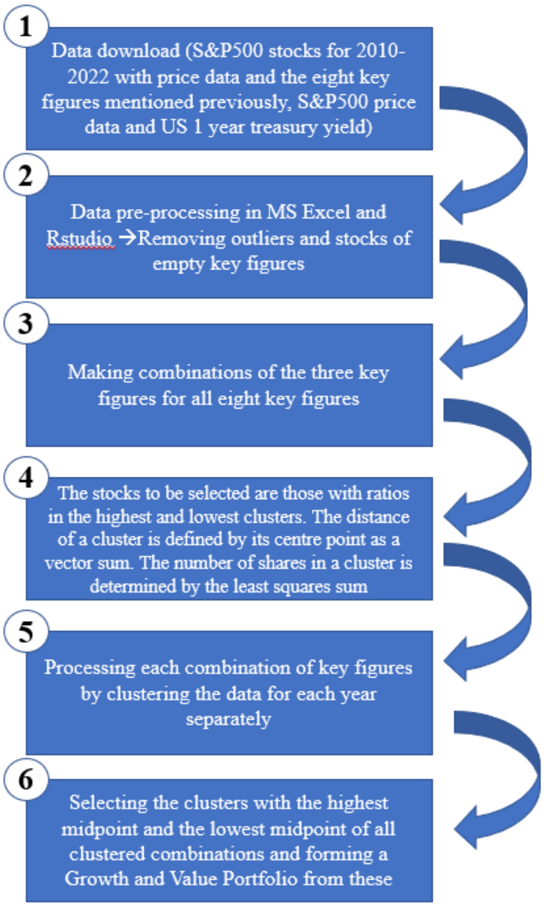

Figure 3. Clustering process in this study

The clustering and the processing of the clusters formed was done using R programming with the data stored in Excel files. In the data pre-processing stage, all outliers were removed from the data so that all values that were more than three standard deviations away from the mean of the indicators were eliminated from the analysis. After this filtering, the sample was normalized for each key figure so that the observations were normally distributed. The z-score method was used as a normalization tool, where the observations were normalized by the standard deviations.

The K-means clustering method has been used in previous studies and has shown good results (Medellu and Nugraha, 2021; Herman, Zsido and Fenyves, 2022; Aslam, Bhuiyan and Zhang, 2023). The purpose of this study was to examine a wide range of combinations of key figures and find the combinations that produce excess returns. The clustering was performed with one year at a time, the companies included in the S&P500 index for that year and 3 ratios for each year. All combinations of ratios were reviewed separately and on an annual basis. The purpose was therefore not to optimise the returns of these clustered portfolios, so the K-means method can be considered a suitable clustering method. For this reason, the number of clusters was also left out of this study, and a standard number of five clusters was chosen, based on studies such as those by Reinganum and Kim and Han (Reinganum, 1981; Kim and Ha, 2012), who divided their data into equal parts by quintile. The Value and Growth clusters were separated from the other clusters so that the stocks in the cluster with the highest average score were placed in the Growth portfolio and the stocks in the cluster with the lowest average score were placed in the Value portfolio. The order of the midpoints was calculated in this case based on the sum of the dimensions to be clustered, i.e., a vector sum was used for the three dimensions. The number of shares in the cluster was formed by initially setting five points on the coordinate grid. The different observations were first assigned to a particular cluster based on which observations were closest to the clustering point. The algorithm used to assign the observations to clusters was based on the combination that summed up to the least squares. Once all the observations in the clusters were classified by distance, the clustering point was moved so that it was at the weighted midpoint of the clusters it belonged to. Again, the sum of squares was minimized and then the clustering midpoint was moved. Clusters can have a highly variable number of observations among themselves because of observations weighted at very similar points, and because at the extremes the differences between observations and cluster midpoints were significantly larger. When five clusters were created each year for all combinations, the cluster with the highest midpoint was selected for the Growth portfolio and the cluster with the lowest midpoint was selected for the Value portfolio. This gives a total of 56 Value portfolios and, conversely, the same clustering is used to select the clusters with the highest midpoints as the Growth portfolio. In total, 112 portfolios will be generated. This is repeated annually, and the returns are invested evenly according to the clustering of the following year. The clustering was performed in 25 iterations to maximise the stability of the clusters. 25 iterations have been shown to be a relevant but effective number for the basic k-means method (Rauf, Sheeba, Khusro, Javed, 2012).

From the clustering, all clusters formed with the smallest possible value of the centre point were extracted separately. They were stored in a cluster file, which indicates which companies were in the cluster, according to which indicators it was made and whether it belongs to the "Value cluster" or the "Growth cluster". A growth cluster included all the companies whose cluster centre receives the highest possible value. The size or smallness of the midpoint was measured by the sum of the different dimensions. The smallest sum led to a value cluster and the largest sum to a growth cluster. The number of shares in a cluster was determined by the K-means algorithm, where a predetermined number of centres were placed on a coordinate grid. These centroids were changed so that the position of the centroids no longer changes and the sum of squares of the observations in each cluster was minimised with respect to their centroids. The clustering was thus based on the ordinary least squares method and works in R programming with the syntax kmeans(). Ordinary least squares refer to the situation where the sum of squares of observations with the assigned cluster was the smallest possible.

Clusters were formed for all different combinations and for different years and stored for later use. The total number of combinations to be used was 56, of which two clusters were considered for each combination. This will result in 112 portfolios to be considered. New companies added to the portfolios each year, giving a total of 1456 clusters.

4.3.2. Portfolio returns

The process of calculating portfolio returns is shown in figure 4:

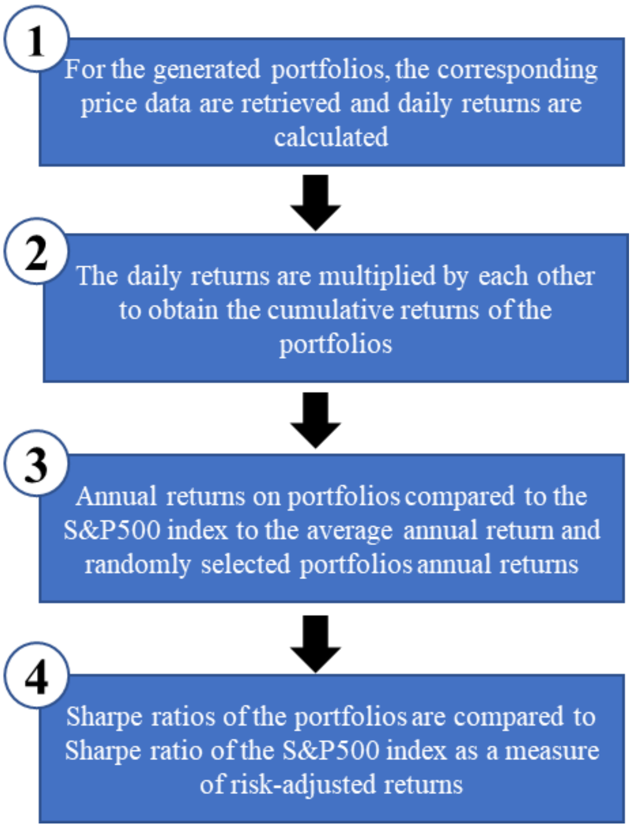

Figure 4. Portfolio returns calculating process

In the phase following clustering, the aim was to examine the returns of the clusters formed, both in absolute terms and in terms of risk adjustment. Returns were measured by finding stock prices retrieved from Refinitv Eikon for the stocks in the clusters created and generated portfolios for the first trading day of each year, equally weighted to all stocks in the portfolio. Portfolio returns were recorded daily for subsequent risk adjustments. Portfolio returns were captured, and the portfolio returns were reallocated to the portfolio for the following year. The portfolio returns were always invested in the stocks of the corresponding cluster for the following year, which were always constructed on the same basis as the previous corresponding portfolios. For example, a Value Portfolio clustered based on P/E, P/CF and D/E multiples with cumulative returns from the beginning to the end of the period was an example of such a portfolio, which was always formed using the same formula.

The result was a return of 112 portfolios, half of which were constructed as Value Portfolios and half as Growth Portfolios. The value portfolios were selected by picking, both on a composite basis and on an annual basis, the stocks in the cluster with the lowest vector sum midpoint of the five clusters. The cluster with the highest vector sum at the midpoint was selected as the Growth portfolio. Thus, two clusters were used for each clustering on an annual and combinatorial basis. First, portfolio returns were compared with other portfolios and the S&P500 index. The returns were obtained by multiplying the daily returns by the portfolio returns for the previous days. The absolute returns of the equity portfolios were examined first, looking at which portfolios had outperformed, and which have outperformed the S&P500 index.

Portfolio performance was measured in two different ways: using the Sharpe ratio and in absolute terms by comparing the performance of portfolios to randomly selected portfolios of 50 stocks. Since the average cluster size was expected to be around 100 stocks, but the value and growth clusters were assumed to be smaller on average due to the normal distribution of the data, a random portfolio of 50 stocks was chosen. The assumption here is that, based on the normal distribution, the dispersion is largest at both the largest and smallest tail, which is why the quantity is calculated from the average downwards. Sharpe ratio measures how well stock portfolios perform relative to volatility and risk. Sharpe ratio has to be positive for an investor to get a return on the risk he was taking. The comparison was also made against the Sharpe ratio of the S&P500 index, and a deeper look was taken at those stocks that outperform the S&P500 as measured by the Sharpe ratio. The second measure of return was randomly valued portfolios.

