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Backtesting trading strategies on the Oslo Stock Exchange

Can a non-professional investor beat the market with financial ratios?

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Abstract

This thesis analyzes if a non-professional investor can outperform the market with trading strategies based on easy-accessible financial information from companies on the Oslo Stock Exchange. To answer this question, we backtest strategies from 2001 to 2021 with a monthly rebalancing frequency through three weightings: equal, market capitalization, and revenue. We evaluate each strategy through risk-adjusted measures, sector exposures, and risk-factor regressions. All strategies include a two-percent transaction cost to make the backtests realistic.

Our results show that several strategies outperform the OSEBX. Strategies based on EBITDA margin, debt-to-equity ratio, current ratio, and interest coverage ratio outperform the market in both absolute and risk-adjusted returns. Furthermore, we find an optimal multiple-metric strategy, in which we combine the EBITDA margin, net profit margin, and current ratio. The multiple-metric strategy outperforms all other strategies tested. Additionally, it outperforms the OSEBX by 7.5 percentage points in average annual return and delivers a 54 percent higher Sharpe ratio throughout the 20 years. The results imply that trading strategies based on specific financial ratios are as relevant for the future, as for the past.

Keywords – Backtest, trading strategy, financial ratio, Fama and French, OSEBX, Oslo Stock Exchange

Contents

List of Figures

List of Tables

1 Introduction

We study different long-only, monthly rebalanced trading strategies on the Oslo Stock Exchange from 2001 to 2021. We backtest the strategies to which we go back in time, invest according to the trading rules, and analyze the results. To make the backtest comparable to real-life investing; we include transaction costs, we only use easy-accessible data, and the trading rules are easy to implement for a non-professional investor. For each strategy, the portfolio is weighed three different ways; (1) equally, (2) by market capitalization, and (3) by revenue. We aim to find trading strategies that outperform the market adjusted for various risk factors. Thus, our problem definition is:

> *Can a non-professional investor beat the market by implementing trading strategies based on easy-accessible financial ratios?*

The number of retail investors has increased substantially in the past year and a half, and investing in the stock market has become a more popular way of saving money. During 2020, the number of new individual investors on the OSE increased from around 385 000 to 476 000, and reached 531 000 by the second quarter of 2021 (AksjeNorge, 2021). We observe high stock-market returns, low interest rates, and increased marketing targeting non-professionals. The observations contribute to the increased number of individual investors.

Our main point-of-view is from a non-professional investor's perspective. A non-professional investor is a person who prefers long-term investments and is less risk-averse than people who save in savings accounts. We exclude day-trading and set the rebalancing frequency to monthly. The investor defines investing in the market index as a good investment due to high risk-adjusted returns. Hence, an alternative investment strategy should outperform the market index. The investor invests through a share savings account. The share savings account avoids taxes on gains and dividends as long as the trader keeps the value within the account (The Norwegian Tax Administration, 2021). Thus, we exclude taxes from our study, as taxes affect holding a market index fund and frequently trading stocks the same way. We also exclude short selling from our study. Due to the theoretical unlimited loss potential, investors must be certified to short sell securities. Additionally, short selling includes borrowing costs which may vary from investors.

2 Theory and previous studies

2.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) argues that stock prices include all available information, as news travel fast and affects the pricing without delay (Malkiel, 2003). The EMH implies that neither technical nor fundamental analysis will help investors gain excess market returns. Including transaction costs, the chance of generating alpha should be further limited. Hence, the theory suggests that the best strategy for investors is long-term investing in the market index (Niroomand et al., 2020).

2.2 Quality investing

Quality investing is the strategy of investing in high-quality companies, in which the hypothesis is that these companies will outperform the market in the long run (NBIM, 2015). The definition of quality varies. Graham (1973) defined quality as low debt ratios, stable earnings, and moderate valuation metrics. Piotroski (2000) and Asness et al. (2019) rank stocks based on quality measures such as return on assets, cash flow, net income, and dividend payouts. Furthermore, Fama and French (2015) add the RMW profitability factor to their risk-factor model, and Greenblatt (2006) finds the return on invested capital to deliver excess returns. Even though these studies define quality differently and vary in complexity, we find some common intuition. The metrics measure a company's profitability, liquidity, solvency, and value.

These studies, and many more, argue that quality investing delivers higher returns in the long run. Inspired by these definitions, we study quality investing through financial ratios for profitability, liquidity, and solvency. We exclude valuation ratios due to insufficient data, and partly due to high levels of quantitative easing and a low interest-rate environment after the financial crisis which may reduce the importance of such ratios.

2.3 Backtesting

We use backtesting to investigate trading strategies on the Oslo Stock Exchange. Backtesting refers to simulations of trading strategies using historical data (Schumann, 2019). Even though historical data does not predict the future, this method is still helpful to evaluate whether an investment strategy has potential or not. Backtesting teaches the investor about the risks a strategy imposes (Pedersen, 2015).

In order to backtest successfully, we must define which securities to buy and sell, the signals that determine which stocks to trade, and how to trade on these signals (Pedersen, 2015). Furthermore, to avoid look-ahead bias, we need to define time lags to ensure that the input data is available when the trade occurs. Another bias is survivorship, in which we only choose the current stocks trading on the exchange and exclude the delisted (Schumann, 2019).

2.4 Portfolio theory

2.4.1 Weightings

The investor has to decide how to weigh the portfolio. There are probably unlimited ways of weighing stocks in a portfolio, and the choice of weights can significantly impact portfolio returns. A standard way of weighing stocks is through equal weighting, in which each stock has the same proportion of the portfolio. A second way is weighing based on market capitalization. Each security captures the equivalent proportion of the portfolio as their market capitalization. This method can also be seen as a standard weighing method as most indices use this weighting.

Another way of weighing the assets is through their revenues. A study done by Cohen et al. (2019) brings new evidence to weightings in which revenue-weighting outperforms market capitalization-weighting in both absolute and risk-adjusted returns. They also find evidence that revenue-weighting provides a more stable exposure to the different sectors. Even though this study analyzes the U.S. stock exchange, we test whether the same results appear through our strategies on the OSE.

2.4.2 Number of stocks in a portfolio

The number of stocks in a portfolio affects both the risk and the transaction costs of a strategy. In theory, increasing the number of stocks in a portfolio decreases the portfolio's exposure to unsystematic risk (Bodie et al., 2014). At the same time, we do not want to invest in all the stocks available. We want to include *enough* stocks in our portfolio to achieve most of the diversification effect. Statman (1987) argues for 30 stocks, while others find 10 and 15 stocks to be optimal (Evans and Archer, 1968) (Wagner and Lau, 1971). Ødegaard (2021) tests the number of stocks needed to diversify in the Norwegian market. His result implies that ten stocks are sufficient to diversify portfolios on the OSE.

2.5 Evaluating portfolio performance

2.5.1 Portfolio statistics

Average annual return

The Average Annual Return (AAR) is calculated by taking the arithmetic average of all monthly returns and multiplying by 12.

$$AAR = \overline{r}_{monthly} \cdot 12$$

Annual standard deviation

Standard deviation measures fluctuations in stock returns and is defined as total risk. The annual volatility is the monthly standard deviation multiplied by the square root of 12.

$$\sigma_{annual} = \sigma_{monthly} \cdot \sqrt{12}$$

Beta

Beta is another measure of volatility but measures the portfolio's risk compared to the market. Hence, the beta reveals the portfolio's systematic risk, meaning how the portfolio fluctuates compared to the market. The formula is;

$$\beta_p = COV(r_p, r_m)/VAR(r_m)$$

in which r_p is the monthly portfolio returns, and r_m is the monthly market returns.

Sharpe ratio

The Sharpe ratio (1966) measures the risk-adjusted return of an investment and is the reward to total volatility trade-off (Bodie et al., 2014). The return is measured excess of the risk-free rate over the period's standard deviation. The formula is;

$$SR = (\overline{r}_p - \overline{r}_f)/\sigma_p$$

in which $\overline{r}_p$ is the average annual portfolio return, $\overline{r}_f$ is the average annual risk-free rate, and σ_p is the portfolio's standard deviation. The risk-free rate is subtracted from the portfolio return to isolate the returns generated from risky investments.

Jensen's alpha

Jensen's alpha (1968) is another way of measuring risk-adjusted returns. The measure uses the capital asset pricing model (CAPM) to calculate if the portfolio return is higher or lower than expected. The difference between realized and expected portfolio returns is Jensen's alpha. If the alpha is above zero, the portfolio generates excess return concurrent to the risk and vice versa (Bodie et al., 2014). The formula is;

$$\alpha_p = \overline{r}_p - [\overline{r}_f + (\overline{r}_m - \overline{r}_f) \cdot \beta_p]$$

in which $\overline{r}_p$ is the average annual portfolio return, $\overline{r}_f$ is the average annual risk-free rate, $\overline{r}_m$ is the average annual market return, and β_p is the portfolio's beta.

Treynor's measure

Treynor's measure is similar to the Sharpe ratio and measures risk-adjusted excess return. What separates the two measures is that Treynor's measure uses systematic risk instead of total risk (Bodie et al., 2014). The formula is;

$$TM = (\overline{r}_p - \overline{r}_f)/\beta_p$$

in which $\overline{r}_p$ is the average annual portfolio return, $\overline{r}_f$ is the average annual risk-free rate, and β_p is the portfolio's beta. If the beta is negative, Treynor's measure does not provide meaningful information.

2.5.2 Fama and French risk factors

Researchers have discovered that additional factors can help explain the average stock and portfolio returns, other than the beta coefficient in the CAPM. For example, Banz (1981) finds that smaller firms, in terms of market capitalization, on average, achieve higher risk-adjusted returns than larger firms. In addition, Basu (1983) finds significant evidence that common stocks of high earnings-to-price ratios, on average, earn higher returns than common stocks of low earnings-to-price ratios. Rosenberg (2015) discovers a positive relationship between common stocks with high book-to-market ratios and high returns. Fama and French (1993) develop a model that, in addition to market risk premium, adjusts expected returns for risk factors associated with company size and book-to-market ratio. The model is known as the traditional Fama French three-factor model and minimizes firm-specific factors through mimicking portfolios for common risk factors.

Small Minus Big (SMB)

The size factor SMB captures the risk in average returns related to company size (Fama and French, 1993), as smaller companies tend to outperform larger companies. SMB measures the difference in monthly returns of small-sized and big-sized stock portfolios. Specifically, the average return of nine small-stock portfolios minus the average return of nine big-stock portfolios. A positive SMB factor implies that the portfolio tilts toward small-sized firms.

$$SMB_{B/M} = \frac{1}{3}\begin{pmatrix}\text{Small Value}\\ +\text{ Small Neutral}\\ +\text{ Small Growth}\end{pmatrix} - \frac{1}{3}\begin{pmatrix}\text{Big Value}\\ +\text{ Big Neutral}\\ +\text{ Big Growth}\end{pmatrix}$$

$$SMB_{OP} = \frac{1}{3}\begin{pmatrix}\text{Small Robust}\\ +\text{ Small Neutral}\\ +\text{ Small Weak}\end{pmatrix} - \frac{1}{3}\begin{pmatrix}\text{Big Robust}\\ +\text{ Big Neutral}\\ +\text{ Big Weak}\end{pmatrix}$$

$$SMB_{INV} = \frac{1}{3}\begin{pmatrix}\text{Small Conservative}\\ \text{+ Small Neutral}\\ \text{+ Small Aggressive}\end{pmatrix} - \frac{1}{3}\begin{pmatrix}\text{Big Conservative}\\ \text{+ Big Neutral}\\ \text{+ Big Aggressive}\end{pmatrix}$$

$$SMB = 1/3(SMB_{B/M} + SMB_{OP} + SMB_{INV})$$

Chen and Bassett find that "a positive SMB coefficient does not necessarily mean returns are attributable to exposure to small stocks" (2014). Big firms account for more than 90 percent of the market value, while small stocks account for around 80 percent of publicly traded firms. In the Fama French three-factor model, the high representation of large-cap firms in terms of market value can cause large-cap portfolios and individual stocks to get positive SMB coefficients.

High Minus Low (HML)

The HML factor captures the risk in average returns related to book-to-market equity (Fama and French, 1993). It is calculated similarly as the SMB; the difference in return of the two high book-to-market ratio portfolios and the two low book-to-market ratio portfolios. The intuition behind the factor is that high book-to-market stocks tend to outperform low book-to-market stocks.

$$HML = \frac{1}{2}\begin{pmatrix}\text{Small Value}\\ \text{+ Big Value}\end{pmatrix} - \frac{1}{2}\begin{pmatrix}\text{Small Growth}\\ \text{+ Big Growth}\end{pmatrix}$$

A positive HML factor implies that the portfolio tilts toward high book-to-market firms.

Momentum factor

Jagadeesh and Titman (1993) discover that one could achieve significant positive returns when buying stocks that have performed well in the past and selling stocks that have performed poorly. Carhart (1997) introduces a momentum factor that expands the Fama French three-factor model. The factor is called PR1YR and supports the findings of Jagadeesh and Titman. The PR1YR is the difference between the top and bottom 30 percent of stocks ranked by cumulative returns in the past eleven months. Carhart finds a low correlation between the SMB, HML, and PR1YR factors, and concludes that the four-factor model explains more variation in stock returns than the three-factor model alone.

French introduce an alternative momentum factor. The Up-Minus-Down (UMD) factor is calculated similarly to the PR1YR. French explains UMD as;

> We use six value-weight portfolios formed on size and prior (2-12) returns to construct Mom. The portfolios, which are formed monthly, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (2-12) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles. (French, 2021a)

It is simply the average return of two high prior return portfolios (Small High + Big High) less the average return of the two low prior return portfolios (Small Low + Big Low) (French, 2021). One of the main differences between the UMD and PR1YR factors is that UMD attempts to correct for the size effect (Næs et al., 2009). A positive UMD factor implies the portfolio tilts toward current month's winner firms, with high prior returns.

Fama French five-factor model

Fama and French expand the three-factor model, adding two variables to capture profitability and investment patterns in average stock returns. The expanded model is the Fama French five-factor model and performs better in explaining average stock returns than the three-factor model (Fama and French, 2015).

RMW, the profitability factor, is the difference in returns of diversified portfolios with robust and weak profitability;

$$RMW = \frac{1}{2}\left(\substack{\text{Small Robust}\\ +\text{ Big Robust}}\right) - \frac{1}{2}\left(\substack{\text{Small Weak}\\ +\text{ Big Weak}}\right)$$

CMA is the difference in returns of portfolios with conservative and aggressive stocks and explains the variation in average returns related to investment activity. The conservative stocks have inactive investment styles, whereas the aggressive ones have active investment styles.

$$CMA = \frac{1}{2}\left(\substack{\text{Small Conservative}\\ \text{+ Big Conservative}}\right) - \frac{1}{2}\left(\substack{\text{Small Aggressive}\\ \text{+ Big Aggressive}}\right)$$

Positive RMW and CMA factors imply that the portfolio tilts toward robust firms with conservative asset growth.

Liquidity

The liquidity factor measures several dimensions of trading: the cost, how fast, and how much one can trade (Næs et al., 2009). Hence, it is a complex factor and depends on several variables. Næs et al. construct the liquidity factor as the difference between the return of the least liquid portfolio and the most liquid portfolio. They use three equal-weighted portfolios in which stocks are ranked based on their level of liquidity the previous month and followingly placed into their respective portfolios. A positive LIQ factor indicates that the portfolio tilts toward illiquid stocks, as the coefficient subtracts returns of high-liquid stocks from low-liquid stocks.

The definition of liquid stocks is a low relative spread between the bid and ask price. Hence, investors pay relatively more for illiquid stocks and get compensated by higher expected returns (Pastor and Stambaugh, 2003). Furthermore, the illiquid stocks tend to be smaller, supporting the higher expected returns (ref. SMB). Næs et al. (2009) find that the correlation between SMB and LIQ to be 0.51 on the OSE. Hence, the two factors capture some of the same effects.

Leirvik et al. (2017) find that liquidity affects stock returns in the Norwegian market. However, they conclude that the liquidity factor is not economically significant due to low R-squares, despite statistically significant coefficients. Thus, the liquidity factor has a negligible impact on stock returns in Norway.

The Fama French five-factor model, including momentum and liquidity, is;

$$\begin{aligned} R_{it} = \alpha_i + \beta_{iM} R_{Mt} + \beta_{iSMB} SMB_t + \beta_{iHML} HML_t + \beta_{iRMW} RMW_t \\ + \beta_{iCMA} CMA_t + \beta_{iUMD/PR1YR} UMD_t/PR1YR_t + \beta_{iLIQ} LIQ_t + e_{it} \end{aligned}$$

in which the variables have the following definitions:

R_{it}	total excess return of a stock or portfolio i at time t
α_{it}	constant
β_i	factor coefficients
R_{Mt}	excess market return at time t
SMB_t	size premium (Small Minus Big)
HML_t	value premium (High Minus Low)
RMW_t	profitability measure (Robust Minus Weak)
CMA_t	investment activity (Conservative Minus Aggressive)
$UMD_t/PR1YR_t$	French's/Carhart's momentum factor (high return minus low return)
LIQ_t	liquidity premium (low liquidity minus high liquidity)

R-squared

The R-squared ranges from zero to one and estimates the proportion of the dependent variable's variations explained by the independent variables (Wooldridge, 2009). Specifically, R-squared tries to measure the accuracy of the risk factors predicting portfolio returns. Even though this measure has many caveats, it helps us understand how the different factors may explain a portfolio's return.

2.6 Trading strategies

Trading strategies are a set of predefined rules and criteria used for buying and selling securities in the market. Strategies may include rules and criteria based on companies' market capitalization, revenue, industry sector, or other fundamental indicators. We will focus on specific ratios derived from a company's financial statement to define our strategies. Ideally, we would like to test more ratios; however, we must restrict ourselves because of insufficient data. See further discussion in the data section of our thesis.

2.6.1 EBITDA margin

First, we evaluate a trading strategy in which we invest in the top ten stocks based on EBITDA margin. The EBITDA margin is earnings before interest, taxes, depreciation and amortization, scaled by revenue. Companies with a high EBITDA margin have a reliable operation and generate cash through their primary business area. Investors view these companies as healthy, and their stocks can consequently perform well in the stock market. One of the reasons for EBITDA's popularity is that it measures corporate performance as it reveals earnings without including accounting and financial deductions, such as taxes, interest expenses, and depreciation (Buscemi, 2015). Another reason is that investors value companies through the profitability of their operations, amongst other metrics. Fundamental discounted cash flow analysis is based on a company's free cash flow, whereas the free cash flow springs out of the EBITDA.

