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Industries and the momentum effect at Oslo Stock Exchange

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Abstract

Based on data from OSE from 1985-2010, an investor forming (industry) momentum portfolios achives significant positive return, even when controlling for the Fama-French risk factors. By forming a self-financing portfolio by shorting the worst-performing stocks in the last period, and taking a long position in the best-performing ones, an investor achives low-risk positive returns.

There is a discrepancy between the industry distribution in the momentum portfolios and on the index as whole, suggesting that industries could be an explantory variable for which stocks are included in the momentum portfolios. This might suggest that the momentum effect is a industry story instead of an individual stock story.

Sammendrag

Basert på et dataset fra OSE fra 1985-2010 kan en investor oppnå signifikant positiv avkastning ved å forme momentumportføljer. Ved å shorte de verstpresterende aksjene fra forrige periode og kjøpe de best presterende kan en investor oppnå signifikant positiv avkastning.

Det er avvik mellom industridistribusjonen i momentumportføljene og indeksen som helset, noe som foreslår at industries kan være en forklaringvariabel for hvilke aksjer som blir inkludert i momentumportføljene. Dette kan peke mot momentumeffekten forårsakes av industrier og ikke individuelle aksjer.

Handelshøyskolen ved HiOA

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Forord:

Denne oppgaven ble skrevet våren 2016, som avsluttende oppgave for mitt masterstudie i økonomi og administrasjon ved Høyskolen i Oslo og Akershus. Masteroppgaven er en obligatorisk oppgave og tilsvarer 30 studiepoeng, med fagkode ØAMAS5900.

Denne oppgaven er en fordypning i finansiell økonomi.

Tema for oppgaven er momentumeffekten og hvilken påvirkning industrier har på denne. Dette teamet ble valg siden denne effekten har vist seg og være robost, vedvarende og vanskelig å forklare. Det var også begrenset med litteratur om momentum og industri på det norske aksjemarkedet.

Det har vært en lang, vanskelig men også utrolig lærerik prosess der jeg har fått benyttet meg av kunnskapen opparbeidet gjennom fem år med utdanning. Jeg har lært å jobbe med store oppgaver, ny programvare, store datasett og det å jobbe helt selvstendig over lengre tid.

Jeg vil også takke Knut Nygaard for veiledning og oppmuntring, Andrea Alecu for hjelp med programmering og Espen Sirnes for hjelp med å få tak i datagrunnlaget.

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1 Introduction:

The momentum effect in which winning stocks keep winning, and losing stocks keep losing is a well-studied financial phenomenon, but is yet to be fully explained. It was first discovered by Jagadeesh and Titman (1993), and they observed that stocks that did good (bad) in the past intermediate horizon would continue to do good (bad) in the future intermediate horizon. An investor could therefore take a short position in the worst performing stocks, and a long position in the best performing stocks and achieve a significantly higher return that the market.

These findings have shown to be both persistent and significant, as they have been confirmed in most financial markets (Rouwenhorst 1998; Griffin, Ji and Martin 2005; Stensland and Rabben 2012). They have also shown substantial returns even when controlled for standard risk factors. However, there are yet to be a consensus over what causes these returns. One theory is that the market is efficient, and that the momentum returns are compensation for risk. Another is that the returns are driven by investors' irrationality, by either over- or underreacting to new information.

The way we think about momentum has changed when it was shown empirically that large proportions of the momentum returns appears to be due to industry momentum returns. Moskowitz and Grinblatt (1999) found that the individual stock momentum returns turned insignificant once they controlled for industry momentum returns. This identifies industry return persistence as the source of much of the momentum returns – not individual stock momentum. This has been confirmed later as well (Chordia and Shivakumar, 2002; Su 2011), even though individual stock momentum still were present in Chordia and Shivakumars paper after controlling for industry momentum returns.

They had no clear answer to why industries seems to perfectly capture the momentum returns, but used industries as the unit to analyse since companies within the same industry tend to be higher correlated that those across industries, and are therefore exposed to the same macroeconomic shocks and supply and demand changes.

Due to its significance and persistence, I want to investigate whether the Norwegian stock market follows the same return patterns as Jagadeesh and Titman and Moskowitz and Grinblatt found. By investigated the Norwegian stock market for both the individual stock momentum and the industry momentum, I want to test the relationship between the two, and check if industry returns might be an explanatory factor for the momentum returns.

What effect does industries have on the momentum effect at Oslo Stock Exchange?

To answer this I will start by investigating whether the Norwegian stock markets show momentum returns and/or industry momentum returns, and test the robustness of those. This will be done by replicating the approach done by Moskowitz and Grinblatt. In addition to regressing the results for the Fama French risk factors, I will descriptively check if industries appears to be a factor when choosing companies for momentum portfolios.

The rest of the paper is structured as follows: The next section will go through the relevant earlier research on the subject. Section 3 describes the data and how it will be used. Section 4 goes through the empirical analyses and the results of those. Then the paper will be concluded in section 5. Section 6 shows the references used, and section 7-9 contains my appendixes.

2 Earlier research:

The momentum effect was first discovered by Jagadeesh and Titman (1993). They showed that you could achieve a significant abnormal positive return on the US stock market between 1963 and 1995 by following a momentum trading strategy. Their strategy were to select stocks based on their past 6-month return, and make a self-financiang portfolio. This were done by taking a long position in the best performing stocks and a short position in the worst performing stocks. These positions were held for 6 months and gave an average return of 12,01% per year. Following this strategy an investor would therefore achive near risk-free returns.

This effect is neither limited to the US stock market nor the time period they analysed. They have been confirmed in most of the world's financial markets, over different time periods, and most have found a significant abnormal excess return around 12% per year. There have also been several papers documenting the effect on the Norwegian stock market (Griffin, Ji and Martin 2005; Ubisch 2015; Kloster-Jensen 2006; Rouwenhorst 1998; Reiserud 2013).

This found was very interesting as the momentum returns goes against the semi-strong market efficiency theory. The practical implications was that a momentum trader could achieve risk-free profits by establishing a self-financing momentum portfolio, were the short positions pay for the long positions. Such a portfolio would have an expected positive return at very low risks, and would therefore be close to arbitrage. However, one cannot conclude that the market if inefficient based on the momentum effect, as it is possible that these returns are compensation for risk. By investigating this subject more thoroughly one might produce better models for asset-pricing.

Moskowitz and Grinblatt (1999) found that most of the momentum returns could be explained if you accounted for industry momentum returns. In their paper they took positions in the best- and worst-performing industries instead of indidual stocks.

Their findings indicated that momentum could be an industry story instead of an individual stock story. Since stocks within the same industry tend to be higher correlated with each other than stocks across industries, such a portfolio would be poorly diversified. This increases the idiosyncratic volatility of the portfolios, which would make a rational investor limit his position.

If idiosyncratic volatility is higher in the momentum portfolios, then the mispricing that has caused them to be in those portfolios are more likely to persist (Pontiff, 2006). Many studies have found that those momentum portfolios tend to contain higher idiosyncratic volatility than those outside of the portfolios (Hung, Glascock 2010; Arena, Haggard and Yan, 2008; McLean 2010). Following the limit to arbitrage hypothesis a rational investor would therefore have to limit his position, ceasing to change the mispricing of the asset.

This argues that the momentum returns could be compensation for having higher idiosyncratic volatility – making momentum strategies profitable, but far from arbitrage.

It has been shown that industry momentum contributes more to the momentum returns when idiosyncratic volatility is low (Heidari, 2015). When the idiosyncratic volatility is low, investors’ overreaction is lower, making momentum returns more due to industries. When the idiosyncratic volatility is high, the momentum effect is driven by a higher investor overreaction to information.

However, the reasons why these stocks (or industries) show return continuation in the intermediate horizon remain unclear. Since no risk-based model have been able to fully explain it, researchers have turned to behavioural theory. More specifically that the returns are a result of investors’ irrational reaction to new information. They disagree if investors over- or underreact to the new information, and there are evidence supporting both cases (Heidari, 2015). Some studies supporting the overreaction theory is DeLong et al. (1990) and Daniel, Hishleifer and Subrahmanyam (1998), while some studies supporting the overreaction theory is Chan, Jagadeesh and Lakonishok (1996), Barberis, Shleifer and Vishny (1998) and Hong and Stein (1999).

Other theories claim that investors exhibits overconfidence and self-attribution biases (Daniel et al. 1998). If investors’ show overconfidence in new or changing industries, this might cause the type of returns the industry momentum effect show. Other claims that investors’ show conservatism biases, meaning that they are conservative in updating their estimates of new or changing industries, causing the prices to underreact.

Hong and Stein (1999) proposed that slow information diffusion into prices causes an initial under reaction to new information, but that momentum traders seeking to exploit the slow price movement causes the long-term return reversals we see in momentum returns.

Information might take time to spread to the rest of an industry as investors' updates their priors. It were also showed empirically that stocks with a lower analyst coverage, used as proxy for slow information diffusion, produced higher returns supporting their theory (Hong, Lim, Stein 2000).

Hong and Stein (1999) claims that slow information diffusion into prices causes an initial under reaction to new information, but that momentum traders seeking to exploit this causes subsequent return reversals in the long run. Hong find that momentum is stronger among firms with low analytic coverage, which they see as a proxy for slow information diffusion. Industry leaders might receive new information, which slowly diffuses into the rest of the industry, causing industry momentum as investors view the information as a signal for the industry as a whole.

However, the literature has yet to determine whether momentum is an individual stock or an industry effect. Industries might not even be the best way to group the firms, but is used since companies within an industry are exposed to the same microstructure effects and changes in supply and demand.

This paper contributes by documenting a strong and persistent momentum effect at OSE both for individual stocks and industries. It also shows that the industries of companies might play a role when making the momentum portfolios. Since stocks within an industry are higher correlated than those across industries, a momentum portfolio would have higher idiosyncratic volatility if it chooses many stocks form the same industries. By showing that industries affects which stocks get included in the momentum portfolios, I show that the momentum effect might be due to industries and not individual stocks.

3 Data:

The analysis is based on daily data from Oslo Stock Exchange (OSE) from 1985-2010. This is the only regulated security market in Norway today. The exchange was established in 1819 and is both a mature and liquid market. It is therefor a good source for the data that is required to conduct this analysis.

