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How have different pre-determined screening investment strategies performed over a 22-year period in the Nordic markets, and how have they performed in different market conditions?

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Abstract

This thesis has studied four pre-determined screening investment strategies and whether these strategies are consistently able to generate risk-adjusted returns for a Norwegian investor in the Nordic market throughout different market conditions. The Magic Formula, Dogs of the Dow, ValStrat and Financial Companies' strategies have been backtested on a 22-year timeframe between 1st of July 2000 to 1st of July 2022. Over this period the Magic Formula has yielded the highest average return per year of 16,4% followed by Financial Companies at 15,6%, ValStrat at 14%, and Dogs of the Dow at 3%. Dogs of the Dow being the only strategy that does not outperform the MSCI Nordic index at 4,5%.

The CAPM and Fama and French three-factor model of asset pricing is used to measure alpha. Alpha is the strategies risk-adjusted excess return in comparison to the MSCI Nordic index. The Magic Formula and the ValStrat strategy generated statistically significant alpha under the CAPM model at 18% and 9,6% respectively. However, when more factors are considered in the three-factor model the alpha falls to 15,6% and 8,4% respectively compared to the MSCI Nordic index. All strategies demonstrated better risk-adjusted performance measures in comparison to the chosen MSCI Nordic index.

To measure the alpha in different market conditions, dummy variables were created to test which strategy that generates excess return compared to the index in two periods of market unrest, the 2008 financial crisis and the Covid-19 pandemic in 2020. The ValStrat strategy showed an increase in significant alpha values when including dummy variables for the financial crisis, indicating that this strategy outperforms the index in times of recession. The other strategies showed no significant change in alpha or significant interaction terms when considering specific market conditions.

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1.0 Introduction

The Efficient Market Hypothesis (EMH) by Fama (1970) suggests that stock prices reflect all available information, meaning that it is virtually impossible to consistently outperform the market. Value investors use fundamental information provided by company's financial statements to evaluate companies and estimate if a company is under or overvalued based on the current market value. These inefficiencies have been exploited by investors throughout the years through different types of investing strategies. In a study conducted by Blackburn & Cakici (2017) the Magic Formula was found to yield significant abnormal returns in different markets. To build upon these findings, this thesis examines the use of the Magic Formula as well as other fundamental strategies to determine the best investing strategy for a Norwegian investor investing in the Nordic market. In addition to the Magic Formula, the Dogs of the Dow, a strategy that bases itself upon dividend yield is considered. The ValStrat strategy is developed based on five key company fundamental figures that are deemed necessary for a solid value creating business. The financial companies' strategy picks out of financial firms based on their price over book value. These strategies are backtested on the period from the 1st of July 2000 to the 1st of July 2022 to gauge their performance over time and how they fair in periods of economic instability leading to the following research question:

How have different pre-determined screening investment strategies performed over a 22-year period in the Nordic markets, and how have they performed in different market conditions?

The goal of this thesis is to create implementable strategies that yields excess return compared to the MSCI Nordic index, and therefore counteracts financial theory. Another interesting aspect of this research is the investigation of the strategies performance during the financial crisis as well as the Covid-19 pandemic.

To gauge the strategies risk-adjusted return, The CAPM and the Fama French three-factor model is used to compare the performance of the strategies to the MSCI Nordic index. Using these models, we aim to explain some of the variations in returns of the investment strategies and determine whether the excess return is explainable by market movements. Any excess return that is not explainable by market movements is alpha in the regression equation, alpha is then the risk-adjusted excess return of the strategies. Further, to gain a more complete picture of each strategies risk profile, several risk-adjusted performance measures are considered including the Sharpe ratio, Treynor ratio, Information ratio as well as Jensen's alpha.

All strategies deliver excess cumulative return over this index in the time-period tested, however not all are a better investment when considering the level of risk. Only the Magic Formula and ValStrat strategies produce significant alpha values, meaning that they have a better risk-adjusted return compared to the index. This is true for both the CAPM and the Fama French three-factor models. The Magic Formula generates the best average yearly return with 16,4%, whilst the ValStrat strategy yields 14%, Financial Companies yield 15,6% and the Dogs of the Dow 3%. In the same period the MSCI Nordic index generate a yearly average at 4.5%.

When controlling for different market conditions, the financial crisis has a significant negative effect on the ValStrat strategy. However, the alpha value for this strategy increases when the market condition is considered, meaning that the financial crisis affected the index to a more significant degree than the ValStrat strategy. The Covid-19 pandemic had a positive impact on returns for the Magic Formula. This speaks to the swiftness of recovery in stock markets following the Covid-19 pandemic and the subsequent boom that followed. These findings align with existing literature such as a study conducted by Silvasti et al., (2021) where investing strategies are seen to be affected by changes in market conditions, and therefore their effectiveness varies over time. Further, the existence of market anomalies undermines the EMH as strategies can be seen to yield excess returns.

2.0 Theoretical and Empirical literature

The principal EMH is based upon is the efficiency of a stock market (Rossi, 2015). This theory measures the efficiency in the correlation between prices and the information available for investors in the stock market. Stock prices should, therefore, reflect all available information, implying that selecting stocks based on available information should not generate risk-adjusted excess returns compared to the market. According to Rossi (2015) an efficient market is impossible to beat due to prices adjusting rapidly and are without bias to new information.

There are three different forms of the theory in relation to the EMH. The weak form suggests that the current stock prices already reflect all historical price data (Fama, 1970). The semi-strong form of the EMH states that it should not be possible to consistently profit by trading on any public information. The weak and the semi-strong form imply that an investor should not be able to profit using information, such as an earnings report, that is accessible for everyone (Rossi, 2015). However, Rendleman et al., (1982) found evidence that market prices did not adjust right away, but it took several days for publicly announced information was reflected in market prices. The strong form of this theory implies that a market price of a stock reflects all information including past prices, publicly and private information. However, empirical research has found evidence of inconsistency with the strong form of the EMH, these are often called market anomalies (Rossi, 2015).

According to Rossi (2015) evidence against EMH has grown over the years starting with calendar anomalies. Several other empirical studies have discovered the existence of market anomalies, even though, there are evidence that the EMH, especially the semi-strong form of the EMH holds. According to Jacobs & Levy (1988) abnormal returns in the market occurs when there are calendar turning points. The interesting point of these anomalies is that they do not have a great economic significance, however investor tends to deem them important and therefore behave accordingly.

The most important and the first evidence against semi-strong form of EMH was the January effect, day-of-the-week effect and the holiday effect (Rossi, 2015). The first evidence of these anomalies appeared in the 1930s. According to Jacobs & Levy (1988) there can be several reasons for the calendar anomalies. Some examples of this can be tax-loss selling at the end of a year. Another example can be negative news that are released over the weekend. Evidence presented by Jacobs & Levy (1988) and Rossi (2015) contradict traditional financial theory based on the EMH, especially regarding the semi-strong form of EMH. This study thereby aims to use publicly available fundamental information to try and beat the market index, opposing the theory of EMH.

Blackburn & Cakici (2017) researched the performance of the Magic Formula against different stock markets across the world. The study implies that the Magic Formula was found to yield significant abnormal returns compared to the indices in different stock markets. This strategy is included in this study to determine its effectiveness on Nordic markets.

A paper published by Basu (1977) found evidence of low P/E ratio stocks, tended to outperform the stocks that had a higher P/E ratio. A study by Lakonishok et al., (1994) that tested P/B ratios, found that stocks with low P/B provided higher return compared to the stocks with a high P/B ratio. In addition to this, empirical evidence suggests that investors can possibly predict future stock prices by utilizing, earnings announcements, dividend yields, and IPOs (Thaler, 1999).

As explained by Markowitz (1952) the importance of diversification in investment decision-making is key to reduce overall risk of a portfolio, while maintaining the expected return.

Markowitz (1952) also introduced variance as a measure of risk in a portfolio, this framework eventually evolved into what is now called the mean-variance portfolio theory. Markowitz argues that investment decisions should be based on the trade-off between risk and return of an overall portfolio, as opposed to constructing a portfolio simply based on securities with high risk-return characteristics (Markowitz, 1952). To perform the mean-variance analysis, this thesis has conducted regression analysis to calculate the return of each investment and factor like market returns to estimate the expected return and the variance (β) on the four strategies.

Several studies have found limitations with portfolio selections using the mean-variance theory. These studies assume that the mean-variance theory is a simplification of the reality for an investor. Zhang et al., (2018) studied evidence of small changes in the variance and the expected returns would result in significant changes in the optimized portfolio due to the variables being highly sensitive. Other limitations found in the study showed that the mean-variance theory assumes rationality and homogeneity among investors. The theory also ignores the likelihood of extreme events that can lead to potential downside, as well as it may not reflect the long-term investment goals of an investor due to it being limited to a single-period timeframe.

The assumptions on rationality and homogeneity are not always applicable for an investor. In real life investors have different investing strategies and will invest accordingly. Disparate believes of market outcomes, investment horizons and decision will affect investors to act when extreme events such as the Covid-19 crisis happens. A study conducted by Litner (1975) also argued against Markowitz's framework regarding the mean-variance theory. The study argues that investors tend to make small changes and adjustments to their portfolios gradually, rather than making large changes every turn of a year for example. Litner (1975) also suggests that investors will be more willing to invest in stocks that pay dividends as these securities provide a steady stream of income for the investor. Whether this is a valid approach to investing will be tested in this thesis by comparing the Dogs of the Dow strategy to other pre-determined strategies.

A study performed by Mačiulis et al., (2007) evaluated the performance of three Nordic exchanges and three Baltic exchanges and compared the performance using two different approaches. The first performance evaluation was the traditional measure of Sharpe ratio, Sortino and Treynor ratio often called mean-variance based performance measures. In addition, an alternative measure that was used in the study was the reward to value at risk and reward to expected tail loss. The major findings in this study suggest that the two approaches of portfolio performance do not diverge significantly from each other. This implies that returns of all exchanges were normally distributed. In other words, the traditional mean-variance based measures can be used when analysing the performance of all the exchanges. These findings are significant for our thesis as they provide evidence for using the mean-variance performance measures to test if our strategies outperform the index in risk-adjusted returns.

In the period between 2000 and 2022 there has been several major events that affected the stock market globally. The financial crisis and the Covid-19 pandemic are two of these events and are the focus of this study. The study conducted by Silvasti et al., (2021) provide insight on how the profitability of smart beta investing on the Nordic stock market in different market conditions. To give context, smart beta investing strategies is a type of investment strategy that uses factors like momentum, quality, volatility, and profitability to screen and select stocks. The study uses the Nordic stock market from 2005 to 2019, and the results indicate that the smart beta strategies outperform the market in risk-adjusted returns. Also, the study finds evidence that the performance of the strategies is influenced by different market conditions, and therefore the effectiveness of the strategies varies over time. Silvasti et al., (2021) suggest that investors could consider using these strategies as a part of a diversified investment portfolio. An investor should be cautious when using these strategies due to the risk of narrowly defining the investment universe, leading to a decreased degree of diversification. The result of their study implies that finance theory, such as the efficient market hypothesis gives an incomplete picture. This suggests that investors can create strategies that outperform the market in risk-adjusted returns. Additionally, the result indicates that market conditions influence the selected strategies in the study. On that basis, it will be interesting to see the results of major economic crisis on the strategies assessed in this thesis.

Kat (2005) argues for the danger of using quantitative models and pre-determined investment approaches in stock picking. This study emphasizes the limitations of pre-determined investing strategies due to it being based on historical data and assumptions becoming less effective over time. The reason for this is shifting market conditions and not accounting for other market events, such as geopolitical risks which are some of the similar limitations to the efficient market hypotheses that is being evaluated in this thesis. However, Kat (2005) concludes that quantitative models and pre-determined investment strategies can be used as a part of a more diversified investment approach that emphasizes on professional judgment and other quality analysis (Kat, 2005).

According to Haavisto & Hansson (1992), risk reduction by diversification in the Nordic stock markets was similar in scope to the risk reduction in a global stock market. This is an intriguing finding due to the Nordic countries being somewhat viewed as homogeneous from a social, political, and economic point of view. Contrary, the idea on diversification internationally, is low correlation between different national stock market due to different cultural, political, and economical values. This would imply that the Nordic stock market had few possibilities for risk reduction for an investor. However, the study showed that a long-term investor would have done well by keeping a diversified Nordic portfolio (Haavisto & Hansson, 1992).

Adding to this, a study conducted by Levy & Sarnat (1970) researched the benefits of international investments on diversification. Investor typically tends to focus on investing in assets domestically, rather than foreign countries. Investors may be hesitant to invest in foreign countries due to different concerns regarding political differences, and currency risk to name some examples. Evidence from this study suggests that benefits of international diversification outweigh the concerns. The study concludes that international portfolio can be an effective strategy for an investor to pursue good risk-adjusted returns (Levy & Sarnat, 1970). A Norwegian investor may therefore achieve a similar diversification benefit from investing in the Nordics as one could achieve by investing in the global stock markets.

3.0 Hypotheses

Based on relevant theory such as the efficient market hypothesis and mean-variance theory, and empirical literature on market anomalies, and already existing research on performance of pre-determined investment strategies in different markets, three hypotheses are created to answer the research question.

H1: "Pre-determined screening investment strategies generates significant risk-adjusted excess return over the 22 year-period compared to the MSCI Nordic index"

The first hypothesis is created as a contrast to the semi-strong form of the EMH. This hypothesis aligns with the literature that researches the occurrence of market anomalies in stock markets, and studies that have tested various investment strategies that aims to yield abnormal returns over time.

H2: "The ValStrat investment strategy will be able to outperform Greenblatts Magic Formula as well as the index"

The second hypothesis predicts that a newly created investment strategy will be able to outperform Greenblatts Magic Formula as well as the index. The research conducted by Blackburn & Cakici (2017) found that a modified Magic Formula yielded significant abnormal returns in different global markets. On that basis, our study fills the gap on how the original Magic Formula Greenblatt (2006) performs on the Nordic stock market.

H3: "The four strategies will outperform the index in different market conditions"

Silvasti et al., (2021) found that smart beta investing varied over time as market conditions changes. As the strategies seek to find value stocks, it is believed that market turmoil should affect the performance of portfolios to a lesser negative degree than can be seen in the index.

4.0 Methodology

4.1 Data

Annual key-figure information and other fundamental data was retrieved between the 1st of July 2000 and the 1st of July 2022 from the Refinitiv Eikon database. The end of the fiscal year was chosen to ensure the accessibility of fundamental data. First and foremost, the Nordic market was chosen due to cultural, geographical, and political similarities. However, due to limitation in downloading financial data from DataStream, as well as the small size of the market, Iceland is not included in the dataset.