The absolute Compound Annual Growth Rate (CAGR) returns of the clustered portfolios were compared both with the CAGR of the S&P500 over the corresponding period and with the returns of randomly valued portfolios. Clustered portfolio returns that were more than two standard deviations from the average of random portfolios could be interpreted as having better returns than purely randomly valued portfolios at the 95% confidence level. Returns were compared with average annual growth rates for a randomly valued portfolio. Finally, the portfolios and their returns were analysed by comparing the Sharpe ratio and the average of the random portfolios to the standard deviation.

4.3.3. Random portfolio

In addition to the Sharpe ratio, the performance of portfolios was examined using random portfolios. Random portfolios were generated to investigate whether randomness has anything to do with the clustered portfolios, or whether the clustered portfolios perform significantly better than the randomly generated portfolios (Burns, 2006). Thus, comparisons with randomly generated portfolios can be used to determine whether chance influences the performance of clusters. The portfolios were reconstituted each year between 2010 and 2022 and 50 stocks were randomly included in the portfolio. This simulation was run 5,000 times to ensure that the random sample was sufficiently large. The random portfolios were created by random number generators that draw portfolios of 50 companies from all companies in the S&P500 index. Due to data sparsity, it was possible that price data were not available for all companies, so in this study the missing data were replaced by setting the average annual return to 8% with a standard deviation of 20%. These uncorrected price data were broken down by day.

5. RESULTS

This section discusses the results and compares them in absolute terms with the index returns and in risk-adjusted terms with the Sharpe ratio. Appendix 1 shows the portfolios created their contents and whether they belong to the Value or Growth portfolio.

5.1. Average returns for Value and Growth portfolios

A total of 112 portfolios were generated, out of which 35 outperformed the S&P500 index in absolute terms and 77 underperformed. The results therefore show that on average, looking at different key figures, it is not possible to outperform by investing in Value or Growth portfolios using this method. The distribution of these outperforming portfolios was such that of the 35 portfolios, 20 were Growth portfolios and 15 were Value portfolios. Thus, 36 Growth portfolios and 41 Value portfolios underperformed the S&P500 index. The S&P500 index returned an average of 9.82 % per annum over the period 2010-2022, with the best performing portfolio returning 22.67 % per annum on average and the worst performing portfolio returning 3.50 % per annum on average. Figure 5 shows the returns of all the portfolios generated compared to the S&P500 index:

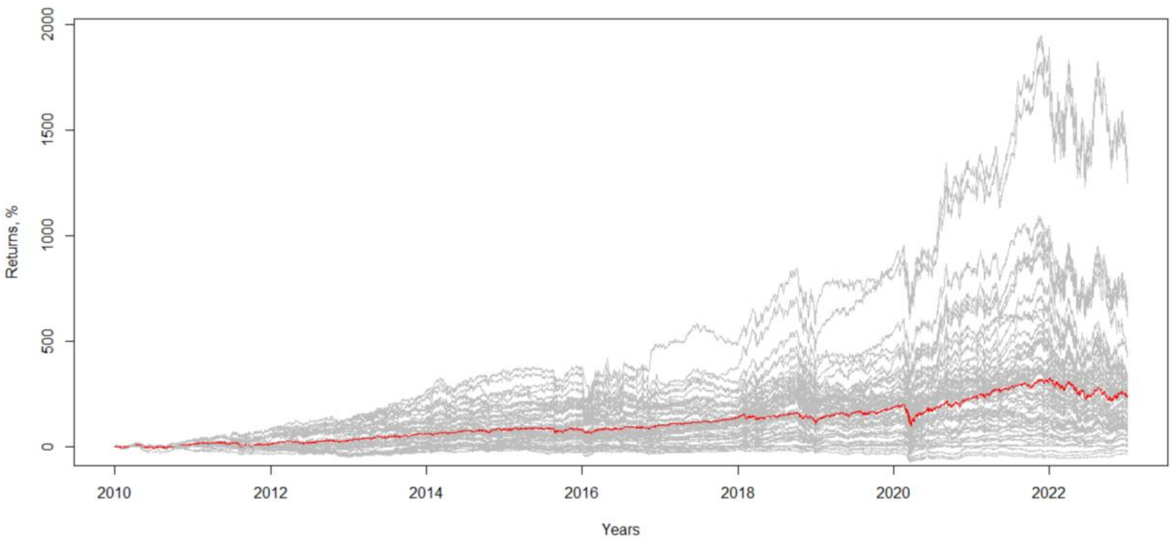

Figure 5. Returns for all portfolios formed, S&P500 index in red

For practical reasons, the extent of the data makes it not practical to cover all the portfolios formed, so this study focuses on the portfolios that performed particularly well, as well as the average of the Value and Growth portfolios. The average annual returns of all the portfolios generated their difference relative to the randomly scored portfolios and the Sharpe ratios are presented in full in Appendix Appendix 1. Figure 6 shows the average returns of the Value and Growth portfolios compared to the S&P500 index.

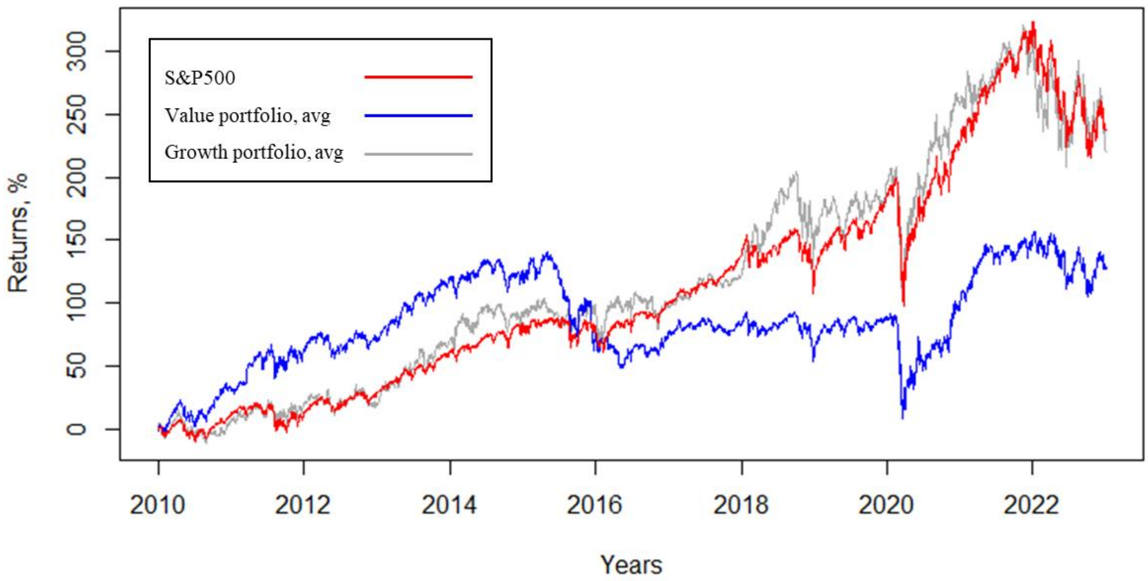

Figure 6. Average Value and Growth portfolios compared to S&P500

Figure 6 shows that the average Value portfolio has significantly underperformed compared to the S&P500 index and the Growth portfolio. In contrast, the Growth portfolio has returned roughly the same as the S&P500 index. The graph shows that the Growth portfolio is more volatile than the S&P500 index. Higher volatility lowers the risk-adjusted return of the average portfolio, even if the absolute annual return is high.

Average of Value portfolio and Growth portfolio performance is tested against randomly assigned portfolios to study the statistical significance. Performance is compared in terms of total return. A total of 50 companies are randomly selected for each portfolio each year. A total of 5000 random portfolios will be formed. The average return of the S&P 500 index has been 9.82%, while the return of the randomly selected portfolios has been only 9.51%. The standard deviation for the randomly assigned portfolios is 0.96 percentage points, making the two standard deviations 1.92 percentage points from the mean. Two standard deviations above the mean thus brings the 95% confidence limit to 11.42%. Thus, above this limit, it can be said that with 95% probability, the portfolio outperforms a portfolio of randomly valued stocks. The distribution of random portfolios is shown in the figure 7 and the average returns of the Value and Growth portfolios are shown in the figure 8 relative to the S&P500 index and randomly valued portfolios.