I acquired the daily prices from all listed companies on OSE from 1984-2010 from TITLON[1]. It is a financial database for Norwegian academic institutions and contains detailed financial data aquired from OSE. The data is therefore highly reliable as it comes from a source that is publically available. The database contains various financial information from each company for each traded date. Since I need historical data to start trading I included 1984. This way I can test for momentum returns starting in January 1985.

For each date and each listed company, I downloaded 10 variables: The date, ISIN-code, Company ID issued by OSE, company name, best bid-price, best ask-price, adjusted price, the factor for dividend adjustment, the factor for stock splits adjustments, the currency traded in and the exchange rate between foreign currency and NOK on the traded date. These exchange rates are the one quoted by Norges Bank on the traded date.

The adjusted price (from here called price) in the dataset is both adjusted for dividend and stock splits. This standardizes each price making them comparable.

TITLON contains data for every date since 1980, but my analysis will look at the time period from 01.01.1985 until 31.12.2010. I begin in 1985 since that is the first year OSE passed 100 listed companies, which increases my sample size. In addition, I end after 2010 since updated industry classifications after 2010 were unavailable to me. The data is stretching over 25 years, or 300 months, which should be sufficient for this analysis. It also includes many years both before and after the momentum effect first were documented.

In total I had 1 248 495 observations between 6 774 unique dates and 611 unique companies.

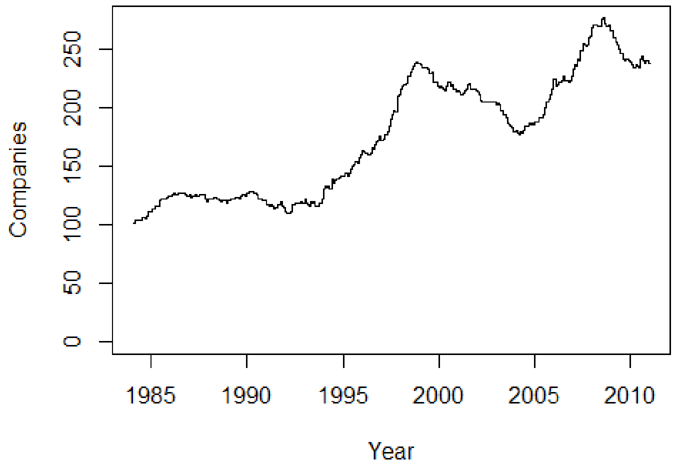
[1] https://titlon.uit.no/ (28.02.2016)

For the Fama French risk factors and the risk-free market rate, I got those from professor Bernt Arne Ødegaards homepage[2]. He is a professor at UiS and NHH and have constructed the monthly Fama-French factors and the risk-free market rate factor from Norwegian data.

The Fama French factors SMB (small stocks minus big stocks) and HML (high market capitalizations minus low market capitalization) is calculated by taking the average return of the small (high) stocks minus the average return of the big (low) stocks.

Figure 1: Number of companies on OSE 1985-2010

This graph show the total number of listed companies on OSE for each month between the start of 1985 to the end of 2010. The minimum number of companies listed were 101, the maximum were 277 and on average there were 175,25 listed companie each month. The figure shows that the number of listed companies on OSE have increased steadily throughout the time period, except for a dip in 2005.



Industry classifications were acquired from OSEs own database for research and development focus. These are called Global Industry Classification Standard (gics) and was developed in 1999 by MSCI and S&P for the financial community. They divide compaies into ten different sectors, and then further down on industry level. Due to the number of listed stocks on OSE, I divide them between the ten sectors.

These sectors are energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunication services and utilities. In

[2] http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html (24.03.2016)

total OSE have listed over 600 unique companies between 1985 and 2010, with a maximum of 277 companies, a minimum of 101 and had 175,25 listed companies each month on average.

There were 29 companies in the dataset that were without industry classifications, and those were excluded from the analysis.This is because a missing industry classification excludes them from the industry momentum analysis, and by excluding them the industry momentum analysis' dataset will be identical to that in the individual stock momentum analysis.

Table 1: Overview of the different sectors

The table underneath display descriptive statistics of the different sectors. The gics are the industry code each sector have; the average number of stocks is the average number of listed stocks each month per sector. Therefore, a stock is counted if it is listed at least once in a month. The maximum and minimum number of stocks show the maximum and minimum number of stocks in the same sector for a month. The final column show the average logarithmic monthly return for all the companies in the sector.

Sector	gics	Average number of stocks	Max number of stocks	Min number of stocks	Average return pr month
Energy	10	30,6	78	10	0,158 %
Materials	15	10,1	14	7	0,336 %
Industrials	20	45,8	75	31	-0,132 %
C Discretionary	25	15,3	28	7	-0,127 %
C Staples	30	7,9	19	2	0,215 %
Health care	35	6,1	18	1	0,075 %
Financials	40	34,3	45	21	0,190 %
IT	45	23,4	44	5	-0,815 %
Telecom	50	0,8	2	0	-0,234 %
Utilities	55	0,9	2	0	0,683 %

As we can see in Table 1 there is an overweight of energy, industrials, financials and IT companies listed on OSE, while only four companies is listed as either a telecom or a utility company. Most sectors have a large difference between the average number of stocks listed and the minimum number of stocks listed, and is due to OSE having a large growth of listed companies in the time period investigated. It also shows the average logarithmic return per month for each sector.

Except for the exclusion of stocks without available industry classification, I have made no other selection of the data. I will include all sectors in the empirical analysis, even though the telecom and utilities sector averages less than one listed company per month.

3.1 Bid/ask-spread:

If a stock went a day untraded, OSE had no price for that day, and the price in my dataset would be missing. To minimize the number of trading trades without a price, I used the mid bid/ask-spread if the price were missing. This were then adjusted for dividends, stock splits and exchange rates for stocks traded in foreign currencies.

$$Bid/ask - spread = \frac{(Bid + Ask)}{2} * Div\ adj * Split\ adj * FXR$$

Formula 1 - Bid/ask-spread

Here (Bid + Ask)/2 is the mid bid/ask-price, div adj is the factor for dividend adjustments, split adj is the factor for split adjustments and FXR is the foreign exchange rate. Note that I only used the bid/ask-spread if I had both a bid and an ask price available.

3.2 Industry classification

The companies on OSE were divided into industry sectors based on the industry classifications from OSEs own database. Even though companies without gics were excluded from the analysis, there were around 76, 000 observations were the industry classification were missing. This was due to some companies only having industry classifcations avaliable for parts of the time they were listed on OSE.

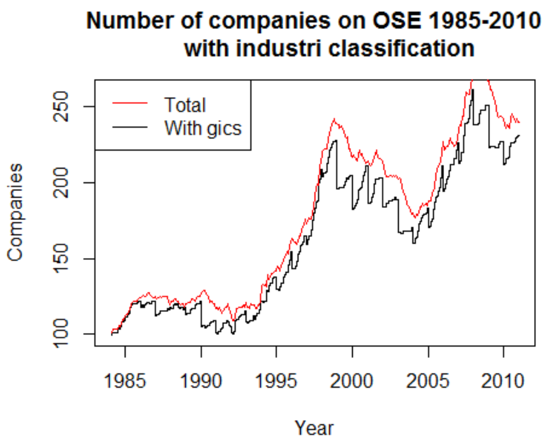
To remove this issue, I replaced the missing values with the closest non-missing variables. This means that a company listed from 1998 to 2002, which were listed as an energy company in 1999, and utilities in 2000 will be listed as an energy company from 1998 to 1999 and a utility company from 2000 to 2002.

This removes the problem of missing industry classifications, but might cause a few companies to be listed with the wrong industry classifications. However, since I only had around 6% missing industry classifications and companies in my dataset rarely changes industry, I feel confident that this will not affect my results. Figure 2 shows the number of companies without industry classifications before and after I replaced the missing values.

Figure 2: Number of companies with industry classification:

These graphs show the number of listed companies at OSE with industry classification avaliable compared to listed companies in total, between 1985-2010. Panel A shows the distribution before I filled in missing industry observations with the closest non-missing industry observation, while Panel B shows the distribution afterwards. This removes the problem of missing industry classifications as shown in Panel B.

Panel A: Before I replace missing observations



Panel B: After I replace missing observations

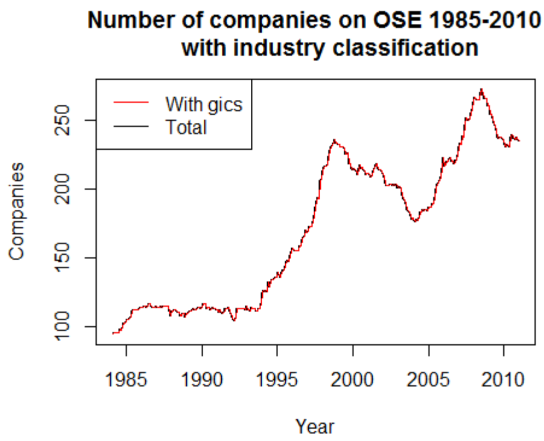
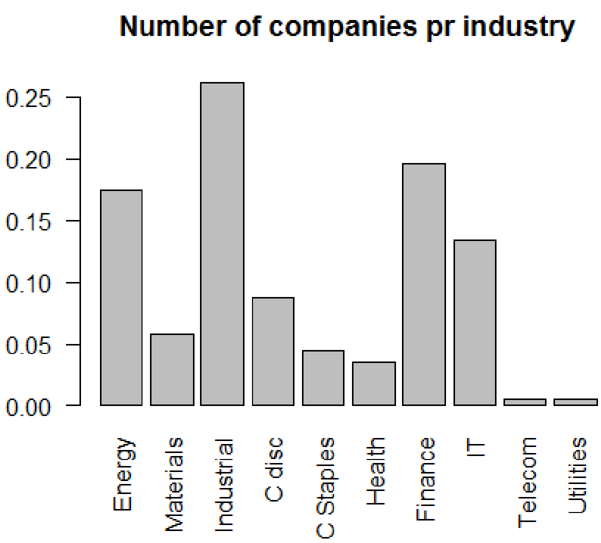


Figure 3: The company distribution per sector

This figure show the relative share each sector had on average each month on OSE. The figure shows that industrials is the dominant sector with over 25% of the companies on average, followed by finance, energy and IT. Telecom and utilities companies are barely represented.