On the other hand, the Generally Accepted Accounting Principles (GAAP) do not include EBITDA as a measure of financial performance (Grant and Parker, 2002). Non-GAAP measures may vary across companies and potentially weaken credibility. For instance, some companies may include a large sale of property or equipment in revenues. EBITDA will, as a result, be artificially high due to the sale, and the company's operations will appear healthier than they are. Thus, there could be red flags when companies suddenly decide to report EBITDA. The metric tends to be reported by companies that hide their actual profitability and guide investors' focus away from its actual profitability.

2.6.2 Debt-to-equity ratio

Next, we evaluate a trading strategy in which we invest in ten companies based on the debt-to-equity ratio. The debt-to-equity ratio is a leverage ratio and measures the weight of total debt and financial liabilities against the total shareholders' equity (CFI, 2021a). We choose to invest in the ten companies with the lowest debt-to-equity ratio, implying that the companies are solid and can quickly pay off outstanding debt. In contrast, high-ratio companies tend to be associated with high risk, as the companies have financed growth by borrowing (Berk, 2014).

On the other hand, companies in the development stage tend to have low debt-to-equity ratios as they need financial flexibility, hence, more equity and a lower leverage ratio (Killi et al., 2011). Therefore, we cannot be sure that we only include low-risk companies in our portfolio, as we may also include companies in the development stage. Another risk is that companies that take on high-profitable projects usually finance such projects through borrowing. Through leverage, the companies can reduce asymmetric information and create higher returns on equity for shareholders, as long as the return from the project is greater than the interest payments on the debt. This phenomenon is related to the Pecking Order Theory, which states that companies prefer external financing through debt to external financing through equity issuance (CFI, 2021b).

2.6.3 Net profit margin

We also evaluate a trading strategy in which we invest in the top ten stocks based on net profit margin. Net profit margin is a company's net income or profit as a percentage of revenue (Nariswari and Nugraha, 2020). It reveals how revenue translates into profit after deducting total expenses. The intuition is that stocks with high ratios generate profits through their operations, which should increase the company's value over time.

A disadvantage regarding the net profit margin is that large one-off items can influence or manipulate the ratio. These one-offs can be sales of assets that are not a normal part of a company's operation, leading to an unusually high net profit margin. Another potential pitfall is when companies reduce their expenses in a short-term manner: the reduction will increase the net profit margin, but only short term. For a company to increase its stock price over time, it needs a constant high, or a long-term increasing net profit margin, and these are the companies we look for through this strategy.

2.6.4 Current ratio

Next, we study a trading strategy that invests in the ten stocks with the highest current ratios. The current ratio is a liquidity ratio and reveals a company's ability to pay its short-term obligations (Berk, 2014). The current ratio divides current assets by current liabilities. The intuition behind this strategy is that companies with a high current ratio are financially strong and can remain solvent. The stocks with high ratios should fall less than those with low ratios through crises and recessions.

On the other hand, the current ratio only gives a quick peek at a company's short-term liquidity at one specific point in time. It is not a complete representation of a company's financial state. For instance, it may not consider slow-paying customers and write-offs in the accounts receivables.

2.6.5 Interest coverage ratio

Last, we evaluate a trading strategy in which we invest in the top ten stocks based on interest coverage ratio. The interest coverage ratio measures how easily a company can pay its interest expenses on outstanding debt (Berk, 2014). The interest coverage ratio is a debt and profitability ratio and weighs EBIT on the interest expenses for the given period. Investors often use this measure to calculate the riskiness of a company relative to its current debt. The intuition behind this strategy is that companies with a high ratio are considered financially stable, hence, a safe investment.

Companies with a too high ratio may also indicate that they could safely leverage their operations to increase profits and shareholder returns. That is under the assumption that the projects generate higher returns than the additional interest expenses. Therefore, a high ratio could also indicate a lack of profitable projects.

2.6.6 Limitation

One limitation is that the metrics listed above may be sector dependent. Sector averages vary, which means that a company with an apparent low ratio is not necessarily a poor-performing company. The company's ratio could be among the best in its sector. As a result, some trading strategies will mainly focus on specific sectors, not equally spread amongst the different sector-tops. Thus, we include sector analysis for each strategy.

3 Data

Limited data availability restricts us to a twenty-year period analysis from 2001 to 2021. We collect relevant data on all stocks listed on the OSE from from this period. We mainly use NHH's Børsprosjektet and Thomson Reuters' Refinitiv Eikon to download data. Børsprosjektet contains various financial data on all stocks listed on the OSE from 1980 (Børsprosjektet, 2021). Oslo Børs Informasjon provides the financial data to Børsprosjektet. However, Børsprosjektet stopped receiving accounting data in 2011. Thus, we mainly use Refinitiv Eikon to download the financial accounting data. The financial news and database solution, Refinitiv Eikon, offers data from various financial markets worldwide, including the Oslo Stock Exchange (Eikon, 2021).

3.1 Selection of stocks for the analysis

We download all available monthly equity prices and filter the dates to be greater or equal to 30/11/2000. Furthermore, we filter the data to be only stocks, thus excluding securities such as ETFs and warrants. Next, we only include stocks from the main list on the OSE to exclude smaller and less regulated stocks listed on Euronext Expand and Growth, previously known as Oslo Axess and Merkur Market. Last, we only include stocks classified as ordinary shares and primary capital certificates to exclude share types such as preference, A, and B.

We use ISIN (International Securities Identification Number) as a standard ID for each stock. Both Børsprosjektet and Refinitiv Eikon have records of each stock's ISIN. However, Børsprosjektet has only one observed ISIN per stock, while for some stocks, Refinitiv Eikon has several. In addition, some ISINs from Børsprosjektet are outdated or nonexistent at Refinitiv Eikon. To correct the wrong ISINs, we replace ISINs from Børsprosjektet with correct and updated ISINs from Refinitiv Eikon. This is to ensure we have a common ID, which enables us to connect price and accounting data from two different sources.

3.2 Price data

Using the selections above, we download monthly price data for all stocks listed on the OSE from Børsprosjektet. However, due to the OSE's transition to Euronext, the pricing data stops at 27/11/2020. To complete data for 2020, we add November and December prices to our dataset from Refinitiv Eikon.

We use adjusted generic as our pricing variable. Generic refers to the closing price when the closing price is observed. Otherwise, it uses the high, low, bid, or offer price. The adjusted generic variable corrects for corporate events such as stock splits but not dividends. Hence, we multiply the adjusted generic variable with the cumulative dividend factor to adjust prices for dividends. Furthermore, we filter non-adjusted prices to be higher than 5 NOK to exclude penny stocks from our data sample. Lastly, we ensure that the stocks are tradable by removing non-availables (NAs) and filtering the number of shares issued to be more than zero.

We only include the last monthly price observation for each stock, which must be within the last five trading days of the month. A significant proportion of the price data has prices before the month's end date, and many have multiple price observations within one month. We correct it to ensure that each stock has a maximum of one price observation each month.

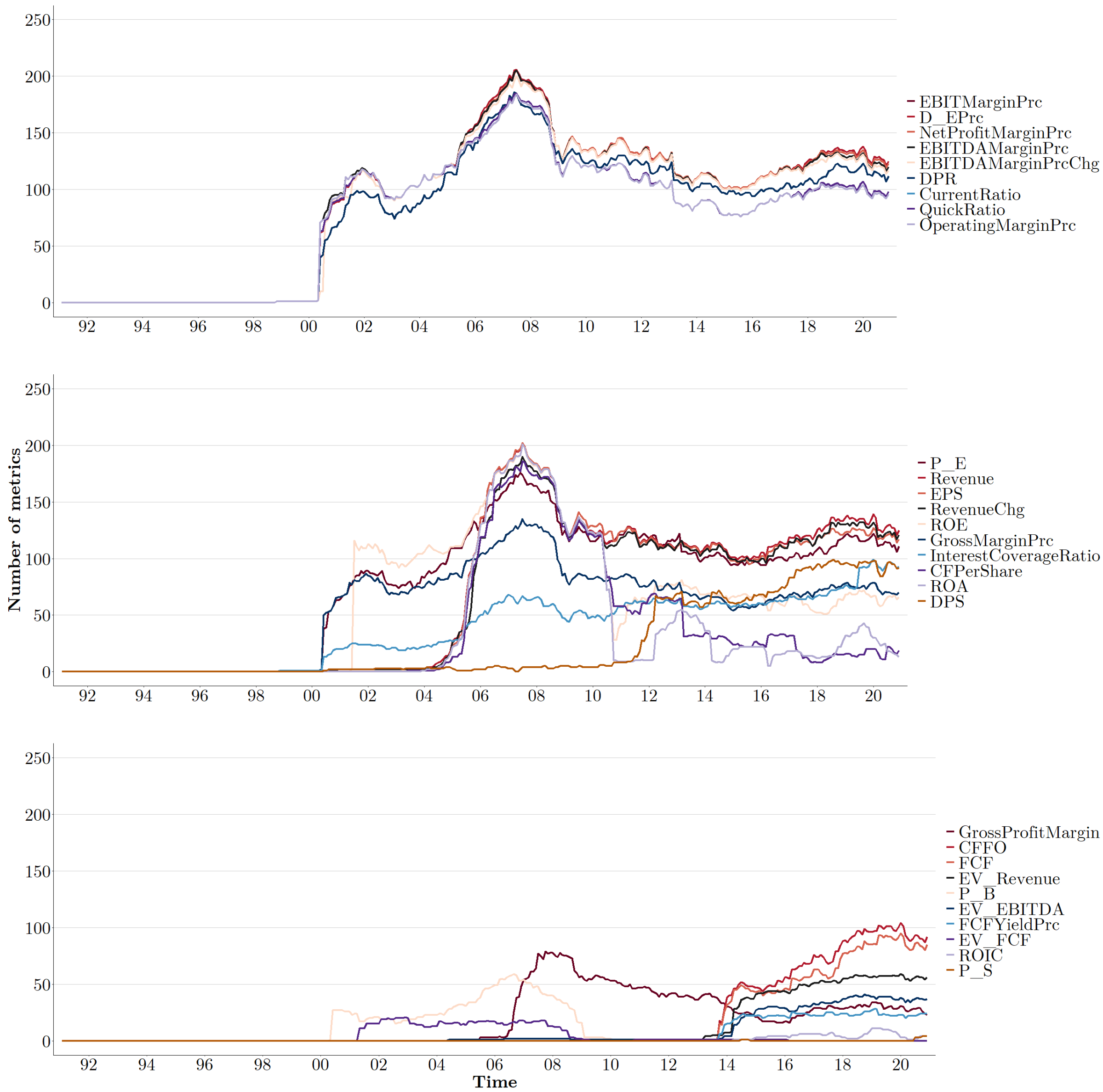
3.3 Portfolio weightings

We weigh stocks in the portfolio by three measures: equally, by market capitalization, and by revenue. Hence, we need data for market capitalization and revenue. We do not need additional data for equal weighting. We multiply the unadjusted close price by the number of shares issued to calculate market capitalization. Børsprosjektet provides all data for market capitalization. Similarly, Refinitiv Eikon provides all the revenue data, but we use Børsprosjektet for months when Refinitiv Eikon is missing data.

3.4 Accounting data

Based on the data available, we choose to analyze the following metrics: EBITDA margin, debt-to-equity ratio, net profit margin, current ratio, and interest coverage ratio. Figure 3.1 shows that we have enough data to test trading strategies based on these metrics.

Figure 3.1: Number of accounting metrics available each month



We choose to exclude the years prior to 2000 from the thesis due to a lack of data. To increase the amount of data, we could add accounting data from Børsprosjektet before the 2000s. The problem is that Børsprosjektet only offers annual accounting data for this period and dividing annual accounting data by four does not necessarily equal quarterly measures, and will result in a static company performance throughout each year.

We exclude several company-performance measures because of insufficient amounts of data. If not excluded, we stand the risk of believing we invest in the companies with the best financial ratio, while in reality, they may not even be within the better half of the total exchange. In other words, the metric should at least have data for more than a third of the companies listed on the stock exchange for all 20 years.

3.5 Risk-free rate data

We choose the 1-month NIBOR as the risk-free rate. NIBOR (Norwegian Interbank Offered Rate) is Norway's money market interest rate and reflects the rate banks require when lending unsecured money between each other (Referanser, 2021). We download NIBOR data between 2000 and 2013 from Norges Bank (2015) and between 2013 and 2020 from Norske Finansielle Referanser AS (2021).

3.6 Index data

We use the Oslo Stock Exchange Benchmark Index (OSEBX) as the market index. OSEBX includes the most traded and largest stocks listed on the OSE (Euronext, 2021). It was introduced in 1996 and is semiannually updated. The stocks included in OSEBX represent the performance of all stocks listed on the OSE. Thus, the index is adjusted for dividends and is comparable to our price data. We download the index data from Børsprosjektet (2021).

3.7 Fama and French data

We download pricing factors estimated on the OSE from Ødegaard's website (2021a), consisting of SMB, HML, UMD, PR1YR, and LIQ. Furthermore, we align the pricing factors with our forward-looking return data by adjusting the data one month back. We also download the European Fama French five-factor model plus momentum, from French's website (2021b). CMA and RMW factors are unavailable for the Norwegian stock market. We adjust the data similar to the Norwegian data to adapt the forward-looking returns.

We further discuss choices regarding the Fama and French factors in the methodology section.

3.8 Sector classification data

To better understand the portfolios' performances, we study which sectors they target. Thus, we download each stock's sector classification on the OSE from Ødegaard's website (2021b). He uses MSCI's Global Industry Classification Standard (GICS), which consists of 11 sectors: energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, communication services, utilities, and real estate (MSCI, 2021). Some stocks change GICS during the listing period on the OSE; however, our data processing accounts for such changes. Also, the list of GICS does not include all the stocks that we include. Thus, some stocks do not have GICS. We classify the sector for these stocks as unknown.

4 Methodology

4.1 Formatting data for backtesting

Each backtest contains five datasets; returns, market capitalizations, GICS sectors, accounting metrics, and revenues. We reshape the datasets to wide formats, with ISINs column-wise and the dates row-wise.

Table 4.1: Monthly return data for each stock, in wide format

	Returns					
i	**Date**	**ISIN 1**	**ISIN 2**	**ISIN 3**	**...**	**ISIN n**
1	30.11.2000	0.034	0.053	NA	...	0.011
2	31.12.2000	-0.015	0.021	NA	...	0.003
3	31.01.2001	0.004	-0.064	0.026	...	0.065
...	...	...	...	...	...	...
241	30.11.2020	NA	NA	0.048	...	0.089

The stock return dataset has forward-looking returns, meaning that returns at month t correspond to the returns of the period between t and $t+1$. For instance, the returns at date 31/12/2000 are the stocks' returns for January 2001. Due to filtering, our dataset includes 454 different stocks for the period, compared to 484 stocks on the OSE (Oslo Børs, 2021).

Table 4.2: Monthly market capitalization for each stock, in wide format

	MktCap					
i	**Date**	**ISIN 1**	**ISIN 2**	**ISIN 3**	**...**	**ISIN n**
1	30.11.2000	1005	6762	NA	...	2057
2	31.12.2000	1025	6790	NA	...	1978
3	31.01.2001	1020	6803	8193	...	1956
...	...	...	...	...	...	...
241	30.11.2020	NA	NA	9843	...	5039

The market capitalization dataset has the same number of observations as the returns dataset. The value at 31/12/2000 corresponds to a stock's market capitalization within the last five days of December 2020.

Table 4.3: Monthly GICS data for each stock, in wide format

				GICS		
i	**Date**	**ISIN 1**	**ISIN 2**	**ISIN 3**	**...**	**ISIN n**
1	30.11.2000	Financial	Unknown	NA	...	Industrials
2	31.12.2000	Financial	Unknown	NA	...	Industrials
3	31.01.2001	Financial	Unknown	Materials	...	Industrials
...	...	...	...	...	...	...
241	30.11.2020	NA	NA	Materials	...	Financial

The GICS dataset has observations for each stock's sector classification. Some stocks change GICS over time, but as illustrated in the last column, the dataset dynamically changes when stocks change sector. Furthermore, we categorize stocks with missing GICS as unknown.

Table 4.4: Monthly accounting data for each stock, in wide format

				Accounting Metric			
i	**Date**	**ISIN 1**	**ISIN 2**	**ISIN 3**	**ISIN 4**	**...**	**ISIN n**
1	30.11.2000	0.434	0.256	NA	0.098	...	0.123
2	31.12.2000	0.434	0.256	NA	0.098	...	0.123
3	31.01.2001	0.434	0.256	NA	0.098	...	0.123
4	28.02.2001	0.458	0.211	NA	0.098	...	0.123
5	31.03.2001	0.458	0.211	NA	0.098	...	0.156
6	30.04.2001	0.458	0.211	NA	0.102	...	0.156
...	...	...	...	...	...	...	...
241	30.11.2020	NA	NA	0.158	0.283	...	0.098

Because of insufficient data quality, the different accounting datasets have various numbers of stocks. The date corresponds to the month when a company publishes the accounting metric, and Refinitiv Eikon uses publishing dates. For instance, in row 4, ISIN1's new metric has become publicly available between 01/02/2001 and 28/02/2001.

Accounting metrics cannot be calculated monthly due to, at best, quarterly updates. We carry forward the last accounting metric observation for a maximum of 11 months, making a metric relevant for 12 months. If a new metric occurs within 11 months, we use the new metric. For instance, ISIN 1 and 2 publish their new metric in February 2001, ISIN n publishes in March 2001, and ISIN 4 does not publish until April 2001. For companies that do not publish new numbers within 11 months, we make the further rows NAs. The NAs cease when the companies publish new numbers.