To investigate the development in returns for the chosen strategies, a 22-year time-period was chosen, beginning at every new fiscal year on the 1st of July. There are some limitations to this due to some companies having non-standard financial years. The dataset does not take this into account as this falls beyond the scope of this thesis. The return for each portfolio is calculated using the price information from one year to the next, adjusted by dividend payments[1]. Highs and lows throughout the financial year has no impact on returns as the strategies are rebalanced the 1st of July every year. To ensure enough observations are present to run the regression analysis, the regressions base itself upon monthly returns. Figure 2 has a breakdown of number of companies per country throughout the analysed period. Norway, Denmark, and Finland have relatively similar number of companies on their respective exchanges, with Sweden being the largest contributor to the dataset in number of companies.

[1] Equation for calculating returns using price information: $Return = \frac{(P_1 - P_0) + D}{P_0}$

Figure 1: Number of Companies in the dataset

The figure shows the number of companies with adequate fundamental data for each country per year.

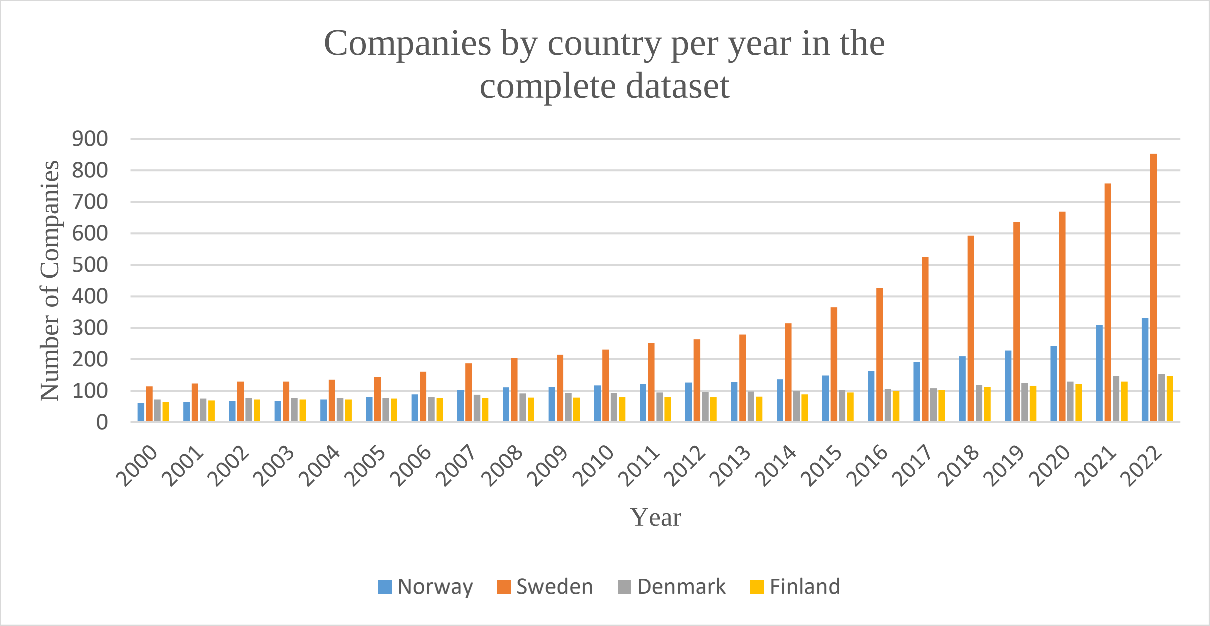


Figure 2: Country distribution of market capitalization

The figure shows the size of total market capitalization for each country per year.

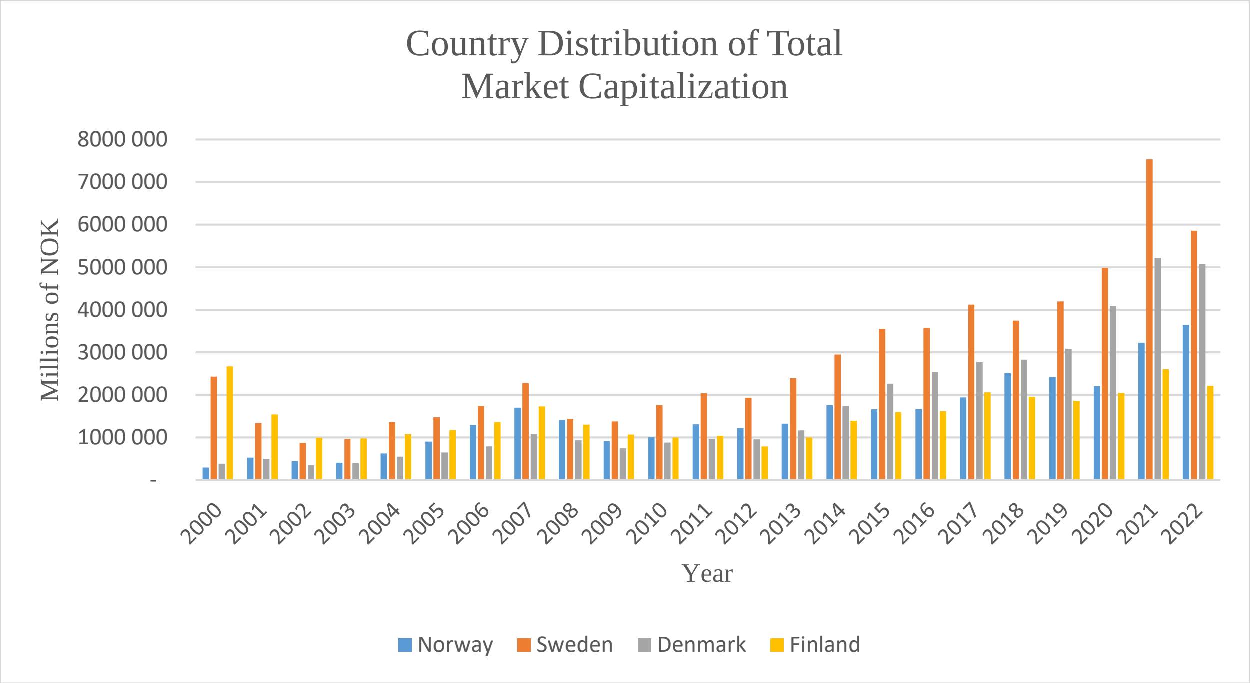


Figure 2 shows the total size of each market in total market capitalization. Although Sweden has by far the greatest number of companies in the dataset as shown in Figure 1, when total market capitalization is considered the difference between the markets are not as pronounced.

This is mostly due to large companies like Equinor, Nokia and Novo Nordisk, hailing from Norway, Finland, and Denmark respectively.

To construct the different strategies a total of 13 variables for each company is downloaded, a more detailed description of these variables is given when the strategies are described.

Table 1: Variables used in creating the strategies

The table shows all downloaded and calculated variables used in creating the portfolios for each strategy. They are gathered on the 1st of July every year between 2000 and 2022.

Variable	Description
P	Price
MV	Market capitalization
DY	Dividend Yield
ROE	Return on equity
OPM	Operating profit margin
EPS	Earnings per share
PTBV	Price to book value
EBIT	Earnings before interests and taxes
CA	Current assets
CL	Current liabilities
CR	Current Ratio
EV	Enterprise value
Three-month Nibor	Risk-free rate
Calculated variables	**Description**
PE	Price over earnings
ROCE	Return of capital employed
P_Div	Dividend adjusted return
EarningsY	Earnings yield
Return	Return

Table 2: Summary statistics

The table depicts summary statistics of the variables of Price, Return and Market capitalization. N is the sum of all observations, the mean, min and max are therefore based on all companies' yearly observations. Data is gathered on the 1st of July every year between 2000 and 2022.

Statistic	N	Mean	St.Dev	Min	25th Pctl	75th Pctl	Max
Price	13794	7328	326689	0,01	8,812	99	30159680
Return	13794	0,107	0,616	-0,99	-0,251	0,313	4,9322
Market Capitalization	13748	11385	50266	0,13	150,4	3957	2103622

4.2 Backtesting

Backtesting is a statistical method used to evaluate the performance of the four strategies that has been found, developed, and created in this study. The strategies will be backtested throughout the 22-year period between 2000-2022. The goal is to simulate the investment strategies as they would act in real time and see if the strategies produce excess returns compared to the index. Another consideration is to compare the strategies with each other to see which strategy that has generated most cumulative returns in the 22-year period.

Choosing a benchmark to measure and compare the selected strategies provides a better understanding of the performance of the selected portfolios and the risk compared to the index. The MSCI Nordic index is used as benchmark and comparable index to the four constructed portfolios, as this was the available comparable index in DataStream.

The analysis is viewed from the point of view of a Norwegian investor, and the returns of the portfolios must therefore be adjusted for changes in the exchange rates. This will account for eventual currency gains or losses year over year. All prices and variables that would be affected by a currency change are converted to NOK when they are downloaded from Refinitive Datastream. The quote for the exchange rate is the 1st of July each year, a summary table of these rates can be found in appendix 5.

In backtesting, there is a danger of only testing the companies that survive to the present, as they are the ones that most likely have data available. Data brokers may not hold on to and store data for companies that are defunct. Datastream does keep data for some companies that are delisted, but not all companies that are removed from an exchange. A consequence of this is that this data source suffers from some degree of survivorship bias. This reduces the accuracy of the study, as companies that could have been selected by the strategies and then gone bankrupt are not present. One mitigating factor to this issue is that the strategies aim to find value portfolios. The models filter out companies with bad fundamentals which would be the case for companies that are about to go bankrupt.

Look ahead bias is combated by constructing the portfolios at the end of the fiscal year. Look ahead bias could occur if the portfolios were constructed on data that would not be available at the time of the backtest. However, all fundamental data for the previous year should be available at the end of the fiscal year.

As this analysis is based on predetermined investment strategies, issues with data snooping and overfitting should not be present. These issues occur if the strategies are based upon historical data and then the analysis is conducted on the same data which created the strategies. As the investment criteria are predetermined, we predict no such issues.

An observation is categorized as an outlier when it falls far beyond the range of other observations. A return of over 500% within one year is seen as unlikely and is therefore removed. 28 observations exceed this threshold, representing 0,2% of the dataset.

Investing has in the recent years been more accessible to retail investors. According to a report written by Deloitte (2021) the reason for this is that transaction cost has significantly been reduced by low-cost market players such as Robinhood and Etoro especially in the US. The growth of these digital trading platforms is to some degree due to their offering of zero-commission trading and fractional shares trading. According to the same report the growing influence of retail investor should impact the established brokerages and how they operate. To stay ahead of this transformation, Deloitte suggest that established brokerages should renew their processes. Low-cost market players have started to enter the Norwegian market with Nordnet and DNB leading the way for young adults. Due to these reasons, transaction cost has not been considered. This limits our research because traditional high transaction cost could have impacted returns to some degree.

4.3 Description of linear regression

To test the impact of market movements and the risk-adjusted return of each strategy, a linear regression is suitable[2]. A multicollinearity test is used to identify the degree of predictability among the explanatory variables in a regression. To test the multicollinearity in the variables in the regression, their variance inflation factor (VIF) is estimated. The rule of ten is commonly used as a rule of thumb for severe multicollinearity. A variance inflation factor lower than this threshold can indicate small forms of multicollinearity among the explanatory variables (O'Brien, 2007).

Presence of autocorrelation and heteroskedasticity in the error term of a regression could reduce the precision of the analysis. This is because the variance of the estimates can be artificially reduced by an affected error term. A consequence of this, is an exaggeration of the significance of the explanatory variables. Autocorrelation is defined as correlation between two observations

[2] Equation for linear regression: $y_t = \alpha + \beta x_t + u_t$ Where the dependant variable is the return on the portfolio

on specific points in a time series (Hill et al., 2011). To detect possible heteroskedasticity and autocorrelation a Breusch-Pagan test is utilized. To remove autocorrelation and heteroskedasticity from the regression, the variables need to be HAC adjusted.

Stationarity in time series can be defined as a series of data “that is not explosive, nor trending, and nor wandering aimlessly without returning to its mean” (Hill et al., 2011, p. 376). Contrary, a non-stationary time series can be defined as a series of data that wanders slowly upwards and downwards without a specific pattern. This is often referred to as a random walk. Should the data follow a “random walk” pattern, stationarity in the variables is assumed. An augmented dickey fuller test is used to test for stationarity in the variables. Non-stationarity in the variables could lead to inaccurate results (Hill et al., 2011).

5.0 Strategies

Table 3: Variables that contribute to portfolio construction

The table shows what variables go into selecting companies for each strategy. Companies are ranked based upon these variables and are consequently either selected or discarded from the portfolio.

Strategy	Determining variables
ValStrat	Operating Margin Dividend Yield Return on Equity Debt to Equity Ratio Price over earnings
Magic Formula	Return on common equity Earnings yield
Financial Companies	Price over bookvalue
Dogs of the Dow	Dividend yield

5.1 Magic Formula

The first strategy for building a portfolio based on the dataset was the Magic Formula created by Joel Greenblatt. The Magic Formula is a pre-determined investing strategy that is based on certain criteria designed to yield high returns within reach of the average investor (Greenblatt, 2006). This allows investors to identify outperforming and undervalued companies and stocks, without being affected by emotion or other factors that can affect an investor when investing in the stock market. The model ranks companies based on two fundamental factors. The first is a company's return on capital employed, calculated in the following manner.

$$ROCE = \frac{EBIT}{Current\ Assets - Current\ Liabilities} \tag{1}$$

A firm's EBIT, which is its earnings before interest and tax, gives an indication of a company's ability to generate positive cashflows. By dividing this on the working capital, which is found by subtracting liabilities from assets, one can discover how large a return one can expect from capital employed in the company (Greenblatt, 2006).

The next ranking measure is a company's earnings yield, a measure that seeks to find companies that have good earnings in comparison to their value. It is calculated as:

$$Earnings\ Yield = \frac{EBIT}{EV} \tag{2}$$

Where EV is the enterprise value, calculated by adding up a company's market capitalization and total debt, and then subtracting a company's highly liquid assets such as cash (Greenblatt, 2006).

This model also excludes any companies with a market capitalization of under $50 million[3], the reasoning being that lower market capitalization may have some liquidity risks (Greenblatt, 2006). This filter on market capitalization removes 38% of available companies from the dataset for consideration in the Magic Formula portfolio.

Additionally, Greenblatt's model excludes banks and other financial institutions because their financial reporting is deemed to be too complicated. Banks and other financial institutions are therefore dropped from the dataset. After this initial filter on market capitalization and sector, the dataset is ranked on the aforementioned factors. The next step is to create a portfolio where the top 25 companies in total rank are selected, and then investigate what kind of return one will have in the following period. This method is then repeated for each year in the timeframe.