3.3 Portfolio weights:

Portfolios can be either value-weighted or equal-weighted. When they are value-weighted stocks are weighted based on their market share, while size and value is irrelevant when equal-weighing them.

When value-weighing, high capitalization stocks has more influence than low capitalization stocks. This has some advantages since high-value stocks tend to be more liquid than low-value stocks giving them a lower spread between the bid and ask price. On the other side, it might skew the result a lot by focusing solely on the largest stocks.

I use equally weighted portfolios in my momentum test; so that each company is valued the same to avoid getting skewed results by a few large companies.

3.4 Calculating prices

The monthly logarithmic return were computed from the daily prices. I first went to monthly prices by taking the last observed price for each month, and then to logarithmic returns. Argumentation for logarithmic returns over arithmetic are in appendix A.

$$\log(1 + r_i) = \log\left(\frac{p_i}{p_j}\right) = \log(p_i) - \log(p_j)$$

Formula 2 - Logarithmic return

Here r_i is the return at time i, p_j is the price at time j and p_i is the price at time i.

3.5 Ranking- and holding periods:

In the literature there have been done momentum tests with both long and short ranking- and holding periods. The most common are either 1, 3, 6, 9 or 12 month holding- and ranking periods or a combination of those. This paper will do every combination of the mentions strategies, 25 in total. However, I will mainly focus on the 6-month holding, 6-month ranking strategy since both Jagadeesh and Titman (1993) and Moskowitz and Grinblatt (1999) focus most on it. This will make the results directly compareable to the earlier reseach.

This means that an investor would need 6 months of historical return as a basis for making his momentum portfolio. The dataset starts in 1984, but I will start the momentum test in 1985 so I have 12 months of historical data to base it on. The practical implication is that my dataset will get momentum returns from January 1985, since there are historical data to base the trading strategy on.

3.5.1 Overlapping- or non-overlapping periods:

An investor following a 6-month holding, 6-month trading strategy can either rebalance his portfolio monthly or every sixth month. When rebalancing it every month, an investor would still hold the earlier portfolios, meaning that he will hold more than one portfolio at the same time. When rebalancing every sixth month, this a process done once every sixth month.

The empirical evidence show that there are no real difference in the returns if you change from an overlapping strategy to a non-overlapping strategy or vica verca (Jegadeesh, Titman 1993).

4 Empirical analysis:

The paper first looks at the momentum effect at OSE, then the industry momentum effect at OSE before testing the relationship between the two.

4.1 Momentum portfolio returns

To identify the companies to include in the momentum portfolio, they were sorted based on their *R*-month lagged return. Here R is the number of month in the ranking period for the momentum strategy. The 30% best-performing stocks in the previous period were included in the winning (long) portfolio, and stocks among the 30% worst-performing in the same period were included in the losing (short) portfolio.

In the industry analysis, the top two performing industries were put in the winning (long) portfolio, and the two worst were put in the losing (short) portfolio.

An investor would then form a self-financing momentum portfolio by taking a long position in the winning portfolio, financed by a short position in the losing portfolio. These positions would be held for *H* months, were H is the number of months in the holding period of the momentum strategy. After H months, the positions are liquefied. This procedure is repeated for each month, and the monthly returns for each portfolio can be computed using formula 3.

$$Portfolio\ return_j = \frac{1}{H} * \frac{1}{N} \sum logreturns_{j-1,j-6}$$

Formula 3 – Equal-weighted average monthly portfolio return

Here portfolio $return_j$ is the equal-weighted monthly return for month j, H is the number of holding months and $logreturns_{j-1,\ j-6}$ is the logarithmic return for each listed company from period j-1 to j-6.

By taking the return of the long portfolio minus the returns of the short portfolio, we get the momentum returns for each month. This will be repeated each month throughout the dataset, giving the average monthly momentum returns on OSE in the time period.

4.2 Test-statistics

To verify that the results are statistically significant I conduct a series of t-tests. This is a statistical hypothesis test, which tests weather a test statistically differs from another value – in my case zero.

$$t - value = \frac{(Average\ return - My\ hypothesis)}{s/\sqrt{N}}$$

Formula 4 - t-test

Where N is the number of observations and s is the standard deviation:

$$s = \sqrt{\frac{\sum(r_i - \bar{r})^2}{N}}$$

Formula 5 - Standard deviation

Here r_i is the return at time i, while $\bar{r}$ is the average return for the portfolio.

By putting in zero for my hypothesis in formula 4, the test-statistic can be compared to a critical t-value to check for statically significance. If the produced t-value is higher than a critical t-value, it is assumed as statistically significant. The t-values can also be used to produce p-values, which shows the probability that the result is statistically insignificant. If the p-value for instance is 0.1, there is 10% chance that the results are a result of random variation, making the results insignificant. I will compare the p-values at the 99% and 95% confidence interval, meaning that all p-values above 0.01 and 0.05 respectively will be assumed as statistically insignificant.

4.3 Fama-French regression

The robustness of the momentum returns were checked by controlling the excess returns for the Fama-French risk factors. This asset-pricing model attempt to explain excess returns with three risk factors. These are the market factor ($r_m - r_f$), capturing excess market returns, the size-factor (SMB) and the value-factor (HML) (Fama, French 1992; Fama French 1993).

The SMB factor is computed as the difference in returns between small and big companies, while the HML factor is the difference in returns between companies with high book-to-market ratio and low book-to-market ratio.

Regressing the observed momentum return minus the risk-free rate against these risk factors will test if this model can fully explain its excess returns. If the point of intersection (α) in this model is zero, the model explain all of the returns. If it is higher than zero the model fails to fully explain the returns. By including the individual stock momentum returns when regressing the industry momentum returns, and the other way around, we can see if one of the momentum returns explain the other. Formula 6 show the mathematical formula for the regression.

$$E(r_t) - r_f = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t$$

Formula 6 - Fama-French 3 factor model regression

Here $E(r_t) - r_f$ is the expected excess return, alpha is point of intersection, $(r_m - r_f)$ is the market factor, SMB is the size factor, HML is the value factor and the betas are the risk factors sensitivities.

4.4 Descriptive analysis:

To investigate the relationship between individual stock momentum returns and industries, I conduct some statistical tests to see weather industries could be a decisive factor for which companies are included in the momentum portfolio. This section will assume a null hypothesis were industries and individual momentum returns are completely unrelated. With this assumption, the industry distribution in the momentum portfolios are summed to be normally distributed and similar to the distribution of the entire index.

For instance there are on average 30,5 energy companies listed on OSE, giving them an average share of 17,5% of the index. If there truly is no relationship between industry and momentum returns the momentum portfolios should contain approximately 17,5% energy stocks on average. If however, there exists a relationship I would expect the momentum portfolios to either overrepresent or underrepresent energy companies. This was tested by comparing each sectors share in the momentum portfolios with their share on the exchange as a whole, by using formula 7.

$$Difference\ in\ industry\ distribution = \frac{(Share\ of\ portfolio - Share\ of\ exchange)}{Share\ of\ exchange}$$

Formula 7 - Difference in industry distribution

4.5 Momentum results:

Table 2 reports the average monthly return achieved by following either an individual stock momentum trading strategy or an industry momentum trading strategy, with 6 month ranking periods and 6 month holding periods . The tables include the number of observations, the mean return, standard deviation, maximum and minimum returns. In addition, the tables is decomposed into three: The long position (buy), the short position (sell) and the total position (buy – sell). In line with the literature, both the individual momentum and industry momentum yields significantly positive returns.

Table 2: Momentum returns for a 6-month holding and ranking strategy

The following table show the returns an investor would get by following a (industry) momentum trading strategy where he ranks stocks based on their 6-month return and hold them for 6 months. The buy row show the result of the long positions, the sell row the result of the short positions and the buy-sell row show the results of both positions combined. N is the number of observations, mean is the average monthly logarithmic return, the standard deviation is the average monthly standard deviation and min and max represent the highest and lowest return achieved during one month.

Panel A shows the result of an individual stock momentum strategy, while Panel B shows the same for an industry momentum strategy.

Panel A: Individual stock momentum

Statistic	N	Mean	St. Dev.	Min	Max
Buy	312	0.005	0.035	-0.127	0.078
Sell	312	-0.008	0.047	-0.159	0.102
Buy-Sell	312	0.013	0.025	-0.053	0.131

Panel B: Industry momentum

Statistic	N	Mean	St. Dev.	Min	Max
Buy	312	0.007	0.039	-0.190	0.135
Sell	312	-0.006	0.050	-0.236	0.115
Buy-Sell	312	0.013	0.042	-0.127	0.223

Both strategies yields an average return of 1,3% per month, which is slightly higher than observed by Jagadeesh and Titman (1993). However, the findings are also consistent with the earlier research on the Norwegian stock market (Reiserud, 2013; Kloster-Jensen 2006; Rouwenhorst 1998).

The individual stock momentum returns and the industry momentum returns are almost equal in size, which according to Moskowits and Grinblatt (1999) is no coincidence. They claim that the industry momentum returns are responsible for a large portfolio of the individual stock momentum returns.

An industry momentum strategy would yield most of its return from the long positions, while most of the profitability of the individual stock momentum comes from the short positions. This is consistent with earlier research, and might make the industry strategy more implementable. Since individual momentums profitability is dependent on the short positions, some of the profitability might come from shorting illiquid stocks, which at least is a smaller problem with an industry momentum strategy.

These findings are extremely robust, and the strategies yield significantly positive return for most of the investment strategies. Table 3 shows the returns from following each of the 25 different momentum investment strategies investigated in this paper. The only negative returns comes from the 1-month ranking, 1-month holding individual stock momentum strategy. This is in line with the findings of Jagadeesh (1990), which documented strong return reversal in the short-term. These have later been attributed to microstructure effects such as bid-ask bounce and liquidity effects.