Table 4.5: Monthly revenue data for each stock, in wide format

			Revenue			
i	**Date**	**ISIN 1**	**ISIN 2**	**ISIN 3**	**...**	**ISIN n**
1	30.11.2000	234	720	NA	...	1203
2	31.12.2000	234	743	NA	...	1203
3	31.01.2001	234	743	893	...	1203
...	...	...	...	...	...	...
241	30.11.2020	NA	NA	4078	...	5039

Revenues follow the same procedure as accounting metrics. However, to increase the number of revenue observations, we merge revenue data from Børsprosjektet and Refinitiv Eikon. While Refinitiv Eikon uses publishing date, Børsprosjektet reports the end-month of a fiscal quarter. For instance, in 2015, Equinor publishes its Q2 report on the 16$^{\text{th}}$ of August; in this case, Refinitiv Eikon reports 16/08/2015 as the date for the Q2 report, while Børsprosjektet reports 30/06/2015. To merge the data, we push every observation from Børsprosjektet two months ahead to avoid using unpublished revenues as weights for a given period. The two-month delay reduces the chance of look-ahead biases.

4.2 Backtesting

We backtest our strategies through a loop that starts 31/12/2000 at $i = 2$ and ends 30/11/2020 at $i = 241$. Thus, calculating the returns from January 2001 to December 2020 - a full 20 years.

Each month, the loop extracts stocks that;

- are listed on the OSE
- have market capitalization data
- have revenue data

The process ensures that we only pick listed stocks and can weigh the stocks by the three weightings.

Further, the loop extracts the stocks' accounting metrics from the *previous* month, at $i - 1$, to eliminate the chance of predicting the future. If we extract prices and accounting metrics from the same month, we can unintentionally predict the future in some cases.

For instance, a price observation initially dated 26/03/2005 and an accounting metric published on 28/03/2005 are both formatted to 31/03/2005. Thus, we can end up trading stocks based on accounting metrics that have not yet been published. We eliminate the risk of predicting the future through the one-month delay. The downside is cases in which new accounting metrics are, for instance, published 05/05/2010, transforming to 31/05/2010 in the dataset. In such cases, the accounting metrics will not be available until 30/06/2010, almost two months past initial publishing date.

When the loop finds the available stocks to pick, it ranks them based on the different metrics and picks the highest or lowest ten ranked stocks. Whether the loop picks the highest or the lowest ranked stocks depends on the metric. We put the stocks in the current month's portfolio and compare them with the previous one. Through the comparison, we make three lists: stocks bought, held, and sold.

4.2.1 Weightings

We weigh the portfolio three different ways each month; equal-weighted (EW), market capitalization-weighted (MCW), and revenue-weighted (RW). For the first month, we only buy stocks, while we buy, hold, or sell stocks in any other months. Furthermore, we use the same weights to calculate GICS proportions within the portfolio each month. We calculate the weights through the following formulas:

Equal:

$$w^E_{bh,i,t} = \frac{1}{n_t}$$

$$w^E_{s,i,t} = w^E_{bh,i,t-1} = \frac{1}{n_{t-1}}$$

Market capitalization and revenue:

$$w^j_{bh,i,t} = \frac{Value_{i,t}}{\sum Value_{i,t}}$$

$$w^j_{s,i,t} = w^j_{bh,i,t-1} = \frac{Value_{i,t-1}}{\sum Value_{i,t-1}}$$

in which,

bh	buy/hold
s	sell
t	time
n	number of stocks in portfolio
j	market capitalization, revenue
Value	Value of market capitalization, revenue

4.2.2 Transaction costs

We set the total transaction cost to be two percent. Transaction costs play a vital part in backtesting and trading in general as they may cut deep in investors' portfolio returns. Transaction costs are split into two groups; direct and indirect transaction costs. The most direct form of transaction costs is the commissions paid to brokers (Ødegaard, 2009b).

Relative spread is the most commonly used measure for indirect transaction costs. The relative spread is the difference in bid and ask price relative to the average of the best buy and sell price. Slippage is another indirect transaction cost and is the difference in price from when a transaction is intended to happen versus executed. Market impact is the last part of indirect transaction costs and refers to when investors have to accept a sub-market price when selling large numbers of shares. We focus on non-professional investors who do not impact market prices. Thus, we focus more on commissions and relative spread.

According to Nordnet, a leading retail broker in Norway, the typical direct transaction cost is 4.9 basis points (Nordnet, 2021). Fisher and Krauss (2018) only consider the direct transaction costs when trading at adjusted prices and use around five basis points. Underestimating the transaction costs can create huge biases. In Ødegaard's paper regarding the cost of trading on the OSE, he calculates the relative spread cost for three periods (2009a). He estimates the relative spread medians to be 3.0 percent from 1980 to 1989, 2.6 percent from 1990 to 1999, and 2.0 percent from 2000 to 2008. Simplifying and digitizing stock trading has contributed to a lower spread throughout the years as the stocks' liquidity has increased (Ødegaard, 2009b). We see this effect through the decrease in relative spread throughout the testing period from 1980 to 2008. Today's relative spread on the OSE is likely lower than two percent by continuing the trend. However, we choose to set the total transaction cost to be two percent to avoid underestimating the transaction costs.

We charge the investor for each transaction executed. To realistically account for transaction costs, the investor immediately gains a negative return, equal to the transaction cost, on the position after a purchase. Usually, brokers charge transaction costs from investors' cash reserves or bank accounts. In practice, investors are usually never fully invested in the market, as they need some money to pay for daily necessities. However, in our backtest, we assume the investor to be fully invested in the market as we focus on trading strategies compared to the index. As a result, we account for transaction costs through returns. In a month in which the investor buys a stock, the stock will have the following return:

$$r_{b,t} = (1 + r_i) \cdot (1 - t)$$

In the equation, t is the transaction cost. The same principle goes for stocks sold, but in such cases, we add the transaction cost from the sale to next month's portfolio return.

$$r_{s,t} = -t$$

The investor must own the stock for the entire month to gain the respective month's return. If we add the transaction costs to the same month, the investor will have to sell the stock after the stock exchange closes, the last trading day of the month. Therefore, it is more natural to sell a stock on the first trading day of the following month, resulting in a one-month lagged transaction cost. We weigh transaction costs according to the stock's proportion of the portfolio. We use the stock's current month's weight for purchases, while we use the previous month's for sales.

We choose to exclude transaction costs in the first and the last period. We do this to study the difference between holding the index and investing in the different portfolios more precisely. If we include transaction costs for our portfolios' first and last period, we should do the same for the index portfolio. Hence, in these cases, transaction costs are considered irrelevant costs and excluded.

4.2.3 Returns

We extract a vector containing the portfolio stocks' returns for each iteration in the loop and weigh each return with each stock's respective weight:

$$r_t^p = \sum(w_{s,i,t}^k \cdot t) + \sum(w_{bh,i,t}^k \cdot r_{i,t})$$

k = equal, market capitalization, revenue

4.3 Fama and French models

Consistency is essential when running a Fama and French regression. The model regresses portfolio returns on several factors computed from a specific market. Thus, it is crucial to be consistent on which market to use. From Ødegaard's website (2021a), we access factors calculated from the Norwegian stock market data: the Fama French three-factor model plus momentum and liquidity. However, we are also interested in the Fama French five-factor model. In order to regress the portfolios on the five-factor model, we have to collect data for the RMW and CMA factors. However, the two remaining factors are not calculated for the Norwegian stock market, and the closest we get is the European market. We violate the consistency criteria by adding the two remaining factors from the European market to the Norwegian model. Our solution is to run both the Norwegian and European factor models on the portfolios.

We choose the UMD factor over the PR1YR factor. As both factors account for momentum, we should only include one. In Ødegaard's (2017) paper about asset pricing results on the OSE, he finds the correlation between UMD and PR1YR to be 0.78. When two variables highly correlate, a change in one variable will cause change to the other. It will result in multicollinearity, and we have to omit one of the variables from the regression (Wooldridge, 2009). By running a few tests, we find that the two factors provide the same explanatory power. The PR1YR factor is not available for the European market, whereas the UMD factor is available for both. Thus, we choose to omit PR1YR from the regression and keep UMD.

Thus, the two models we regress are;

Norwegian model
$(FF3F{+}MOM{+}LIQ)$

$$(r_p - r_f) = \alpha + \beta_1(r_m - r_f) + \beta_2 SMB + \beta_3 HML + \beta_4 UMD + \beta_5 LIQ$$

r_p = portfolio returns; r_m = OSEBX returns; r_f = Norwegian risk-free rate

European model
$(FF5F{+}MOM)$

$$(r_p - r_f) = \alpha + \beta_1(r_m - r_f) + \beta_2 SMB + \beta_3 HML + \beta_4 RMW + \beta_5 CMA + \beta_6 UMD$$

r_p = portfolio returns; r_m = European market index returns; r_f = European risk-free rate

4.4 Backtesting multiple metrics

We slightly adjust the original backtesting method to identify the best-performing combination of multiple accounting metrics. We include two extra financial ratios to the strategy, resulting in three ratios in total. Furthermore, we sort each metric and categorize the stocks in ten deciles. The decile number equals the score of which a stock receives. For instance, if a stock's EBITDA margin, net profit margin, and current ratio lie in the 10^{th}, 9^{th}, and 8^{th} decile, the stock's total score is 27. Here, the 10^{th} decile equals the highest score. We calculate all metrics this way, except for the debt-to-equity ratio. If the debt-to-equity ratio scores a 10, it has one of the lowest values. After each scoring, we invest in the ten stocks with the highest total score each month.

We backtest every possible combination of the different metrics and provide portfolio statistics for these combinations in the Appendix Table A2.4. We define the best combination as the one with the highest Sharpe ratio.

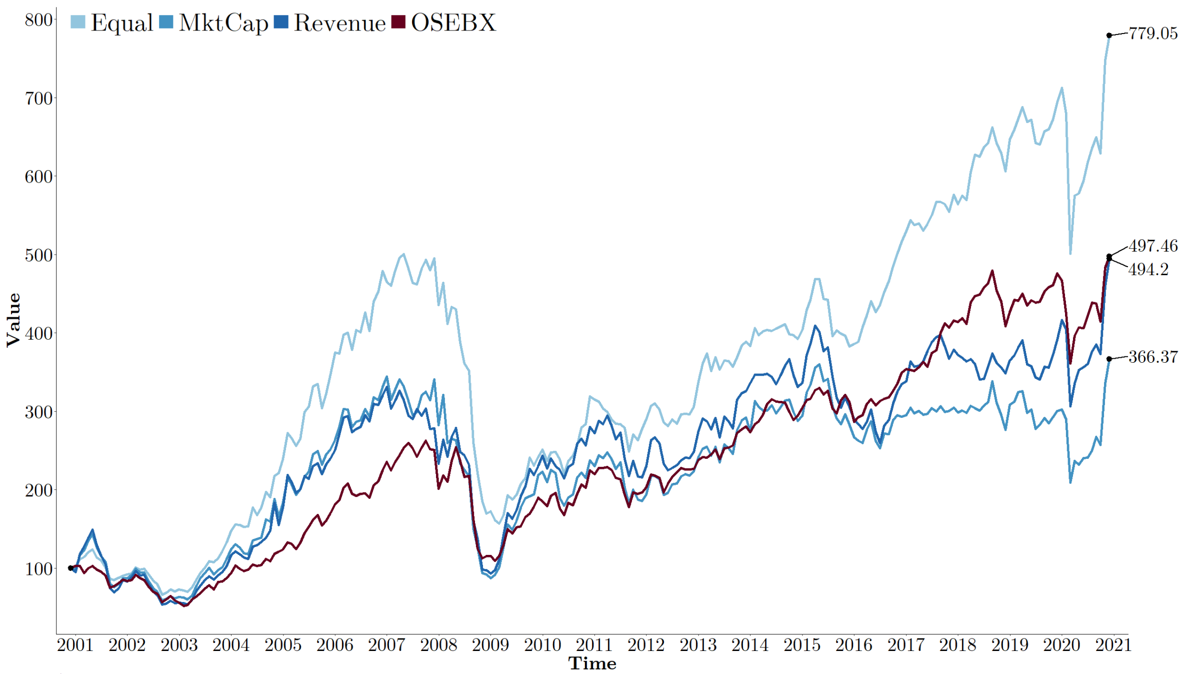
5 Analysis

We evaluate each trading strategy separately with the respective weightings and discuss findings. First, we analyze the portfolio's performance through general statistics and risk-adjusted measures, understand the impact of the transaction cost, identify sector characteristics, and discuss risk-factor regression results.

5.1 EBITDA margin

5.1.1 General overview

Figure 5.1: EBITDA Margin Strategy: Backtesting from Jan. 2001 to Dec. 2020



*Strategy: Every month, invest in the 10 stocks listed on OSE with the highest EBITDAMarginPrc
*Transaction cost: 2 %

Figure 5.1 shows that the EW portfolio performs the best. The portfolio manages to capture big economic upswings, but big economic downswings as well. We see this specifically throughout the financial crisis in 2008 and the COVID-19 outbreak in 2020. The two other portfolios manage to capture a great deal of the upswing prior to the financial crisis but strive to continue the growth in the period after.

5.1.2 Performance statistics

Table 5.1: EBITDA Margin Strategy: Performance statistics

	Annual Avg. Return	**Annual St. Dev.**	**Sharpe Ratio**	**Beta**	**Jensen's Alpha**	**Treynor's Measure**
OSEBX	0.1021	0.2043	0.3662	1.0000	0.0000	0.0748
Equal	0.1262	0.2123	0.4661	0.8344	0.0365	0.1186
MktCap	0.1055	0.2812	0.2783	1.1023	-0.0042	0.0710
Revenue	0.1207	0.2819	0.3316	1.0384	0.0158	0.0900

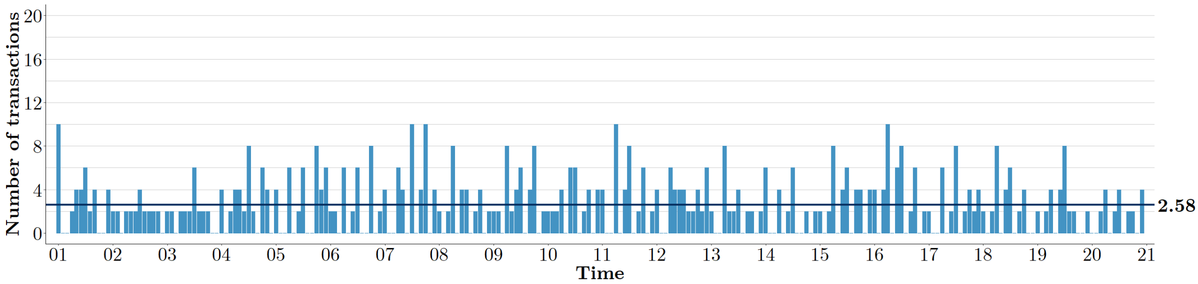
Through 20 years, the EW portfolio generates a total cumulative return of 679.05 percent, which in turn calculates to an AAR of 12.62 percent. The index gets an AAR of 10.21 percent throughout the same period. Hence, the EW portfolio outperforms the index by 2.4 percentage points on average each year.

On the other hand, absolute returns describe little of the portfolio's performance, and one will have to account for risk to understand the portfolio's actual performance. The EW portfolio achieves the highest Sharpe ratio of the three portfolios at 0.47. The second highest is the RW portfolio at 0.33, followed by the MCW portfolio at 0.28. On the other hand, the market index scores a Sharpe ratio of 0.37 and is ranked number two. The results show that an investor should choose the EW portfolio in terms of compensation per unit of risk. Treynor's measure results show that the EW portfolio still comes first, with a value of 0.12. The RW portfolio is better than the MCW portfolio. In contrast to the Sharpe ratio, the index scores lower than the RW portfolio, and ends up in between the RW and the MCW portfolio, with a score of 0.07.

Another way to estimate the portfolio's performance is through Jensen's alpha. Two portfolios manage to deliver alpha as they get values above zero, and the MCW portfolio ends up with an alpha of -0.42 percent. The order between the three portfolios is; EW, RW, and MCW. When including the market index, the MCW portfolio comes fourth.

5.1.3 Transaction statistics

Figure 5.2: EBITDA Margin Strategy: Transactions over time



For the EBITDA strategy portfolio, the average number of transactions executed per month is 2.58, and the maximum is ten. Each stock substituted by another stock equals two transactions. Therefore, the maximum number of stocks in the portfolio swapped simultaneously is five stocks for this strategy.

5.1.4 Sector exposure

Figure 5.3: EBITDA Margin Strategy: GICS Sector Proportions over time

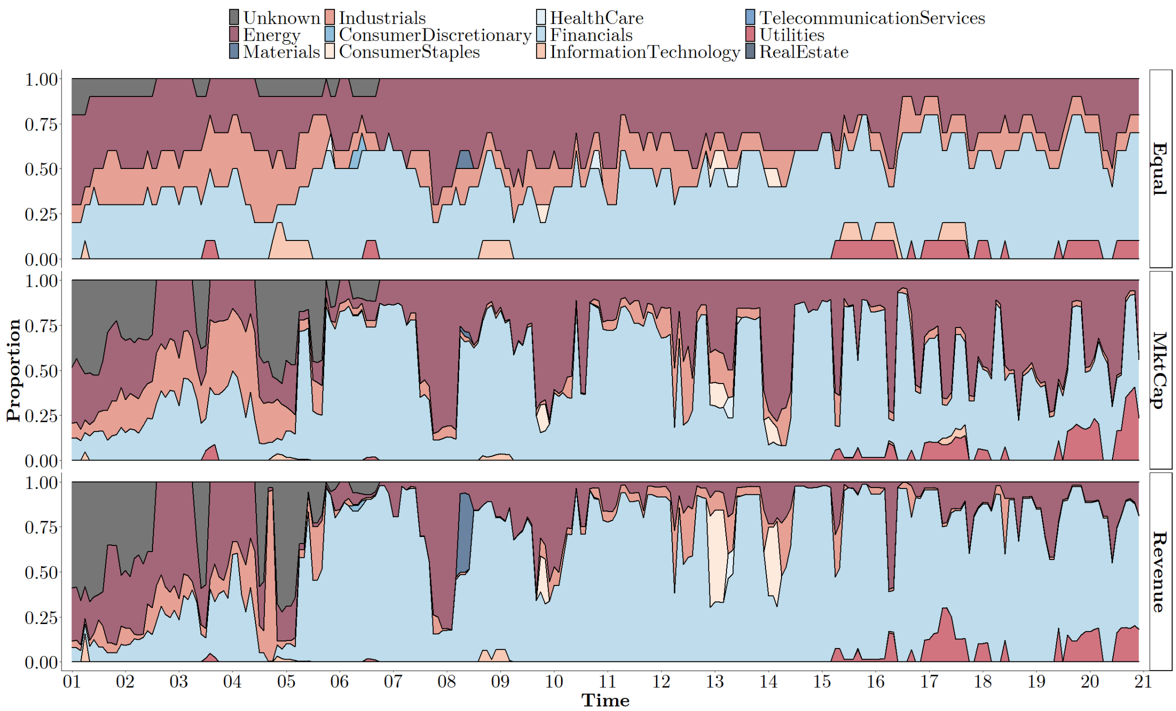


Figure 5.3 shows that the financial sector makes up a considerable proportion of the three portfolios, while Appendix Table A2.3 confirms that this sector has the highest average representation. The result is surprising, as the EBITDA margin is considered irrelevant for companies in the financial sector. Interest is an essential part of financial companies' revenue and expenses, and measuring profitability through EBITDA causes the sector to have an artificial high margin (Choudhry, 2012). Even though our data sources report EBITDA margin for financial companies, one should not trust these measures blindly. One must consider other measures of operating profitability for financial companies when implementing this specific strategy in practice.