[3] Approximatly 500 million NOK in 2023.

5.2 ValStrat Strategy

The aim of this strategy is to find solid, value-creating businesses that are currently undervalued. The frameworks that were deemed best suited included the following factors:

The first factor deemed a good fit for the strategy was a company's operating margin. This factor is making sure the company that is chosen, has a good underlying profitability. This is according to the value investing approach developed by Graham (1973) that an investor wants to see earnings stability from a company. It is believed that if a company has a good operating margin, the company can produce stable earnings over a long period of time and, therefore, continue to add value to the business and the investment.

The second factor that the ValStrat method emphasizes is the dividend yield. This is a measure that implies favourable returns to shareholders, and that the business is generating returns that the shareholder can benefit directly from. In addition to this, the dividend yield serves as an accountability measure for the leaders in the company, in terms of performance requirements and that the leaders do not benefit economically on the behalf of the shareholders. Finally, a long historical dividend record can indicate that a company have earned money in the past and most likely will be able to increase profitability and earnings in the future (Graham, 1973).

Furthermore, the return on equity (ROE) factor is deemed valuable to the framework of the ValStrat strategy. The reason for this is that the ROE is considering the amount of return an investor can expected to be generated on the invested firm's capital (Graham, 1973).

The debt-to-equity ratio is utilized in the ValStrat strategy. The reason for the importance of this factor in the ValStrat investment framework is that it prevents the strategy from selecting companies that are heavily burdened by debt. This will lead to reducing the risk of the investment, which is in alignment with the most known quote by Warren Buffet: *"Rule NO. 1 is never lose money. Rule No. 2 is never forget rule No.1"* (Sarwa Digital Wealth Limited, 2022).

The last factor that is included in the ValStrat strategy is the P/E-ratio. This ratio is included because it is a factor that mainly allows for the discovering of underprized or fairly priced stocks. "*It's far better to buy a wonderful company at a fair price, than a fair company at a wonderful price"* (Sarwa Digital Wealth Limited, 2022). The P/E ratio will find these companies, and hopefully screen fairly or under-priced stocks into the portfolio.

The ValStrat strategy is based on each one of these variables, if above or below a certain threshold it yields one point towards the company's total score. The companies with the highest total score for any given year are chosen as investments for that period and held in equal weighting for one year, or for however long they fulfil the criteria to be in the portfolio. The threshold for each variable is described in the table below.

Table 4: ValStrat variable thresholds

The table illustrates the required threshold of each financial figure to gain one point towards the company's total score under the ValStrat strategy.

Variable	Threshold
Operating Margin	Min 15%
Dividend Yield	Min 1,5%
Return on Equity	Min 15%
Debt to Equity Ratio	Max 100%
PE	Max 10

The 15 different companies with the highest score each year are selected for the portfolio. In devising the strategy, a market capitalization minimum of at least 100m NOK is set. This is to filter out smaller companies that are not yet mature enough to be considered true value companies. One observation is that this minimum is less than the market capitalization limit set by other strategies such as the Magic Formula, which sets the limit at $50m[4]. This decision has been made to screen companies that have good fundamentals as well as having the potential for growth. Another factor is the limited liquidity and size of Nordic exchanges in comparison to the American exchanges, in which the Magic Formula was first based upon. A lower required market capitalization is therefore accepted. A 100 million NOK minimum market capitalization removes 23% of the companies from consideration.

5.3 Dogs of the Dow

The third strategy that is being tested in this study is the "Dogs of the Dow" investment strategy. This method is a long-term investing strategy that provides an investor with a set of companies that pay dividends. The dividend yield provided by the companies to the investors form the criteria for selection in this strategy. The top ten performers regarding dividend yield each year is selected. For this model especially, it is important to consider the impact of these dividend payments on the returns of the model.

[4] Approximately 500m NOK, which is what is employed in this study

The companies are ranked based on the previous fiscal year's dividend yield. Dividends may be paid out at different points during the calendar year, however since the study bases itself around the fiscal years, it ensures some form of uniformity as all reported dividends need to be reported by then.

5.4 Financial Companies

The final strategy that is being tested is a portfolio consisting of banks and financial companies in the Nordic market. This portfolio is constructed based on the price over book value for financial companies, where the lower P/B the better. The portfolio is constructed by choosing ten financial companies each year with the lowest price over book value. The reason for choosing the P/B method is due to its relatively accessible value measure. P/B measures the market capitalization to the book value of equity, and banks are required to hold a specific amount of cash due to government regulation in Nordic countries (Finanstilsynet, n,d,). The P/B measure is an effective way to examine if a bank is under or overpriced for that reason. A rule of thumb, is that a P/B measure of lower than one, is considered a solid investment.

According to FCG (2020), Martin Rex a Swedish business newspaper writer wrote an article in 2020 that compared the Nordic banks to the European and US banks. This article emphasizes on the robustness of the Nordic banks compared to banks in other countries. Rex also suggests that Nordea, the largest bank in the Nordic would play major role in the consolidation in the European banking industry. Rupeika-Apoga et al., (2018) conducted a study on the Nordic and non-Nordic banks operating in Latvia, and examined the differences between the two. The study found that ownership structure of banks is an important factor in determining a banks stability. Evidence of Nordic owned banks tended to be more stable than non-Nordic banks. The reason for this is that Nordic banks are subject to greater oversight and regulation from their respective government (Rupeika-Apoga et al., 2018).

According to FCG (2020) the Nordic banking sector is general viewed as providing consistent and high returns to shareholders. The reasoning behind this is the consolidation of the Nordic banking sector post the 90s banking crisis. According to the ministry of finance in Norway, there has been developed strict standards and principals that a Norwegian bank must follow. In terms of licensing, organisational rules, general operational rules and rules on guarantees schemes and failure (Finanstilsynet, n.d.).

On that basis, and due to the Magic Formula eliminating all financial stocks because of its complexity (Greenblatt, 2006) the Financial Companies' portfolio is included to compare and see if this portfolio manages to outperform especially the Magic Formula, and also the other strategies.

5.5 Calculating explanatory variables

5.5.1 CAPM

$$r_I = r_f + \beta_I \times \left(E[R_{Mkt}] - r_f\right) \quad 3$$

The CAPM explains a firms return as a function of the markets systematic risk and the risk-free rate. For this analysis, a linear regression is utilised to find the beta between the return of the portfolio and the return of the market. The variables that are needed for this is the return on the constructed portfolio, the risk-free rate, and the return of the market portfolio, as can be seen in equation 3. The risk-free rate is set at the three-month forward NIBOR rate, as this is the rate that we assume an investor can get in an alternative risk-free position (Ødegaard, 2023). The risk-free rate also varies over time as the rate set by the Norwegian central bank changes.

To calculate the return of the market portfolio, the MSCI Nordic index is considered. The performance of the index is gathered from the 1st of July 2000 to the 1st of July 2022, and the percentage change of this index is the basis for the markets return. The full development of the MSCI Nordic index can be viewed in appendix 4. To calculate the market risk premium, the risk-free rate is subtracted from the market return, giving us the value that will be used in the OLS regression. Development of the risk-free rate over the time period can be viewed in appendix 5.

5.5.2 Fama French Three-factor model

Due to limitations of the CAPM model in regard to explaining the cross-section of average stock returns Fama & French (1993) suggested a three-factor model that included market risk, size and value as variables to better express the variation in average stock returns. The research conducted by Fama and French suggest that the three-factor model provides more extensive explanation in the variation of average stock returns compared to the CAPM model founded by Sharpe (1964) and Litner (1965).

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + e_{it} \quad 4$$

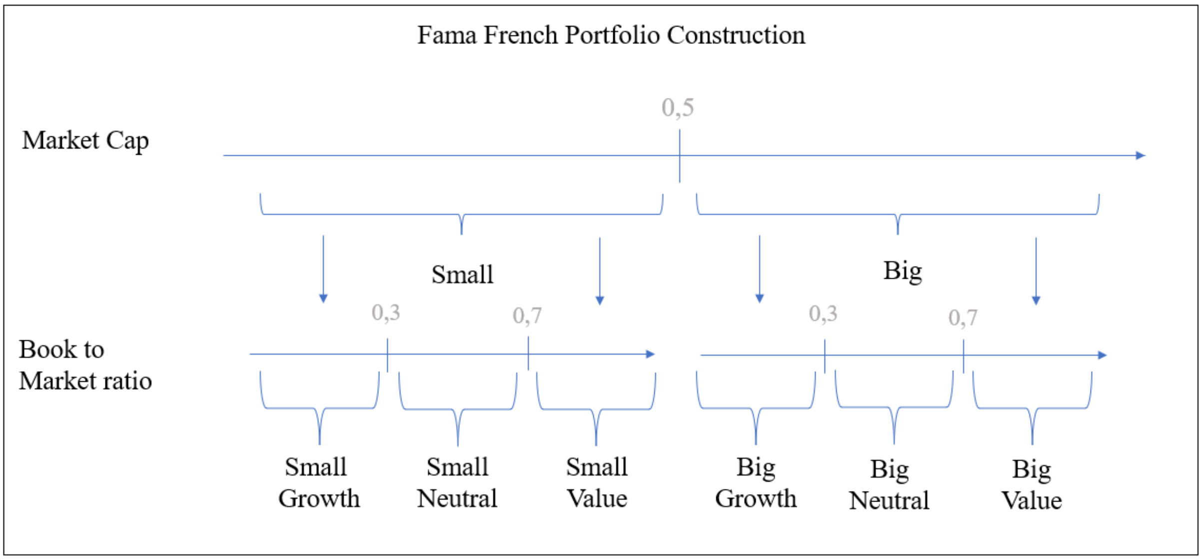
In the equation above, R_{it} is the return on a security or a portfolio I for period t. Moreover, the R_{Ft} is the risk-free return, meanwhile the R_{Mt} is the return on the value-weighted market portfolio, e_{it} is the zero-mean residual (Fama & French, 2015).

The Small Minus Big (SMB) variable is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks (Fama & French, 2015). This variable is calculated by finding a stocks market capitalization and price and multiply these variables with shares outstanding. The High Minus Low (HML) variable can be described as the difference between the returns on diversified portfolios of high and low Book value/Market value stocks (Fama & French, 2015). This variable is used to capture the difference in average return based on a company's book value compared to its market value.

The Fama French three-factor model is an expansion of the CAPM. CAPM is the first factor in fact, whilst the Small Minus Big (SMB) and High Minus Low (HML) factors represent the other two. In similar regard to the CAPM, these other factors are based on portfolios constructed in the market, albeit more narrowly defined than the general market as a whole. The SMB and HML is based upon six portfolios constructed in the market. To accomplish this, the selection is first divided into big and small market capitalization stocks. Next several other criteria are passed onto the dataset to extract the full six portfolios, three for each initial division. Figure 3 illuminates this process.

Figure 3: Fama French Portfolio Construction

The figure shows how the Fama French portfolios for the three-factor model is constructed. Companies are divided into small and big based on market capitalization. Companies are ranked based on their book to market ratio within their allotted segment. Cutoffs for the final six portfolios are between 0-0,3 for the growth portfolio, 0,3-0,7 for the neutral portfolio, and 0,7-1 for the value portfolio.



The Growth, Neutral and Value portfolios are based on the rankings of each company's book to market value. For example, the small growth portfolio contains the lower third of ranked companies within the small market capitalization division. Figure 3 illustrates the rest of the cut-offs for inclusion in each portfolio.

To calculate the return of these portfolios, the value weighted mean of each is calculated. The portfolios are value weighted to ensure a fair representation of each market segment (Fama, 1970). For simplicities sake, the six portfolios are abbreviated to their first letters, (e.g., Small Growth = SG). SMB and HML is calculated using equal weighting between the value weighted portfolios using the following formulas:

$$SMB = \big((0{,}33) * (SG + \mathrm{SN} + \mathrm{SV})\big) - \big((0{,}33) * (\mathrm{BG} + \mathrm{BN} + \mathrm{BV})\big) \tag{5}$$

$$HML = \big((0{,}5) * (SV + BV)\big) - \big((0{,}5) * (SG + BG)\big) \tag{6}$$

The calculation of these variables is grouped by month, and the returns one gets can then be used to run an OLS regression against the returns we gather based on the strategies assessed. It is then possible to investigate how the return of each strategy is influenced by these market segments.

5.5.3 Calculated Linear models

The following linear models produce the regression outputs for the CAPM and Fama French three-factor model.

$$lm(Excess\ Return\ of\ the\ Strategy \sim MarketPremium) \qquad 7$$

$$lm(Excess\ Return\ of\ the\ Strategy \sim MarketPremium + SMB + HML) \qquad 8$$

The return of each strategy is the dependant variable, while the Market risk premium, SMB and HML are explanatory variables. In this manner each strategy is tested to see if they generate a significant positive alpha. Alpha is the y intercept of the linear model, and should the models return a positive alpha, one can determine that the model generates a better risk vs reward relationship than what can be found in the market.

5.5.4 Controlling for different market conditions

The betas that the regression generates also indicate how much the portfolios return are influence by different parts of the market. With this knowledge we can analyse how the portfolios act in different market conditions using dummy variables.

Dummy variables are used to isolate the specific points in time, and therein different market conditions. In the time period chosen for this analysis, there have been several crises that have severely affected financial markets including the financial crisis and the Covid-19 pandemic. These two events specifically are of interests as they caused a major unrest in global stock markets, and the study aims to see how well the strategies would perform in such scenarios.

The effects of the financial crisis could be felt by February of 2007, and a recession quickly followed. As the price data is loaded in monthly intervals, it is impossible to be specific on the exact dates that the crisis unfolded, reducing the potency of the investigation. The models are tested for one year post this date to discern what kind of impact this had on the portfolios.

Covid-19 first tanked global stock markets as the illness gained the status as pandemic. Of course, this is not a perfect measure of when Covid-19 first effected markets, however one point in time needs to be settled as the definitive start. Covid-19 gained the status as pandemic in March of 2020, and it is this point that is the starting point of the dummy period (World Health Organization, n.d.). In similar fashion to the financial crisis, the effect is tested for one year post the initial date.

The expression for the linear models, while considering the dummy variables become:

$$lm(Excess\ Return\ of\ the\ Model \sim MarketR + Covid + Fin\_Crisis) \tag{9}$$

$$lm(Excess\ Return\ of\ the\ Model \sim MarketR + SMB + HML + Covid + Fin\_Crisis) \tag{10}$$

6.0 Risk-adjusted performance indicators

When an investor is seeking higher returns, they should also be prepared for higher risk (Mossin, 1966). However, an investor should be compensated for a greater risk exposure. The following measures is described to evaluate risk-adjusted performance of the chosen portfolios.