In contrast, the 1-month ranking, 1-month holding industry momentum strategy yields significant average profits of 1,53%. It is interesting that momentum and industry momentum exhibits the same 3-12 months returns, but that the one-month serial correlation of individual stocks appears to be of the opposite sign than the one-month serial correlation for industries. This discrepancy might be because the microstructure effect affecting the individual stock momentum reduces by forming industry portfolios (Moskowitz, Grinblatt 1999).

Industry momentum returns shows to be equal or higher than individual stock momentum returns for most strategies. Individual momentum maximum yields 0,39% higher return than industry momentum, while industry momentum maximum yields 2,1% higher than individual momentum (or approximately 1% if we exclude the 1-month ranking and holding strategy). Industry momentum also exhibits higher significance levels than individual momentum, and is only surpassed in the 1-month holding strategies. Industry momentum therefore seems to be more robust than the individual stock momentum.

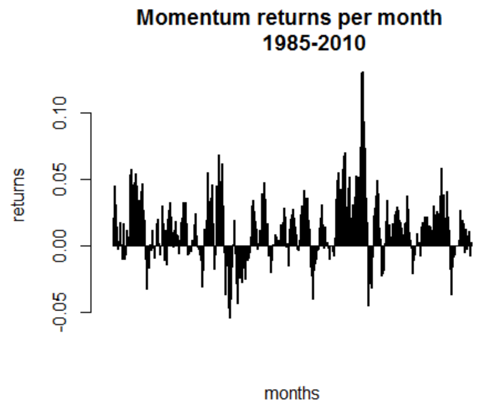
When controlling for the Fama-French risk factors, both investment strategies produces statistically significant Jensen's alpha, meaning that these strategies would give a significantly positive return even after controlling for market returns, size and market capitalization. Table 5 shows the output of such a regression for the 6-months holding and ranking strategies, and documents that an individual stock momentum strategy would yield an excess return of 0,7%. Since the returns remains statistically significant, the Fama-French risk factors are unable to fully explain the returns.

These returns have shown to be persistent over time and Figure 4 shows a bar plot over the returns each month from 1985-2010. It shows a similar trend throughout the time, and the returns were not affected much by having the momentum effects documented in 1993 and 1999 respectively. Appendix C show that the individual stock momentum is almost identical before and after discovery, while the industry momentum returns have declined some, but remains significantly positive.

Figure 4: Momentum returns and industry momentum returns

These figures show the momentum and industry momentum returns for each month between 1985-2010. These graphs show that the returns are not acquired during a small period of time, but that it is a consistent effect. Panel A shows the momentum returns, while Panel B shows the industry momentum returns.

Panel A:



Panel B:

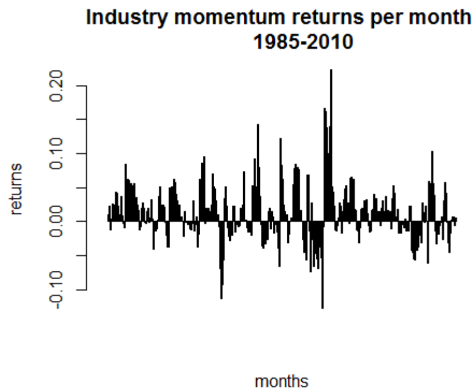


Table 3: Momentum returns and significance tests

This table shows the results from a momentum test on the dataset. The returns are achieved by taking a long position in the 30% best performing stocks in the last *R* months and financing this by a short position in the 30% worst performing stocks from the same period. These positions are held for *H* month, and the returns under show the average monthly return achieved by following such strategies. Both R and H can be 1, 3, 6, 9 and 12 months, giving 25 combinations in total.

The results are tested with a t-test, showing their significance level. Stocks with a p-value of less than 0.05 are significant at the 95% confidence level, while stocks with a p-value lower than 0.01 are statistically significant at the 99% confidence level.

Panel A shows the returns an investor would have gotten by following an R-month ranking period and an H-month holding period strategy. Panel B shows the p-values computed from a t-test on the results.

Panel A: Momentum returns

Rank|Hold	1	3	6	9	12
1	-0,005816	0,004501	0,006273	0,006043	0,005578
3	0,008352	0,013335	0,011730	0,010060	0,008930
6	0,011267	0,014227	0,013119	0,012299	0,009878
9	0,011843	0,015449	0,015091	0,012795	0,009986
12	0,014195	0,016185	0,014231	0,011298	0,008960

Panel B: P-values from a t-test

Rank|Hold	1	3	6	9	12
1	0,052353	0,005529	0,000000	0,000000	0,000000
3	0,020454	0,000000	0,000000	0,000000	0,000000
6	0,002357	0,000000	0,000000	0,000000	0,000000
9	0,002114	0,000000	0,000000	0,000000	0,000000
12	0,000267	0,000000	0,000000	0,000000	0,000000

Table 4: Industry momentum returns and significance test:

This table shows the results from an industry momentum test on my dataset. The returns are achieved by taking a long position in the best two performing industries in the last *R* months and financing this by a short position in the worst two performing industries from the same period. These positions are held for *H* month, and the returns under show the average monthly return achieved by following such strategies. Both R and H can be 1, 3, 6, 9 and 12 months, giving 25 combinations in total.

The results are tested with a t-test, showing their significance level. Stocks with a p-value of less than 0.05 are significant at the 95% confidence level, while stocks with a p-value lower than 0.01 are statistically significant at the 99% confidence level.

Panel A shows the returns an investor would have gotten by following an R-month ranking period and an H-month holding period strategy. Panel B shows the p-values computed from a t-test on the results

Panel A: Industry momentum returns

Rank|Hold	1	3	6	9	12
1	0,015298	0,013539	0,009201	0,006074	0,005824
3	0,018458	0,014020	0,010716	0,007763	0,007137
6	0,018309	0,016506	0,012933	0,012447	0,010527
9	0,016441	0,014876	0,013022	0,010220	0,007601
12	0,016988	0,014879	0,010334	0,008669	0,006958

Panel B: P-values from a t-test

Rank|Hold	1	3	6	9	12
1	0,003253	0,000003	0,000037	0,002794	0,000958
3	0,000282	0,000010	0,000003	0,000225	0,000011
6	0,000522	0,000001	0,000000	0,000000	0,000000
9	0,001222	0,000002	0,000000	0,000006	0,000092
12	0,000648	0,000002	0,000023	0,000069	0,000323

Table 5: Fama-French regression of momentum returns

This table shows a regression of the excess momentum returns, controlled for the Fama-French factors. MKT is the market factor, HML is the factor controlling for market capitalization and SMB controls for size of the companies. The bottom statistics shows the number of observations, the R^2, the residual error and an F-statistics. It follows the following formula, where $E(r_t) - r_f$ is the excess momentum return and the βs are the risk factors sensitivities. Jensen's Alpha (α) captures the unexplained returns.

$$E(r_t) - r_f = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t$$

	Dependent variable:
	Mom - rf
SMB	-0.011
	(0.033)
HML	0.003
	(0.028)
MKT	-0.027
	(0.026)
Constant	0.007***
	(0.002)
Observations	318
R2	0.004
Adjusted R2	-0.006
Residual Std. Error	0.025 (df = 314)
F Statistic	0.372 (df = 3; 314)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6: Fama-French regression of industry momentum returns

This table shows a regression of the industry momentum returns – the risk free rate, controlled for the Fama-French factors. MKT is the market factor, HML is the factor controlling for market capitalization and SMB controls for size of the companies. The bottom statistics shows the number of observations, the R^2, the residual error and an F-statistics. It follows the following formula, were $E(r_t) - r_f$ is the excess industry momentum return and the βs are the risk factors sensitivities. Jensen's alpha captures the unexplained returns.

$$E(r_t) - r_f = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t$$

	Dependent variable:
	iMom - rf
SMB	-0.034
	(0.054)
HML	0.0001
	(0.045)
MKT	-0.107**
	(0.042)
Constant	0.009***
	(0.002)
Observations	318
R2	0.020
Adjusted R2	0.011
Residual Std. Error	0.041 (df = 314)
F Statistic	2.186* (df = 3; 314)
Note:	*p<0.1; **p<0.05; ***p<0.01

The industry momentum yields 0,9% average return per month after controlling for the same factors, as shown in Table 6. Therefore, the model captures more of the individual momentum returns than the industry momentum returns. This implies that an industry momentum strategy would produce a higher excess return unexplainable by standard risk factors.

To see whether the industry momentum returns captures the individual stock momentum returns, the momentum factor were included in the regression. Table 7 shows two regressions, were Panel A is the individual momentum returns controlled for industry momentum returns, and Panel B is the industry momentum returns controlled for individual stock momentum returns.

Panel A indicate that individual stock momentum remains significant with a Jensen's alpha of 0.003, indicating that a momentum strategy yields 0,3% returns even when including industry momentum returns as a factor. The significance falls from being significant at the 99% level to being significant at the 95% level.

Panel B shows that the industry momentum returns turns insignificant once we include individual stock momentum returns as a risk factor. These results are conflicting with the findings of Moskowitz and Grinblatt (1999), who found that the industry momentum returns almost perfectly captured the individual stock momentum returns. The risk factors also indicate that individual momentum explains industry momentum more than the other way around, with 0.293 versus 0.828.

Table 7: Industry and individual momentum return regressions:

This table show the regression output when regressing the (industry) momentum returns for the standard Fama-French risk factors in addition to the (industry) momentum returns. I control the momentum returns for industry momentum returns and vica verca. The mathematical formula is shows underneath, and here $E(r_t) - r_f$ is the excess (industry) momentum return after controlling for the standard risk factors and the (industry) momentum return.