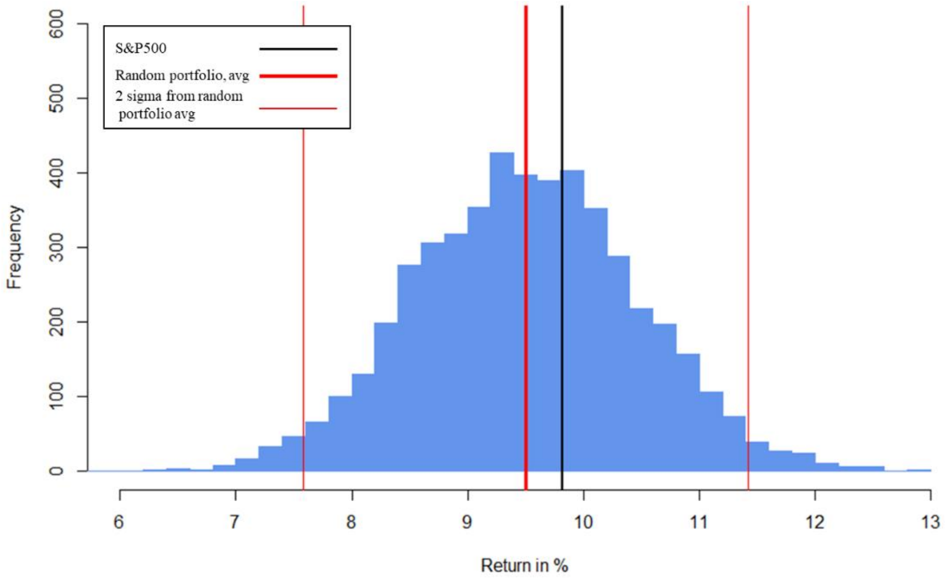

Figure 7. Random portfolios from S&P500 stocks 2010-2022, n=5000

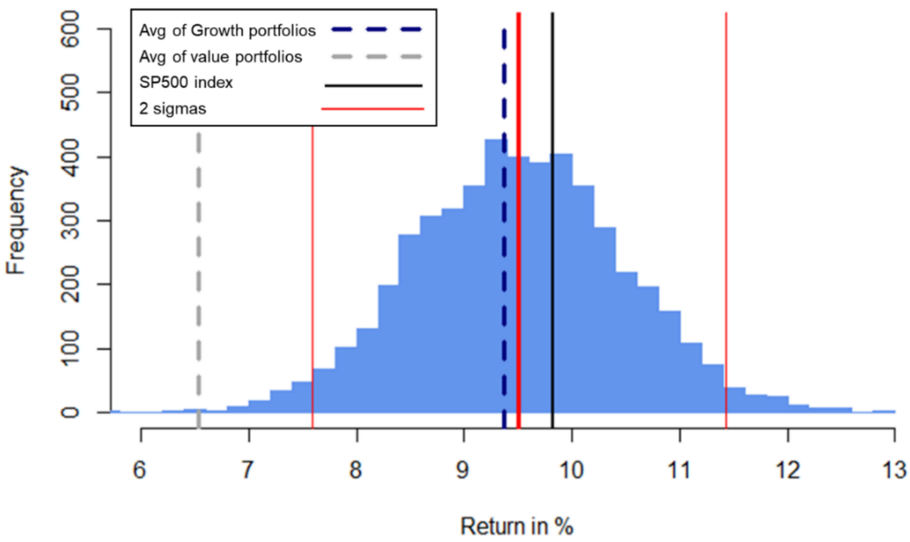

Figure 8. Average of Value portfolios and Growth portfolios

When Value and Growth portfolios are compared to randomly allocated portfolios, it can be seen that the average return of randomly allocated portfolios is very close to the average return of Growth portfolios. However, the Growth portfolio has slightly underperformed the randomly valued portfolios. Both have underperformed the S&P500 index in general. In contrast, the Value portfolio has on average significantly underperformed the Growth portfolio and the randomly selected portfolios. The Value portfolio has also statistically significantly underperformed the Random portfolios. Statistical significance can be established by the fact that the Value portfolio is more than two sigmas (standard deviation) away from the average return of the randomly valued portfolios. However, the same conclusion cannot be reached for the Growth portfolios in either direction, but only the Value portfolios can be considered statistically significantly underperforming the random portfolios on average.

These previously presented results can be further examined in which shows the average annual returns and Sharpe ratios for the Value and Growth portfolios. In addition, the number of standard deviations between the averages of the Value and Growth portfolios and the average of the randomly selected portfolios is also examined. The data are presented in table 5.

Table 5. S&P500 and average of value portfolio and growth portfolio annual returns and Sharpe ratios

PORTFOLIO	ANNUAL RETURN	SHARPE RATIO	SIGMAS FROM RANDOM PORTFOLIO MEAN	SD OF PORTFOLIOS RETURNS
S&P500	9.82 %	3.36	0.32	-
AVG OF VALUE PORTFOLIOS	6.53 %	2.00	-2.95	3.64 %
AVG OF GROWTH PORTFOLIO	9.36 %	2.58	-0.16	5.16 %

The annual return on the Growth portfolio has been a high 9.36%, compared to 9.82% for the S&P500 index and 9.51% for the average random portfolio. The Value portfolio formation method used in this study is found to be statistically significantly worse than the randomly formed portfolios, as the average of the Value portfolios has been less than two standard deviations away from the average of the random portfolio. In contrast, when comparing the performance of random portfolios against the S&P500 index, no similar significance can be observed.

The annual returns of the portfolios can be observed to be quite dispersed across portfolios. The standard deviation of average annual returns for the Value portfolios has been 3.64%, while the corresponding figure for the Growth portfolio has been as high as 5.16%. So while the Growth portfolio has on average performed much better than the Value portfolio, the deviation was also found to be much higher. The large deviation in the average returns of the portfolios is also evident in the corresponding Sharpe ratios, as they remain significantly lower for both average stock portfolios compared to the S&P500 index. Since the high degree of diversity was found and the large number of portfolios means that not all of the portfolios formed can be considered, the portfolios that performed statistically significantly better than the S&P500 index and the randomised portfolios are taken for further analysis.

5.2. Portfolios outperforming the S&P500 index

The performance of stock portfolios in absolute terms was highly diversified (Table 5). Most portfolios returned mid-range compared to the S&P500 index, which gave a cumulative annual growth rate of 9.82% over the period 2010-2022, which is above the long-term average return. This strong average growth rate is explained by the fact that the period under study is a sample of bull markets and there were no significant, long-term down markets. Short-term down markets include the Covid-19 pandemic and the rapid bear market in 2022. On average growth portfolios outperformed value portfolios. In the table 6 shows the portfolios that outperformed the S&P500 index.

Table 6. Better absolute returns portfolios than S&P500 index

PORTFOLIO	AVERAGE ANNUAL PORTFOLIO RETURNS	VALUE/GROWTH PORTFOLIO	KEY FIGURES
S&P500	9.82 %	-	-
79	22.67 %	Growth	EVEBIT/PE/PCF
59	22.17 %	Growth	EVEBITDA/EVEBIT/PCF
83	17.09 %	Growth	EVEBIT/PB/PCF
89	16.78 %	Growth	EVEBIT/PCF/ $ROIC^{-1}$
87	16.36 %	Growth	EVEBIT/PCF/PS
80	13.76 %	Growth	EVEBIT/PE/PS
65	13.59 %	Growth	EVEBITDA/PE/PS
88	11.84 %	Growth	EVEBIT/PCF/DE
86	11.72 %	Growth	EVEBIT/PB/ $ROIC^{-1}$
64	11.64 %	Growth	EVEBITDA/PE/PCF
58	11.33 %	Growth	EVEBITDA/EVEBIT/PB
93	11.17 %	Growth	PE/PB/PCF
108	11.16 %	Growth	PB/DE/ $ROIC^{-1}$
10	10.74 %	Value	EVEBITDA/PE/DE
110	10.57 %	Growth	PCF/PS/$ROIC^{-1}$
25	10.54 %	Value	EVEBIT/PE/DE
62	10.48 %	Growth	EVEBITDA/EVEBIT/ $ROIC^{-1}$
19	10.37 %	Value	EVEBITDA/PS/DE
105	10.31 %	Growth	PB/PCF/ROIC2
17	10.31 %	Value	EVEBITDA/PCF/DE
81	10.29 %	Growth	EVEBIT/PE/DE
94	10.26 %	Growth	PE/PB/PS
5	10.25 %	Value	EVEBITDA/EVEBIT/DE
42	10.17 %	Value	PE/PCF/DE
78	10.15 %	Growth	EVEBIT/PE/PB
44	10.13 %	Value	PE/PS/DE
9	10.09 %	Value	EVEBITDA/PE/PS
53	10.09 %	Value	PCF/PS/DE
4	10.04 %	Value	EVEBITDA/EVEBIT/PS
98	10.03 %	Growth	PE/PCF/DE
34	10.02 %	Value	EVEBIT/PS/DE
32	9.93 %	Value	EVEBIT/PCF/DE
24	9.91 %	Value	EVEBIT/PE/PS
1	9.86 %	Value	EVEBITDA/EVEBIT/PE
3	9.83 %	Value	EVEBITDA/EVEBIT/PCF

The 35 stock portfolios outperforming the S&P500 represent around 31% of the total number of portfolios formed. From the point of view of this study it is interesting to examine which of the selected metrics were able to generate returns that outperform the S&P500 index. Each key figure is also examined in terms of whether it is worth putting into a value portfolio or a growth portfolio, i.e. how growth portfolios and value portfolios are formed. In the figure 9 is shown the key figures used to generate the portfolios that outperformed the S&P500 index are shown.