6.1 Sharpe ratio

To generate and achieve the highest possible excess return for any level of volatility an investor must create a portfolio that generates the steepest possible line when combined with a risk-free investment. The slope of the line through a created portfolio is called the Sharpe ratio of the chosen portfolio (Berk & DeMarzo, 2014). This method of evaluating risk-adjusted performance was founded by Sharpe (1964).

$$Sharpe\ ratio = \frac{Portfolio\ Excess\ Return}{Portfolio\ Volatility} = \frac{E[R_p]-r_f}{SD(Rp)} \tag{11}$$

Where the risk-free rate (rf) is the three-month forward NIBOR rate gathered on the 1st of July every year. The return of the portfolio is the average of the equal weighted portfolio of stocks created by each strategy. Standard deviation of the returns is gathered when the regressions are conducted. The sharp ratio measures the ratio of reward-to-volatility provided by a portfolio (Berk & DeMarzo, 2014).

6.2 The Treynor ratio

The Treynor Ratio was developed by Treynor (1965). Many of the aspects of the Treynor Ratio is similar to the Sharpe ratio measurement of risk-adjusted performance. However, the two measurements diverge as the Treynor ratio only considers the investments exposure to market risk. In contrast to the Sharpe Ratio which measures the total risk of an investment. This makes the Treynor Ratio more appropriate for evaluating the performance of individual securities or portfolios with high level of systematic risk.

$$Treynor\ Ratio = \left(\bar{r}_p - \bar{r}_f\right)\beta_\rho \quad 12$$

In similarity to the Sharpe ratio, Treynor's measure gives excess return per unit of risk. However, the Treynor measure uses systematic risk instead of total risk (Bodie et al., 2019). The difference between the Sharpe ratio and the Treynor ratio is therefore its exposure to diversifiable risk. Using these two measures in conjunction with one another, we can determine a strategies exposure to systematic risk.

6.3 Information ratio

The information ratio measures the excess return an investor can obtain from security analysis compared to company specific risk (Bodie et al., 2019).

$$Information\ Ratio = {}_{\alpha_p}/\sigma\left(e_p\right) \quad 13$$

The information ratio divides the alpha of the portfolio by the non-systematic risk of the portfolio, often referred to as the tracking error. Therefore, it measures abnormal return per unit of risk that in principle could be diversified away by holding a market index portfolio (Bodie et al., 2019). In other words, the information ratio measures how much a portfolio has generated in excess returns in relation to the market portfolio, measured against the active risk of the portfolio.

These performance measures can thus give insight into each strategies risk profile. Where the Sharpe ratio measures total risk, Treynor ratio measures systematic risk and the information ratio measuring the abnormal return per unit of risk.

6.4 Jensen's alpha

This measure of risk-adjusted returns is based on the CAPM model and is introduced by Jensen (1968). Jensen's measure puts emphasis on the individual investor or fund managers ability to predict future changes in the stock market, in contrast with the theoretical approach of the EMH. In addition to this, Jensen underlines the importance of diversification to reduce risk on a portfolio (Jensen, 1968). Jensen's alpha can be explained by the following formula.

$$\text{Jensen's Alpha } (\alpha) = R_p - \left[R_f\left(Rm - R_f\right)\beta_p\right] \quad 14$$

7.0 Results

Table 5 has an overview over how the index and the different strategies have performed over the 22-year period. There are several takeaways to point out throughout the timespan. The first main takeaway from the table, is that all the four strategies have cumulatively outperformed the reference index. In other words, the accruing performance of the four strategies each year of the time span, has outperformed the index. In addition to this, the Financial Companies' strategy has accumulated the most return in total. Furthermore, the strategy that had the highest average return throughout the period was the Magic Formula, yielding an average return of 16,4% each year. Comparing this to an index that refers to a representation of the global financial markets, the Standard & Poor's 500 index (S&P Global Inc) & Kristiufek (2020). The Magic Formula has outpaced the return of the S&P 500 index of 8,2% each year since 1995 (S&P Global Inc).

Table 5: Cumulative returns of the Strategies and performance measures

This table illustrates the cumulative returns as well as average return per year yielded from the MSCI Nordic index compared to the yield generated by the equal weighted portfolios constructed based on the pre-determined strategies. Returns are calculated using yearly price observations on the 1st of July between 2000 and 2022, when the portfolios are rebalanced. Total cumulative returns are rounded to the nearest whole percentage.

Returns	MSCI Nordic Index	Magic Formula	Financial Companies	Dogs of the Dow	ValStrat
Total cumulative returns	36 %	1374 %	1380 %	60 %	1097 %
Average return per year	4,5 %	16,4 %	15,6 %	3,0 %	14,0 %
Performance measures					
Sharpe Ratio	0,0416	0,834	0,343	0,142	0,662
Information Ratio		0,831	0,118	0,0208	0,45
Treynor Ratio		0,824	0,222	0,166	0,443
Jensens Alpha		1,40 %	0,30 %	0,21 %	0,70 %

During the first year of the Covid-19 pandemic, the market experienced a steep decline. Indices all over the world recovered historically quick due to central banks lowering the interest rate to zero and initiated aggressive quantitative easing. A full overview of the returns of the strategies can be viewed in appendix 4, where the strategies can be seen to yield a return from 37% to as high as 72% that year. This contrasts with the economic outlook since the pandemic in 2020. Inflation has begun to increase in the last two years. One of the reasons for this is that savings was amassed by people all over the world locked in at home, massive Covid-19 relief programs, and interest rates at zero (Marks, 2021).

The Sharpe-ratio for the four strategies indicate that all four strategies have generated a higher risk-adjusted return compared to the index. Therefore, the investment risk for the four strategies is relatively low. Similar to the Sharpe ratio, the Information ratio and Treynor ratio also measures the excess return of the strategies compared to the benchmark index. The Magic Formula has the highest information ratio, followed by the ValStrat strategy. In other words, this means that these two strategies have performed the best over the period while adjusting for risk. Lastly, a positive Jensen's alpha suggests that the strategies with positive alpha, is considered to beat the benchmark index. The Magic Formula also has a low disparity between its different performance measures, indicating that the difference between its total risk and diversifiable risk is minimal. As the strategy selects the largest number of stocks, it is no surprise that it shows the greatest diversification benefit.

Figure 4: Performance of the Strategies over time

This figure illustrates the evolution of a 1000 NOK investment at the beginning of the time period on the 1st of July 2000 to the 1st of July 2022.

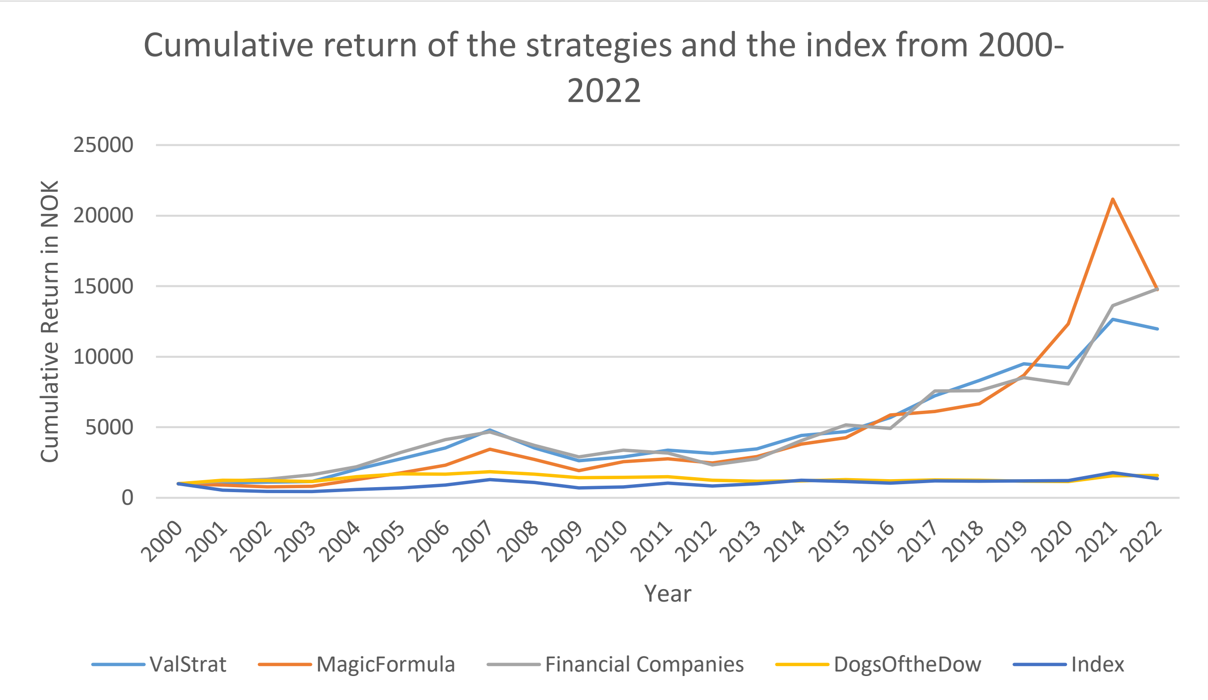


Figure 4 illustrates the performance of the strategies based on an initial investment of 1000 NOK at the beginning of the fiscal year in 2000, no further injections of funds are considered. The Magic Formula outperforms the other models by a significant margin, especially in 2020. A possible explanation for this spike can be that companies screened by the Magic Formula has a high valuation and potential upside due to low interest rate, which inflated stock prices to record highs. There is also a significant reduction in returns in 2022 for the Magic Formula, this causes the Magic Formulas performance to drop to such a degree that it is overtaken by the financial companies' strategy[5].

To test the validity of the returns, a linear regression model is performed, using CAPM and Fama French three-factor model. Should the Y intercept show significant positive values, one can surmise that the strategy produces excess return that is not wholly attributed to the movements in the market. Even though the models generate higher return over the period than the market, it is important to see if this is because the strategy is better or if the strategy simply took on more risk, and "got lucky".

7.1 CAPM

Table 6: CAPM regression outputs

Regressions are run on monthly price observations, to convert these to yearly values, alpha is multiplied by 12.

CAPM	Magic Formula	Financial Companies	Dogs of the Dow	Valstrat
Market Return	0,638***	0,331***	0,353***	0,465***
Alpha	0,015***	0,004	0,005	0,008***
Adjusted Rsquare	0,428	0,269	0,071	0,487
Standard deviation	0,05	0,037	0,085	0,033
Yearly Alpha in %	18%***	4,80 %	6 %	9,6%***

*P-value of 0,1 = **

*P-value of 0,05 = ***

*P-value of 0,01 = ****

Using the CAPM model, two of the strategies produce statistically significant alpha values. The Magic Formula generate an alpha of 18% per year and the ValStrat strategy generates an alpha of 9,6%[6] per year. The Dogs of the Dow and Financial companies' strategies produce no statistical significance in their alpha values and are thus indistinguishable from zero. Further their adjusted R-square statistic are rather low in comparison to the other strategies, indicating that the models are not a good fit for this kind of regression. The explanatory factor of the markets return is significant for all models, giving betas (β) towards the market at 0,638, 0,331, 0,353 and 0,465 respectively. A beta below one would suggest that the strategies are less volatile than the index.

[5] Of the 25 companies that the Magic Formula selected for the portfolio, only four yielded a positive return between 2021 – 2022.

[6] To interpret how the alpha values interact with within the CAPM model, the following equation for monthly observations can be considered: $ValStrat\ Return = 0{,}465(Market\ Return) + 0{,}008$

7.2 Fama French three-factor model

Table 7: Fama French regression outputs

Regressions are run on monthly price observations, to convert these to yearly values, alpha is multiplied by 12.

FF3	Magic Formula	Financial Companies	Dogs of the Dow	ValStrat
Market Return	0,717***	0,401***	0,457***	0,499***
SMB	0,436***	0,378***	0,566***	0,183***
HML	-0,034	0,205***	0,182	0,109**
Alpha	0,013***	0,002	0,003	0,007***
Adjusted Rsquare	0,480	0,266	0,131	0,518
Standard deviation	0,048	0,033	0,082	0,032
Yearly Alpha in %	15,6%***	2,40 %	3,60 %	8,4%***

*P-value of 0,1 = **

*P-value of 0,05 = ***

*P-value of 0,01 = ****

The Factors presented in the three-factor model are related to the market, companies market capitalization and book to market value. The output of the regression is the value of the beta that can be seen in Fama and French's equation illustrated in equation 4. Conversely, a significant value for the market return at 0,717 means that the Magic Formula has a beta of 0,717 regarding the market.

All strategies display significant betas toward the SMB factor, indicating some correlation with changes in this factor. Some level of the returns on the portfolios can thus be explained by market factors as derived by Fama and French. A positive correlation with the SMB factor would indicate that smaller market capitalization firms tend to outperform larger market capitalization firms. This may be a bit counter intuitive regarding the strategies tested in this thesis, as the models aim to select high value companies. However, larger more analysed companies tend to be more accurately priced in the market due to investor sentiment and market expectations (Cutler et al., 1988). Therefore, smaller market capitalization companies have a greater chance at outperforming large capitalization stocks, as is evidenced by the regression outputs.

The HML factor is significant at the 1% level for the Financial companies' strategy, while at the 5% level for the ValStrat strategy. A significant positive HML would indicate that value stocks tend to outperform growth stocks, and this is true for both large and small market capitalization market segments. Performance of the Financial Companies' strategy can be attributed somewhat to the performance of low book to market stocks, as can be expected as it is the only screener used for that strategy. The same can be argued for the ValStrat strategy, albeit to a lesser extent. An interesting observation however is the ValStrat screeners sensitivity to HML stocks when there is no specific screener in place for book to market value. One possibility is that the attributes focused on are more commonplace in firms that display a low book to market value.

The addition of more explanatory factors also sees a decrease in significant alpha values. The Magic Formula sees a reduction from 18% under the more simplistic CAPM model to 15,6% under the three-factor model. The alpha for the Magic Formula as well as the ValStrat strategy remain significant despite the addition of more explanatory factors. Some of the unattributable excess return that was seen in the CAPM model is thereby attributable to these additional factors.

7.3 Results when controlling for different market conditions

Table 8: CAPM regression outputs controlling for different market conditions

Regressions are run on monthly price observations, to convert these to yearly values, alpha is multiplied by 12.