In Panel A I control the momentum returns for the Fama-French factors and the industry momentum returns (MOM), and in Panel B I control the industry momentum returns for the Fama-French factors and individual stock momentum returns (MOM).

$$E(r_t) - r_f = \alpha_i + \beta_{1,i}(r_{m,t} - r_{f,t}) + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}MOM_t$$

Panel A:

	Dependent variable:
	Mom - rf
SMB	-0.001
	(0.029)
HML	0.001
	(0.024)
iMom	0.293***
	(0.030)
MKT	0.008
	(0.023)
Constant	0.003**
	(0.001)
Observations	318
R2	0.234
Adjusted R2	0.224
Residual Std. Error	0.022 (df = 313)
F Statistic	23.910*** (df = 4; 313)
Note:	*p<0.1; **p<0.05; ***p<0.01

Panel B:

	Dependent variable:
	iMom - rf
SMB	-0.021
	(0.047)
HML	-0.008
	(0.039)
Mom	0.828***
	(0.082)
MKT	-0.077**
	(0.037)
Constant	-0.003
	(0.002)
Observations	318
R2	0.262
Adjusted R2	0.253
Residual Std. Error	0.036 (df = 313)
F Statistic	27.846*** (df = 4; 313)
Note:	*p<0.1; **p<0.05; ***p<0.01

4.6 Descriptive results

The findings above indicate that there exists both an individual stock momentum effect and an industry momentum effect at OSE. These returns are similar in strength and have a significant effect on each other as shown in Table 7. The tests underneath will further show that industries might be an important factor when making momentum portfolios.

Figure 5 shows the difference in industry distribution between the energy sectors share in the momentum portfolio with the share of the exchange. Panel A shows the difference in industry distribution between the winning portfolios and the index, while Panel B shows it for the losing portfolios. These results are not exclusive to the energy sector, as most sectors show similar results. These are shown in Appendix B.

The first graph in Panel A shows a histogram over the differences between expected and actual distribution of energy companies in the winning portfolio. The energy share of the index is used as the expected distribution. The Y-axis is in percentages and the X-axis show the percentage difference from the energy share on the index. A value of -1.0 indicates that there were 0% energy companies in the winning portfolio, while +1.0 indicates that the winning portfolio contains twice as many energy stocks as the index did at that particular time. This means that roughly 5% of the winning portfolio contains zero energy stocks, and over 5% contained twice as many or more. The plot is also skewed to the right meaning that the winning portfolio on average contained more energy stocks than the index.

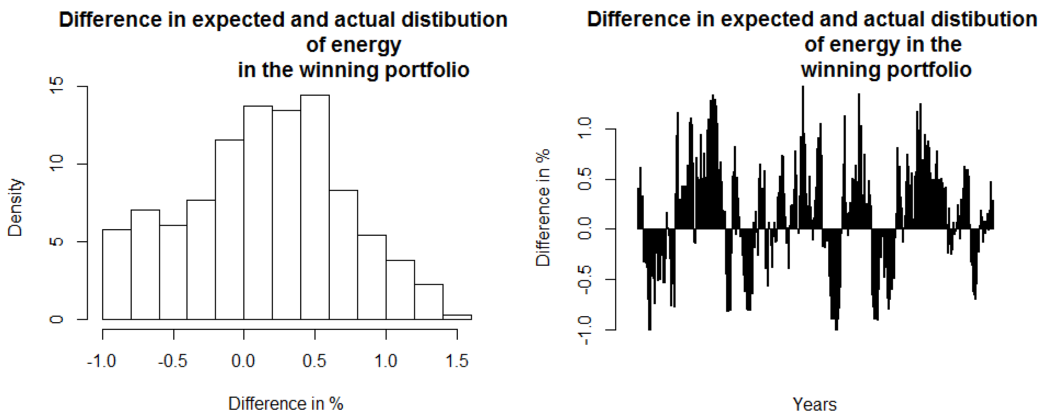
The second graph in Panel A show the same dataset, but as a bar plot. This visualizes how the industry distribution contains many extreme values. If these factors were unrelated one would expect most values around the zero line, and fewer extreme values.

Panel B shows the same type of plots, but for the losing portfolios. The plots show much of the same story, with a skewed histogram and a bar plot showing many extreme values. The results for the other sectors were similar to the results from the energy sector.

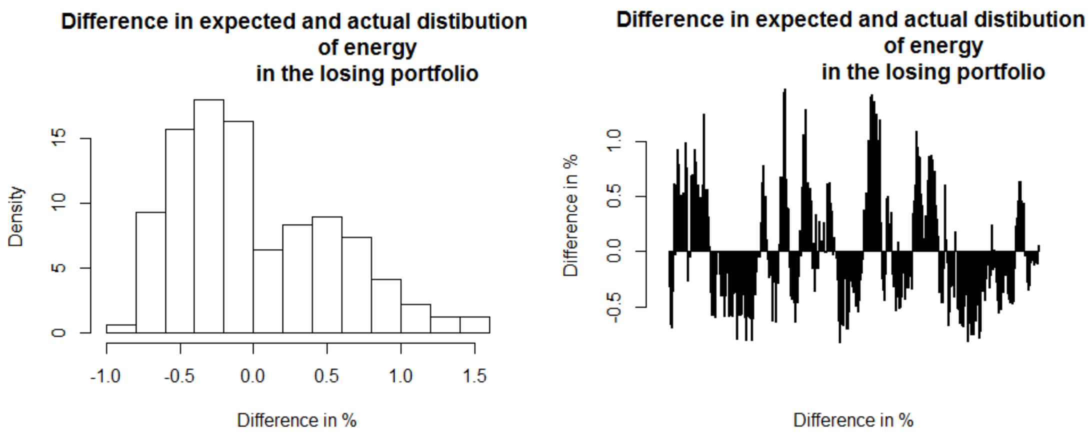
Figure 5: The difference in expected and actual distribution of the energy sector

The figures below show the differences in the expected industry distribution and actual industry distribution, for both the winning and losing portfolios. The differences in distribution is calculated with formula 10. Both graphs in the panels show the same data, just visualized different. Panel A show the difference between expected and actual distribution of energy companies in the winning portfolio, while Panel B shows the same for the losing portfolio.

Panel A:



Panel B:



The significance of these results were tested with a Shapiro-Wilk normality test. This tests null hypothesis is that the data is normally distributed, and if the test observator is higher than its critical value the null hypothesis is rejected. This implies that the data comes from a non-normally distributed sample. This test were conducted for both the winning and the losing portfolios for each sector. The results are shown in Table 8.

$$W = \frac{(\sum a_i x_i)^2}{\sum(x_i - \overline{x})^2}$$

Formula 8 - Shapiro-Wilk test-observator

Here W is the test observator, a_i is a constant, x_i is the values in my portfolio, and $\bar{x}$ is the mean of my portfolio.

The test rejects the null hypothesis for all portfolios at the 99% confidence level except for industrials (losing), consumer discretionary (winning and losing) and IT (losing). The null hypothesis is therefore rejected for all other portfolios, and this supports that these portfolios comes from a non-normally distributed dataset. It therefore seems to be a relationship between individual momentum returns and industries.

Table 8: P-values from Shapiro-Wilk normality test

This table presents the P-values testing for normality in my dataset. These are computed from the following formula:

$$W = \frac{(\sum a_i x_i)^2}{\sum(x_i - \overline{x})^2}$$

In this test, the null hypothesis is that the data is normally distributed. So if the p-value is lower than the critical p-value, the null hypothesis is rejected. For the 99% confidence level the critical p-value is 0,01.

Portfolios	Energy	Materials	Industrials	C Discretionary	C Staples	Health care	Financials	IT	Telecom	Utilities
Winning	0,004096	0,000182	0,009106	0,090502	0,000000	0,000000	0,000000	0,000196	0,000000	0,000000
Losing	0,000000	0,000011	0,887323	0,149310	0,000000	0,000000	0,000001	0,493068	0,000000	0,000000

If the implications from Table 8 are correct, industries seems to be a factor for which stocks are included in the momentum portfolios. If this is correct, then there should be a clear negative correlation between the industry distribution of the same sector in the winning and losing portfolio. If many stocks within an industry are doing well, and this is partially because of their industry, that industry should be overrepresented in the winning portfolio and underrepresented in the losing portfolio.

Panel A in Table 9 presents the correlations between the industry distribution in the winning and losing portfolio for the individual stock momentum 6-month holding, 6-month ranking strategy. The numbers highlighted with blue is the correlation between the industry distribution in the winning and losing portfolio of the same industry.

The results show that 8/10 industries have negative correlations, and only health care has a significantly positive correlation. Industrials, consumer discretionary, IT and telecom were sectors with insignificant correlations, were the other six sectors showed significance at the 99% confidence level. The implications of this is that once stocks within an industry gets placed in the winning (losing) portfolio, it is less likely for other stocks in the same industry to get placed in the losing (winning) portfolio.

Table 9: Correlation between the winning and losing portfolios industry distribution:

This table shows the results of a correlation test between the industry distribution of the winning and losing portfolios and their significance levels. Panel A show the correlation results. The cells coloured blue is the correlation between the industry distribution in the winning and losing portfolio of the same industry. A negative number here indicates that as a sector goes in the winning portfolio, it is less likely to also be in the losing portfolio. A positive number would mean the opposite, that once a sector is in the winning portfolio, it is more likely to also be in the losing portfolio.

Panel B shows the significance levels with the same cells coloured blue.