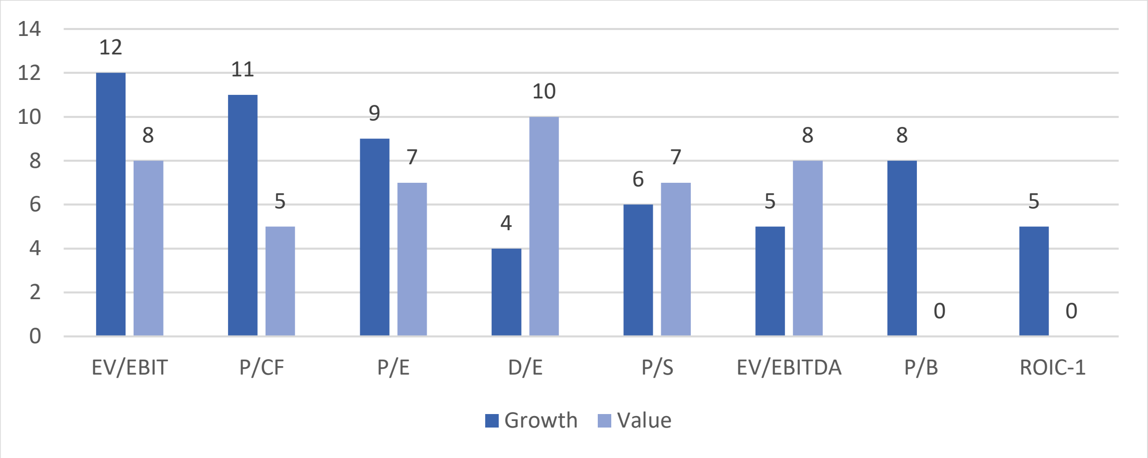

Figure 9. Number of components of portfolios generated outperforming the S&P500 index

Highly represented key figures, especially in the well-performing Growth portfolios, were EV/EBIT and P/CF, while D/E was highly represented in the well-performing Value portfolios. P/B and ROIC^{-1} performed well only in the Growth portfolio. In contrast, P/E and P/S were evenly distributed across both the Value and Growth portfolios. In both portfolio types, however, the different key figures were evenly represented, with no single key figure standing out clearly. Attention should still be paid to ROIC^{-1} and P/B, as they have not once outperformed the S&P500 index in the Value portfolio.

5.3. Outperforming portfolios of random portfolio

This section examines those individual portfolios that have performed statistically significantly better than randomly selected portfolios.

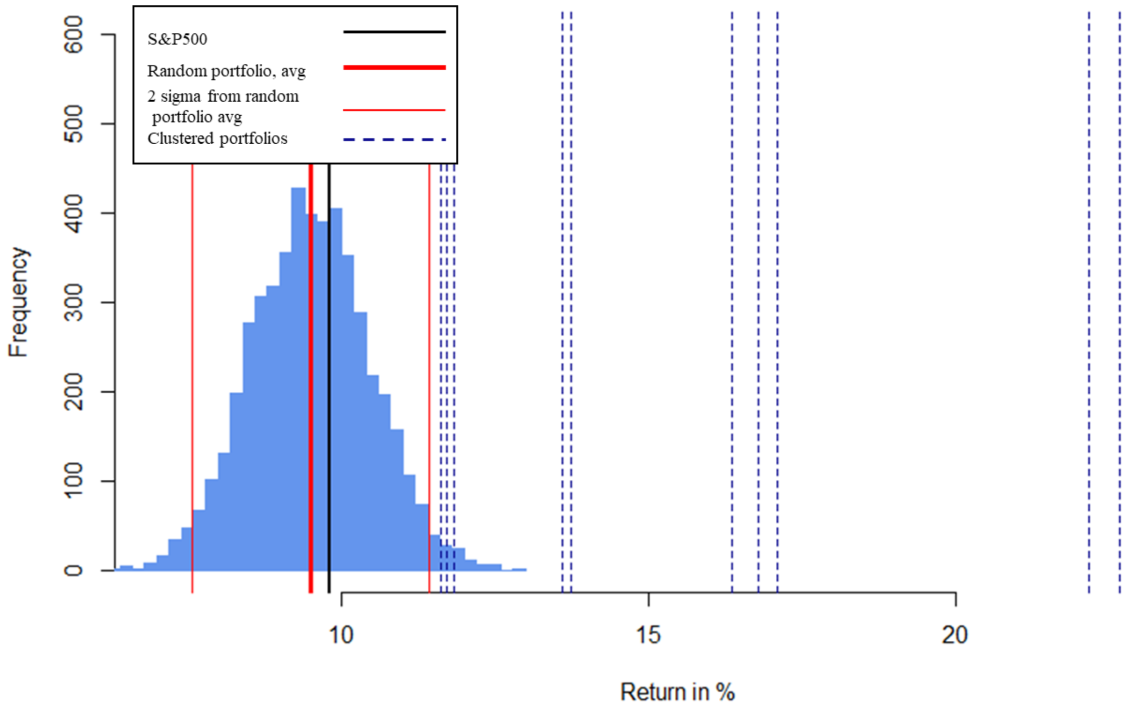

Figure 10. Random portfolios and clustered portfolios that have outperformed random portfolios

Only a fraction of portfolios performs better than two sigmas statistically significantly above random portfolios. There are ten such portfolios in total, making up only about 9% of all portfolios. There are seven portfolios that clearly exceed the two-sigma threshold, two of which have returned 22.7% and 22.2% over the 13-year period under review. Three portfolios have also returned more than 16% on average annually. These returns can be considered very good in terms of absolute returns. The following table lists the portfolios that have returned more than two sigmas of the average random portfolio and the corresponding sigma amounts.

The above average performance of the S&P500 index is an excellent illustration of the phenomenon that, on average, the stocks in the index do not perform in the same way. Instead, most of the stocks included underperform the index, with only a small fraction of the stocks in the index leading the index upwards. This phenomenon is facilitated by the fact that the companies within the index are not of equal weight, but the companies that increase their share price constantly increase their own share in the index.

Table 7. Portfolios that performance statistically significantly better than a random portfolio

PORTFOLIO NO	COMBINATION	PORTFOLIO	ANNUAL RETURN	SIGMAS FROM RANDOM PORTFOLIO AVERAGE
79	EVEBIT/PE/PCF	Growth	22.67 %	13.70
59	EVEBITDA/EVEBIT/PCF	Growth	22.17 %	13.18
83	EVEBIT/PB/PCF	Growth	17.09 %	7.90
89	EVEBIT/PCF/ROIC^{-1}	Growth	16.78 %	7.58
87	EVEBIT/PCF/PS	Growth	16.36 %	7.14
80	EVEBIT/PE/PS	Growth	13.76 %	4.42
65	EVEBITDA/PE/PS	Growth	13.59 %	4.25
88	EVEBIT/PCF/DE	Growth	11.84 %	2.43
86	EVEBIT/PB/ROIC^{-1}	Growth	11.72 %	2.30
64	EVEBITDA/PE/PCF	Growth	11.64 %	2.22

The number of portfolios that have performed statistically significantly better than the randomly generated portfolio is 10. They have had a compound annual return of more than 11.5% and the most strongly represented ratios have been EV/EBIT and P/CF with 8 and 7 respectively, while D/E has only appeared once. The overall distribution of their occurrence is shown in the figure 12.

5.4. Portfolio outperforming the S&P500 index by Sharpe ratio

This section presents the risk-adjusted performance of portfolios. The measure of risk-adjusted return is Sharpe ratio, which describes how well equity portfolios have performed relative to their riskiness. Sharpe ratio is the most widely known measure of stock portfolio returns, which considers the riskiness of stocks through volatility. Riskiness is considered by dividing the difference between the portfolio's daily returns and the US 1-year treasury yield by the difference between the standard deviation of the portfolio's daily returns and the standard deviation of the US 1-year treasury yield. In this way, volatility is considered, and less volatile portfolios are worth more than more volatile ones if their absolute returns are the same.

In terms of Sharpe ratios, stock portfolios are compared to the US 1-year treasury, which is considered a risk-free rate, and to the S&P500 index. The S&P500 index could also be considered risk-free because of its large size and the large number of stocks (ca. 500) it contains. Therefore, stock portfolios are considered according to which stock portfolios have outperformed the S&P500 index. Table 8 shows the portfolios that have returned more than two sigmas compared to the random portfolio or the Sharpe ratio is higher than the S&P500 index.