Overall, and specifically after the financial crisis, the energy and financial sector perform well, as shown in Appendix Figure A3.2. All three portfolios share a high representation of energy and financial stocks, whereas the energy sector is highest represented in the EW portfolio. However, according to Appendix Figure A3.2, the financial sector gains higher total compounded returns than the energy sector. Thus, the higher representation of energy stocks is not the reason for the EW portfolio's success.

The EW portfolio has the highest proportion of industrial stocks on average. The industrial sector performs well but is still outperformed by the energy and financial sector. In the meantime, the difference in the representation of industrial stocks is not high between the portfolios. Hence, the industrial sector cannot be the only reason for the EW portfolio's outperformance of the other two. The utility sector has magnificent development throughout the years. However, the proportions of utility stocks are equal between the portfolios on average.

During the financial crisis, the proportion of financial stocks drops more for the MCW and the RW portfolio than for the EW. The same happens for the energy sector during the oil price decrease. All portfolios include the same stocks and execute equal numbers of transactions. In many cases, it seems like the MCW and the RW portfolio reduce the weight of sectors too late when crises in the respective sectors occur. At the same time, their substantial proportion reductions cause them to miss out on the stock-price increase after the crisis. The stock-price increase often happens when investors believe stocks are priced at their minimum. Stock prices depend on future expectations and often change before revenues increase. Thus, the EW portfolio's steady proportions can be the reason for its outperformance.

5.1.5 Fama and French regressions

Table 5.2: EBITDA Margin Strategy: Regression Results

	Norwegian Model (FF3F + MOM + LIQ) | European Model (FF5F + MOM)					
	Equal-rf	MktCap-rf	Revenue-rf	Equal-rf	MktCap-rf	Revenue-rf
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.001	−0.0002	0.001	0.004	0.0003	0.004
Index-rf	1.021*	1.166*	1.163*	0.682*	0.859*	0.718*
SMB	0.322*	0.045	0.148	0.805*	0.793*	0.960*
HML	0.265*	0.286*	0.382*	0.202	0.663*	0.654*
RMW				0.032	0.421	0.117
CMA				−0.352	−0.581	−0.728*
UMD	0.028	−0.033	−0.012	0.005	−0.132	−0.184
LIQ	0.097	0.052	0.079			
Observations	239	239	239	239	239	239
Adjusted R^2	0.697	0.664	0.607	0.470	0.496	0.457
Notes						*p<0.05; Transaction cost: 0.02

Table 5.2 shows the three portfolios of the EBITDA strategy regressed on the Norwegian and European Fama and French models, and that none of the portfolios for either regression has a significant alpha.

All the portfolio weightings have a statistically significant market-factor beta near one, which implies that the systematic risk of the portfolio is close to the systematic risk of the respective market index.

The EW portfolio in the Norwegian model tilts toward small-sized value stocks, whereas the European model only suggests a tilt toward small-sized stocks. The Norwegian model suggests that the MCW and the RW portfolios tilt toward high book-to-market stocks. In contrast to the Norwegian model, the European suggests they also tilt toward small-sized stocks. For the RW portfolio, the European factors suggest that its behavior is similar to portfolios with an active investment style as the CMA coefficient is negative and statistically significant.

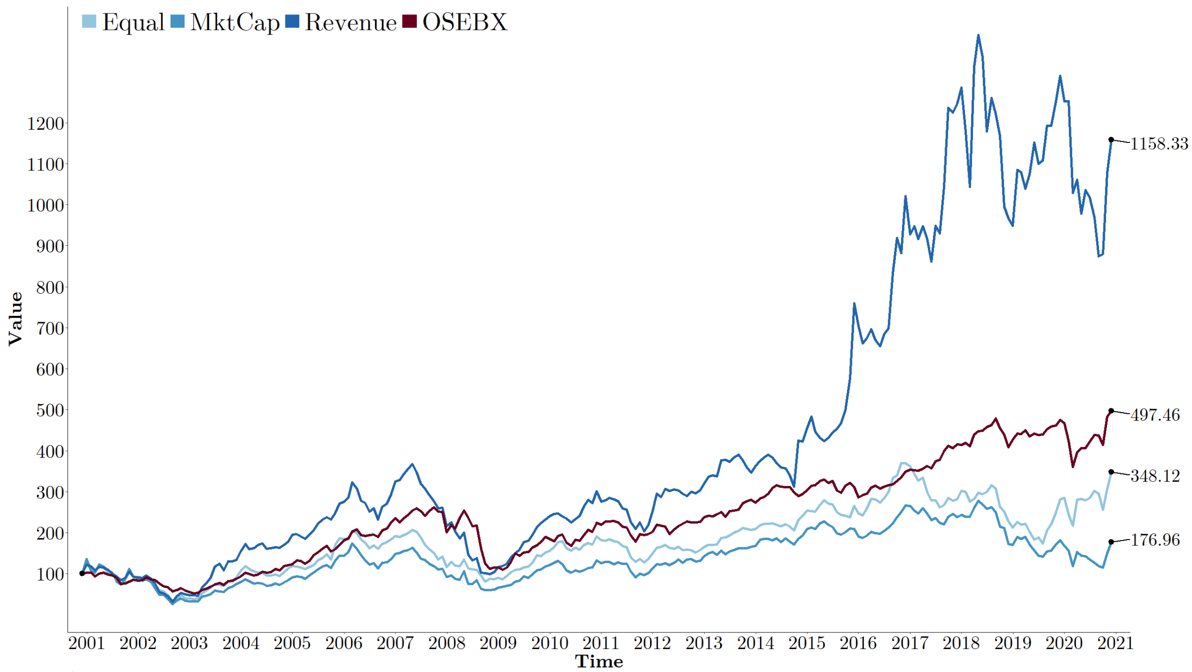
5.1.6 Conclusion

The EW portfolio performs best when investing based on EBITDA margin. Throughout the period, it achieves an AAR of 12.62 percent and is ranked number one when evaluating through Sharpe ratio, Treynor's measure, and Jensen's alpha. Through Fama and French regressions, the EW portfolio tilts toward small-sized value stocks. The majority of the stocks included in the portfolio is from the energy and financial sector. The results show that EBITDA margin is helpful when choosing an investment strategy.

5.2 Debt-to-equity ratio

5.2.1 General overview

Figure 5.4: Debt-to-Equity Strategy: Backtesting from Jan. 2001 to Dec. 2020



*Strategy: Every month, invest in the 10 stocks listed on OSE with the lowest D_EPrc
*Transaction cost: 2 %

The debt-to-equity ratio strategy invests in the ten stocks with the lowest ratio. Figure 5.4 shows the return development for the different portfolios and the OSEBX. The EW and the MCW portfolio have a similar development to the index. However, the RW portfolio accelerates from 2015 and delivers significantly higher returns.

5.2.2 Performance statistics

Table 5.3: Debt-to-Equity Strategy: Performance statistics

	Annual Avg. Return	**Annual St. Dev.**	**Sharpe Ratio**	**Beta**	**Jensen's Alpha**	**Treynor's Measure**
Index	0.1021	0.2043	0.3662	1.0000	0.0000	0.0748
Equal	0.1060	0.2975	0.2647	0.9712	0.0061	0.0811
MktCap	0.0855	0.3381	0.1722	1.0950	-0.0237	0.0532
Revenue	0.1797	0.3439	0.4435	0.9673	0.0801	0.1577

Throughout the period, the RW portfolio manages to go from 100 to 1158.33 and is equivalent to a 1058.33 percent cumulative return. Table 5.3 shows that the portfolio return equals an AAR of approximately 18 percent.

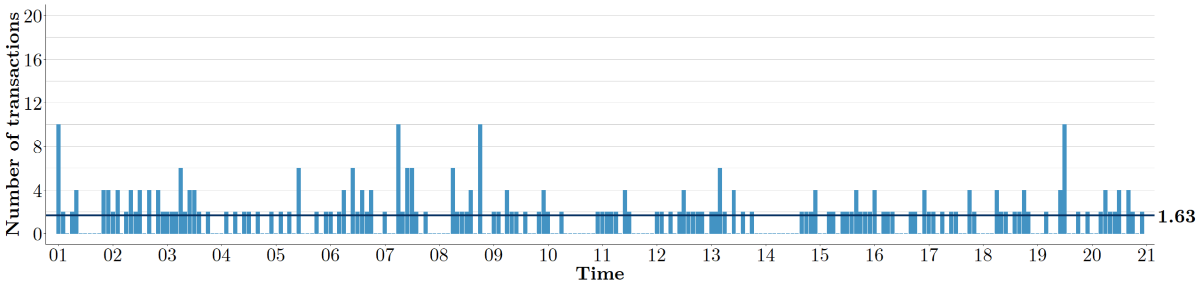
Even though the index has the second-highest compounded return, the EW portfolio has a higher AAR. The portfolio with the lowest AAR is the MCW portfolio, with an AAR of 8.55 percent, and it is also the portfolio with the lowest compounded return. The order of the AAR is not equivalent to the order of the compounded returns because a strategy must increase by more than it falls, in percentage, to end up where it started. For example, say a stock's price decreases by 50 percent, then it must increase by 100 percent to end up back at the same price as before. Hence, high return fluctuations can cause the orders between AAR and compounded returns not to correspond.

As for the EBITDA strategy, we get a clearer picture of the portfolios' performance while studying the risk-adjusted measures. Through studying the Sharpe ratios, the RW portfolio scores the highest, with a ratio at 0.44. The index comes next with a Sharpe ratio of 0.37. The EW and MCW are ranked third and fourth, respectively. Their Sharpe ratios are low because of their high standard deviations relative to their returns. Despite having low returns, they have close to the same standard deviation as the RW portfolio.

All three portfolios have betas close to one and have similar fluctuations as the market index. When studying Treynor's measure, we find the order from best to worst to be equivalent to the order of the AAR. Jensen's alpha estimates that two of the portfolios generate a positive alpha. The portfolio that generates the highest alpha is the RW portfolio and generates a yearly alpha of eight percent. Second is the EW portfolio, with a yearly alpha of 0.6 percent. The results indicate that given their levels of risk, these portfolios manage to earn excess returns from their investments compared to the market. On the other hand, the MCW portfolio generates a negative alpha of 2.4 percent, indicating that the investor would be better off with the market portfolio, ceteris paribus.

5.2.3 Transaction statistics

Figure 5.5: Debt-to-Equity Strategy: Transactions over time



The total number of transactions executed throughout the period is 392, with an average of 1.63 transactions each month. Compared to the EBITDA strategy, this trading strategy has approximately one less transaction per month. Portfolios with a low number of transactions perform better than portfolios with a high number of transactions, ceteris paribus, due to the transaction cost. Hence, the low number of transactions executed within this strategy can positively affect the portfolio returns.

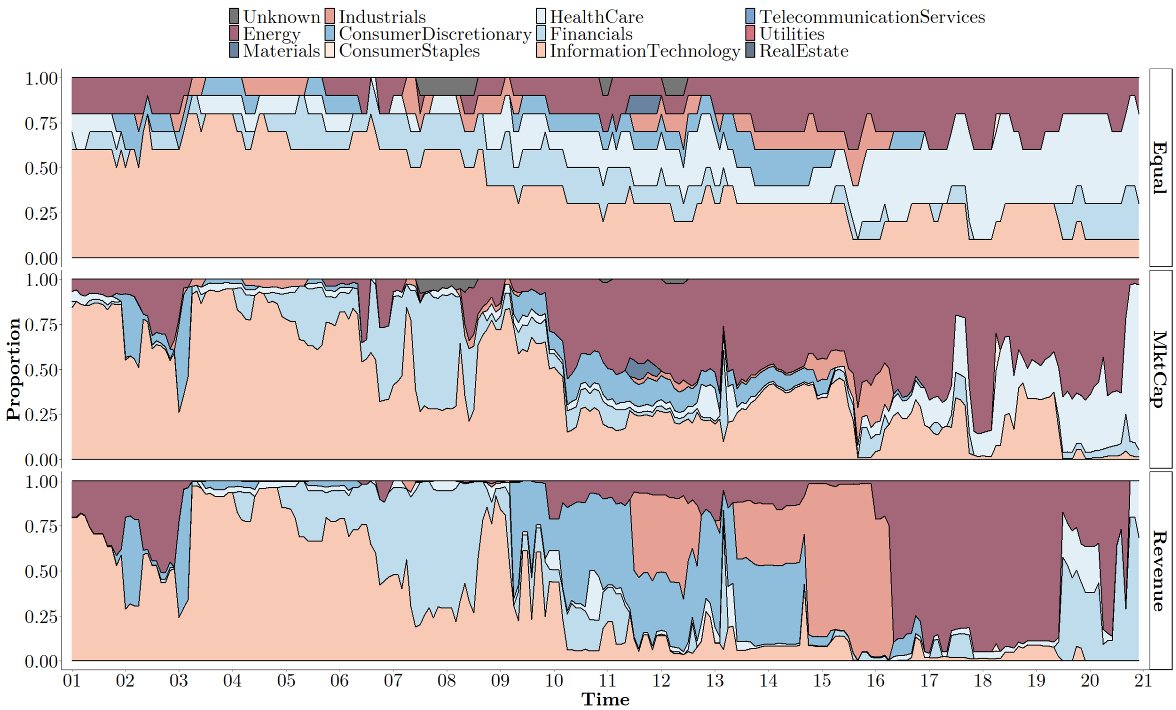
An explanation for the low number of transactions may be that debt-to-equity ratios change slower than other metrics, such as EBITDA, revenue, and net profits. The ranked order of the companies from month to month will, in many cases, experience few changes, resulting in fewer transactions.

5.2.4 Sector exposure

A quick overview of the average weightings of each sector in Appendix Table A2.3 tells us that information technology and energy are the most represented sectors for the debt-to-equity portfolios. The health care sector also captures a significant proportion, but only for the EW portfolio. Figure 5.6 shows a generally high representation of companies within the information technology sector in the first half of the testing period. During the second half, the energy sector captures the most considerable proportion.

The MCW and RW portfolios increased their financial sector proportions during the

Figure 5.6: Debt-to-Equity Strategy: GICS Sector Proportions over time



financial crisis. The increase may seem odd, as the financial crisis hit the financial sector relatively hard, causing their revenues and market capitalizations to decrease. One reason may be that revenue and market capitalization for companies in the IT sector decrease by more than the financial sector's during this period, resulting in lower proportions. As many IT companies tend to be in a growth stage, their stock prices may suffer significant reductions due to the ongoing crisis.

When the oil price decreases, Appendix Figure A3.2 shows that the industrial sector performs well, in contrast to the energy and health care sector. During 2015, the RW portfolio mainly consists of industrial stocks, whereas the EW and the MCW portfolio keep high proportions of the energy and health care sector.

Between 2016 and 2019, the energy sector captures more than 75 percent of the RW portfolio and eliminates the industry sector's proportion. Through increased cost-efficiency and increasing oil prices, the energy sector increases revenues enough to capture a large share of the portfolio after the oil price decrease. From Appendix Figure A3.2, the energy sector generates excellent returns in this period, while the health care sector suffers further losses. It is probably another reason for the RW portfolio's outstanding performance compared to the EW and the MCW portfolio, as they keep more significant proportions of stocks within the health care sector.

5.2.5 Fama and French regressions

Table 5.4: Debt-to-Equity: Regression Results

	Norwegian Model (FF3F + MOM + LIQ)			European Model (FF5F + MOM)		
	Equal-rf	MktCap-rf	Revenue-rf	Equal-rf	MktCap-rf	Revenue-rf
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	−0.002	−0.003	0.007	0.012*	0.012*	0.021*
Index-rf	0.870*	0.824*	0.677*	0.737*	0.777*	0.645*
SMB	0.768*	0.717*	0.382*	0.966*	0.431	0.507
HML	0.006	0.057	0.170	−1.228*	−1.201*	−1.230*
RMW				−1.504*	−1.393*	−1.909*
CMA				0.207	0.130	0.458
UMD	−0.113	−0.268*	−0.219*	−0.411*	−0.546*	−0.452*
LIQ	−0.595*	−0.836*	−0.724*			
Observations	239	239	239	239	239	239
Adjusted R^2	0.531	0.525	0.368	0.448	0.399	0.308
Notes						*p<0.05; Transaction cost: 0.02

Table 5.4 suggests that none of the portfolios generates alpha when using the Norwegian factors, and the portfolio tilts toward small-cap stocks. Further, the model suggests that the portfolios are also exposed to high-liquidity stocks as the liquidity coefficient is negative and statistically significant. Furthermore, the MCW and the RW portfolio tend to buy last month's winners and this month's losers.

All the portfolio weightings have a statistically significant market-factor beta slightly below one, which implies that the systematic risk of the portfolio is close to the systematic risk of the respective market index.

For the European model, all portfolios tilt toward growth stocks with low profitability that were last month's winners and this month's losers. Only the EW portfolio is significantly exposed to risks related to small-sized stocks. Further, the regression suggests that all portfolios have significant alphas. Significant alphas can mean one of two things: either the portfolios generate alpha, or the model omits explaining variables.