Panel A:

Winning | Losing	Energy	Materials	Industrials	C Discretionary	C Staples	Health care	Financials	IT	Telecom	Utilities
Energy	-0,465	0,051	-0,340	0,123	0,360	0,477	0,127	0,278	0,155	0,263
Materials	0,163	-0,303	0,332	-0,187	-0,263	-0,262	0,115	-0,194	-0,117	-0,206
Industrials	-0,266	0,232	0,009	0,056	-0,121	-0,368	0,467	-0,171	-0,088	-0,216
C Discretionary	0,055	-0,006	0,417	-0,012	-0,311	-0,250	-0,047	-0,265	-0,109	0,038
C Staples	0,129	0,058	0,112	-0,318	-0,233	-0,053	0,101	-0,098	-0,054	-0,152
Health care	0,283	-0,080	-0,353	-0,034	0,285	0,150	0,002	0,032	0,015	0,120
Financials	0,344	0,014	0,167	-0,166	-0,141	-0,110	-0,435	0,110	-0,060	-0,251
IT	0,122	-0,154	-0,095	0,270	0,164	0,153	-0,176	-0,039	0,106	0,353
Telecom	0,381	-0,069	-0,223	0,018	0,258	0,265	-0,360	0,086	-0,091	0,255
Utilities	0,151	-0,166	-0,414	0,038	0,243	0,411	-0,207	0,351	0,307	-0,164

Panel B:

	Energy	Materials	Industrials	C Discretionary	C Staples	Health care	Financials	IT	Telecom	Utilities
Energy	0,00000	0,37286	0,00000	0,02957	0,00000	0,00000	0,02503	0,00000	0,00597	0,00000
Materials	0,00398	0,00000	0,00000	0,00091	0,00000	0,00000	0,04187	0,00057	0,03959	0,00024
Industrials	0,00000	0,00004	0,86941	0,32280	0,03311	0,00000	0,00000	0,00245	0,11966	0,00012
C Discretionary	0,33512	0,92187	0,00000	0,83132	0,00000	0,00001	0,40891	0,00000	0,05414	0,50380
C Staples	0,02218	0,30475	0,04750	0,00000	0,00003	0,35389	0,07511	0,08250	0,34338	0,00733
Health care	0,00000	0,15960	0,00000	0,55486	0,00000	0,00797	0,97618	0,57378	0,78909	0,03340
Financials	0,00000	0,80955	0,00307	0,00320	0,01251	0,05151	0,00000	0,05132	0,28676	0,00001
IT	0,03066	0,00626	0,09553	0,00000	0,00371	0,00665	0,00183	0,48851	0,06089	0,00000
Telecom	0,00000	0,22258	0,00007	0,75351	0,00000	0,00000	0,00000	0,13031	0,10816	0,00001
Utilities	0,00759	0,00329	0,00000	0,50133	0,00001	0,00000	0,00023	0,00000	0,00000	0,00365

5 Conclusion:

In this study I look at the momentum effect at Oslo Stock Exchange and the effects industries might have on it. Through testing the market for momentum effects and testing these, I show that that there exists a persistent and significant momentum effect in the Norwegian stock market.

A portfolio with a long position in the best-performing stocks of the last period, financed by a short position in the worst-performing stocks of the same period yields significant excess return. This strategy provided approximately 1,3% average per month, which is in line with other empirical research on the subject.

Even after controlling for the Fama-French risk factor, the returns remains significantly positive. The data showed an approximately identical industry momentum return, which is no coincidence according Moskowitz and Grinblatt (1999).

By following an industry momentum strategy over an individual stock momentum strategy, an investor would yield the same returns, but a higher share would be due to the long portfolios. The individual stock momentum strategy makes most of its return from the shorted portfolio. This could lead to problems with illiquid stocks. By using an industry momentum strategy instead, this problem is reduced, meaning that this might be a more implementable strategy.

The industry momentum returns turns insignificant once it is controlled for individual stock momentum returns, while individual stock momentum returns remains significant when controlling for industry returns. These regressions provide an opposite result compared to Moskowitz and Grinblatt (1999), but still supports the theory that there exists a relationship between individual stock momentum and industry momentum. However, it is hard to establish a causal relationship between the two.

Descriptive statistics show that the industry distribution in the momentum portfolios differs from that of the index. If there were no relationship between industries and momentum returns, the momentum portfolios should have the same industry distribution as the index had. I show that the ten sectors do not follow a normal distribution for the winning and losing portfolios in 16 of 20 cases. This is supportive evidence that the industry of a company could be an important factor behind which companies get included in the momentum portfolios.

In addition, the industry distribution of the same sector is negatively correlated between the long and the short positions. When a stock from a sector is placed in one of the portfolios, stocks from that sector becomes less likely to be in the other portfolio. This further supports the relationship between momentum returns and industries.

The results of my paper show that industries might be an important factor behind momentum returns, but why remains unclear. Since momentum portfolios seems contain stocks partly based on industries, a momentum portfolio would contain many stocks within the same industry, increasing the idiosyncratic volatility. Following behavioural theory this could be due to investors' overconfidence and self-asstribution within certain industries, which exaggerates industries mispricing. It could also be due to investors becoming too optimistic (pessimistic) of industries with a series of good (bad) performances. This could produce momentum returns in the intermediate term and long-run return reversals.

This paper shows that industries might have an important role in understand momentum returns. Even though it is hard to pinpoint what role industries have, it might be an important research area to understand the momentum effect.

6 References:

Arena, Matteo P., K. Stephen Haggard, and Xuemin (Sterling) Yan. "Price Momentum and Idiosyncratic Volatility." *Financial Review The Financial Review* 43.2 (2008): 159-90. Web.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny. "A Model of Investor Sentiment." (1998): n. pag. Web.

Chan, Louis K., Narasimhan Jegadeesh, and Josef Lakonishok. "Momentum Strategies." (1996): n. pag. Web.

Chordia, Tarun, and Lakshmanan Shivakumar. "Momentum, Business Cycle, and Time-varyingExpected Returns." *The Journal of Finance* 57.2 (2002): 985-1019. Web.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam. "Investor Psychology and Security Market Under- and Overreactions." *The Journal of Finance* 53.6 (1998): 1839-885. Web.

Ødegaard, Bernt Arne. "Asset Pricing Data at OSE." *BI Finance*. N.p., n.d. Web. 24 Mar. 2016. <http://finance.bi.no/~bernt/financial_data/ose_asset_pricing_data/index.html>.

Fama, Eugene F., and Kenneth R. French. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33.1 (1993): 3-56. Web.

Fama, Eugene F., and Kenneth R. French. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 47.2 (1992): 427. Web.

Griffin, John M., Susan Ji, and J. Spencer Martin. "Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole." *SSRN Electronic Journal SSRN Journal* (n.d.): n. pag. Web.

Heidari, Mahdi. "Over or Under? Momentum, Idiosyncratic Volatility and Overreaction." *SSRN Electronic Journal SSRN Journal* (2015): n. pag. Web.

Hong, Harrison, and Jeremy C. Stein. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *The Journal of Finance* 54.6 (1999): 2143-184. Web.

Hong, Harrison, Terence Lim, and Jeremy Stein. "Bad News Travels Slowly: Size, Analyst Coverage and the Profitability of Momentum Strategies." (2000): n. pag. Web.

Hung, Szu-Yin Kathy, and John L. Glascock. "Volatilities and Momentum Returns in Real Estate Investment Trusts." *The Journal of Real Estate Finance and Economics J Real Estate Finan Econ* 41.2 (2010): 126-49. Web.

Jegadeesh, Narasimhan, and Sheridan Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *The Journal of Finance* 48.1 (1993): 65. Web.

Jegadeesh, Narasimhan. "Evidence of Predictable Behavior of Security Returns." *The Journal of Finance* 45.3 (1990): 881. Web.

Kloster-Jensen, Christian. "Markedseffisiensteorien Og Momentum På Oslo Børs." N.p., n.d. Web. 2006.

Long, J. Bradford De, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann. "Noise Trader Risk in Financial Markets." *Journal of Political Economy* 98.4 (1990): 703-38. Web.

Mclean, R. David. "Idiosyncratic Risk, Long-Term Reversal, and Momentum." *Journal of Financial and Quantitative Analysis J. Financ. Quant. Anal.* 45.04 (2010): 883-906. Web.

Moskowitz, Tobias J., and Mark Grinblatt. "Do Industries Explain Momentum?" *The Journal of Finance* 54.4 (1999): 1249-290. Web.

Pontiff, Jeffrey. "Costly Arbitrage and the Myth of Idiosyncratic Risk." *Journal of Accounting and Economics* 42.1-2 (2006): 35-52. Web.

Reiserud, Camilla. "Momentum På Oslo Børs – En Analyse Av Momentumeffekten Før Og Etter Finanskrisen." N.p., n.d. Web. 2013.

Rouwenhorst, K. Geert. "International Momentum Strategies." *The Journal of Finance* 53.1 (1998): 267-84. Web.

Stenstad, Kristoffer, and Kristoffer Rabben. "Dispersion in Analysts' Forecasts and Momentum Strategies in the Norwegian Stock Market." N.p., n.d. Web. 2012.

Su, Dongwei. "An Empirical Analysis of Industry Momentum in Chinese Stock Markets." *Emerging Markets Finance and Trade* 47.4 (2011): 4-27. Web.

TITLON. *Https://titlon.uit.no/*. N.p., n.d. Web. 28 Feb. 2016. <https://titlon.uit.no/>.

Ubisch, Sverre Søyland Von. "The 52-Week High as a Reference Point in Trading Behavior." N.p., n.d. Web. 2015.

7 Appendix A: Logarithmic returns

The main reason to use logarithmic over arithmetic returns is that it is easier to use when you have long time series. When computing cumulative arithmetic return for longer periods of time, the formula expands rapidly, making it more difficult to deal with:

$$(1+r_1)(1+r_2)\dots(1+r_n) = \sum(1+r_i)$$

Formula 9 – Cumulative arithmetic return

However, when the time series expands the formula for cumulative logarithmic return remains small and simple:

$$\sum \log(1+r_i) = \log(1+r_1) + \log(1+r_2) + \cdots + \log(1+r_n) = \log(p_n) - \log(p_0)$$

Formula 10 - Cumulative logarithmic return

This greatly reduces the expression, since all you need is the value at the beginning and at the end of the period, and since we can add them up instead of multiplying them.

8 Appendix B: Industry distribution differences between momentum portfolio and OSEs index

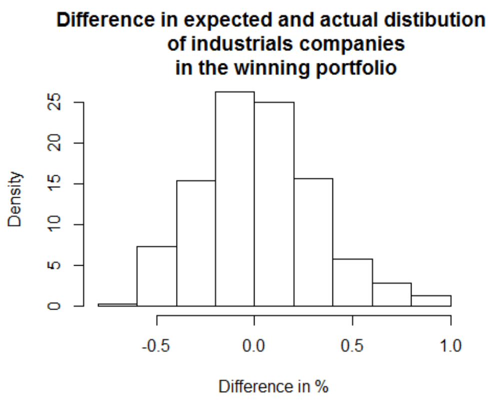
Figure 6: Differences in momentum portfolios and OSEs index industry distribution

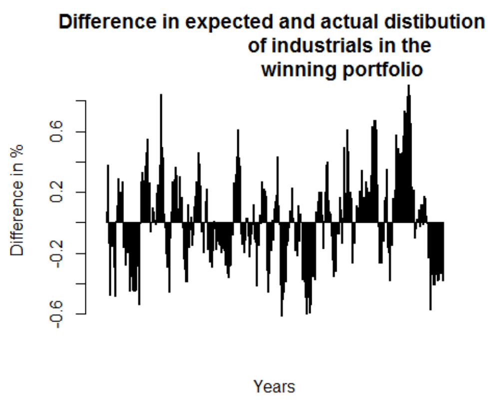
The plots underneath show the differences in the industry distribution in the momentum portfolios and on the index as a whole. A value of -1.0 means that an industry were 100% less represented in the momentum portfolio than on the index – in other words it were excluded from the momentum portfolios. A value of +1.0 means that an industry had twice as many companies in the momentum portfolios as on the index.