Table 8. Portfolios with bigger Sharpe ratio than S&P500 or random portfolios (over 2 sigmas)

PORTFOLIO NO	COMBINATION	PORTFOLIO	ANNUAL RETURN	SHARPE RATIO
-	**S&P500 index**	**-**	**9.82 %**	**3.360**
59	EVEBITDA/EVEBIT/PCF	Growth	22.17 %	4.684
79	EVEBIT/PE/PCF	Growth	22.67 %	4.584
83	EVEBIT/PB/PCF	Growth	17.09 %	3.847
87	EVEBIT/PCF/PS	Growth	16.36 %	3.700
10	EVEBITDA/PE/DE	Value	10.74 %	3.441
25	EVEBIT/PE/DE	Value	10.54 %	3.420
89	EVEBIT/PCF/$ROIC^{-1}$	Growth	16.78 %	3.339
42	PE/PCF/DE	Value	10.17 %	3.259
80	EVEBIT/PE/PS	Growth	13.76 %	2.855
86	EVEBIT/PB/$ROIC^{-1}$	Growth	11.72 %	2.732
64	EVEBITDA/PE/PCF	Growth	11.64 %	2.668
88	EVEBIT/PCF/DE	Growth	11.84 %	2.587

Compared to absolute returns, there is clearly more dispersion when looking at Sharpe ratios. The S&P500 reaches a Sharpe ratio of 3.36 when using the US 1 year treasury as a benchmark. However, there are only six companies that have significantly outperformed the benchmark index using the Sharpe ratio. Of these six, two are Value Portfolios. However, four Growth portfolios have the best Sharpe ratios. What these four have in common is that the EV/EBIT ratio is included in all of them. None of the portfolios that underperform the absolute return of the S&P500 index have achieved a higher Sharpe ratio than S&P500. The top six portfolios in table 8, on the other hand, are those that both outperformed the random portfolios and achieved higher Sharpe ratios than the S&P500 index.

5.5. Best performance portfolios

In this section, we present in more detail those clusters that have outperformed the S&P500 index in absolute terms, as measured by Sharpe ratio. It also requires that the portfolio has performed statistically significantly better than a random portfolio. There are 4 of these portfolios in total, representing less than 4% of the total portfolios created. In addition, these portfolios are opened based on the ratios used to construct them and the annual number of companies in the portfolios. The best performing clusters are presented in the table 9:

Table 9. Four best performance portfolios

PORTFOLIO NO	ANNUAL RETURN	SIGMAS FROM RANDOM PORTFOLIO MEAN	SHARPE RATIO
79	22.67 %	13.70	4.58
59	22.17 %	13.18	4.68
83	17.09 %	7.90	3.85
87	16.36 %	7.14	3.70

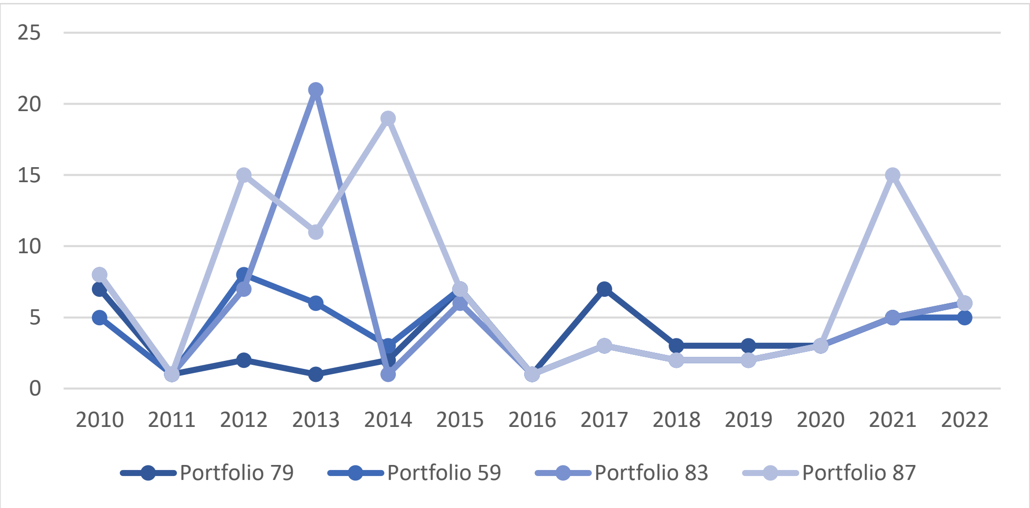

Figure 11. Number of companies in portfolios per year

Figure 11 shows the yearly stock count for the top four portfolios. The number of companies in the top 4 portfolios varied widely. The number ranged from 1 to 21. The most striking feature, however, is the low number of stocks in the portfolios, which helps to explain the good returns. The average number of stocks per cluster was around 100, as the number of stocks is around 500 and 5 clusters were created at each stage. When the number of stocks is small and the return is high, the high returns accumulate quickly compared to a portfolio of lower performing stocks. Another observation is that the number of stocks in the portfolios are very similar. The number of stocks in the best portfolios ranges from 5 to 8 in 2010, in 2011 all portfolios have only one stock, while in 2012-2014 the dispersion is significantly higher, ranging from 1 to 21. Only a cluster of one observation can be formed when the inclusion of another observation would increase their sum of squares so much that clustering would no longer work on the same principle. Such a single observation cluster would suggest that it would be an outlier. The initial editing of the data by removing outliers and re-standardising would probably have required a re-check of the data quality. The lowest number of shares over this period is in the portfolio generated from EV/EBIT, P/E & P/CF ratios, while on average the highest number of stocks in 2012-2014 is in the portfolio generated from EV/EBIT, P/CF & P/S. From 2015 onwards, the number of stocks in the portfolios flattens out and decreases, ranging from 1 to 7, except for 2021, when the portfolio based on EV/EBIT, P/CF & P/S has 15 stocks. While one portfolio that has performed well each year has only a few stocks, the other portfolios that have performed well have a similar number of stocks. The logic works the same way for larger numbers of stocks. If the key figures are formed in roughly the same way from one portfolio to another, it is likely that the same stocks belong to the same clusters. On the other hand, it is the small differences that are significant to be found.

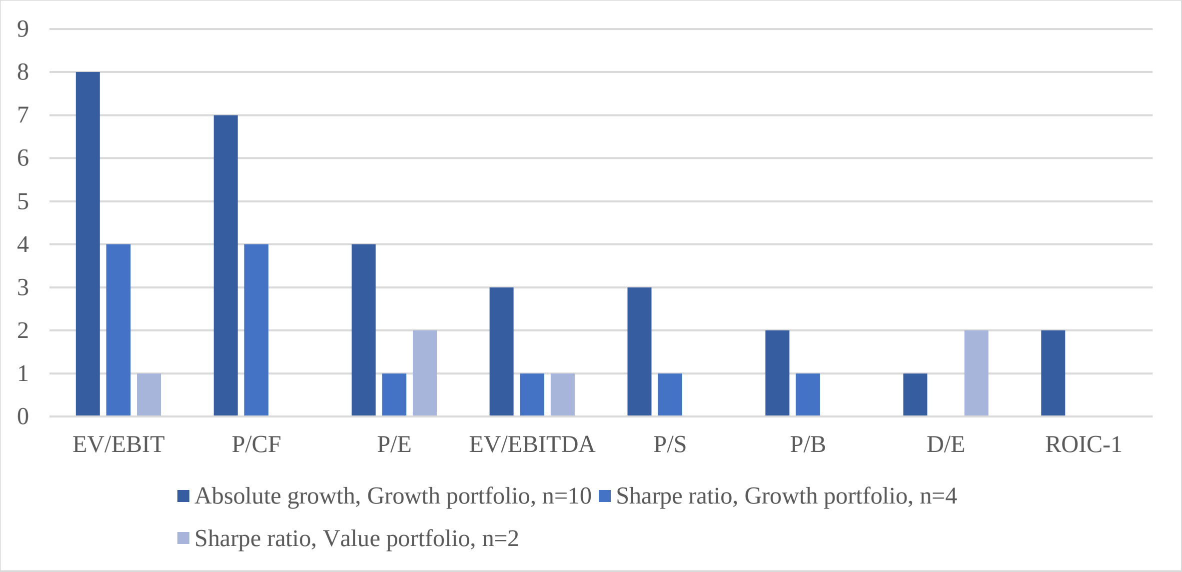

Figure 12. Breakdown of components generated outperformed portfolios

There are ten portfolios that have outperformed the random portfolio in absolute terms, with the clearest majority based on EV/EBIT and P/CF. When looking at the same key figures, they are also forming all Growth portfolios, with EV/EBITDA, P/E, P/B and P/S coming third in turn. Two Value portfolios are in turn generated by low P/E and D/E figures. The third key figures in these portfolios are EV/EBITDA and EV/EBIT key figures, which are widely represented in both the Value and Growth portfolios, are EV/EBIT and P/E. In contrast, D/E is generating far more value portfolios.

Finally, the return curves of the four portfolios that have outperformed the S&P500 index are presented. The charts illustrate well that although there were up to 35 portfolios that outperformed the S&P500 index, only a fraction outperformed the index when risk is considered. As the risk is significantly higher compared to a larger index, returns need to be multiples of the index to compensate the investor for the risk of volatility in the form of returns.