CAPM Dummy	Magic Formula	Financial Companies	Dogs of the Dow	ValStrat
Market Return	0,628***	0,326***	0,389***	0,466***
Financial crisis	-0,023	-0,029**	-0,021	-0,030***
Covid-19	0,034**	0,013	0,051**	-0,0003
Alpha	0,014***	0,004*	0,001	0,009***
Adjusted Rsquare	0,439	0,269	0,14	0,487
Standard deviation	0,05	0,037	0,072	0,032
Yearly Alpha in %	16,8%***	4,80 %	1,20 %	10,8%***

*P-value of 0,1 = **

*P-value of 0,05 = ***

*P-value of 0,01 = ****

The ValStrat strategy has three significant explanatory variables, and has an R-squared at 0,487, meaning that these explanatory variables can explain 48,7% of the variations in the strategy's return. The Covid-19 dummy variable is not significant and is therefore not considered in the model, as it is statistically indistinguishable from zero[7].

As the ValStrat strategy has a significant negative coefficient towards the financial crisis, the strategy's return is negatively impacted. This market condition reduces the model's performance; however, it still has a positive alpha value. In fact, the alpha value increases

[7] Let's assume we investigate the return of the market over a one-month period during the financial crisis. Should the market return equal negative 1%, then the return of the ValStrat strategy should be $Valstrat\ Return = 0{,}009 + 0{,}466(-0{,}01) - 0{,}03(1) = -0{,}02566 \approx -2{,}6\%$

compared to the regression where other market conditions are not considered. This may be because the market condition has a greater negative effect on the market compared to the strategy, which is not captured by the linear formula. Therefore, one can assume that the index suffered more than the ValStrat strategy under the financial crisis.

The Covid-19 dummy, has significant values for both the Magic Formula and the Dogs of the Dow strategies. An interesting fact is that these are positive values, meaning they add to the models expected return during this time of crisis. This is in line with what can be seen in appendix 4, where these strategies yielded large returns at 72% and 69% respectively.

Table 9: Fama French regression outputs when controlling for different market conditions

Regressions are run on monthly price observations, to convert these to yearly values, alpha is multiplied by 12

FF3 Dummy	Magic Formula	Financial Companies	Dogs of the Dow	ValStrat
Market Return	0,709***	0,399***	0,498***	0,501***
SMB	0,412***	0,368***	0,559***	0,180***
HML	-0,045	0,198***	0,08	0,099**
Financial crisis	-0,02	-0,022**	-0,014	-0,027***
Covid-19	0,021	0,003	0,034	-0,005
Alpha	0,013***	0,003	-0,001	0,008***
Adjusted Rsquare	0,486	0,266	0,206	0,529
Standard deviation	0,048	0,033	0,069	0,031
Yearly Alpha in %	15,6%***	3,60 %	-1,20 %	9,6%***

*P-value of 0,1 = **

*P-value of 0,05 = ***

*P-value of 0,01 = ****

When including more explanatory factors, the alpha values of all models decrease as can be seen in table 9. With these extra factors, even more of the ValStrat strategy's variance can be explained, evidenced by the increase of the R-square from 48,7% under the CAPM to 52,9% under the Fama French three-factor model. Additionally, the effects of the dummy terms decrease as more factors are added. Only the ValStrat strategy and the Financial Companies' strategy contain significant interaction terms, and they both decrease with additional factors.

As the Covid-19 dummy generates no significant results, no assumptions can be made regarding its impact on the return of the portfolios under the three-factor model.

7.4 Testing for statistical anomalies

To test for these various statistical anomalies that can impact a regression, various built in RStudio functions can be used. To test for stationarity the *adf.test* function tests each variable.

Should the p-value return an insignificant value, i.e., a value above 0,05, stationarity can be assumed in the variables. However, none of the variables tested showed insignificant results, indicating no issues with stationarity.

Multicollinearity is tested by running the regression outputs through the *ols_vif_tol()* function in RStudio. If the function returns a value of more than five, one can conclude that there are issues with multicollinearity. None of the regressions seem to have this problem.

Homoscedasticity and Autocorrelation is tested for using the Breusch-Pagan test. Should this test return a significant value, one can conclude that there may be issues with homoscedasticity or autocorrelation. The tests return no significant results, indicating that there are no issues with homoscedasticity or autocorrelation.

8.0 Discussion

Previous research on EMH has shown the existence of market anomalies that contradict the EMH (Lakonishok et al., 1994) & (Thaler, 1999). However, Rendleman et al., (1982) found evidence that the EMH is valid in semi strong form. The EMH theory states that selecting stocks based on available information should not generate risk-adjusted excess returns compared to the market consistently due to the price of the stock already reflects all public available information. However, the results from the regression outputs implies that the Magic Formula and the ValStrat model produces statistically significant alpha values. This implies that the results from the regression can with some degree of certainty be trusted, meaning that these two methods generate risk-adjusted excess returns over the period compared to the MSCI Nordic Index. This contrasts with the theory of semi-strong form EMH and in accordance with research previously presented on the subject.

In contrast, the results showed that the Dogs of the Dow and the Financial companies' strategies did not produce a statistical significance compared to the benchmark index. Meaning that the results that are produced for these strategies cannot be trusted. The backtesting showed that the two strategies that did not produce a statistical significance had fewer turnover of companies in the portfolios over the 22- year period. This might have led to less explanatory value in market changes, and on that basis led to not producing a statistical significance. Greenblatt also suggest that financial companies in general, are complicated stocks to evaluate due to the complexity of the accounting. This led to Greenblatt and, therefore, Magic Formula excluding financial institutions and banks from the strategy. This can also be a factor for Financial Companies not producing a statistical significance regarding market movements.

The study of the profitability of smart beta investing in the Nordic stock market examined by Silvasti et al., (2021) suggests that the performance of their investments is influenced by market conditions to a separate degree than the index. Under the CAPM model, the financial crisis had significant negative effects on the Financial Companies and the ValStrat strategy. The Magic Formula and the Dogs of the Dow strategies were not impacted by this market condition in a significant manner. However, the Covid-19 pandemic impacted these strategies positively in a statistically significant way. When adding more factors to the analysis and using the Fama French three-factor model, the negative impacts of the financial crisis was still significant for the Financial Companies and ValStrat strategy. However, the positive impact of the Covid-19 pandemic on the Magic Formula as well as the Dogs of the Dow strategies fell away. These impacts are illustrated in table 9 in the results.

The results shown in figure 4 as well as in table 5 are also worth discussing. The strategy that has accumulated most returns during the 22-year period is the Financial Companies' strategy, accumulating 1380%. This is an interesting observation due the expectation beforehand. This strategy was constructed as a counterbalance to the Magic Formula strategy due it excluding financial institutions and banks for complexity reasons. The Financial Companies' were measured on its relatively easy Price-To-Book-Value criteria where the ten best ranked financial companies were chosen. In addition to this, Rupeika-Apoga et al., (2018) found evidence of Nordic owned banks tended to be more stable in terms of structure, risk of failure and stock prices due to Nordic banks being subject to greater oversight and regulation from their respective government. Greenblatts reasoning for exclusion is predominantly based on the American banking system as this is the market where the strategy was devised. The results of this study may suggest a modified Magic Formula that can include banks when the strategy is applied to Nordic markets as they are seen to generate good returns.

Other observations from table 5 is that the Magic Formula generated average yearly return at 16,4%, followed by the Financial Companies' model at 15,62%, trailed by the ValStrat model that generated an average of 14% returns on a yearly basis. The Dogs of the Dow was the only strategy to be beaten by the index generating a yearly return of only 3% whilst the index returned 4,5%. The Magic Formula is a well-established strategy and therefore it is no surprise that this strategy outperforms the newly established and constructed ValStrat strategy. The Dogs of the Dow strategy was not able to beat the index, this indicate that the strategy is not applicable and therefore usable on the securities on the Nordic market, compared to the original fundaments of investing in the highest dividend-yielding stocks on the Dow Jones Industrial Average. This was also the case for Rinne & Vahamaa (2011), they examined the effectiveness of the Dogs of the Dow strategy in the Finnish stock market. The takeaways from a ten-year period suggested that the strategy did not generate excess return on the Finnish stock market. These results indicates that The Dogs of The Dow strategy is hard to replicate to other stock markets indices around the world.

In 2007 a study researched the performance of traditional measure of Sharpe ratio, Sortino and Treynor ratio to evaluate the performance of three Nordic exchanges and three Baltic exchanges. The findings of this study implied that the traditional mean-variance based measures can be used when analysing the performance of all the exchanges (Mačiulis et al., 2007). Table 5 presents the findings of these performance measures when comparing the strategies to the index. All strategies outperform the index in terms of Sharpe ratio, while the Magic Formula outperforms all others in all measures. Interestingly, the Financial Companies strategy does not outperform the ValStrat strategy, indicating that ValStrat may have a better risk-adjusted return.

9.0 Conclusions

Three hypotheses have been created to answer the research question. The research question and the hypotheses has been researched through a linear regression model based on the CAPM and Fama and French calculations, using monthly price data for the period of 1st July 2000 to 1st July 2022.

The first hypothesis emphasized if the pre-determined screening investment strategies generates excess return over the selected time-period compared to the MSCI Nordic index. Regression outputs on both CAPM and Fama French three-factor model found significant alpha values for the Magic Formula and ValStrat strategy. The regression outputs from the CAPM model suggests that the alpha value is higher for both strategies compared to the Fama French three-factor model. This means that the ValStrat strategy and the Magic Formula generates risk-adjusted excess returns compared to the index. This aligns with the expectation due to the FF3 being a more complex and reliable model. The other strategies show no significant alpha values, meaning that the Financial companies and the Dogs of the Dow do not generate risk-adjusted returns compared to the index. These also follow similar patterns with the reduced alpha values in the FF3 model, although they are not significant. Overall, the explanatory power of the models does not exceed 52,9% which is to be expected to some degree in this type of analysis.

The second hypothesis concerns if the ValStrat investment strategy would be able to outperform Greenblatts Magic Formula as well as the index. The Financial Companies strategy generated the largest accumulated return at 1380% over the period, outperforming the Magic Formula by just 4%. This is mostly attributed to the Magic Formulas major decrease in 2021. The Magic Formula generated the best average yearly return at 16,4%, trailed by the ValStrat strategy that generated an average of 14% returns on a yearly basis. In terms of risk-adjusted returns in comparison to the index, all strategies seem to perform well. Factors such as the Sharpe ratio, Treynor ratio, Jensen's alpha and information ratio all indicate that the strategies generate a good risk vs reward. With the Magic Formula performing the best on a regular basis. The second hypothesis fails as the ValStrat strategy is outperformed in cumulative returns as well as in risk-adjusted returns by the Magic Formula.

The third hypothesis predicts that the four strategies will outperform the index in different market conditions. Under the CAPM model, the financial crisis had significant negative effects on the Financial Companies and the ValStrat strategy. The Magic Formula and the Dogs of the Dow strategies were not impacted by this market condition in a significant manner. However, the Covid-19 pandemic impacted them positively in a statistically significant way. When adding more factors to the analysis in the three-factor model, the negative impacts of the financial crisis was still significant for the Financial Companies and ValStrat strategies, however the positive impact of the Covid-19 pandemic on the Magic Formula as well as the Dogs of the Dow strategies fell away.

The alpha value of the ValStrat strategy increased when the dummies for market conditions are considered. Even though the ValStrat strategy was negatively impacted to a significant degree, the alpha indicates that the index was more severely affected. The only conclusive statement regarding different market conditions is applicable to the ValStrat strategy as it has the only significant results. Therefore, the final hypothesis is somewhat answered, the ValStrat strategy outperforms the index in periods of market turmoil.

The outcomes of these hypotheses have laid the foundations for answering the research question. The Magic Formula and ValStrat have outperformed the MSCI Nordi index using only publicly available fundamental data as the criteria for investment, contradicting the semi-strong form of EMH. While the ValStrat strategy have shown evidence of outperforming the index during periods of market turmoil.

9.1 Areas of further study

The study contributes to existing literature by investigating newly constructed investment strategies and evaluating the effectiveness of investing based on fundamentals in different market conditions. However, there are some limitations to this study. Firstly, transaction costs are not considered as the low volume of transactions, paired with the evolving trend of cost-free trading approaches. Other similar studies have found that transaction costs affect the significance of the outputs, decreasing the explanatory power of the studies. Further the datasets are not validated between data sources and given the size of the data sets individual data points may be wrong. To account for some of this, outliers are removed. Further the data source suffers from survivorship bias as not all delisted companies are included.

Future research could seek to understand how the Magic Formula would perform with the addition of financial institutions in its company pool for Nordic exchanges. Nordic banks seem to perform differently than their American counterparts, and Greenblatts precautions may not apply. The effectiveness of these strategies could also be tested on other global markets to better determine their usefulness as investing strategies.

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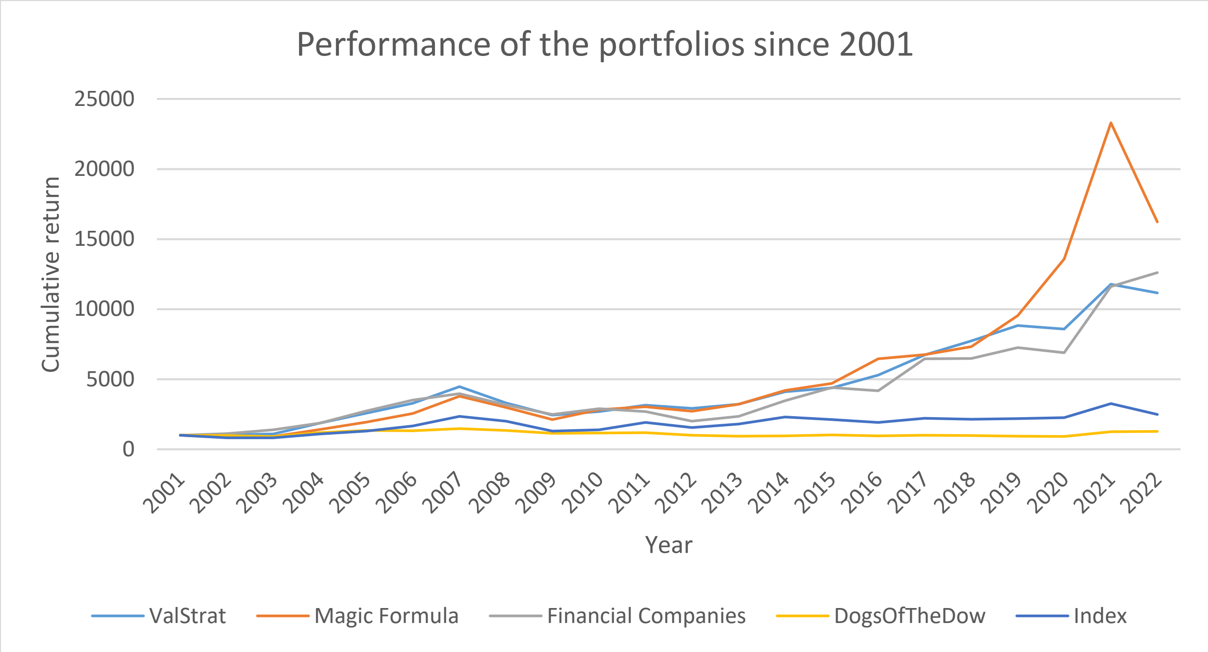
11.0 Appendix

Appendix 1:

The figure illustrates the cumulative returns of the strategies and the index should the analysis begin in 2001 instead of 2000.