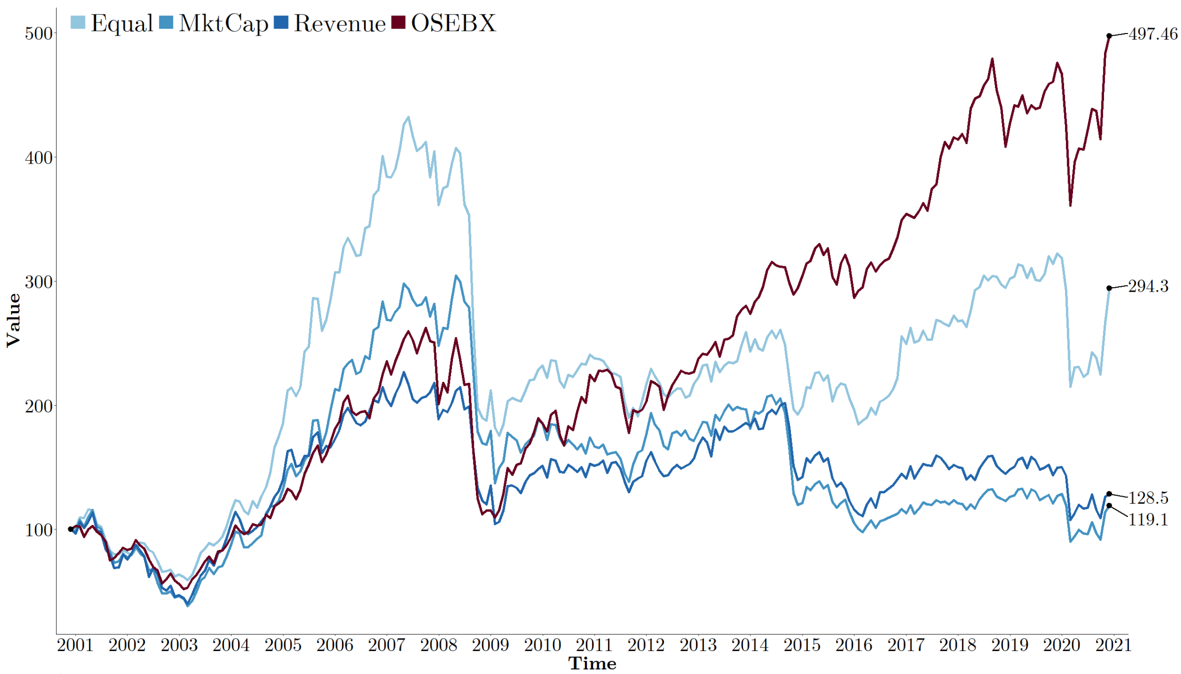
5.2.6 Conclusion

The debt-to-equity ratio strategy is a good strategy when weighting the portfolio on revenue, as it beats the market index. The portfolio is mainly exposed to the energy and information technology sector, but at the same time, it seems to manage the rebalancing relatively well. The combination of low debt-to-equity ratios and revenue weighting makes the portfolio prioritize stocks that generate high returns. In addition, maintaining this strategy involves relatively low numbers of transactions to keep the portfolio updated as the debt-to-equity ratio is slow-changing. The RW portfolio is exposed to risks related to liquid small-sized stocks that were last month's winners and this month's losers.

5.3 Net profit margin

5.3.1 General overview

Figure 5.7: Net Profit Margin Strategy: Backtesting from Jan. 2001 to Dec. 2020



*Strategy: Every month, invest in the 10 stocks listed on OSE with the highest NetProfitMarginPrc
*Transaction cost: 2 %

Figure 5.7 shows that investing in the ten stocks with the highest net profit margin each month does not outperform the market. Before the financial crisis, the EW portfolio is ahead of the OSEBX. However, after a significant downfall, the strategy does not surpass the market afterward. The performance of the other two weightings is even worse after the financial crisis.

One reason could be that growth stocks have outperformed value stocks after the financial crisis (Thomas, 2021). Net profit margin can be used as a metric to classify a value or growth stock. Since net profit is at the bottom of the income statement, this is a strict classification of value versus growth. Thus, investing based on this metric, we ensure the stocks are indeed value stocks. As the period after the financial crisis has favored growth stocks, this strategy fails to outperform the index.

5.3.2 Performance statistics

Table 5.5: Net Profit Margin Strategy: Performance statistics

	Annual Avg. Return	**Annual St. Dev.**	**Sharpe Ratio**	**Beta**	**Jensen's Alpha**	**Treynor's Measure**
Index	0.1021	0.2043	0.3662	1.0000	0.0000	0.0748
Equal	0.0770	0.2107	0.2362	0.7724	-0.0080	0.0644
MktCap	0.0392	0.2444	0.0491	0.8816	-0.0540	0.0136
Revenue	0.0420	0.2398	0.0614	0.8267	-0.0471	0.0178

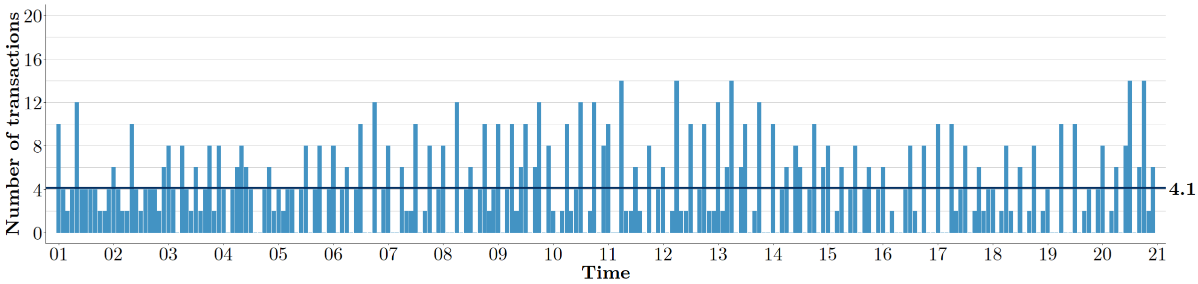
As expected, none of the strategies generate a higher AAR throughout the investing period than OSEBX. Furthermore, all strategies have higher volatility, measured in standard deviation, than the index. The outcome leads to terrible Sharpe ratios, especially for the MCW and the RW portfolio, as the strategies do not compensate the investor for the excess risk taken.

All three strategies have beta values lower than one. On the other hand, the negative return difference from the market index is more significant in percentages than their negative beta difference. The result is as expected, none of the weightings deliver a positive alpha or a better Treynor's measure than the index.

5.3.3 Transaction statistics

One reason for the poor performance of using net profit margin as a strategy is the number of transactions. As net profit margin is an accounting ratio that varies a lot, partly due to being affected by one-off items, it causes many transactions each month. The total sum of transactions during the period is 984, which is more than the other single-metric

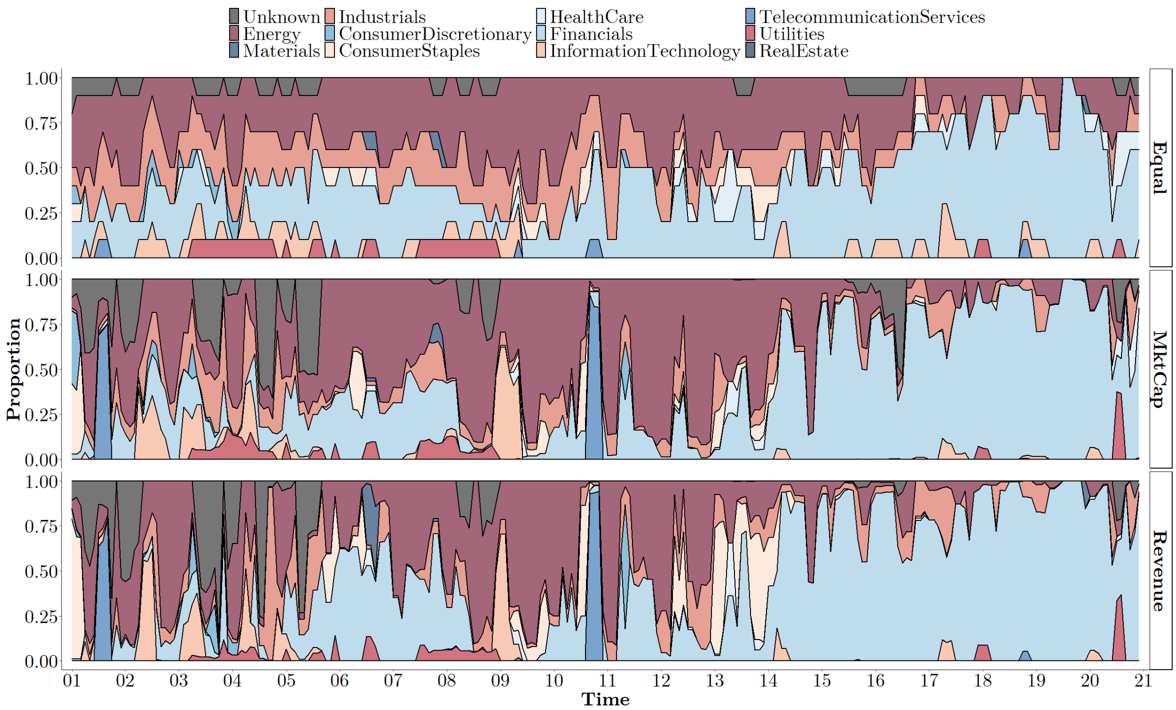
Figure 5.8: Net Profit Margin Strategy: Transactions over time



strategies tested. On average, the strategy replaces more than two stocks each month, resulting in high transaction costs and supporting the idea that net profit margin is a poor metric to base a trading strategy.

5.3.4 Sector exposure

Figure 5.9: Net Profit Margin Strategy: GICS Sector Proportions over time



As shown in Appendix Table A2.3, on average, the net profit margin portfolios invest highly in the energy, financial, and industrial sectors. The energy sector dominates before the financial crisis, while financial companies dominate after the oil price fall in 2014. The portfolios have an overweight of financials, compared to the exchange as a whole, shown in Appendix Figure A3.3. According to Appendix Figure A3.2, the financial companies on the OSE performs better than the index, which implies that the strategy favors the wrong stocks in the selection process. The weightings enhance this effect, as the poorest performers are the MCW and the RW portfolio, weighting financials higher.

5.3.5 Fama and French regressions

Table 5.6: Net Profit Margin: Regression Results

	Norwegian Model (FF3F + MOM + LIQ)			European Model (FF5F + MOM)		
	Equal-rf	MktCap-rf	Revenue-rf	Equal-rf	MktCap-rf	Revenue-rf
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	−0.003	−0.005	−0.005	−0.001	−0.003	−0.001
Index-rf	0.888*	0.861*	0.870*	0.663*	0.669*	0.588*
SMB	0.318*	0.068	0.209	0.815*	0.397*	0.434*
HML	0.258*	0.107	0.213*	0.210	0.382	0.287
RMW				0.198	0.220	−0.086
CMA				−0.191	−0.504	−0.326
UMD	0.032	−0.028	−0.023	0.003	−0.044	−0.088
LIQ	−0.031	−0.088	−0.075			
Observations	239	239	239	239	239	239
Adjusted R^2	0.606	0.542	0.510	0.427	0.341	0.310
Notes						*p<0.05; Transaction cost: 0.02

None of the portfolios deliver a positive and significant alpha. The EW portfolio tilts toward small-sized value stocks, as coefficients for both SMB and HML are positive and statistically significant. The RW portfolio also tilts toward stocks with high book-to-market ratios, implying exposure to value stocks.

The portfolios' only observable risk factor for the European model is a tilt toward small-sized stocks. There is no exposure to the RMW or CMA factors, implying no tilt in profitability or asset growth. The result is somewhat surprising, as a high net profit margin should indicate profitability for a firm. However, RMW is calculated as operating income before depreciation and amortization minus interest expense scaled by assets. The difference comes from the net profit margin being further down the income statement and scaled by revenue.

All the portfolio weightings have a statistically significant market factor-beta near one, which implies that the systematic risk of this portfolio is close to the systematic risk of the market.

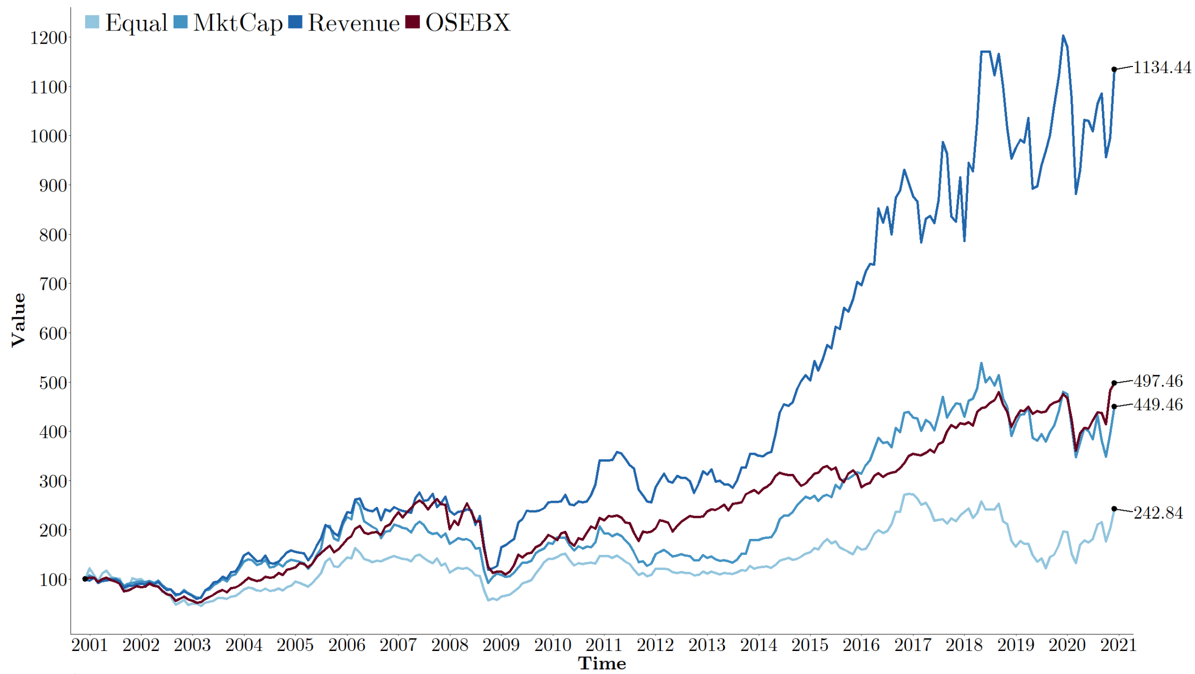
5.3.6 Conclusion

Regardless of weighting, the net profit margin is not a good strategy, as none outperform the market index. The portfolios deliver lower returns and higher volatility, which is not preferable when investing. One of the reasons for the poor performance is that the strategy chooses value stocks, which have performed poorly since the financial crisis. Another reason is that net profit margin is an accounting metric that varies a lot and causes the portfolio to replace stocks often - resulting in lower overall returns.

5.4 Current ratio

5.4.1 General overview

Figure 5.10: Current Ratio Strategy: Backtesting from Jan. 2001 to Dec. 2020



*Strategy: Every month, invest in the 10 stocks listed on OSE with the highest CurrentRatio
*Transaction cost: 2 %

Figure 5.10 shows that investing in the ten stocks with the highest current ratio outperforms the market when using an RW portfolio. Before the financial crisis, the RW and the MCW portfolio have similar performance to the OSEBX, while the EW underperforms. The crisis impacted all the weightings in a similar matter, with a sharp downfall. The MCW portfolio underperforms for a few years until it catches up with the market, ending with a similar value as the OSEBX. However, the attractive portfolio is the RW portfolio, which outperforms the market significantly. It quickly recovers from the financial crisis, and between 2014 and 2017, the returns are extraordinary.

5.4.2 Performance statistics

Table 5.7: Current Ratio Strategy: Performance statistics

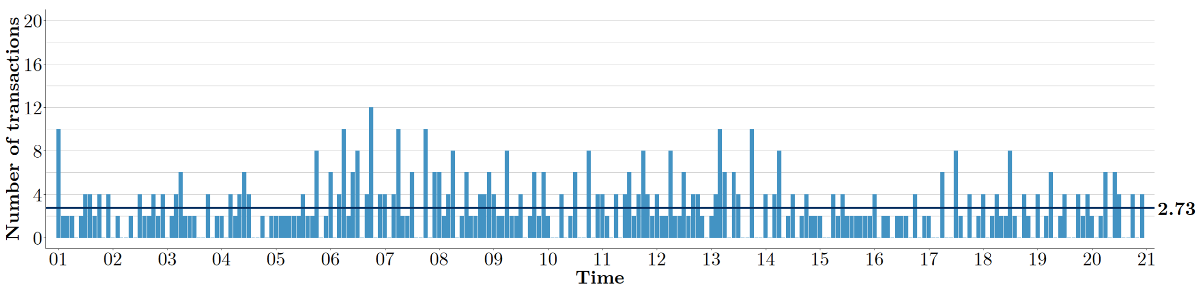
	Annual Avg. Return	Annual St. Dev.	Sharpe Ratio	Beta	Jensen's Alpha	Treynor's Measure
Index	0.1021	0.2043	0.3662	1.0000	0.0000	0.0748
Equal	0.0852	0.2834	0.2045	0.9311	-0.0117	0.0622
MktCap	0.1066	0.2503	0.3171	0.8285	0.0174	0.0958
Revenue	0.1543	0.2535	0.5013	0.7580	0.0704	0.1677

The RW and the MCW portfolio delivers an AAR higher than the market throughout the investment period, at 15.43 and 10.66 percent. Furthermore, all strategies have a higher standard deviation than the market index. However, the RW portfolio still achieves a higher Sharpe ratio than the market index, giving it the best portfolio return per risk taken.

The portfolios have lower volatility than the market, with a beta below one. The RW portfolio delivers a positive excess return with Jensen's alpha at 7 percent. Furthermore, the portfolio achieves a Treynor's measure of more than double the index, at 0.17.