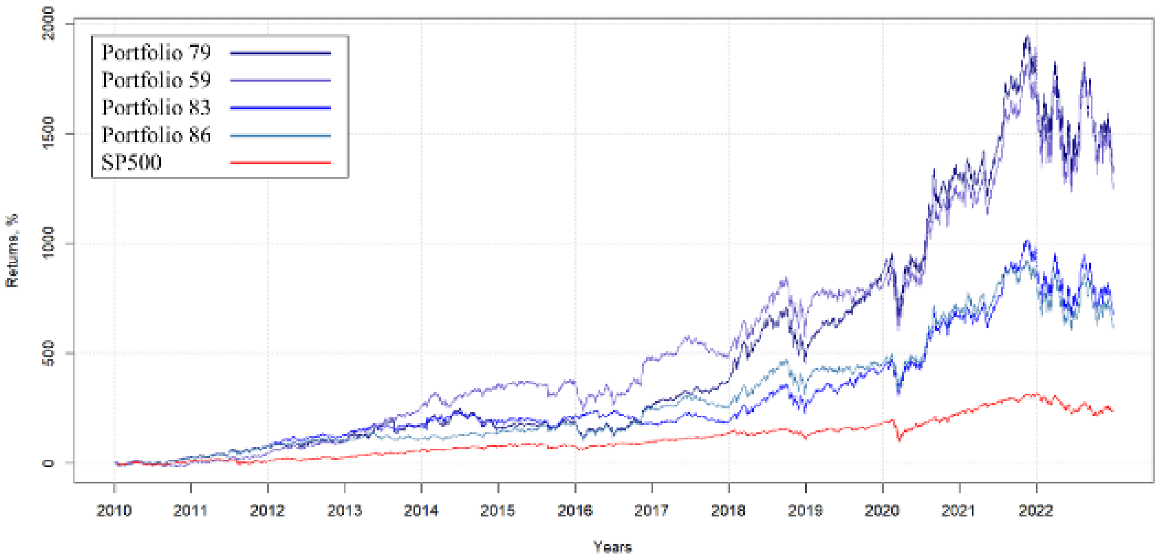

Figure 13. Best portfolios return charts

Figure 13 presents the return charts of the top 4 portfolios. Absolute returns are far better than the S&P500 index, but largely due to the low number of stocks in the portfolios, there is also a large dispersion. Portfolios 59 and 79 significantly outperform the other portfolios from 2018 onwards, after which they start to perform very similarly. On the other hand, portfolios 83 and 86 also perform very similarly, but the difference is largely explained by the difference in scale. Since the ratios on which the portfolios are based are 2/3 the same, it is not surprising that the performance curves are very similar. Given that the third ratios used are generated because of each other in the financial statements, the similarity in returns is also to be expected.

5.6. Analysis of results

This section provides an analysis of the average portfolio and the best performing portfolios.

5.6.1. Analysis of average Value and Growth portfolios

The Value and Growth portfolios on average did not perform particularly well, with returns averaging 6.53% and 9.36% respectively, while the S&P500 index performed at 9.82% per annum over the 13-year period 2010-2022. The Growth portfolio can be said to have performed at a satisfactory level, and in such a way that no conclusions can be reliably drawn. However, the standard deviation with the Growth portfolio was high, with an average annual return of 5.16%. The corresponding figure was significantly lower for the Value portfolio, with an average annual return variance of 3.64% for the Stock portfolio. This suggests that the Value portfolios have less variation in returns and are therefore more stable than the Growth portfolios. The Value portfolio was found to be statistically significantly worse performing than the randomly generated portfolio.

In terms of Sharpe ratios, both average portfolios performed quite well, with ratios of 2.00 for the Value portfolio and 2.58 for the Growth portfolio. Although the absolute difference in annual returns was quite large, the difference in Sharpe ratios was moderate. The main reason for the moderate difference in the Sharpe ratio is volatility, with the Value portfolio performing more consistently on average, and there was not much variation between portfolios compared to the Growth portfolio. The Sharpe ratio, on the other hand, remained low in the Growth portfolio due to higher volatility compared to the S&P500 index, which had a Sharpe ratio of 3.36 over the same period. The difference in Sharpe ratio between the Value portfolio and the Growth portfolio is smaller than the difference between the Growth portfolio and the S&P500 index. The absolute annual returns would have suggested otherwise, but the large dispersion of the Growth portfolio explains this result.

Figure 6 shows that the returns of the Value and Growth portfolios are very different from each other. Both tend to move in the direction of the index. The Growth portfolio follows a very similar pattern compared to the index, while the Value portfolio is significantly more divergent from it. The Growth portfolio moves in line with the S&P500 index, but outperformed the index for most of the period under review. Had the review period started in 2010 and ended earlier, it is likely that the Growth portfolio would have outperformed the index. The main reason for the movement in the index is possibly due to the weighting of the index towards large cap companies. Typically, large-cap companies derive some of their value from high trading multiples, which could explain why the Growth portfolio would include the large companies that the S&P500 tracks. This would be an interesting topic to research at a later stage. It would also be useful to know more precisely how many companies are included in the portfolios on average. This would also be worth investigating in future studies.

What is remarkable about the price curves is that the Value portfolio has on average moved lower than the S&P500 index. The exception to this is the first one third of the period under review, where the Value portfolio has on average clearly outperformed the S&P500 index and the Growth portfolio on average. However, between 2015 and 2022, the Value portfolio ended up underperforming the index and has not caught up with the index since 2015. Clearly outperforming the index over the 2010-2015 period leads to the question of whether the Value portfolio is always statistically significantly worse than the index, after all. The study does not take dividends into account, which significantly distorts the returns of Value portfolios. For Growth portfolios, this is less relevant, as typically dividends are not paid as much for growth companies. With Value portfolios, however, it would be essential to include dividends in order to better estimate total returns. Dividends become particularly important over the longer term as the interest rate-to-interest rate effect begins to accumulate. In the past, the Value portfolio has been found to significantly outperform the index (Pätäri and Leivo, 2009), and for this reason it could be interesting to study the same topic over more different time periods in the future. The 2010s have been widely discussed in the investment world as having been a favourable decade, especially for growth companies, and therefore longer and more frequent periods of observation would bring an additional perspective to the results.

5.6.2. Analysis of best performed portfolios

The top 4 portfolios were constructed in a relatively similar way. All the components were involved in generating the outperforming Growth Cluster, but EV/EBIT and P/CF stood out from the rest by their large number of components, being involved in generating 8 and 7 different Growth Portfolios respectively. With clear clusters of EV/EBIT and P/CF ratios, especially for high multiples, it is natural to have clear portfolios for similar ratios. EV/EBIT and P/CF represent the net debt price of a company relative to its ability to generate operating income, and the debt price relative to the cash coming into the company's coffers. Both are valuation ratios, and it is not unexpected that clusters are formed based on similar measures. As the third dimensions for these ratios are EV/EBITDA, P/E, P/B and P/S, the formation of successful clusters based on similar ratios seems reasonable also compared to previous studies (Fama and French 1992; Pätäri et al. 2009; Yan and Zhao 2011). On the other hand, in these studies, high performing portfolios were generated from the low end of these ratios, while in this study high values formed outperforming portfolios. Of particular note in this case is that the other important ratio is EV/EBIT and not EV/EBITDA. EV/EBITDA is used significantly more frequently when looking at valuation multiples, which makes the higher representation of EV/EBIT unexpected. Instead, it is expected that it is the EV-based rather than the Equity-based ratios that are represented when considering the owners and creditors of the companies.

$ROIC^{-1}$, which is highly valued by investors, is very poorly represented, with only 6 of the 35 best performing portfolios having $ROIC^{-1}$ as one of their components. ROIC is considered a measure whose high value guarantees good performance for a stock in terms of its ability to create significant shareholder value (McKinsey & Company et al. 2015, 131). ROIC in this study was raised to the exponent -1, which reversed the stock's ROIC. Originally, the ratio was interpreted as the higher the value, the better. So, after pre-processing the data, the ratio worked the other way round. The lower the value, the more it creates shareholder value. However, the other ratios used were valuation coefficients, not performance measures. It is therefore impossible to interpret whether it was appropriate to reverse the ROIC figure after all, or whether the original value would have been sufficient. Low valuation multiples were assumed to be automatically positive for the stock, so this solution was seen as the best.

Investing in high valuation multiples was found to be the best way to generate returns. However, it should be noted that these are long bull markets, where downturns have been only temporary. During the bull market, growth stocks performed exceptionally well, which in turn allowed high value stocks to outperform value stocks. An important single explanatory factor is that the largest stocks in the S&P500 are growth stocks, dragging the entire index upwards. Investing in these large growth companies has generated returns over the past few years.

Compared to previous studies, the cash flow-based ratio P/CF was relatively less used in generating value portfolios (Lakonishok et al. 1994; Dhatt et al. 2004; Pätäri et al. 2009). The assumption was that value portfolios constructed using the P/CF ratio would have performed exceptionally well. Similarly, as previous studies have found, low P/E stocks generate excess returns, especially when risk-adjusted (Reinganum 1981; Chan et al. 1991).

On a risk-adjusted basis, the performance of Growth and Value portfolios was clearly more evenly distributed across portfolios in terms of absolute returns. Value portfolios gave higher Sharpe ratios relative to Growth portfolios with similar absolute returns. This suggests that Value portfolios were significantly less volatile compared to Growth portfolios, supporting previous studies (Pätäri and Leivo, 2009). Sharpe ratios provide a more objective picture of the actual returns of portfolios when an investor is exposed to volatility.