Appendix: 2

The table shows the cumulative returns of the strategies and the index should the analysis begin in 2001 instead of 2000.

	Valstrat	Magic Formula	Financial Companies	DogsOfTheDow	Index
Cumulative Return	1015 %	1523 %	1161 %	27 %	149 %

Cumulative return since 2001

Appendix: 3

The table shows the largest company in the dataset per year based upon market capitalization in NOK.

Year	Company	Country	Market Capitalization
2000	Nokia	Finland	2 103 622 100 000
2001	Nokia	Finland	1 016 007 530 000
2002	Nokia	Finland	514 680 370 000
2003	Nokia	Finland	555 004 060 000
2004	Nokia	Finland	475 865 270 000
2005	Nokia	Finland	483 938 630 000
2006	Nokia	Finland	521 078 290 000
2007	Nokia	Finland	651 868 160 000
2008	Equinor	Norway	596 276 800 000
2009	Equinor	Norway	409 741 000 000
2010	Equinor	Norway	389 333 700 000
2011	Equinor	Norway	441 627 500 000
2012	Equinor	Norway	455 976 400 000
2013	Novo Nordisk	Denmark	428 531 460 000
2014	Equinor	Norway	609 031 400 000
2015	Novo Nordisk	Denmark	902 362 480 000
2016	Novo Nordisk	Denmark	912 170 960 000
2017	Novo Nordisk	Denmark	699 927 210 000
2018	Novo Nordisk	Denmark	729 553 340 000
2019	Novo Nordisk	Denmark	822 739 810 000
2020	Novo Nordisk	Denmark	1 129 725 170 000
2021	Novo Nordisk	Denmark	1 288 431 940 000
2022	Novo Nordisk	Denmark	1 905 621 030 000

Appendix: 4

The table shows the total return for each strategy as well as the index for each year in the period for a Norwegian investor.

Year	Index	Magic Formula	Financial Companies	DogsOftheDow	ValStrat
2000	-45 %	7 %	-9 %	17 %	**26 %**
2001	-18 %	4 %	-14 %	**12 %**	-3 %
2002	0 %	4 %	6 %	**24 %**	-5 %
2003	33 %	**73 %**	57 %	35 %	29 %
2004	20 %	38 %	37 %	**47 %**	13 %
2005	27 %	27 %	**31 %**	28 %	-1 %
2006	42 %	36 %	**49 %**	13 %	11 %
2007	-15 %	-26 %	-21 %	-20 %	**-9 %**
2008	-36 %	-26 %	-29 %	-22 %	**-15 %**
2009	8 %	10 %	**34 %**	16 %	3 %
2010	**37 %**	17 %	7 %	-6 %	3 %
2011	-19 %	**-7 %**	-10 %	-26 %	-17 %
2012	17 %	10 %	**18 %**	18 %	-6 %
2013	27 %	27 %	30 %	**47 %**	3 %
2014	-8 %	6 %	12 %	**27 %**	7 %
2015	-9 %	21 %	**37 %**	-5 %	-8 %
2016	15 %	27 %	4 %	**54 %**	6 %
2017	-2 %	**15 %**	9 %	0 %	-2 %
2018	1 %	14 %	**30 %**	12 %	-5 %
2019	3 %	-3 %	**42 %**	-5 %	-2 %
2020	45 %	37 %	**72 %**	69 %	37 %
2021	-24 %	-5 %	-30 %	**9 %**	2 %
Total cumulative returns	36 %	1374 %	**1380 %**	60 %	1097 %
Average return per year	4,5 %	**16,4 %**	15,6 %	3,0 %	14,0 %

Appendix: 5

The table shows the summary statistic for the Exchange rates employed as well as the risk-free rate and the MSCI Nordic index.

Variable	N	Mean	St.Dev	Min	Max
EUR/NOK	23	8,631	0,9326	7,47	10,72
SEK/NOK	23	0,907	0,0580	0,82	1,02
DEK/NOK	23	1,159	0,1251	1,004	1,44
Three-month Nibor	23	0,028	0,0222	0,002	0,07
MSCI Nordic index	22	0,045	0,2508	-0,45	0,45

12.0 R-script

```
library(tidyverse)[8]

library(openxlsx)

library(janitor)

library(sf)

library(tidyverse)

library(openxlsx)

library(stargazer)

library(olsrr)

library(rms)

library(tidyquant)

library(tseries)

library(lavaan)

library(sweep)

library(lmtest)

library(sandwich)

library(plm)

library(pder)

library(knitr)

library(ggplot2)

library(quantreg)

library(dplyr)

library(writexl)

library(PerformanceAnalytics)

library(rportfolio)


setwd("C:/Users/hocky/OneDrive/Skrivebord/Master data")
```

[8] The financial companies' strategy was initially called the Banks strategy when the code was written. Where the Banks strategy is mentioned, it is the financial companies' strategy that is referenced

```
################################################################################
# Uploading monthly data #
################################################################################


NorMonthlyP <- read.xlsx("MonthlyPrice.xlsx", sheet = "Nclean", colNames= T,
rowNames=F, detectDates=T,
                        skipEmptyRows = F,skipEmptyCols=F)
SweMonthlyP <- read.xlsx("MonthlyPrice.xlsx", sheet = "Sclean", colNames= T,
rowNames=F, detectDates=T,
                        skipEmptyRows = F,skipEmptyCols=F)
DenMonthlyP <- read.xlsx("MonthlyPrice.xlsx", sheet = "Dclean", colNames= T,
rowNames=F, detectDates=T,
                        skipEmptyRows = F,skipEmptyCols=F)
FinMonthlyP <- read.xlsx("MonthlyPrice.xlsx", sheet = "Fclean", colNames= T,
rowNames=F, detectDates=T,
                        skipEmptyRows = F,skipEmptyCols=F)


NorMonthlyP <- NorMonthlyP %>% pivot_longer(cols=starts_with("20"),names_to =
"Date")
NorMonthlyP <- NorMonthlyP %>% pivot_wider(id_cols = c("Date","C_id","Variables"),
                              names_from = "Variables", values_from = "value")
SweMonthlyP <- SweMonthlyP %>% pivot_longer(cols=starts_with("20"),names_to =
"Date")
SweMonthlyP <- SweMonthlyP %>% pivot_wider(id_cols = c("Date","C_id","Variables"),
                              names_from = "Variables", values_from = "value")
DenMonthlyP <- DenMonthlyP %>% pivot_longer(cols=starts_with("20"),names_to =
"Date")
DenMonthlyP <- DenMonthlyP %>% pivot_wider(id_cols = c("Date","C_id","Variables"),
                              names_from = "Variables", values_from = "value")
FinMonthlyP <- FinMonthlyP %>% pivot_longer(cols=starts_with("20"),names_to = "Date")
FinMonthlyP <- FinMonthlyP %>% pivot_wider(id_cols = c("Date","C_id","Variables"),
                              names_from = "Variables", values_from = "value")
```

```
NordicMonthlyP <- rbind(NorMonthlyP,SweMonthlyP,DenMonthlyP,FinMonthlyP, na.rm =
T)

NordicMonthlyP <- NordicMonthlyP%>%
  group_by(C_id) %>%
  dplyr::mutate(P1= dplyr::lead(P, n= 1, default = NA) ) %>%
  as.data.frame()
NordicMonthlyP$return =
  (NordicMonthlyP$P1 / NordicMonthlyP$P)-1
NordicMonthlyP$return[is.infinite(NordicMonthlyP$return)==T] = NA



NordicMonthlyP$Date <- as.Date(NordicMonthlyP$Date)
NordicMonthlyP$Year <- format(NordicMonthlyP$Date,"%Y")

#Joining returns variables
FF3Returns <- data.frame(Date = NordicMonthlyP$Date,
                         Year = NordicMonthlyP$Year,
                         C_id = NordicMonthlyP$C_id,
                         return = NordicMonthlyP$return)

################################################################################
# Uploading and formatting data #
################################################################################
#Reading in Data
Nm <- read.xlsx("FullData.xlsx", sheet = "Nm", colNames= T, rowNames=F, detectDates=F,
                skipEmptyRows = F,skipEmptyCols=F)
Sm <- read.xlsx("FullData.xlsx", sheet = "Sm", colNames= T, rowNames=F, detectDates=F,
                skipEmptyRows = F,skipEmptyCols=F)
Dm <- read.xlsx("FullData.xlsx", sheet = "Dm", colNames= T, rowNames=F, detectDates=F,
```

```
        skipEmptyRows = F,skipEmptyCols=F)
Fm <- read.xlsx("FullData.xlsx", sheet = "Fm", colNames= T, rowNames=F, detectDates=F,
        skipEmptyRows = F,skipEmptyCols=F)

#Formatting data
Nm <- Nm %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Nm <- Nm %>% pivot_wider(id_cols =
c("Index","Country_Index","Year","C_id","Variables"),
            names_from = "Variables", values_from = "value")
Sm <- Sm %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Sm <- Sm %>% pivot_wider(id_cols =
c("Index","Country_Index","Year","C_id","Variables"),
            names_from = "Variables", values_from = "value")
Dm <- Dm %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Dm <- Dm %>% pivot_wider(id_cols =
c("Index","Country_Index","Year","C_id","Variables"),
            names_from = "Variables", values_from = "value")
Fm <- Fm %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Fm <- Fm %>% pivot_wider(id_cols =
c("Index","Country_Index","Year","C_id","Variables"),
            names_from = "Variables", values_from = "value")

#Merging into one dataset
Nordic <- rbind(Nm,Sm,Dm,Fm)

#Counting the number of companies in the dataset
NordicCount <- data.frame(Year = Nordic$Year,
            C_id = Nordic$C_id,
            P = Nordic$P)
NordicCount <- NordicCount %>% na.omit()
NordicCount <- NordicCount %>% group_by(Year)
NordicCount <- data.frame(N = count(NordicCount, "C_id"))
```

```
#Dividend adjusted return
Nordic <- Nordic %>% mutate(P_DIV = (DY/100)*P)
Nordic <- Nordic %>% mutate(Ptotal = P_DIV + P)

#Making a returns variable
Nordic <- Nordic%>%
  group_by(C_id) %>%
  dplyr::mutate(P1= dplyr::lead(Ptotal, n= 1, default = NA) ) %>%
  as.data.frame()
Nordic$return =
  (Nordic$P1 / Nordic$Ptotal)-1
Nordic$return[is.infinite(Nordic$return)==T] = NA

##############################################################################
# ValStrat #
##############################################################################
ValStrat <- data.frame(Index = Nordic$Index,
                       Country_Index = Nordic$Country_Index,
                       Year = Nordic$Year,
                       C_id = Nordic$C_id,
                       P = Nordic$P,
                       MarketCap = Nordic$MarketCap,
                       DY = Nordic$DY,
                       EPS = Nordic$EPS,
                       OPM = Nordic$OPM,
                       ROE = Nordic$ROE,
                       CR = Nordic$CR,
                       return = Nordic$return)
```

```
ValStrat <- ValStrat %>% mutate(PE = P/EPS)



ValStrat <- ValStrat[which(ValStrat$MarketCap >= 100),]


ValStrat <- ValStrat %>% mutate(DYI=ifelse(DY>"1,5",1,0))
ValStrat <- ValStrat %>% mutate(CRI=ifelse(CR<"1",1,0))
ValStrat <- ValStrat %>% mutate(ROEI=ifelse(ROE>"15",1,0))
ValStrat <- ValStrat %>% mutate(OPMI=ifelse(OPM>"15",1,0))
ValStrat <- ValStrat %>% mutate(PEI=ifelse(PE<"10",1,0))


ValStrat <-  ValStrat %>% mutate_at(c('DYI','CRI',"ROEI","OPMI","PEI"), ~replace_na(.,0))


#Creating weights
ValStrat <- ValStrat %>%  mutate(DYIw = (DYI*2))
ValStrat <- ValStrat %>%  mutate(CRIw = (CRI*2))
ValStrat <- ValStrat %>%  mutate(ROEIw = (ROEI*2))
ValStrat <- ValStrat %>%  mutate(OPMIw = (OPMI*2))
ValStrat <- ValStrat %>%  mutate(PEIw = (PEI*2))


ValStrat <- ValStrat %>% mutate(Score = (DYIw + CRIw + ROEIw + OPMIw +
PEIw),na.rm=T)


ValStrat <- ValStrat %>% na.omit()


ValStrat15 <- ValStrat  %>%
  arrange(desc(Score)) %>%
  group_by(Year) %>%
  slice(1:15)
```

```
#Adding Returns variable for regressions
ValStratMP <- ValStrat15 %>% left_join(FF3Returns, by =c("C_id", "Year"))
ValStratMP <- ValStratMP %>% na.omit()

ValStratTotalR <- ValStratMP %>% group_by(Date) %>%
  mutate(Summonth=sum(return.y,na.rm=T)/15)

ValStratTotalR<- ValStratTotalR%>%
  group_by(Date) %>% summarise(totalReturn=sum(Summonth, na.rm=T)/15)

#Calculating yearly returns on the portfolio
ValstratR <- data.frame(Year = ValStrat15$Year,
                        C_id = ValStrat15$C_id,
                        return = ValStrat15$return)

ValstratR<- ValstratR %>% group_by(Year) %>%
  mutate(sumyear=sum(return)/15)
ValstratR<- ValstratR %>%
  group_by(Year) %>% summarise(totalReturn=sum(sumyear, na.rm=T)/15)

################################################################################
#Magic Formula
################################################################################
Nmf <- read.xlsx("MagicformulaData.xlsx", sheet = "Nmf", colNames= T, rowNames=F,
detectDates=F,
                 skipEmptyRows = F,skipEmptyCols=F)
Smf<- read.xlsx("MagicformulaData.xlsx", sheet = "Smf", colNames= T, rowNames=F,
detectDates=F,
                skipEmptyRows = F,skipEmptyCols=F)
Dmf <- read.xlsx("MagicformulaData.xlsx", sheet = "Dmf", colNames= T, rowNames=F,
detectDates=F,
                 skipEmptyRows = F,skipEmptyCols=F)
```

```
Fmf <- read.xlsx("MagicformulaData.xlsx", sheet = "Fmf", colNames= T, rowNames=F,
detectDates=F,
                skipEmptyRows = F,skipEmptyCols=F)


Nmf <- Nmf %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Nmf <- Nmf %>% pivot_wider(id_cols = c("Country_Index","Year","C_id","Variables"),
                         names_from = "Variables", values_from = "value")
Smf <- Smf %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Smf <- Smf %>% pivot_wider(id_cols = c("Country_Index","Year","C_id","Variables"),
                         names_from = "Variables", values_from = "value")
Dmf <- Dmf %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Dmf <- Dmf %>% pivot_wider(id_cols = c("Country_Index","Year","C_id","Variables"),
                         names_from = "Variables", values_from = "value")
Fmf <- Fmf %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Fmf <- Fmf %>% pivot_wider(id_cols = c("Country_Index","Year","C_id","Variables"),
                         names_from = "Variables", values_from = "value")


Magic_formula <- rbind(Nmf,Smf,Dmf,Fmf)


#Creating a returns variable
Magic_formula <- Magic_formula%>%
  group_by(C_id) %>%
  dplyr::mutate(P1= dplyr::lead(P, n= 1, default = NA) ) %>%
  as.data.frame()
Magic_formula$returns =
  (Magic_formula$P1 / Magic_formula$P)-1
Magic_formula$returns[is.infinite(Magic_formula$returns)==T] = NA


#Adding a data frame for original data
Magic_formula_Orig <- Magic_formula
```

```
#Setting the Market cap limit

Magic_formula <- Magic_formula %>% na.omit()

Magic_formula <- Magic_formula[which(Magic_formula$MarketCap >= 500),]


#Removing outlier

Magic_formula <- Magic_formula %>% slice(-c(791))


Magic_formula <- Magic_formula %>% mutate(ROCE = EBIT/(CurrentAssets-
CurrentLiabilities),

                                          EarningsY = EBIT/EnterpriseValue)


Magic_formula <- Magic_formula %>% group_by(Year) %>%
mutate(Rank_ROCE=order(ROCE,decreasing = F),

                                                      Rank_EarningsY = order(EarningsY,decreasing = F))

Magic_formula <- Magic_formula %>%  mutate(TotalRank = (Rank_ROCE +
Rank_EarningsY)/2)

#%>% filter(Year >= 2000)


Magic_formula_top25 <- Magic_formula %>%

  arrange(desc(TotalRank)) %>%

  group_by(Year) %>%

  slice(1:25)


Magic_formula_top25Date <- Magic_formula_top25%>% left_join(FF3Returns, by
=c("C_id", "Year"))


#Magic_formulaReturns <- Nordic %>% inner_join(Magic_formula_top25, by =
c("C_id","Year"))

#Magic_formulaReturns <- Magic_formulaReturns  %>%
select(c("Index","Country_Index.x","Year",

#                                                 "C_id","returns","TotalRank"))


Magic_formulaR <- Magic_formula_top25Date %>% group_by(Date) %>%
```

```
  mutate(summonth=sum(return,na.rm = T)/25)

Magic_formulaTotalR<- Magic_formulaR %>%
  group_by(Date) %>% summarise(totalReturn=sum(return, na.rm=T)/25)

#Calculating the yearly returns
Magic_formula_YearlyR <- Magic_formula_top25 %>% group_by(Year) %>%
  mutate(sumyear=sum(returns)/25)

Magic_formula_YearlyR<- Magic_formula_YearlyR  %>%
  group_by(Year) %>% summarise(totalReturn=sum(returns, na.rm=T)/25)



################################################################################
#Financial companies/ Banks[9]#
################################################################################
Banks <- read.xlsx("Bank_Nordic.xlsx", sheet = "BankNordic", colNames= T, rowNames=F,
detectDates=F,
                   skipEmptyRows = F,skipEmptyCols=F)

Banks <- Banks %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Banks <- Banks %>% pivot_wider(id_cols = c("Year","C_id","Variables"),
                               names_from = "Variables", values_from = "value")

Banks <- Banks%>%
  group_by(C_id) %>%
  dplyr::mutate(P1= dplyr::lead(P, n= 1, default = NA) ) %>%
  as.data.frame()
Banks$returns =
```