5.4.3 Transaction statistics

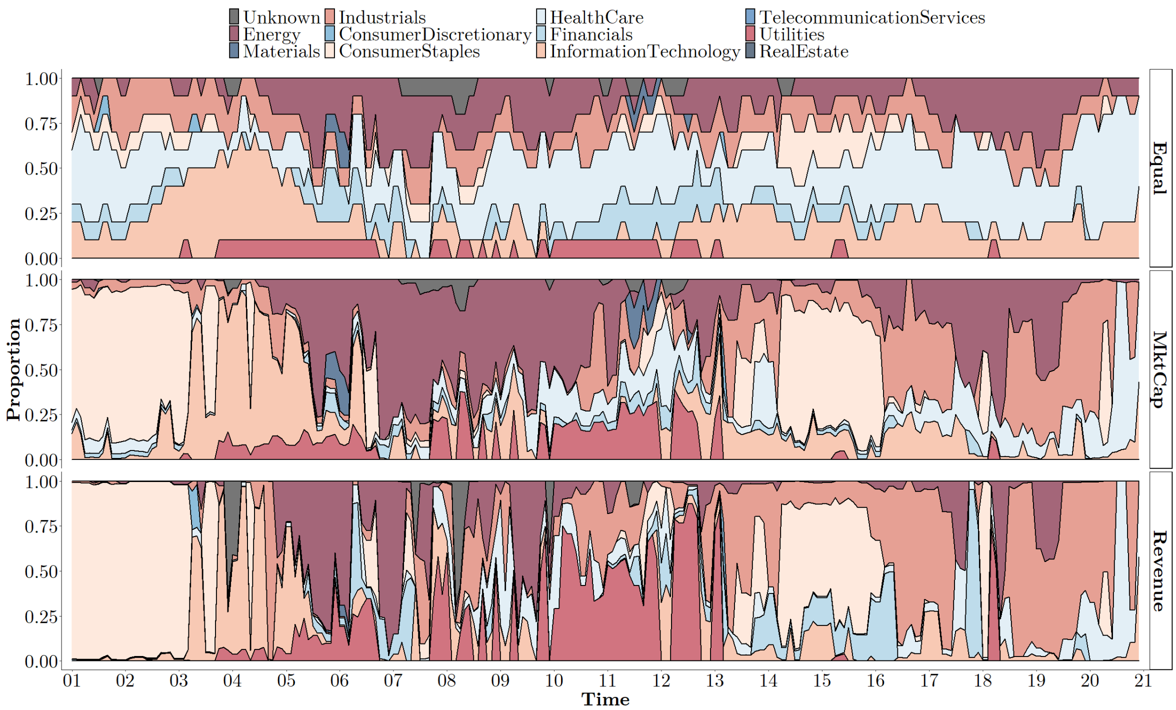
Figure 5.11: Current Ratio Strategy: Transactions over time



The number of transactions for the Current ratio strategy are moderate. The strategy replaces more than one stock each month with a new one. There are no periods with a specifically high number of transactions; however, the strategy has few transactions between 2014 and 2017. These few transactions can explain some of the extraordinary returns from the RW portfolio during this period.

5.4.4 Sector exposure

Figure 5.12: Current Ratio Strategy: GICS Sector Proportions over time



The EW portfolio tilts toward the healthcare, energy, and IT sectors, and Appendix Figure A3.2 shows that these sectors underperforms compared to the index and explains why this weighting underperforms. The MCW portfolio tilts toward energy, consumer staples, and industrial firms. As shown in Appendix Figure A3.2, consumer staples significantly outperforms the index and can be a reason for the MCW portfolio almost beating the index.

The RW portfolio tilts mainly toward the industrial, consumer staples, and energy sector. We can see that during the excellent return period for this weighting, the portfolio chooses many stocks from the consumer staples sector, which could explain the significant deviation from the OSEBX. Furthermore, the MCW portfolio also has a high proportion of stocks from the consumer staples sector during the same period. As a result, we see a similar performance in the MCW portfolio. Given that consumer staples contribute to excellent returns, the RW portfolio must target the best-performing stocks more than the MWC portfolio. It indicates that the sector's top-performing stocks generate high returns and do not have exceptionally high market capitalization.

5.4.5 Fama and French regressions

Table 5.8: Current Ratio Strategy: Regression Results

	Norwegian Model (FF3F + MOM + LIQ)			European Model (FF5F + MOM)		
	Equal-rf	MktCap-rf	Revenue-rf	Equal-rf	MktCap-rf	Revenue-rf
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	−0.005	−0.001	0.004	0.004	0.004	0.008
Index-rf	1.003*	0.851*	0.827*	0.766*	0.807*	0.657*
SMB	0.784*	0.272*	0.205	1.351*	0.892*	1.038*
HML	0.034	0.033	0.105	−0.903*	−0.822*	−0.716*
RMW				−0.702*	−0.284	−0.150
CMA				0.072	0.753*	0.422
UMD	−0.092	0.046	0.052	−0.291*	−0.206	−0.159
LIQ	−0.298*	−0.135	−0.027			
Observations	239	239	239	239	239	239
Adjusted R^2	0.541	0.467	0.376	0.427	0.362	0.258
Notes						*p<0.05; Transaction cost: 0.02

As shown in Table 5.8, none of the portfolios have significant alphas. All portfolios have a statistically significant market factor-beta near one, which implies that the systematic risk of this portfolio is close to the systematic risk of the OSEBX. The same is true for the European model as well. Further, the EW and the MCW portfolio have significant coefficients for SMB, indicating that both portfolios tilt toward small-sized stocks. The EW portfolio has negative exposure to the liquidity factor, indicating a tilt toward high-liquid stocks. The European model suggests all weightings tilts toward small-sized growth stocks. In addition, the model also suggests that the EW portfolio tilts toward low-profitable stocks that were last month's winners and this month's losers. The MCW portfolio favors stocks with low investment activity.

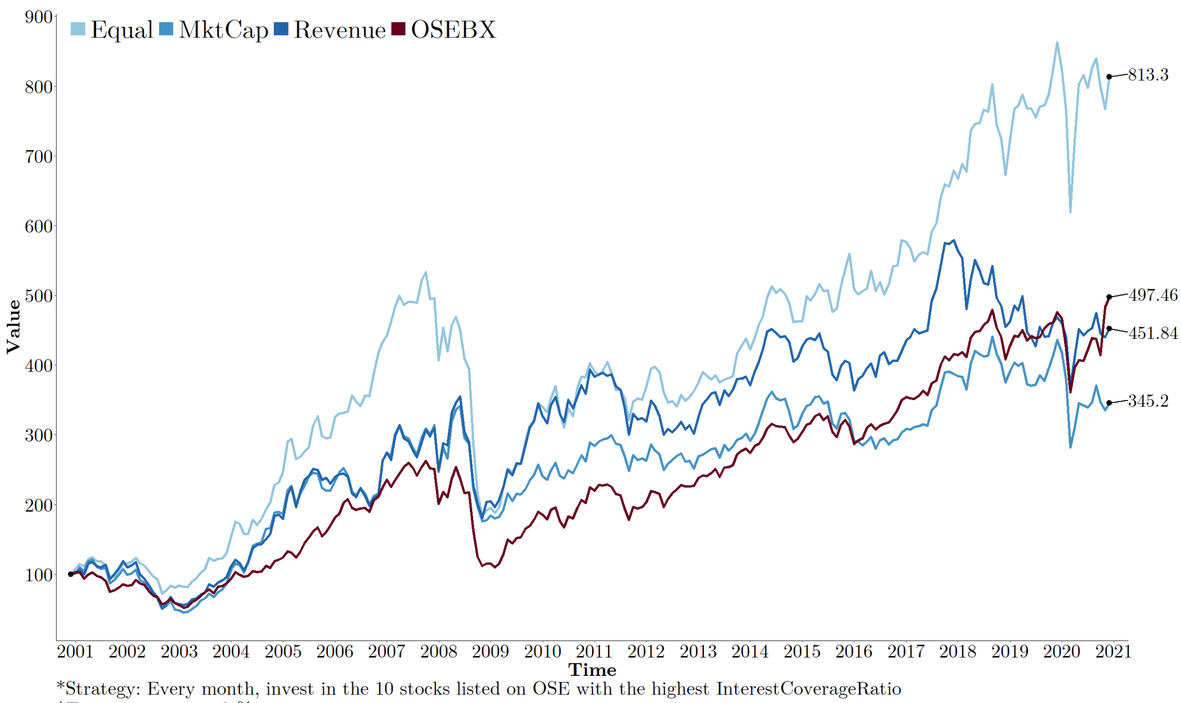
5.4.6 Conclusion

Investing based on companies with the highest current ratio is perhaps a good strategy. However, only the RW portfolio outperforms the OSEBX, and the EW portfolio underperforms. The MCW portfolio has a similar performance to the index. The RW portfolio delivers extraordinary performance between 2014 and 2017. It is hard to point at specific reasons for the performance, and thus, it may be luck. On the other hand, the strategy and weighting did outperform the benchmark after the financial crisis and delivered a higher Sharpe ratio than the index. In a Norwegian context, the RW portfolio is not exposed to any risk-factors other than the market factor and does not deliver a significant alpha. In a European context, the strategy favors small-sized growth stocks.

5.5 Interest coverage ratio

5.5.1 General overview

Figure 5.13: Interest Coverage Ratio Strategy: Backtesting from Jan. 2001 to Dec. 2020



*Strategy: Every month, invest in the 10 stocks listed on OSE with the highest InterestCoverageRatio
*Transaction cost: 2 %

The EW portfolio outperforms the index when we backtest the interest coverage ratio strategy and manages to capture the market's upswings by the looks of Figure 5.13.

However, the portfolio seems to lose a large share of the returns during downswings. We specifically see these phenomena during the financial crisis and the COVID-19 outbreak.

5.5.2 Performance statistics

Table 5.9: Interest Coverage Ratio Strategy: Performance statistics

	Annual Avg. Return	**Annual St. Dev.**	**Sharpe Ratio**	**Beta**	**Jensen's Alpha**	**Treynor's Measure**
Index	0.1021	0.2043	0.3662	1.0000	0.0000	0.0748
Equal	0.1311	0.2239	0.4640	0.9045	0.0362	0.1149
MktCap	0.0941	0.2512	0.2664	1.0076	-0.0085	0.0664
Revenue	0.1064	0.2472	0.3201	0.9715	0.0064	0.0814

Figure 5.13 shows that the EW portfolio generates a total compounded return of 713.30 percent throughout the period and has an AAR of 13.11 percent. We experience the same phenomenon for this strategy as the debt-to-equity ratio strategy; a mismatch between the ranked order from the compounded returns and AARs. The index generates a higher compounded return than the RW portfolio, but the RW portfolio has a higher AAR.

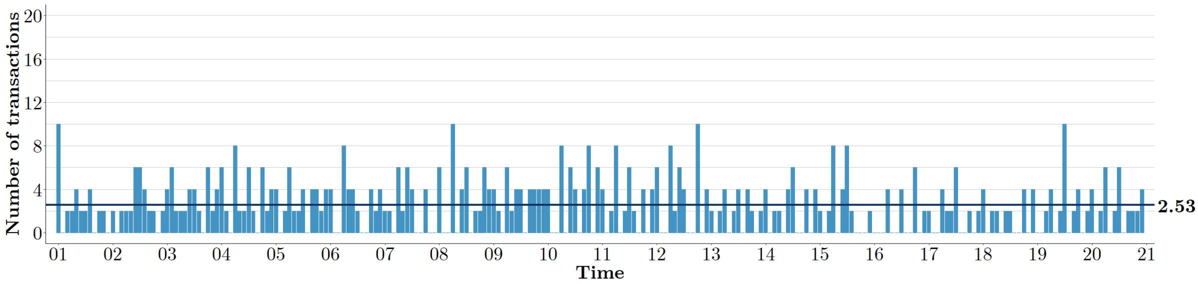
The order is the same for the Sharpe ratio as for the compounded return. That means the excess AAR the RW portfolio earns comes with a higher cost in terms of risk. However, Treynor's measure suggests that the RW portfolio generates more return per unit of systematic risk than the index. Jensen's alpha also provides the same ranked order as Treynor's measure.

The EW portfolio performs best for all the risk-adjusted measures, and the MCW portfolio performs worst. However, as the ranked order between the index and the RW portfolio seems to vary, the investor would probably be better off investing in the index than in the RW portfolio.

5.5.3 Transaction statistics

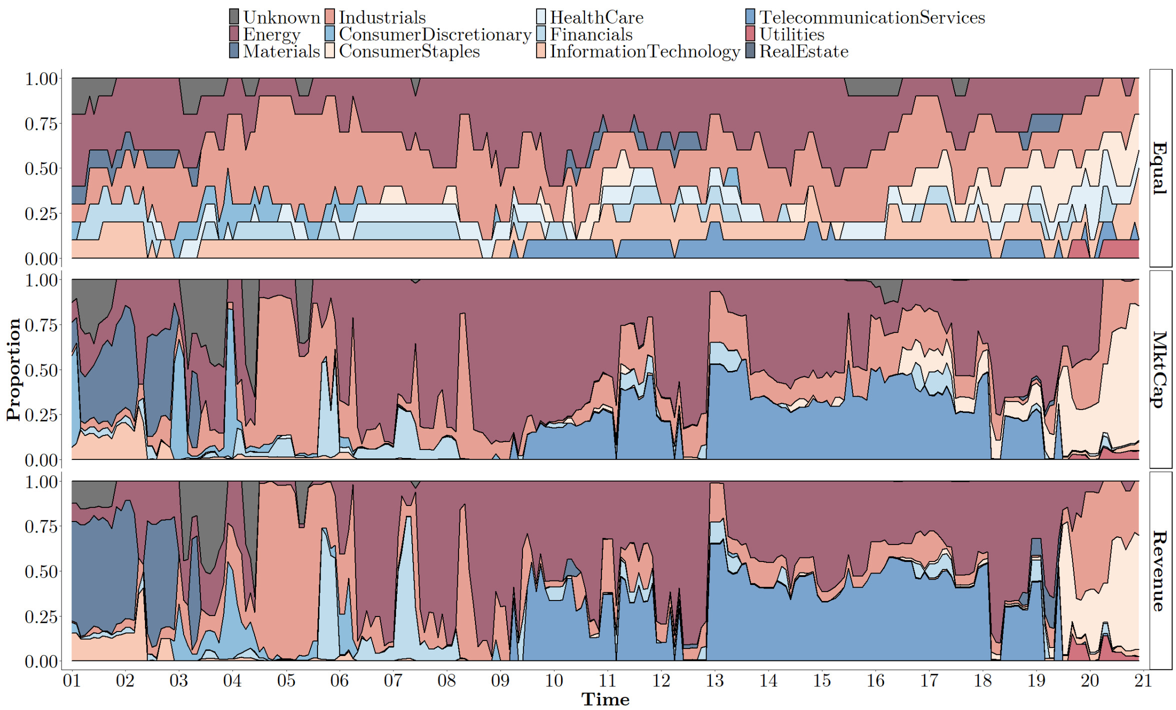
The strategy has a total of 608 transactions throughout the testing period. It is a relatively moderate number of transactions, with a monthly average of 2.53 transactions. Through Figure 5.14, it is hard to spot specific periods with a high number of transactions as the trading strategy has a relatively flat and steady development.

Figure 5.14: Interest Coverage Ratio Strategy: Transactions over time



5.5.4 Sector exposure

Figure 5.15: Interest Coverage Ratio Strategy: GICS Sector Proportions over time



The energy and industrial sectors make up a large proportion of the interest coverage ratio strategy portfolios. When studying why the EW portfolio outperforms the other two, we use Appendix Figure A3.2 to compare the different sectors' return performance. From around mid-2017, the EW portfolio's returns accelerate compared to the others. The EW portfolio has a good mix of energy, industrial, and consumer staple stocks, and all these sectors perform well during the period. However, during 2018, the MCW and the RW portfolio hold large proportions of energy stocks, and Appendix Figure A3.2 shows that the energy sector performs poorly after 2017. At the same time, the EW portfolio holds a significantly smaller proportion of energy stocks, contributing to its outperformance of the other portfolios.

Another factor contributing to the performance difference between the portfolios is the small proportion of stocks from the utility sector during the last 2.5 years. According to Appendix Figure A3.2, the utility sector performs significantly well. Hence, a small proportion of well-performing stocks from the utility sector might contribute to the strong performance of the EW portfolio.

5.5.5 Fama and French regressions

Table 5.10: Interest Coverage Ratio: Regression Results

	Norwegian Model (FF3F + MOM + LIQ)			European Model (FF5F + MOM)		
	Equal-rf	MktCap-rf	Revenue-rf	Equal-rf	MktCap-rf	Revenue-rf
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.002	−0.001	−0.00004	0.003	0.002	0.004
Index-rf	0.961*	1.069*	0.949*	0.828*	0.863*	0.872*
SMB	0.226*	0.004	0.024	0.822*	0.270	0.180
HML	0.104	0.044	0.046	−0.098	−0.282	−0.402
RMW				0.111	−0.273	−0.433
CMA				−0.323	−0.270	−0.174
UMD	0.002	0.064	0.052	0.020	0.127	0.100
LIQ	−0.047	0.086	−0.077			
Observations	239	239	239	239	239	239
Adjusted R^2	0.690	0.671	0.643	0.519	0.379	0.406

Notes *p<0.05; Transaction cost: 0.02

None of the portfolios have significant alphas, according to Table 5.10. All portfolios have a statistically significant market-factor beta near one, which implies that the systematic risk of this portfolio is close to the systematic risk of the OSEBX. Further, the EW portfolio tilts toward small-cap stocks. There are no statistically significant interpretations for the rest of the coefficients in the Norwegian model.

For the European model, the interpretation is the same as for the Norwegian; the EW portfolio tilts toward small-cap stocks. Hence, we cannot interpret any portfolio's profitability or investment activity measure.

5.5.6 Conclusion

The interest coverage ratio strategy outperforms the market index when using the EW portfolio. The EW portfolio manages to capture the upswings in the economy well and has an AAR of 13.11 percent. It has the highest Sharpe ratio, Treynor's measure, and Jensen's alpha of all the portfolios and the market index. Energy and industrial stocks make up the most significant proportions of the portfolio. However, a substantial part of the performance is due to a healthy sector-diversification and the inclusion of stocks from the utility sector. Through Fama and French regressions, both models suggest that the EW portfolio's returns only tilt toward the market and small-sized stocks.