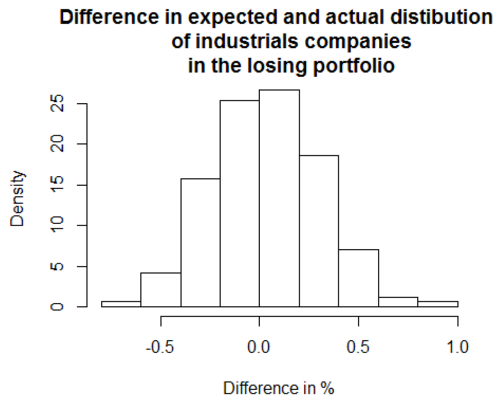
Both plots in each panel show the same information, visualized different. The left one is a histogram showing the frequency distribution of the different values, while the right one is a bar plot showing each months difference in industry distribution. The higher the spikes, the more the momentum portfolios industry distribution deviates from the index industry distribution.

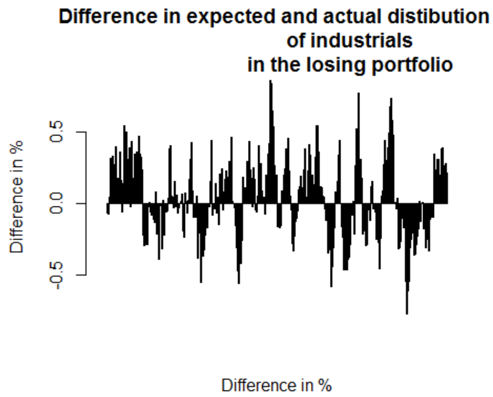
Panel A shows the differences for both the winning and the losing momentum portfolios for the industrial sector, Panel B shows it for the financial sector, Panel C shows it for the IT sector, Panel D for the materials sector, Panel E shows the consumer staples sector, Panel F shows the health care sector and Panel G shows it for the financial sector.

Panel A: Differences in momentum portfolios and OSEs index industry distribution

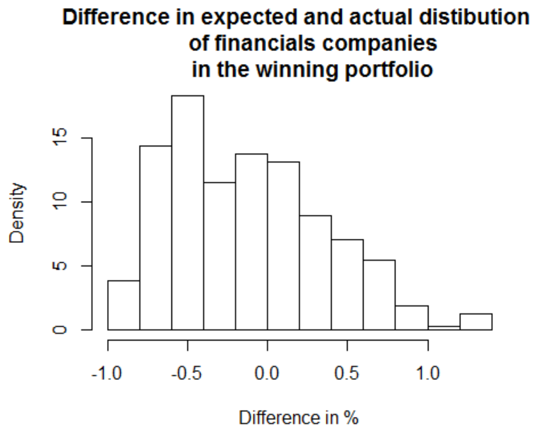


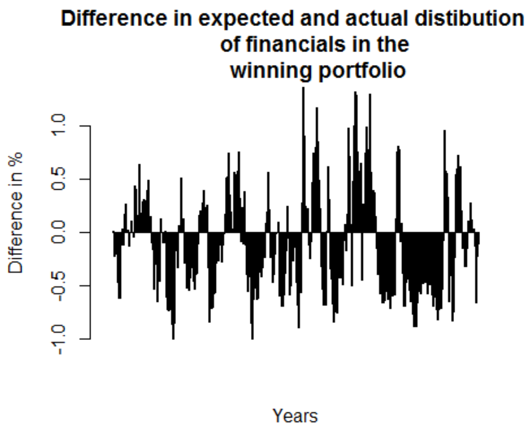


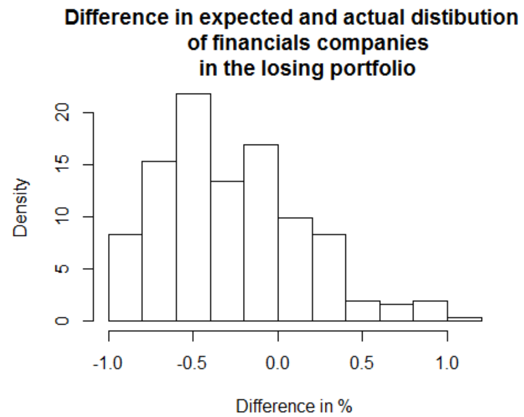


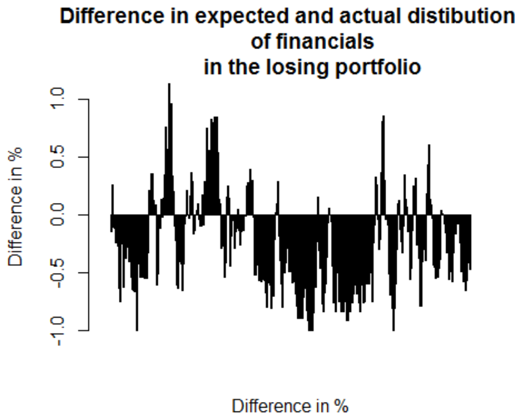


Panel B: Differences in momentum portfolios and OSEs index financial distribution