[9] The financial companies' strategy was initially called the Banks strategy when the code was written. Where the Banks strategy is mentioned, it is the financial companies' strategy that is referenced

```
  (Banks$P1 / Banks$P)-1
Banks$returns[is.infinite(Banks$returns)==T] = NA

Banks <- Banks %>% na.omit()

#Removing Outlier
Banks <- Banks %>% slice(-c(466))

Banks20 <- Banks%>%
  arrange(-desc(PB)) %>%
  group_by(Year) %>%
  slice(1:20)

#Creating yearly returns
BanksYearlyR <- Banks20 %>% group_by(Year) %>%
  mutate(sumyear=sum(returns)/20)

BanksYearlyR<- BanksYearlyR  %>%
  group_by(Year) %>% summarise(totalReturn=sum(returns, na.rm=T)/20)

#Joining returns for regressions
Banks20 <- Banks20 %>% left_join(FF3Returns, by =c("C_id", "Year"))

Banks20 <- Banks20 %>% group_by(Date) %>%
  mutate(summonth=sum(return,na.rm=T)/20)

Banks20TR<- Banks20 %>%
  group_by(Date) %>% summarise(totalReturn=sum(summonth, na.rm=T)/20)
```

```
################################################################################
# Dogs of the Dow #
################################################################################
DogsOftheDow <- data.frame(Country_Index = Nordic$Country_Index,
                           Year = Nordic$Year,
                           C_id = Nordic$C_id,
                           P = Nordic$Ptotal,
                           DY = Nordic$DY,
                           returns = Nordic$return)

DogsOftheDow <- DogsOftheDow %>%
  group_by(C_id) %>%
  dplyr::mutate(P1= dplyr::lead(P, n= 1, default = NA) ) %>%
  as.data.frame()
DogsOftheDow$returns =
  (DogsOftheDow$P1 / DogsOftheDow$P)-1
DogsOftheDow$returns[is.infinite(DogsOftheDow$returns)==T] = NA

#Removing Companies with dividends above 100%
DogsOftheDow <- DogsOftheDow %>% filter(DY <=100)
DogsOftheDow <- DogsOftheDow %>% na.omit

DogsOftheDow10 <- DogsOftheDow %>%
  arrange(desc(DY)) %>%
  group_by(Year) %>%
  slice(1:10)

#Creating yearly returns variable
DogsOftheDow10YearlyR <- DogsOftheDow10 %>% group_by(Year) %>%
  mutate(sumyear=sum(returns,na.rm=T)/20)
```

```
DogsOftheDow10YearlyR<- DogsOftheDow10YearlyR  %>%
  group_by(Year) %>% summarise(totalReturn=sum(returns, na.rm=T)/20)

#Creating returns variable for Regressions
DogsOftheDow10 <- DogsOftheDow10 %>% left_join(FF3Returns, by =c("C_id", "Year"))


DogsOftheDow10 <- DogsOftheDow10 %>% group_by(Date) %>%
  mutate(summonth=sum(return)/10)


DogsOftheDow10TR<- DogsOftheDow10 %>%
  group_by(Date) %>% summarise(totalReturn=sum(summonth, na.rm=T)/10)

################################################################################
# CAPM #
################################################################################
CAPM <- read.xlsx("CAPM.xlsx", sheet = "Capm", colNames= T, rowNames=F,
detectDates=T,
                  skipEmptyRows = F,skipEmptyCols=F)


CAPM <- CAPM %>% pivot_longer(cols=starts_with("20"),names_to = "Date")
CAPM <- CAPM %>% pivot_wider(id_cols = c("Date","Variables"),
                             names_from = "Variables", values_from = "value")

#Calculating the market risk premium
CAPM$MarketR <- CAPM$`Percent Change`- CAPM$`3monthNiborPercent `

#Formatting dates
CAPM$Date <- as.Date(CAPM$Date)
```

```
#Creating a returns variable for the index
Index <- read.xlsx("CAPM.xlsx", sheet = "CapmYearlylead", colNames= T, rowNames=F,
detectDates=T,
              skipEmptyRows = F,skipEmptyCols=F)


Index <- Index %>% pivot_longer(cols=starts_with("20"),names_to = "Year")
Index <- Index %>% pivot_wider(id_cols = c("Year","Variables"),
                     names_from = "Variables", values_from = "value")


MarketReturns <- data.frame(Year = Index$Year,
                    Totalreturn = Index$`Percent Change`)


#Creating a dataset for the risk-free rate
RiskfreeR <- data.frame(Date = CAPM$Date,
                 Rf = CAPM$`3monthNiborPercent `)


##############################################################################
# Fama French Three-factor model #
##############################################################################
FF3 <- data.frame(Country_Index = Nordic$Country_Index,
             Year = Nordic$Year,
             C_id = Nordic$C_id,
             P = Nordic$P,
             CA = Nordic$CA,
             CL = Nordic$CL,
             MarketCap = Nordic$MarketCap,
             return = Nordic$return)


#Making a book - to - market variable
FF3$Bookvalue <- FF3$CA - FF3$CL
FF3$B_M <- FF3$Bookvalue/FF3$MarketCap
```

```
#Removing NAs and making sure there are no negative book to market ratios
FF3 <- FF3 %>% filter(is.na(MarketCap) == F)
FF3 <- FF3 %>% filter(is.na(B_M) == F)
FF3 <- FF3 %>% filter(B_M >= 0)

#Counting number of companies each year
FF3N <- FF3 %>% group_by(Year)
FF3N <- data.frame(N = count(FF3N, "C_id"))

#Fixing colnames to join data
colnames(FF3N)[1]  <- "Year"
colnames(FF3N)[3]  <- "N"

FF3 <- FF3 %>% left_join(FF3N, by = "Year")

#Creating a ranking of market caps
FF3 <- FF3 %>% group_by(Year) %>%
  mutate(rank_Mcap = order(order(MarketCap, decreasing=F)))
FF3$PercentMcap = FF3$rank_Mcap / FF3$N

#Creating the Big and small data frames based on the size of Market caps
Small = FF3 %>% filter(PercentMcap <= 0.5)
Big = FF3 %>% filter(PercentMcap >= 0.5)

#Counting number of firms in the data sets
SmallN <- Small %>% group_by(Year)
SmallN <- data.frame(N = count(SmallN, "C_id"))
colnames(SmallN)[1]  <- "Year"
colnames(SmallN)[3]  <- "N"
Small <- Small %>% left_join(SmallN, by = "Year")
```

```
colnames(Small)[16]  <- "N"

BigN <- Big %>% group_by(Year)
BigN <- data.frame(N = count(BigN, "C_id"))
colnames(BigN)[1]  <- "Year"
colnames(BigN)[3]  <- "N"
Big <- Big %>% left_join(BigN, by = "Year")
colnames(Big)[16]  <- "N"

#Ranking companies based on B_M
Small <- Small %>%
  group_by(Year) %>%
  mutate(RankBM = (order(order(B_M, decreasing=F)) / N))
Big <- Big %>%
  group_by(Year) %>%
  mutate(RankBM = (order(order(B_M, decreasing=F)) / N))

#Creating Fama French portfolios
Small_v <- Small %>% filter(RankBM >= 0.7) %>%
  select(C_id, Year, MarketCap, B_M)
Small_n <- Small %>% filter(RankBM <= 0.7 & RankBM >= 0.3) %>%
  select(C_id, Year, MarketCap, B_M)
Small_g <- Small %>% filter(RankBM<= 0.3) %>%
  select(C_id, Year, MarketCap, B_M)

Big_v <- Big %>% filter(RankBM >= 0.7) %>%
  select(C_id, Year, MarketCap, B_M)
Big_n <- Big %>% filter(RankBM <= 0.7 & RankBM >= 0.3) %>%
  select(C_id, Year, MarketCap, B_M)
Big_g <- Big %>% filter(RankBM<= 0.3) %>%
```

```
  select(C_id, Year, MarketCap, B_M)

#Joining returns variables
FF3Returns <- data.frame(Date = NordicMonthlyP$Date,
                         Year = NordicMonthlyP$Year,
                         C_id = NordicMonthlyP$C_id,
                         return = NordicMonthlyP$return)

#Small Value portfolio
Small_v <- Small_v %>%
  inner_join(FF3Returns, by = c("C_id", "Year"))
Small_v <- Small_v %>% na.omit()

Small_v_r<- Small_v %>% group_by(Date) %>%
  mutate(SVR = weighted.mean(return,MarketCap, na.rm=T))

#Small neutral portfolio
Small_n <- Small_n %>%
  inner_join(FF3Returns, by = c("C_id", "Year"))
Small_n <- Small_n %>% na.omit()

Small_n_r<- Small_n %>% group_by(Date) %>%
  mutate(SNR = weighted.mean(return,MarketCap, na.rm=T))

#Small growth portfolio
Small_g <- Small_g %>%
  inner_join(FF3Returns, by = c("C_id", "Year"))
Small_g <- Small_g %>% na.omit()

Small_g_r<- Small_g %>% group_by(Date) %>%
```

```
  mutate(SGR = weighted.mean(return,MarketCap, na.rm=T))

#Big value portfolio
Big_v <- Big_v %>%
  inner_join(FF3Returns, by = c("C_id", "Year"))
Big_v <- Big_v %>% na.omit()

Big_v_r<- Big_v %>% group_by(Date) %>%
  mutate(BVR = weighted.mean(return,MarketCap, na.rm=T))

#Big neutral portfolio
Big_n <- Big_n %>%
  inner_join(FF3Returns, by = c("C_id", "Year"))
Big_n <- Big_n %>% na.omit()

Big_n_r<- Big_n %>% group_by(Date) %>%
  mutate(BNR = weighted.mean(return,MarketCap, na.rm=T))

#Big growth portfolio
Big_g <- Big_g %>%
  inner_join(FF3Returns, by = c("C_id", "Year"))
Big_g <- Big_g %>% na.omit()

Big_g_r<- Big_g %>% group_by(Date) %>%
  mutate(BGR = weighted.mean(return,MarketCap, na.rm=T))

#Extracting relevant variables
SVR <- Small_v_r %>% select("Year","SVR","Date")
SNR <- Small_n_r %>% select("Year","SNR","Date")
SGR <- Small_g_r %>% select("Year","SGR","Date")
```

```
BVR <- Big_v_r %>% select("Year","BVR","Date")
BNR <- Big_n_r %>% select("Year","BNR","Date")
BGR <- Big_g_r %>% select("Year","BGR","Date")

SVR <- SVR %>%  distinct(Date, .keep_all=TRUE)
SNR <- SNR %>%  distinct(Date, .keep_all=TRUE)
SGR <- SGR %>%  distinct(Date, .keep_all=TRUE)
BVR <- BVR %>%  distinct(Date, .keep_all=TRUE)
BNR <- BNR %>%  distinct(Date, .keep_all=TRUE)
BGR <- BGR %>%  distinct(Date, .keep_all=TRUE)


#Constructing the final data frame
FamaFrench <- SVR %>% left_join(SNR, by = "Date")
FamaFrench <- FamaFrench %>% left_join(SGR,by = "Date")
FamaFrench <- FamaFrench %>% left_join(BVR,by = "Date")
FamaFrench <- FamaFrench %>% left_join(BNR,by = "Date")
FamaFrench <- FamaFrench %>% left_join(BGR,by = "Date")

# Calculating SMB and HML
FamaFrench$SMB <- (1/3)*(FamaFrench$SVR+FamaFrench$SNR+FamaFrench$SGR)-
  (1/3)*(FamaFrench$BVR+FamaFrench$BNR+FamaFrench$BGR)
FamaFrench$HML <- (1/2)*(FamaFrench$SVR+FamaFrench$BVR)-
  (1/2)*(FamaFrench$SGR+FamaFrench$BGR)

#Adding market factors
FamaFrench <- FamaFrench %>% left_join(CAPM, by = "Date")
```

```
################################################################################
# Tables  #
################################################################################
Allmodels <- ValstratR %>% left_join(Magic_formula_YearlyR, by = "Year")
Allmodels <- Allmodels %>% left_join(BanksYearlyR, by ="Year")
Allmodels <- Allmodels %>% left_join(DogsOftheDow10YearlyR, by ="Year")
Allmodels <- Allmodels %>% left_join(MarketReturns, by ="Year")

colnames(Allmodels) <-
c("Year","ValStrat","MagicFormula","Banks","DogsOftheDow","Index")

AllmodelsTable <- Allmodels %>% stargazer(type="html",title="Return of all models
",out="Returns.html")

write.xlsx(Allmodels, 'C:/Users/hocky/OneDrive/Skrivebord/Master data/Allmodels.xlsx',
        overwrite = T )

Allmodels$cumMagicFormula <-cumprod(1+Allmodels$MagicFormula)-1
Allmodels$cumBanks <-cumprod(1+Allmodels$Banks)-1
Allmodels$cumDogsOfTheDow <-cumprod(1+Allmodels$DogsOftheDow)-1
Allmodels$cumValStrat <-cumprod(1+Allmodels$ValStrat)-1
Allmodels$cumIndex <-cumprod(1+Allmodels$Index)-1

################################################################################
# Regressions #
################################################################################
#Merging data
Data <- Magic_formulaTotalR %>% left_join(FamaFrench, by = "Date")
Data2 <- Banks20TR %>% left_join(FamaFrench, by = "Date")
Data3 <- DogsOftheDow10TR %>% left_join(FamaFrench, by = "Date")
Data4 <- ValStratTotalR %>% left_join(FamaFrench, by = "Date")
```

```
Data3 <- Data3 %>% slice(-c(266))
#Adding the RF rate
Data <- Data %>% left_join(RiskfreeR,by = "Date")
Data$totalReturn_RF <- Data$totalReturn-Data$Rf

Data2 <- Data2 %>% left_join(RiskfreeR,by = "Date")
Data2$totalReturn_RF <- Data2$totalReturn-Data2$Rf

Data3 <- Data3 %>% left_join(RiskfreeR,by = "Date")
Data3$totalReturn_RF <- Data3$totalReturn-Data3$Rf

Data4 <- Data4 %>% left_join(RiskfreeR,by = "Date")
Data4$totalReturn_RF <- Data4$totalReturn-Data4$Rf

#Creating regression models
regressionCAPM <- lm(totalReturn_RF~MarketR, data = Data)
regressionFF3 <- lm(totalReturn_RF~MarketR+SMB+HML, data = Data)

regressionCAPM %>% summary()
regressionFF3 %>% summary()

regressionCAPM2 <- lm(totalReturn_RF~MarketR, data = Data2)
regressionFF32 <- lm(totalReturn_RF~MarketR+SMB+HML, data = Data2)

regressionCAPM2 %>% summary()
regressionFF32 %>% summary()

regressionCAPM3 <- lm(totalReturn_RF~MarketR, data = Data3)
regressionFF33 <- lm(totalReturn_RF~MarketR+SMB+HML, data = Data3)
```

```
regressionCAPM3 %>% summary()
regressionFF33 %>% summary()

regressionCAPM4 <- lm(totalReturn_RF~MarketR, data = Data4)
regressionFF34 <- lm(totalReturn_RF~MarketR+SMB+HML, data = Data4)

#regressionCAPM4  %>% stargazer(type = "html", out = "CapmValStratReg")
#regressionFF34 %>% stargazer(type = "html", out = "FF3ValStratReg")

stargazer(regressionCAPM,regressionFF3,regressionCAPM2,regressionFF32,
      regressionCAPM3,regressionFF33,regressionCAPM4,regressionFF34,
      type = "html",column.labels = c("Capm Magic Formula","FF3 Magic Formula",
                        "Capm Banks","FF3 Banks",
                        "Capm DogsOftheDow","FF3 DogsOftheDow",
                        "Capm ValStrat","FF3 ValStrat"),
      out="RegressionLeadv2")

#Testing the data for stationarity
adf.test(na.omit(Data$totalReturn_RF,k=0))
adf.test(na.omit(Data2$totalReturn_RF,k=0))
adf.test(na.omit(Data3$totalReturn_RF,k=0))
adf.test(na.omit(Data4$totalReturn_RF,k=0))
#No issues of stationarity

#Testing for Multicollinearity
regressionCAPM %>% ols_vif_tol()
regressionFF3 %>% ols_vif_tol()

regressionCAPM2 %>% ols_vif_tol()
```

```
regressionFF32 %>% ols_vif_tol()

regressionCAPM3 %>% ols_vif_tol()
regressionFF33 %>% ols_vif_tol()

regressionCAPM4 %>% ols_vif_tol()
regressionFF34 %>% ols_vif_tol()
#No issues of multicollonearity


#Testing for Homoscedasticity
regressionCAPM %>% ols_test_breusch_pagan()
regressionFF3 %>% ols_test_breusch_pagan()

regressionCAPM2 %>% ols_test_breusch_pagan()
regressionFF32 %>% ols_test_breusch_pagan()

regressionCAPM3 %>% ols_test_breusch_pagan()
regressionFF33 %>% ols_test_breusch_pagan()

regressionCAPM4 %>% ols_test_breusch_pagan()
regressionFF34 %>% ols_test_breusch_pagan()

################################################################################
#Calculating ratios#
################################################################################
Data <- Data %>% na.omit()
Data3 <- Data3 %>% na.omit()
```