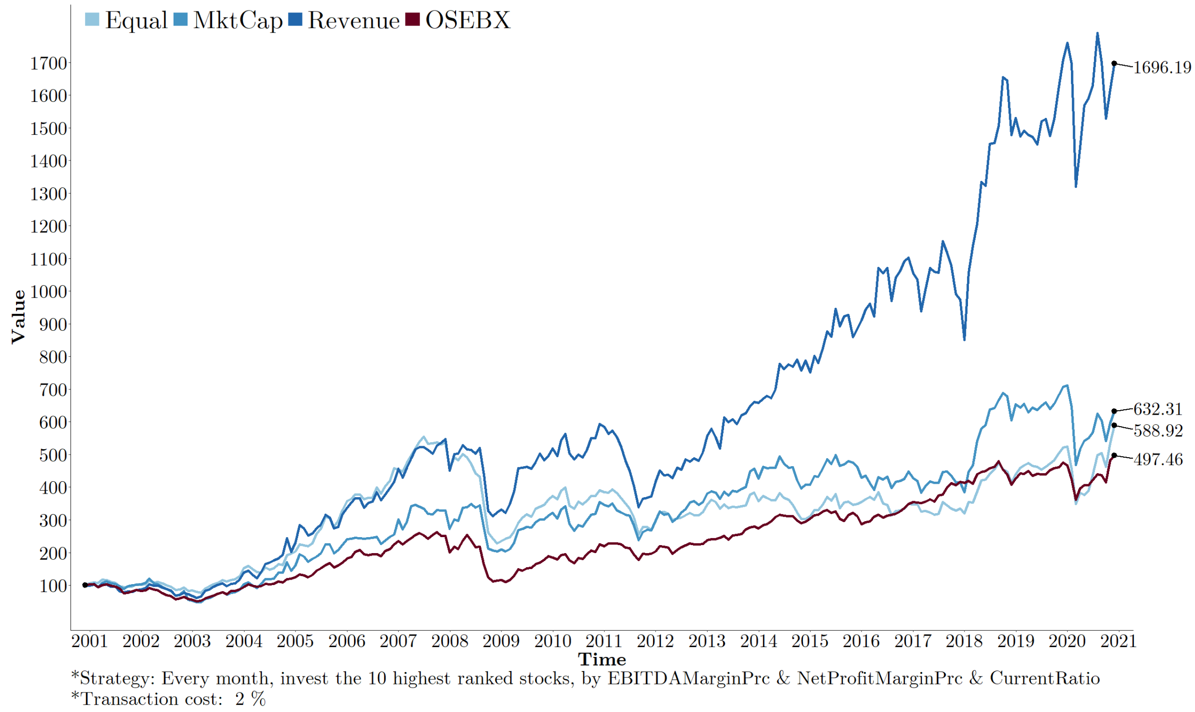
5.6 Multiple-metric strategy

We have studied five different trading strategies, in which each strategy entails investing based on one financial metric. In practice, investors can combine multiple metrics to find a better trading strategy. Appendix Table A2.4 shows the performance of all possible combinations, in which the best risk-adjusted strategy is combining EBITDA margin, net profit margin, and current ratio.

5.6.1 General overview

Figure 5.16 shows that investing in the ten stocks with the highest EBITDA margin, net profit margin, and current ratio outperforms the market throughout the period. The RW portfolio outperforms the market significantly, while the EW and the MCW portfolio slightly outperform the market. The EW and the RW portfolio have similar developments until mid-2008. The RW portfolio manages to get a head start after the financial crisis, as this weighting limits the downfall compared to the others. The RW portfolio accelerates its development from 2012 and throughout the period compared to the other portfolios. In the end, the RW portfolio manages to get a compounded return of 1596 percent, more than three times the market index.

Figure 5.16: Multiple Metric Strategy: Backtesting from Jan. 2001 to Dec. 2020



5.6.2 Performance statistics

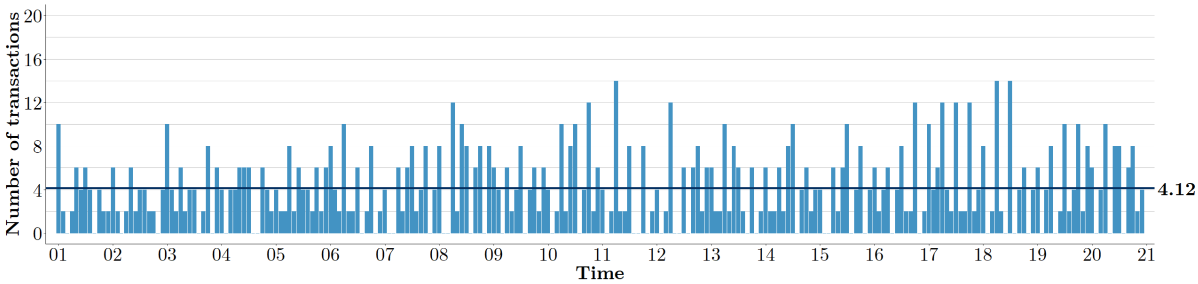
Table 5.11: Multiple Metric Strategy: Performance statistics

	Annual Avg. Return	**Annual St. Dev.**	**Sharpe Ratio**	**Beta**	**Jensen's Alpha**	**Treynor's Measure**
Index	0.1021	0.2043	0.3662	1.0000	0.0000	0.0748
Equal	0.1138	0.2209	0.3917	0.8379	0.0238	0.1033
MktCap	0.1307	0.2728	0.3795	1.0304	0.0264	0.1005
Revenue	0.1769	0.2636	0.5677	0.8664	0.0848	0.1727

The RW portfolio outperforms the other two and the market index on all performance measures, as shown in Table 5.11. With an AAR of 17.69 percent and a Sharpe ratio of 0.57, the RW portfolio outperforms the other two portfolios. In addition, its risk-adjusted measures outperform all other trading strategies that we study in this paper.

5.6.3 Transaction statistics

Figure 5.17: Multiple Metric Strategy: Transactions over time



The combined trading strategy has many transactions throughout the period. With a total number of 990 transactions and an average of 4.12 transactions each month, it is slightly higher than the net profit margin strategy. Hence, it is the trading strategy with the highest number of transactions, which entails high transaction costs and reduces the portfolio return.

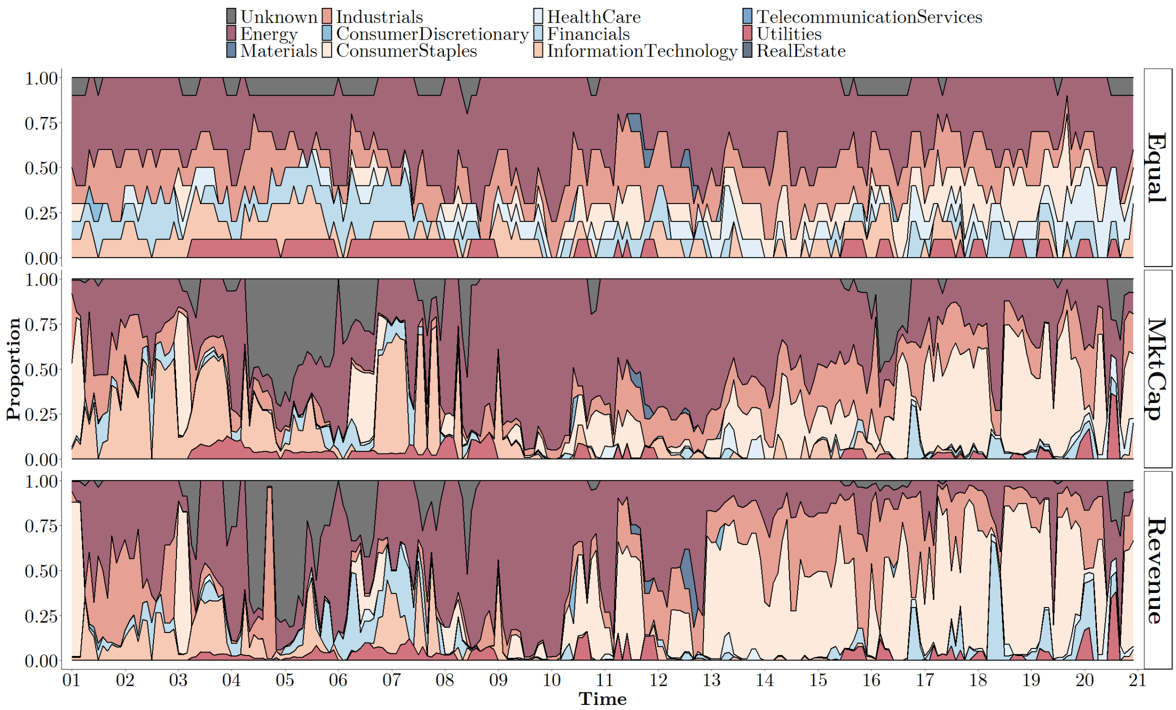
One reason for the high number of transactions can be that including more financial metrics in the trading strategy yields a higher probability of swapping stocks. The strategy includes stocks amongst the top ten based on three different metrics. Hence, it seems likely that the top ten ranking will change more when we use three metrics instead of one.

5.6.4 Sector exposure

The sector proportions of the different weighted portfolios may help us understand why the RW portfolio outperforms the other two and the market. After 2011 the portfolio starts to accelerate, and the RW portfolio has a relatively more significant proportion of consumer staples stocks. Appendix Table A3.2 reveals that from mid-2011 until today, the consumer staples sector has a significant increase in returns and explains why the RW portfolio outperforms the other two. We also find high proportions of consumer staple stocks in the current ratio strategy, and the RW portfolio also performs best for this strategy shown in Figure 5.10.

The industrial sector has a steady increase in returns from 2009 and forward, shown in Appendix Table A3.2. It is hard to tell if the RW portfolio holds a more significant

Figure 5.18: Multiple Metric Strategy: GICS Sector Proportions over time



proportion of industrial stocks, but it is not smaller by the looks of Figure 5.18. Given that the RW portfolio holds a slightly larger proportion of industrial stocks, the industrial proportion also explains why the RW portfolio outperforms the other two.

The energy sector has poor returns from mid-2014 until 2016 and is most likely affected by the fall in oil prices. During this period, the RW portfolio holds a significantly smaller proportion of energy stocks than the MCW and the EW portfolio. The proportion difference between the portfolios further explains the difference in performance.

5.6.5 Fama and French regressions

Table 5.13 suggests that the RW portfolio is only statistically significant to the market-factor beta. In addition, the RW portfolio also tilts toward small-sized stocks in the European model. The model further suggests that the alpha is significant at the five percent level, indicating one of two alternatives; either the portfolio generates alpha, or the model omits other explanatory variables. In this case, it is more difficult to reject the former alternative due to the RW portfolio's strong returns. However, by not rejecting the alternative of significant alpha, we imply that the EMH is wrong. In order to reject

Table 5.13: Multiple Metric Strategy: Regression Results

	Norwegian Model (FF3F + MOM + LIQ)			European Model (FF5F + MOM)		
	Equal-rf	MktCap-rf	Revenue-rf	Equal-rf	MktCap-rf	Revenue-rf
	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	−0.001	0.0003	0.005	0.002	0.006	0.010*
Index-rf	0.840*	0.958*	0.837*	0.789*	0.859*	0.704*
SMB	0.357*	0.247*	0.162	0.842*	0.662*	0.801*
HML	0.160*	0.060	0.118	−0.178	−0.506	−0.251
RMW				0.050	−0.388	−0.173
CMA				−0.033	0.064	−0.127
UMD	0.081	0.063	0.123	0.001	−0.062	−0.093
LIQ	−0.259*	−0.305*	−0.210			
Observations	239	239	239	239	239	239
Adjusted R^2	0.635	0.605	0.459	0.461	0.356	0.295
Notes						*p<0.05; Transaction cost: 0.02

EMH, additional tests are necessary.

5.6.6 Conclusion

The RW portfolio of the multiple-metric strategy outperforms the market and all other trading strategies, with a Sharpe ratio of 0.57. This strategy favors the consumer staples and industrial sector, contributing to the excellent return after the financial crisis. In addition, the RW portfolio avoids the energy sector when it underperforms, while the EW and the MCW portfolio do not. The RW portfolio only tilts toward the market risk-factor in the Norwegian model, while the European model suggests exposure to both the market and small-sized stocks. The European model further suggests that the RW portfolio generates a significant alpha.

6 Conclusion

The number of non-professional investors on the OSE has increased since the COVID-19 outbreak. We study whether investors can outperform the market index through different trading strategies using financial metrics. We use monthly price data and quarterly financial metrics for all stocks listed on the OSE from 2001 to 2021. Then, we define each trading strategy and calculate the returns of an equal-weighted, market capitalization-weighted, and revenue-weighted portfolio. We analyze the winning strategies and look for common characteristics through return statistics, sector exposures, and risk-factor regressions.

The EBITDA strategy outperforms the market index with an AAR of 12.62 percent when using the EW portfolio. The portfolio's primary exposure is to the energy and financial sector and small-sized value stocks. Additionally, the RW portfolio of the debt-to-equity strategy performs well, with an AAR of 17.97 percent. This portfolio has the lowest number of transactions and tilts toward liquid small-sized stocks. However, it tends to pick last month's winner-stocks and this month's losers. The stocks are mainly from the IT and energy sectors. Furthermore, the current-ratio strategy outperforms the index with an AAR of 15.43 percent when using an RW portfolio. The portfolio includes many sectors, whereas the stocks only tilt toward the market factor in the Norwegian model. Last, the EW portfolio of the interest coverage ratio strategy also outperforms the market with an AAR of 13.11 percent. While exposed to several sectors, the energy and industrial sectors are the most significant in the portfolio. This portfolio only tilts toward risks related to small-sized stocks. We find one strategy that does not outperform the market, which is the net profit margin. None of the weightings beat the market.

When we combine multiple metrics to form an optimal trading strategy, we find the combination of the EBITDA margin, net profit margin, and current ratio. With an RW portfolio, the investor can significantly outperform the other trading strategies in addition to the market index, with an AAR of 17.69 percent and a Sharpe ratio of 0.57. The RW portfolio has high proportions of the energy, consumer staples, and industrial sectors. Despite a record-breaking level of transactions executed, the portfolio still manages to gain extraordinary returns. The risk-factor regression suggests that the RW portfolio only tilts toward the market factor coefficient.

One should question if these trading strategies are relevant for the future. Naturally, we cannot answer this question with certainty. However, all strategies that outperform the market index gain a significant proportion of their returns during the end of the testing period. Investor preferences change over time, but companies with healthy financial ratios should perform well in the future stock market as well. Many of the strategies we test, and specifically the combined strategy, work as good indicators for a company's health and operational ability. Thus, we believe the strategies to be as relevant for the future as they have been for the past.

Sources of error

We include Primary Capital Certificates in our backtests to allow investments in savings banks. Financial securities' financial statements are different from non-financial firms, which weakens our findings' robustness. The financial ratios used as trading rules may be irrelevant in these cases or calculated wrong, thus providing false trading decisions. The impact on our results may be significant, such as in the regressions, in which the construction of risk factors excludes financial firms. Another limitation that may bias the results is unfiltered accounting data. Even though we correct unrealistic observations, such as negative returns, we could filter more to get a more realistic dataset, such as eliminating banks' EBITDA margins.

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Appendix

A1 Link to R Code

https://github.com/bkhaakedal/Master-Thesis/blob/main/FIETHE.R

A2 Statistics from backtesting

Table A2.1: Portfolio statistics for each strategy

(a) Portfolio statistics for strategies discussed, including transaction costs at 2 percent. Weight: Equal (E), Market Capitalization (M), and Revenue (R). Multiple Metric strategy ranks stocks each month based on EBITDA Margin, Net Profit Margin and Current Ratio, and invest in top 10 with highest score.