Generally assumed, it is difficult to outperform the index on a risk-adjusted basis with one's own equity portfolios, which is easy to see as only two Value portfolios and four Growth portfolios offered better Sharpe ratios than the S&P500. These Value Portfolios were formed by clustering D/E and P/E, with EV/EBITDA in one and EV/EBIT in the other. Each had an absolute annual return of between 10.5% and 11.0%, compared to an annual return of 9.82% for the S&P500 index. Sharpe's figures revolve around the same ballpark as the S&P500 index, with the S&P500 figure being 3.36 and the corresponding figures for Value Portfolios being 3.42 and 3.44. What makes the performance of value portfolios interesting in this case is that, in contrast to previous studies, the P/B ratio was not involved in generating any value portfolio that outperformed the S&P500 index, even in absolute terms (Fama and French, 1998; Pätäri and Leivo, 2009). Instead, as in previous studies, the P/CF and P/E ratios were involved in generating value portfolios with higher absolute returns than the index (Chan, Hamao and Lakonishok, 1991; Yan and Zhao, 2011).

For the top four portfolios, attention should also be paid to the number of shares per year. The numbers have varied between one and 21, but as a rule the portfolios have been around five stocks. For the best performing portfolios, each portfolio has consisted of only one stock at any point during the period. The number of shares is selected according to the K-means algorithm, which is based on the Ordinary Least Squares method. In this study, clusters are therefore not modelled, but are formed as the least squares sum of the existing observations. While Sharpe's figures are better than the index, it must be recognised that there is a huge risk factor for the portfolio as a whole if it consists of only one stock at any point in the period under review. The risk profile would be significantly lowered if there were more than one stock, rather than the performance of the entire portfolio being dependent on a single company. Further studies need to take this into account, either by forcing portfolios to include at least a certain number of stocks at a time or by changing the clustering method accordingly. Forced modification of this value to include at least a certain number of observations in the clusters would have been possible, but for research reasons it was not desired to limit the algorithm. A minimum number of observations would eliminate small clusters and would probably make the portfolio returns more even in both directions. In addition, the risk for the investor would be reduced. K-means does not seem to be a suitable method in this case because of the huge risk involved. As a method, K-means does not offer the best possible outcome when generating portfolios by clustering generally produces a set of highly valued clusters with few observations.

When comparing returns to randomly valued portfolios, a total of 10 portfolios achieved statistically significantly better returns than the average randomly valued portfolio. Ten portfolios had annual returns greater than two sigmas above the average of the randomly valued portfolios. These portfolios included the top four portfolios, along with six other Growth Portfolios. Thus, no Value Portfolios made it into these portfolios. Given the two-sigma cut-off, it can be concluded at the 95% confidence level that the ten stock portfolios outperformed the randomly scored portfolios (Burns, 2006).

6. SUMMARY AND CONCLUSIONS

The purpose of this study was to find combinations of ratios that could be exploited to generate excess returns on the S&P500 index. The method used to find high performing portfolios was the K-means clustering algorithm. In addition, the aim was to determine how well the Growth portfolios perform relative to the Value portfolios. In addition to these, the aim was to find combinations of metrics that outperform relative to randomly valued portfolios. The first research questions were set out as follows:

RQ1: Within the period of 2010-2022, would it have been possible to beat the S&P500 return index by clustering the index companies by their key figures to form stock portfolios?

Investing in Value or Growth portfolios in general, it has not been possible to beat the S&P500 index. Investing in the Value portfolio has underperformed the S&P500 index and statistically significantly underperformed randomly assigned portfolios. Investing in the Growth portfolio performed almost as well as the S&P500. However, on a risk-adjusted basis, both portfolios significantly underperformed the S&P500. For individual portfolios, it was possible to achieve better returns than the S&P500 both on an average annual return basis and on a risk-adjusted basis. There were four such portfolios and all were Growth portfolios.

RQ2: Which of the key figure combinations would have made the best performing portfolios?

The best performing portfolios were four. They outperformed the S&P500 index in terms of Sharpe ratio and average annual return. In addition, they performed statistically significantly better than the random portfolios. The best performing portfolios were all Growth portfolios and were generated using a combination of EV/EBIT, P/CF & EV/EBITDA; EV/EBIT, P/CF

& P/E; EV/EBIT, P/CF & P/B and EV/EBIT, P/CF & P/S. All four best performing portfolios were generated using the two measures EV/EBIT and P/CF.

RQ3: If clustering based on ratios has been able to generate excess returns, are the results statistically significant compared to randomly selected portfolios?

There were ten random portfolios compared to the returns, all of which were Growth portfolios. It should be noted, however, that these might not have been worth investing in, as they all had risk-adjusted Sharpe ratios no higher than the S&P500 index. Of these criteria, only four of the portfolios mentioned above met both of them.

Outperforming the S&P500 index has been possible between 2010 and 2022. By clustering a total of 56 different combinations and selecting both Value and Growth portfolios, a total of 6 out of 112 portfolios outperformed the S&P500 index in a risk-adjusted manner and 10 portfolios (Table 7) performed statistically significantly better than the randomly selected portfolios. However, there are 4 portfolios that outperformed the S&P500 index by Sharpe ratio and statistically significantly outperformed the randomly selected portfolios.

The distribution of the best portfolios showed that when creating a growth portfolio, EV/EBIT and P/CF have been useful tools to create productive portfolios. The portfolios that have performed well on all metrics were EV/EBIT, P/CF & EV/EBITDA (22.17% average annual growth & 13.18 Sharpe ratio); EV/EBIT, P/CF & P/E (22. 67 % average annual growth & 13.70 Sharpe ratio), EV/EBIT, P/CF & P/B (17.09 % average annual growth & 7.90 Sharpe ratio) and EV/EBIT, P/CF & P/S (16.36 % average annual growth & 7.14 Sharpe ratio). All these portfolios were clustered into a high multiplier cluster, the Growth Cluster. It is also worth noting that by investing in companies with high P/CF and EV/EBIT ratios in the S&P500 index, one is most likely to have statistically significantly better returns compared to a randomly valued portfolio. Overall, however, low valuation stocks did not perform very well relative to high valuation stocks in this study data.

6.1. Limitations of the study and further research

It should be noted that portfolios based on small clusters are very risky compared to the index, which contains around 500 companies separately. This makes portfolios of less than five stocks high-risk, but on the other hand allows them to generate significant returns. However, it is possible that some portfolios that are promising and initially well-developed are destroyed, for example if a single stock portfolio goes bankrupt. The clustering method chosen for this study is K-means, a simple and commonly used clustering method. One possibility was to force the size of the clusters to at least a certain sample size, but this would have skewed the natural function of the clustering algorithm. As a further study, it would be possible to carry out a similar study but using a different clustering method for more appropriate clustering, as it would not make sense to conduct the study with very small portfolios and allow investors to take significant risk.

Another risk associated with clustering is that the number of clusters should be tested by some method. In this study, the number of clusters, and hence the number of stocks, is not considered. The number of clusters has not been considered in this study, as the aim was only to examine which combinations of ratios have been the most profitable. However, it should be noted that it is possible that the results could be different if a separate number of clusters had been made for each clustering.

The S&P500 index was found to outperform the randomly assigned portfolios. The reason for this was interpreted to be that the companies with the largest market capitalization in the index drive the whole index upwards, even though they are few. An interesting question for further research would be how the largest companies in the S&P500 index have performed relative to the index as a whole and whether there would be outperformance by investing in them. In addition, it would be useful to have a longer time horizon, so that longer bear markets would be included and different types of stocks would perform differently in different periods.

A third important limitation and area for further research would be the scale at which the ratios should be considered. In this study, eight ratios were used, six of which were valuation multiples, one leverage factor and one performance measure. In future studies, it would be useful to take these separately and look, for example, at a broader scale, at the valuation ratios alone or at the performance measures. It is difficult to say with any degree of certainty whether the reversal of the ROIC ratio was the right decision in this study. For this reason, it would be useful to consider performance measures separately in their own clustering and valuation factors separately.

Further research could focus on how many key figures should be included in the analysis. This study found that three of the key figures used yielded significant results, but of the top four, all were generated from two key figures. Therefore, it would be essential to look at clusters of only two or even one key figure and examine whether the third clustering variable adds any value at all.