#Sharpe ratio

```
MF_SharpRatio <- round(mean(Data$totalReturn_RF)/StdDev(Data$totalReturn_RF), 3)*sqrt(12)

Banks_SharpRatio <- round(mean(Data2$totalReturn_RF)/StdDev(Data2$totalReturn_RF), 3)*sqrt(12)

DOTD_SharpRatio <- round(mean(Data3$totalReturn_RF)/StdDev(Data3$totalReturn_RF), 3)*sqrt(12)

Valstrat_SharpRatio <- round(mean(Data4$totalReturn_RF)/StdDev(Data4$totalReturn_RF), 3)*sqrt(12)

Index_SharpeRatio <- round(mean(CAPM$MarketR)/StdDev(CAPM$MarketR), 3)*sqrt(12)
```

#Appraisal ratio

```
Data$ExcessR <- (Data$totalReturn-Data$`Percent Change`)

MF_InformationRatio <- round(mean(Data$ExcessR)/StdDev(Data$ExcessR), 3)*sqrt(12)


Data2$ExcessR <- (Data2$totalReturn-Data2$`Percent Change`)

Banks_Informationratio<- round(mean(Data2$ExcessR)/StdDev(Data2$ExcessR), 3)*sqrt(12)


Data3$ExcessR <- (Data3$totalReturn-Data3$`Percent Change`)

DOTD_Informationratio<- round(mean(Data3$ExcessR)/StdDev(Data3$ExcessR), 3)*sqrt(12)


Data4$ExcessR <- (Data4$totalReturn-Data4$`Percent Change`)

Valstrat_Informationratio<- round(mean(Data4$ExcessR)/StdDev(Data4$ExcessR), 3)*sqrt(12)
```

#Treynors ratio

```
MF_TreynorRatio <- round(mean(Data$totalReturn_RF)/StdDev(Data$`Percent Change`), 3)*sqrt(12)


Banks_TreynorRatio <- round(mean(Data2$totalReturn_RF)/StdDev(Data2$`Percent Change`), 3)*sqrt(12)
```

```
DOTD_TreynorRatio <- round(mean(Data3$totalReturn_RF)/StdDev(Data3$`Percent
Change`), 3)*sqrt(12)

Valstrat_TreynorRatio <- round(mean(Data4$totalReturn_RF)/StdDev(Data4$`Percent
Change`), 3)*sqrt(12)

#Jensens alpha
MF_cov <- cov(Data$totalReturn,Data$`Percent Change`)
MF_var <- var(Data$`Percent Change`)
MF_Rmean <- mean(Data$totalReturn)
MF_beta <- MF_cov/MF_var
Index_mean <- mean(Data$`Percent Change`)
rf <- mean(Data$`3monthNiborPercent `)
MF_JensensA <- MF_Rmean - (rf+MF_beta*(Index_mean-rf))

B_cov <- cov(Data2$totalReturn,Data2$`Percent Change`)
B_var <- var(Data2$`Percent Change`)
B_Rmean <- mean(Data2$totalReturn)
B_beta <- B_cov/B_var
Index_mean <- mean(Data$`Percent Change`)
rf <- mean(Data$`3monthNiborPercent `)
B_JensensA <- B_Rmean - (rf+B_beta*(Index_mean-rf))

D_cov <- cov(Data3$totalReturn,Data3$`Percent Change`)
D_var <- var(Data3$`Percent Change`)
D_Rmean <- mean(Data3$totalReturn)
D_beta <- D_cov/D_var
Index_mean <- mean(Data$`Percent Change`)
rf <- mean(Data$`3monthNiborPercent `)
D_JensensA <- D_Rmean - (rf+D_beta*(Index_mean-rf))
```

```
V_cov <- cov(Data4$totalReturn,Data4$`Percent Change`)

V_var <- var(Data4$`Percent Change`)

V_Rmean <- mean(Data4$totalReturn)

V_beta <- V_cov/V_var

Index_mean <- mean(Data$`Percent Change`)

rf <- mean(Data$`3monthNiborPercent `)

V_JensensA <- V_Rmean - (rf+V_beta*(Index_mean-rf))




################################################################################

# Creating dummy variables for specific time periods#

################################################################################


MagicFormulaDummys <- Data %>% mutate(fin_crisis=ifelse(Date>"2007-02-01"&Date<"2008-02-01",1,0))

BanksDummys <- Data2 %>% mutate(fin_crisis=ifelse(Date>"2007-02-01"&Date<"2008-02-01",1,0))

DogsOftheDowDummys <- Data3 %>% mutate(fin_crisis=ifelse(Date>"2007-02-01"&Date<"2008-02-01",1,0))

Valstratdummys <- Data4 %>% mutate(fin_crisis=ifelse(Date>"2007-02-01"&Date<"2008-02-011",1,0))



MagicFormulaDummys <- MagicFormulaDummys %>%

  mutate(Covid=ifelse(Date>"2020-03-01"&Date<"2021-03-01",1,0))

BanksDummys <- BanksDummys %>%

  mutate(Covid=ifelse(Date>"2020-03-01"&Date<"2021-03-01",1,0))

DogsOftheDowDummys <- DogsOftheDowDummys %>%

  mutate(Covid=ifelse(Date>"2020-03-01"&Date<"2021-03-01",1,0))

Valstratdummys <- Valstratdummys %>%

  mutate(Covid=ifelse(Date>"2020-03-01"&Date<"2021-03-01",1,0))
```

```
#Running regressions with dummy variables

MF_CAPM_D <- lm(totalReturn_RF~MarketR+fin_crisis+Covid, data =
MagicFormulaDummys)

MF_FF3_D <- lm(totalReturn_RF~MarketR+SMB+HML+fin_crisis+Covid, data =
MagicFormulaDummys)



Banks_CAPM_D <- lm(totalReturn_RF~MarketR+fin_crisis+Covid, data = BanksDummys)

Banks_FF3_D <- lm(totalReturn_RF~MarketR+SMB+HML+fin_crisis+Covid, data =
BanksDummys)


DOTD_CAPM_D <- lm(totalReturn_RF~MarketR+fin_crisis+Covid, data =
DogsOftheDowDummys)

DOTD_FF3_D <- lm(totalReturn_RF~MarketR+SMB+HML+fin_crisis+Covid, data =
DogsOftheDowDummys)


VS_CAPM_D <- lm(totalReturn_RF~MarketR+fin_crisis+Covid, data = Valstratdummys)

VS_FF3_D <- lm(totalReturn_RF~MarketR+SMB+HML+fin_crisis+Covid, data =
Valstratdummys)


stargazer(MF_CAPM_D,MF_FF3_D,Banks_CAPM_D,Banks_FF3_D,
          DOTD_CAPM_D,DOTD_FF3_D,VS_CAPM_D,VS_FF3_D,
          type = "html",column.labels = c("Capm Magic Formula","FF3 Magic Formula",
                          "Capm Banks","FF3 Banks",
                          "Capm DogsOftheDow","FF3 DogsOftheDow",
                          "Capm ValStrat","FF3 ValStrat"),
          out="RegressionDummysLeadv2")
```

```
################################################################################
#Adding together strategies to create graphs
################################################################################
MarketreturnsMonthly <- data.frame(Date = CAPM$Date,
                                   Index = CAPM$`Percent Change`)
GraphsData <- data.frame(Date = Magic_formulaTotalR$Date,
                         MagicFormula = Magic_formulaTotalR$totalReturn)
GraphsData <- GraphsData %>% left_join(Banks20TR, by = "Date")
GraphsData <- GraphsData %>% left_join(DogsOftheDow10TR, by ="Date")
GraphsData <- GraphsData %>% left_join(ValStratTotalR, by ="Date")
GraphsData <- GraphsData %>% left_join(MarketreturnsMonthly, by ="Date")
colnames(GraphsData)<-
c("Date","MagicFormula","Banks","DogsOfTheDow","ValStrat","Index")
GraphsData <- GraphsData %>% slice(-c(259))



GraphsData$CumulativeMF <-cumprod(1+GraphsData$MagicFormula)-1

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