Strategy	Weight	AAR	St. Dev	Sharpe Ratio	Beta	Jensen's Alpha	Treynor's Measure
OSEBX	-	0.1021	0.2043	0.3662	1.0000	0.0000	0.0748
	E	0.1262	0.2123	0.4661	0.8344	0.0365	0.1186
EBITDA Margin	M	0.1055	0.2812	0.2783	1.1023	-0.0042	0.0710
	R	0.1207	0.2819	0.3316	1.0384	0.0158	0.0900
	E	0.1060	0.2975	0.2647	0.9712	0.0061	0.0811
Debt-to-Equity	M	0.0855	0.3381	0.1722	1.0950	-0.0237	0.0532
	R	0.1797	0.3439	0.4435	0.9673	0.0801	0.1577
	E	0.0770	0.2107	0.2362	0.7724	-0.0080	0.0644
Net Profit Margin	M	0.0392	0.2444	0.0491	0.8816	-0.0540	0.0136
	R	0.0420	0.2398	0.0614	0.8267	-0.0471	0.0178
	E	0.0852	0.2834	0.2045	0.9311	-0.0117	0.0622
Current Ratio	M	0.1066	0.2503	0.3171	0.8285	0.0174	0.0958
	R	0.1543	0.2535	0.5013	0.7580	0.0704	0.1677
	E	0.1311	0.2239	0.4640	0.9045	0.0362	0.1149
Interest Coverage Ratio	M	0.0941	0.2512	0.2664	1.0076	-0.0085	0.0664
	R	0.1064	0.2472	0.3201	0.9715	0.0064	0.0814
	E	0.1138	0.2209	0.3917	0.8379	0.0238	0.1033
Multiple Metrics	M	0.1307	0.2728	0.3795	1.0304	0.0264	0.1005
	R	0.1769	0.2636	0.5677	0.8664	0.0848	0.1727

Table A2.2: Transaction statistics for each strategy

Strategy	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	Sum
EBITDA Margin	0.00	0.00	2.00	2.58	4.00	10.00	620.00
Debt-to-Equity	0.00	0.00	2.00	1.63	2.00	10.00	392.00
Net Profit Margin	0.00	0.00	4.00	4.10	6.00	14.00	984.00
Current Ratio	0.00	0.00	2.00	2.73	4.00	12.00	656.00
Interest Coverage Ratio	0.00	0.00	2.00	2.53	4.00	10.00	608.00
Multiple Metrics	0.00	2.00	4.00	4.12	6.00	14.00	990.00

Table A2.3: GICS Sector proportion averages for each strategy

		GICS Sector Category											
Strategy	**Weight**	**Unknown**	**Energy**	**Materials**	**Industrials**	**Cons. Disc.**	**Cons. Staples**	**Health Care**	**Financials**	**IT**	**Telecom**	**Utilities**	**Real Estate**
EBITDA Margin	E	0.02	0.34	0.00	0.14	0.00	0.00	0.00	0.45	0.01	0.00	0.02	0.00
	M	0.06	0.32	0.00	0.09	0.00	0.00	0.00	0.49	0.00	0.00	0.02	0.00
	R	0.07	0.19	0.01	0.06	0.00	0.02	0.00	0.62	0.00	0.00	0.02	0.00
Debt to Equity	E	0.01	0.17	0.00	0.04	0.06	0.00	0.20	0.11	0.41	0.00	0.00	0.00
	M	0.00	0.31	0.00	0.02	0.05	0.00	0.09	0.10	0.42	0.00	0.00	0.00
	R	0.00	0.24	0.00	0.12	0.14	0.00	0.04	0.15	0.32	0.00	0.00	0.00
Net Profit Margin	E	0.03	0.31	0.00	0.16	0.01	0.02	0.02	0.38	0.04	0.00	0.02	0.00
	M	0.07	0.36	0.00	0.09	0.01	0.02	0.01	0.37	0.04	0.02	0.02	0.00
	R	0.07	0.27	0.01	0.10	0.01	0.06	0.01	0.41	0.03	0.02	0.01	0.00
Current Ratio	E	0.02	0.18	0.01	0.14	0.00	0.05	0.31	0.08	0.18	0.00	0.04	0.00
	M	0.01	0.26	0.01	0.17	0.00	0.20	0.11	0.03	0.16	0.00	0.06	0.00
	R	0.02	0.14	0.00	0.23	0.00	0.22	0.09	0.06	0.11	0.00	0.12	0.00
Interest Coverage Ratio	E	0.02	0.30	0.02	0.30	0.02	0.06	0.07	0.05	0.11	0.05	0.01	0.00
	M	0.04	0.45	0.04	0.18	0.02	0.06	0.00	0.04	0.02	0.15	0.00	0.00
	R	0.03	0.40	0.07	0.19	0.02	0.04	0.00	0.05	0.02	0.19	0.00	0.00
Multiple Metric	E	0.03	0.42	0.00	0.19	0.00	0.09	0.07	0.09	0.08	0.00	0.04	0.00
	M	0.09	0.42	0.00	0.13	0.00	0.17	0.01	0.03	0.11	0.00	0.03	0.00
	R	0.08	0.34	0.00	0.17	0.00	0.26	0.01	0.06	0.05	0.00	0.03	0.00

Table A2.4: Portfolio statistics all possible combinations

	Financial Ratios			**W**	**AAR**	**SD**	**Sharpe**	**Beta**	**Alpha**	**Treynor**
	1	**2**	**3**							
1	N.P.M	E.M	C.R	R	0.177	0.264	0.568	0.866	0.085	0.173
2	E.M	E.M	C.R	R	0.158	0.285	0.459	0.968	0.058	0.135
3	N.P.M	N.P.M	C.R	R	0.144	0.265	0.441	0.807	0.056	0.145
4	E.M	C.R	C.R	R	0.145	0.287	0.411	0.973	0.045	0.121
5	N.P.M	E.M	C.R	E	0.114	0.221	0.392	0.838	0.024	0.103
6	I.C.R	I.C.R	C.R	E	0.113	0.221	0.387	0.909	0.018	0.094
7	N.P.M	E.M	C.R	M	0.131	0.273	0.380	1.030	0.026	0.101
8	N.P.M	N.P.M	C.R	E	0.110	0.223	0.369	0.789	0.023	0.104
		Index		-	0.102	0.204	0.366	1.000	0.000	0.075
9	I.C.R	E.M	E.M	E	0.108	0.226	0.357	0.898	0.014	0.090
10	I.C.R	I.C.R	D.E	E	0.103	0.215	0.354	0.843	0.013	0.090
11	N.P.M	C.R	C.R	R	0.113	0.252	0.341	0.821	0.024	0.105
12	E.M	C.R	C.R	E	0.098	0.226	0.314	0.861	0.006	0.082
13	I.C.R	E.M	D.E	E	0.099	0.233	0.306	0.952	0.000	0.075
14	I.C.R	I.C.R	E.M	E	0.098	0.238	0.296	0.938	0.000	0.075
15	N.P.M	D.E	D.E	E	0.088	0.210	0.289	0.752	0.004	0.081
16	I.C.R	E.M	C.R	E	0.093	0.230	0.288	0.917	-0.002	0.072
17	N.P.M	N.P.M	C.R	M	0.107	0.280	0.285	0.990	0.006	0.080

Table A2.4 continued from previous page

18	E.M	E.M	C.R	M	0.108	0.287	0.283	1.056	0.002	0.077
19	N.P.M	D.E	C.R	E	0.089	0.223	0.280	0.832	-0.000	0.075
20	E.M	D.E	D.E	E	0.090	0.225	0.279	0.816	0.002	0.077
21	N.P.M	E.M	D.E	E	0.088	0.223	0.274	0.859	-0.003	0.071
22	N.P.M	I.C.R	D.E	E	0.087	0.224	0.268	0.904	-0.008	0.066
23	N.P.M	N.P.M	E.M	E	0.085	0.221	0.261	0.855	-0.006	0.068
24	I.C.R	I.C.R	C.R	M	0.093	0.259	0.256	1.013	-0.010	0.065
25	N.P.M	E.M	E.M	E	0.083	0.222	0.251	0.871	-0.009	0.064
26	I.C.R	D.E	D.E	E	0.086	0.233	0.251	0.880	-0.007	0.066
27	N.P.M	N.P.M	I.C.R	E	0.084	0.227	0.249	0.919	-0.012	0.061
28	I.C.R	E.M	C.R	M	0.091	0.258	0.246	1.005	-0.012	0.063
29	D.E	C.R	C.R	E	0.105	0.318	0.245	0.990	0.004	0.079
30	I.C.R	E.M	E.M	R	0.091	0.267	0.238	0.964	-0.009	0.066
31	I.C.R	C.R	C.R	M	0.098	0.301	0.235	1.128	-0.014	0.063
32	E.M	E.M	C.R	E	0.084	0.247	0.231	0.919	-0.012	0.062
33	I.C.R	E.M	E.M	M	0.088	0.267	0.227	1.024	-0.016	0.059
34	E.M	C.R	C.R	M	0.092	0.288	0.227	1.074	-0.015	0.061
35	N.P.M	C.R	C.R	M	0.086	0.260	0.225	0.920	-0.010	0.064
36	N.P.M	I.C.R	E.M	E	0.078	0.227	0.225	0.914	-0.017	0.056
37	E.M	D.E	C.R	E	0.076	0.227	0.217	0.849	-0.014	0.058
38	N.P.M	N.P.M	D.E	E	0.075	0.225	0.212	0.840	-0.015	0.057
39	N.P.M	C.R	C.R	E	0.072	0.215	0.209	0.811	-0.016	0.055
40	E.M	E.M	D.E	E	0.077	0.242	0.207	0.961	-0.022	0.052
41	I.C.R	I.C.R	D.E	R	0.079	0.252	0.204	0.954	-0.020	0.054
42	I.C.R	I.C.R	D.E	M	0.076	0.246	0.199	0.959	-0.023	0.051
43	I.C.R	D.E	C.R	E	0.073	0.246	0.186	0.938	-0.024	0.049
44	I.C.R	D.E	D.E	M	0.077	0.270	0.186	0.967	-0.022	0.052
45	N.P.M	I.C.R	C.R	E	0.069	0.226	0.185	0.920	-0.027	0.045
46	D.E	D.E	C.R	E	0.083	0.306	0.182	0.953	-0.015	0.058
47	I.C.R	I.C.R	E.M	M	0.072	0.251	0.177	0.989	-0.029	0.045
48	N.P.M	E.M	E.M	R	0.074	0.278	0.167	1.034	-0.031	0.045

Table A2.4 continued from previous page

49	I.C.R	I.C.R	E.M	R	0.068	0.243	0.166	0.905	-0.027	0.045
50	N.P.M	D.E	C.R	M	0.074	0.285	0.163	1.005	-0.029	0.046
51	I.C.R	C.R	C.R	R	0.080	0.322	0.162	1.113	-0.031	0.047
52	D.E	C.R	C.R	R	0.080	0.328	0.160	0.870	-0.013	0.060
53	N.P.M	I.C.R	D.E	R	0.071	0.275	0.160	1.022	-0.033	0.043
54	I.C.R	C.R	C.R	E	0.063	0.232	0.154	0.924	-0.033	0.039
55	N.P.M	I.C.R	I.C.R	R	0.064	0.258	0.143	0.954	-0.035	0.038
56	I.C.R	E.M	D.E	R	0.066	0.276	0.141	1.062	-0.040	0.037
57	I.C.R	D.E	C.R	M	0.068	0.291	0.140	1.029	-0.036	0.040
58	N.P.M	D.E	C.R	R	0.066	0.283	0.138	0.923	-0.030	0.042
59	N.P.M	E.M	D.E	R	0.061	0.259	0.131	0.953	-0.037	0.036
60	I.C.R	E.M	C.R	R	0.063	0.280	0.129	1.043	-0.042	0.035
61	I.C.R	I.C.R	C.R	R	0.061	0.261	0.129	0.991	-0.041	0.034
62	N.P.M	D.E	D.E	R	0.060	0.269	0.123	0.790	-0.026	0.042
63	D.E	C.R	C.R	M	0.066	0.326	0.120	0.924	-0.030	0.042
64	I.C.R	E.M	D.E	M	0.058	0.261	0.118	1.024	-0.046	0.030
65	N.P.M	N.P.M	E.M	R	0.058	0.271	0.115	1.004	-0.044	0.031
66	N.P.M	I.C.R	D.E	M	0.054	0.257	0.103	0.980	-0.047	0.027
67	N.P.M	I.C.R	I.C.R	M	0.053	0.255	0.102	0.979	-0.047	0.027
68	N.P.M	D.E	D.E	M	0.055	0.272	0.101	0.895	-0.040	0.031
69	N.P.M	I.C.R	C.R	M	0.055	0.286	0.097	1.142	-0.058	0.024
70	N.P.M	E.M	E.M	M	0.051	0.266	0.088	1.038	-0.054	0.023
71	D.E	D.E	C.R	M	0.056	0.333	0.088	0.988	-0.045	0.030
72	E.M	D.E	C.R	M	0.053	0.311	0.083	1.098	-0.056	0.024
73	N.P.M	I.C.R	C.R	R	0.050	0.306	0.075	1.155	-0.064	0.020
74	E.M	E.M	D.E	R	0.045	0.264	0.068	0.933	-0.052	0.019
75	N.P.M	E.M	D.E	M	0.046	0.276	0.068	1.057	-0.060	0.018
76	D.E	D.E	C.R	R	0.046	0.325	0.057	0.770	-0.039	0.024
77	E.M	D.E	C.R	R	0.040	0.313	0.042	1.020	-0.063	0.013
78	N.P.M	I.C.R	E.M	R	0.039	0.286	0.042	1.071	-0.068	0.011
79	I.C.R	D.E	C.R	R	0.040	0.311	0.041	1.059	-0.066	0.012

Table A2.4 continued from previous page

80	N.P.M	N.P.M	D.E	M	0.038	0.286	0.037	1.078	-0.070	0.010
81	N.P.M	I.C.R	E.M	M	0.037	0.282	0.035	1.103	-0.073	0.009
82	N.P.M	N.P.M	I.C.R	M	0.036	0.289	0.030	1.146	-0.077	0.008
83	E.M	D.E	D.E	M	0.034	0.281	0.025	0.968	-0.065	0.007
84	E.M	D.E	D.E	R	0.026	0.280	-0.004	0.920	-0.070	-0.001
85	N.P.M	N.P.M	I.C.R	R	0.023	0.298	-0.013	1.051	-0.082	-0.004
86	E.M	E.M	D.E	M	0.023	0.281	-0.015	1.061	-0.084	-0.004
87	N.P.M	N.P.M	D.E	R	0.014	0.293	-0.043	0.954	-0.084	-0.013

Note: Backtesting all possible combinations of Financial Ratios, from 2000-11-30 to 2020-11-30, sorted by highest Sharpe Ratio. Definitions for Financial Ratios: D.E = Debt-to-Equity, C.R = Current Ratio, I.C.R = Interest Coverage Ratio, E.M = EBITDA Margin, N.P.M = Net Profit Margin. Weighting (W): E = Equal, M = Market Capitalization, R = Revenue.

A3 Oslo Stock Exchange Statistics

Figure A3.1: Sector Indices over time

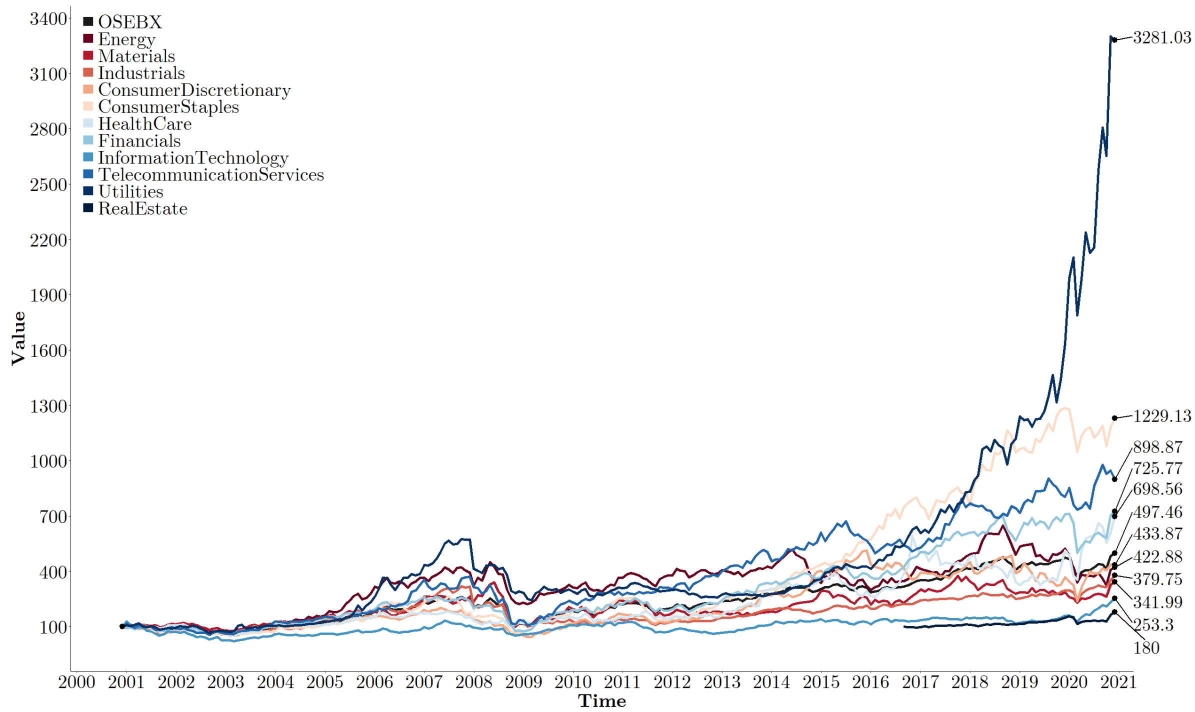

Figure A3.2: Sector Indices over time - excluding Utilities

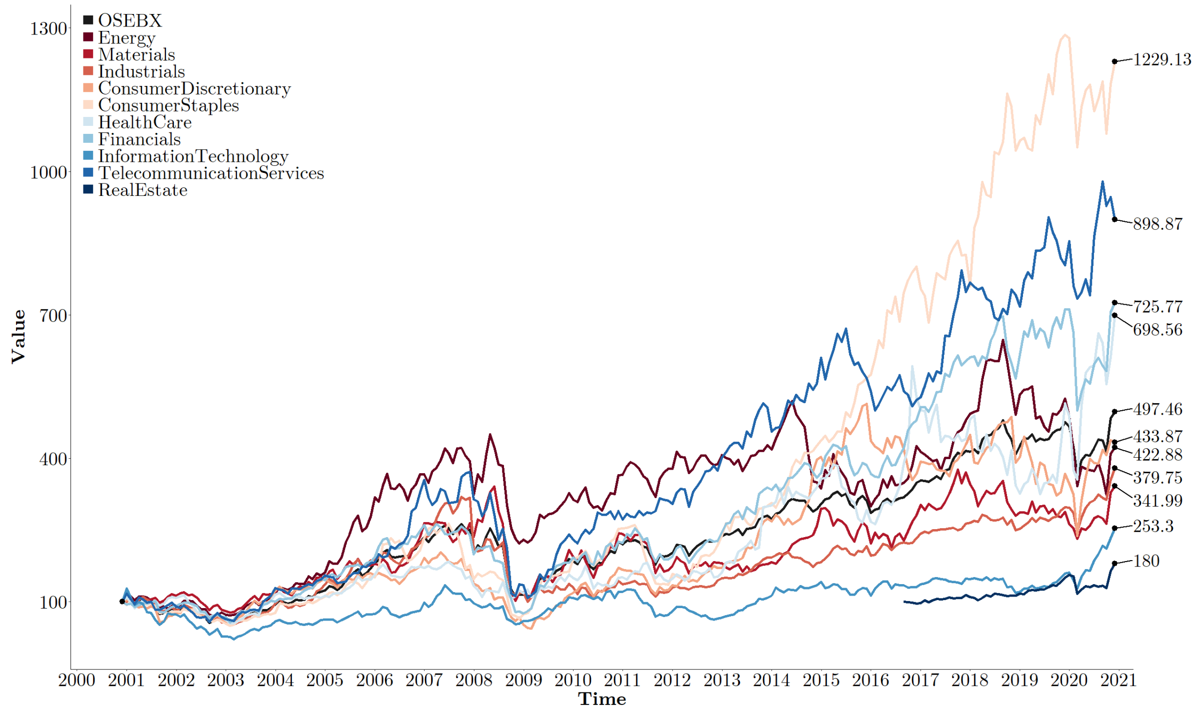

Figure A3.3: Sector proportion over time on the Oslo Stock Exchange