7. References

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APPENDIX

Appendix 1. All generated portfolios, their annual growths and Sharpe ratios

Portfolio No	Combination	Portfolio	Annual growth	Sharpe ratio	Sigmas from average random portfolio
1	EVEBITDA/EVEBIT/PE	Value	9.86 %	3.102	0.37
2	EVEBITDA/EVEBIT/PB	Value	7.13 %	2.002	-2.48
3	EVEBITDA/EVEBIT/PCF	Value	9.83 %	3.119	0.34
4	EVEBITDA/EVEBIT/PS	Value	10.04 %	3.129	0.56
5	EVEBITDA/EVEBIT/DE	Value	10.25 %	3.245	0.77
6	EVEBITDA/EVEBIT/ROIC^{-1}	Value	2.77 %	0.673	-7.01
7	EVEBITDA/PE/PB	Value	7.20 %	2.063	-2.40
8	EVEBITDA/PE/PCF	Value	9.41 %	2.899	-0.10
9	EVEBITDA/PE/PS	Value	10.09 %	3.177	0.61
10	EVEBITDA/PE/DE	Value	10.74 %	3.441	1.28
11	EVEBITDA/PE/ROIC^{-1}	Value	2.95 %	0.712	-6.8204
12	EVEBITDA/PB/PCF	Value	1.27 %	0.332	-8.57384
13	EVEBITDA/PB/PS	Value	6.44 %	1.722	-3.19187
14	EVEBITDA/PB/DE	Value	6.60 %	1.757	-3.02843
15	EVEBITDA/PB/ROIC^{-1}	Value	0.19 %	0.043	-9.69963
16	EVEBITDA/PCF/PS	Value	9.62 %	3.000	0.113946
17	EVEBITDA/PCF/DE	Value	10.31 %	3.247	0.8339
18	EVEBITDA/PCF/ROIC^{-1}	Value	4.66 %	1.097	-5.04673
19	EVEBITDA/PS/DE	Value	10.37 %	3.237	0.90231
20	EVEBITDA/PS/ROIC^{-1}	Value	5.01 %	1.177	-4.68549
21	EVEBITDA/DE/ROIC^{-1}	Value	4.93 %	1.203	-4.76417
22	EVEBIT/PE/PB	Value	4.01 %	1.112	-5.7238
23	EVEBIT/PE/PCF	Value	9.53 %	3.018	0.025996
24	EVEBIT/PE/PS	Value	9.91 %	3.149	0.420034
25	EVEBIT/PE/DE	Value	10.54 %	3.420	1.072685
26	EVEBIT/PE/ROIC^{-1}	Value	2.46 %	0.600	-7.33186
27	EVEBIT/PB/PCF	Value	4.15 %	1.177	-5.5776
28	EVEBIT/PB/PS	Value	1.87 %	0.508	-7.94875
29	EVEBIT/PB/DE	Value	7.75 %	2.233	-1.82773
30	EVEBIT/PB/ROIC^{-1}	Value	0.16 %	0.038	-9.72461
31	EVEBIT/PCF/PS	Value	9.75 %	3.037	0.253712
32	EVEBIT/PCF/DE	Value	9.93 %	3.139	0.437972
33	EVEBIT/PCF/ROIC^{-1}	Value	2.69 %	0.640	-7.0927
34	EVEBIT/PS/DE	Value	10.02 %	3.168	0.531978
35	EVEBIT/PS/ROIC^{-1}	Value	5.13 %	1.218	-4.55269
36	EVEBIT/DE/ROIC^{-1}	Value	4.56 %	1.139	-5.14888

37	PE/PB/PCF	Value	-1.61 %	-0.421	-11.568
38	PE/PB/PS	Value	1.64 %	0.447	-8.1861
39	PE/PB/DE	Value	6.18 %	1.645	-3.4669
40	PE/PB/ROIC^{-1}	Value	0.50 %	0.118	-9.37908
41	PE/PCF/PS	Value	9.61 %	3.012	0.110923
42	PE/PCF/DE	Value	10.17 %	3.259	0.695097
43	PE/PCF/ROIC^{-1}	Value	4.27 %	1.041	-5.44669
44	PE/PS/DE	Value	10.13 %	3.215	0.646403
45	PE/PS/ROIC^{-1}	Value	4.55 %	1.106	-5.15571
46	PE/DE/ROIC^{-1}	Value	3.22 %	0.838	-6.5475
47	PB/PCF/PS	Value	3.94 %	1.056	-5.79682
48	PB/PCF/DE	Value	6.19 %	1.649	-3.45278
49	PB/PCF/ROIC^{-1}	Value	-0.97 %	-0.225	-10.9076
50	PB/PS/DE	Value	7.35 %	2.101	-2.24413
51	PB/PS/ROIC^{-1}	Value	4.21 %	1.056	-5.51196
52	PB/DE/ROIC^{-1}	Value	-0.72 %	-0.166	-10.6447
53	PCF/PS/DE	Value	10.09 %	3.185	0.602979
54	PCF/PS/ROIC^{-1}	Value	4.74 %	1.119	-4.96225
55	PCF/DE/ROIC^{-1}	Value	3.16 %	0.821	-6.60325
56	PS/DE/ROIC^{-1}	Value	4.86 %	1.180	-4.8409
57	EVEBITDA/EVEBIT/PE	Growth	8.60 %	1.812	-0.94413
58	EVEBITDA/EVEBIT/PB	Growth	11.33 %	2.590	1.895106
59	EVEBITDA/EVEBIT/PCF	Growth	22.17 %	4.684	13.18224
60	EVEBITDA/EVEBIT/PS	Growth	8.19 %	1.910	-1.37096
61	EVEBITDA/EVEBIT/DE	Growth	5.78 %	1.324	-3.87419
62	EVEBITDA/EVEBIT/ROIC^{-1}	Growth	10.48 %	2.166	1.017338
63	EVEBITDA/PE/PB	Growth	9.18 %	1.963	-0.34245
64	EVEBITDA/PE/PCF	Growth	11.64 %	2.668	2.217975
65	EVEBITDA/PE/PS	Growth	13.59 %	3.054	4.25487
66	EVEBITDA/PE/DE	Growth	5.18 %	1.329	-4.50776
67	EVEBITDA/PE/ROIC^{-1}	Growth	6.56 %	1.300	-3.06385
68	EVEBITDA/PB/PCF	Growth	9.46 %	2.248	-0.04669
69	EVEBITDA/PB/PS	Growth	6.89 %	1.718	-2.71902
70	EVEBITDA/PB/DE	Growth	2.37 %	0.623	-7.42551
71	EVEBITDA/PB/ROIC^{-1}	Growth	7.40 %	1.835	-2.19103
72	EVEBITDA/PCF/PS	Growth	7.43 %	1.842	-2.15921
73	EVEBITDA/PCF/DE	Growth	3.75 %	0.898	-5.99086
74	EVEBITDA/PCF/ROIC^{-1}	Growth	9.38 %	2.009	-0.13548
75	EVEBITDA/PS/DE	Growth	1.49 %	0.378	-8.34717
76	EVEBITDA/PS/ROIC^{-1}	Growth	8.76 %	1.981	-0.77949
77	EVEBITDA/DE/ROIC^{-1}	Growth	-3.50 %	-0.737	-13.5395
78	EVEBIT/PE/PB	Growth	10.15 %	2.174	0.673023
79	EVEBIT/PE/PCF	Growth	22.67 %	4.584	13.6995
80	EVEBIT/PE/PS	Growth	13.76 %	2.855	4.423915

81	EVEBIT/PE/DE	Growth	10.29 %	2.359	0.812921
82	EVEBIT/PE/ROIC^{-1}	Growth	4.85 %	1.031	-4.84543
83	EVEBIT/PB/PCF	Growth	17.09 %	3.847	7.897551
84	EVEBIT/PB/PS	Growth	3.79 %	0.909	-5.95532
85	EVEBIT/PB/DE	Growth	2.03 %	0.486	-7.78136
86	EVEBIT/PB/ROIC^{-1}	Growth	11.72 %	2.732	2.30129
87	EVEBIT/PCF/PS	Growth	16.36 %	3.700	7.135882
88	EVEBIT/PCF/DE	Growth	11.84 %	2.587	2.427591
89	EVEBIT/PCF/ROIC^{-1}	Growth	16.78 %	3.339	7.576151
90	EVEBIT/PS/DE	Growth	5.04 %	1.170	-4.64962
91	EVEBIT/PS/ROIC^{-1}	Growth	4.22 %	0.930	-5.50392
92	EVEBIT/DE/ROIC^{-1}	Growth	5.29 %	1.158	-4.38838
93	PE/PB/PCF	Growth	11.17 %	2.488	1.727276
94	PE/PB/PS	Growth	10.26 %	2.195	0.782132
95	PE/PB/DE	Growth	3.31 %	0.777	-6.44647
96	PE/PB/ROIC^{-1}	Growth	6.43 %	1.333	-3.20172
97	PE/PCF/PS	Growth	9.56 %	2.008	0.059997
98	PE/PCF/DE	Growth	10.03 %	2.402	0.544447
99	PE/PCF/ROIC^{-1}	Growth	4.12 %	0.770	-5.60536
100	PE/PS/DE	Growth	8.87 %	2.303	-0.66503
101	PE/PS/ROIC^{-1}	Growth	6.40 %	1.263	-3.2308
102	PE/DE/ROIC^{-1}	Growth	0.01 %	0.000	-9.88518
103	PB/PCF/PS	Growth	9.39 %	2.309	-0.1202
104	PB/PCF/DE	Growth	5.37 %	1.363	-4.3104
105	PB/PCF/ROIC^{-1}	Growth	10.31 %	2.494	0.839836
106	PB/PS/DE	Growth	0.67 %	0.187	-9.19557
107	PB/PS/ROIC^{-1}	Growth	8.37 %	2.061	-1.17883
108	PB/DE/ROIC^{-1}	Growth	11.16 %	2.658	1.720382
109	PCF/PS/DE	Growth	4.38 %	1.079	-5.34073
110	PCF/PS/ROIC^{-1}	Growth	10.57 %	2.243	1.106225
111	PCF/DE/ROIC^{-1}	Growth	3.23 %	0.633	-6.53057
112	PS/DE/ROIC^{-1}	Growth	-1.91 %	-0.394	-11.8826