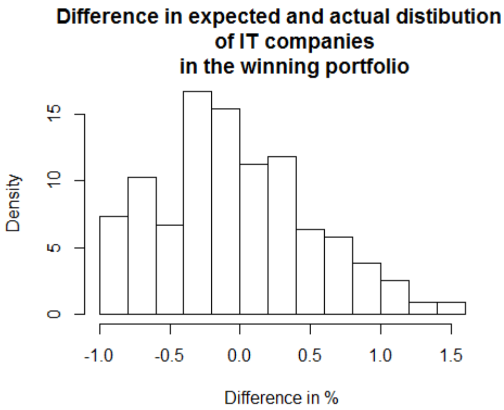


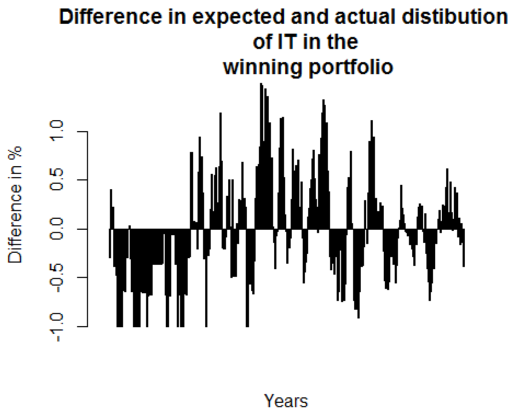


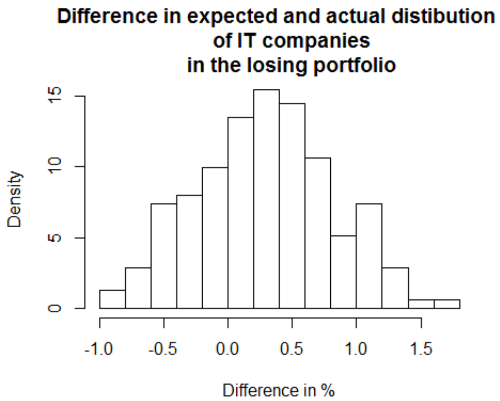


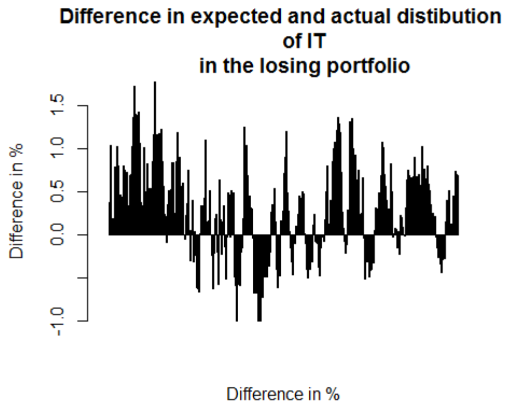


Panel C: Differences in momentum portfolios and OSEs index IT distribution

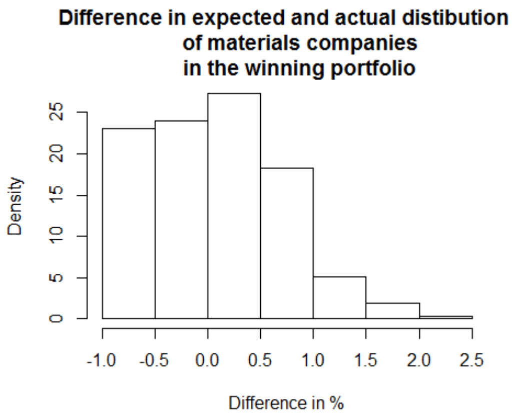


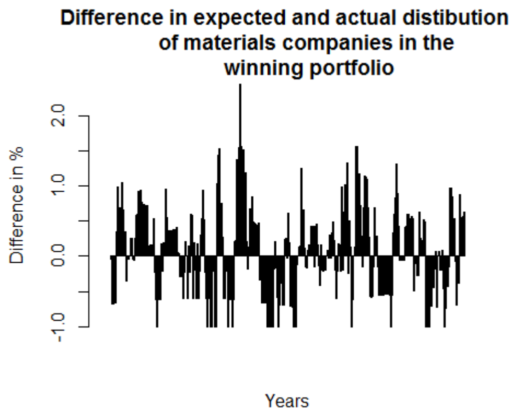


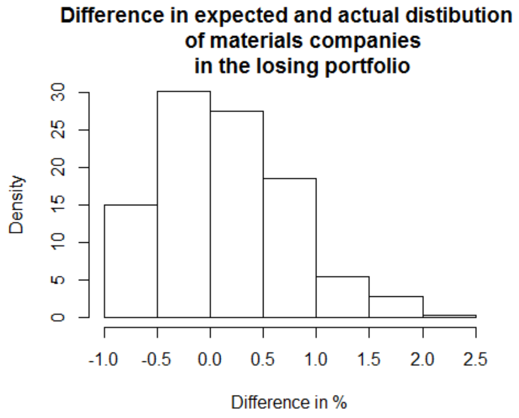


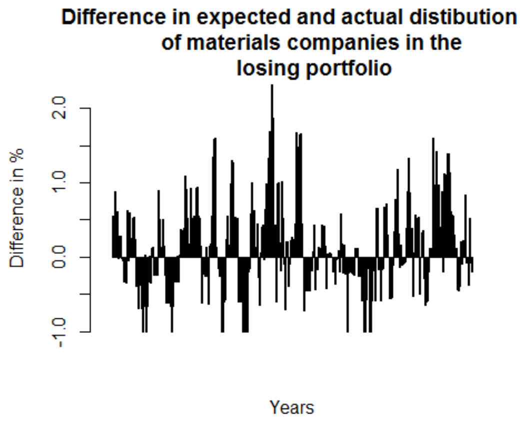


Panel D: Difference in momentum portfolios and OSEs index materials distribution

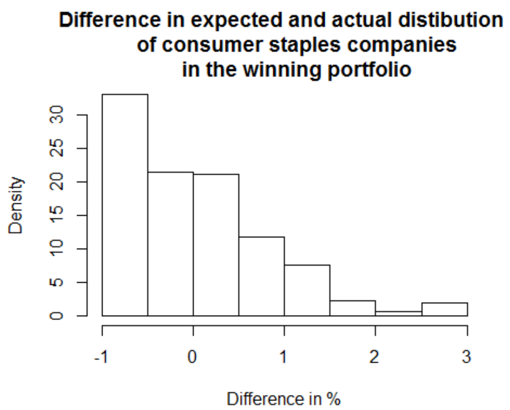


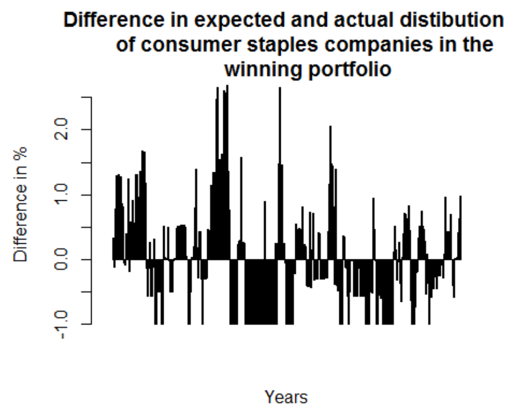


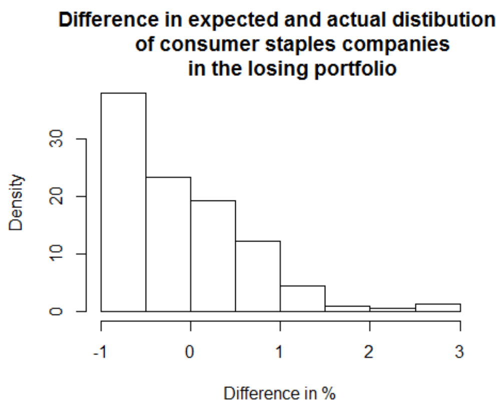


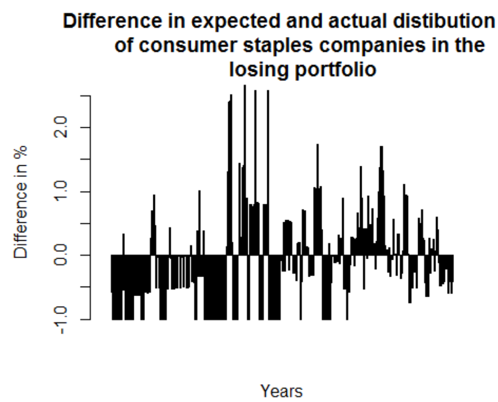


Panel E: Difference in momentum portfolios and OSEs index consumer staples distribution

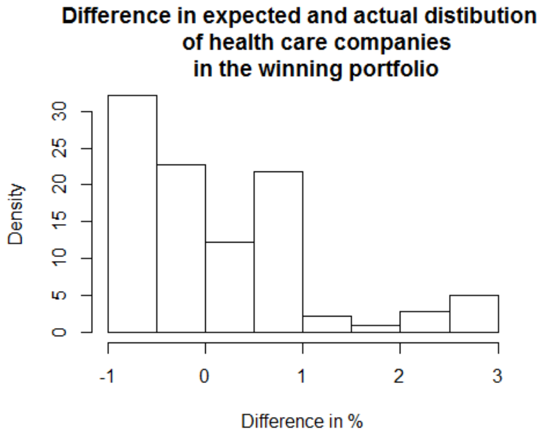


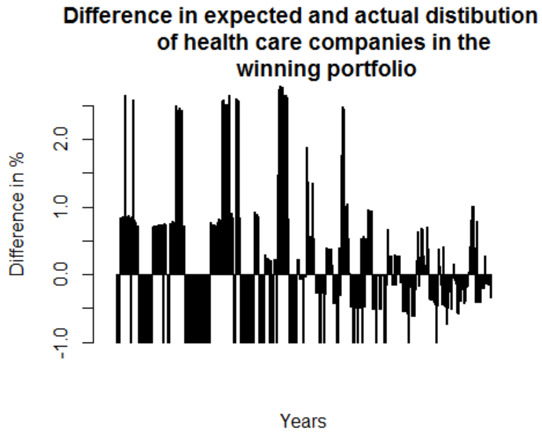


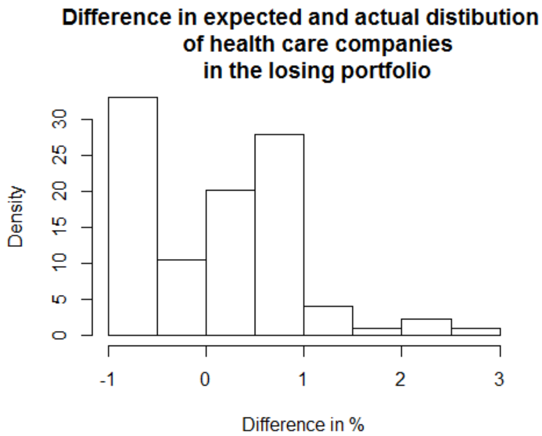


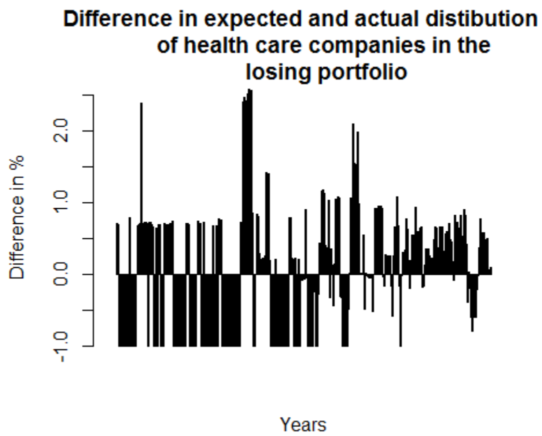


Panel F: Difference in mometum portolios and OSEs index health care distribution

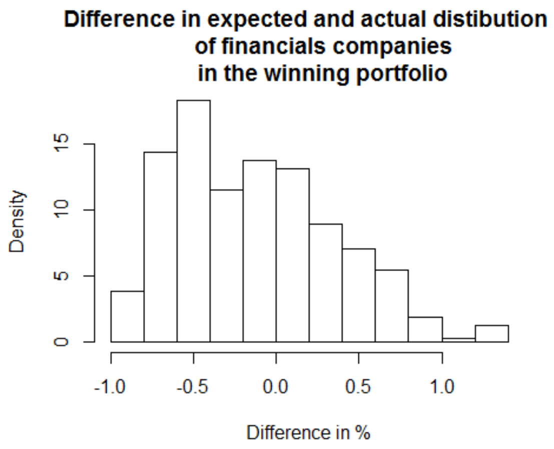


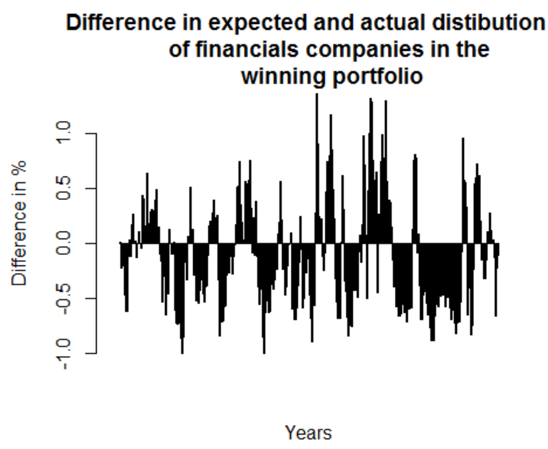


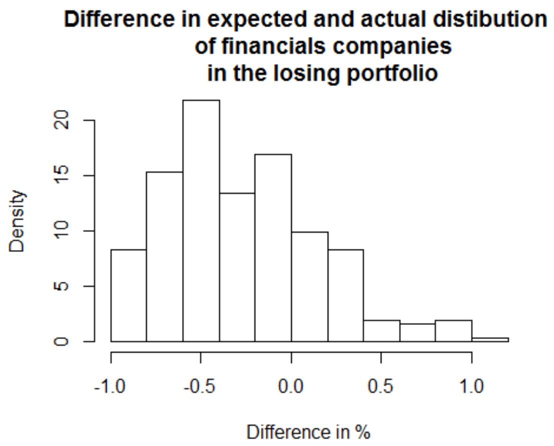




Panel G: Difference in momentum portfolios and OSEs financials distribution


Difference in expected and actual distibution
of financials companies
in the winning portfolio
Density
0
5
10
15
-1.0
-0.5
0.0
0.5
1.0
Difference in %


Difference in expected and actual distibution
of financials companies in the
winning portfolio
Difference in %
-1.0
-0.5
0.0
0.5
1.0
Years


Difference in expected and actual distibution
of financials companies
in the losing portfolio
Density
0
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10
15
20
-1.0
-0.5
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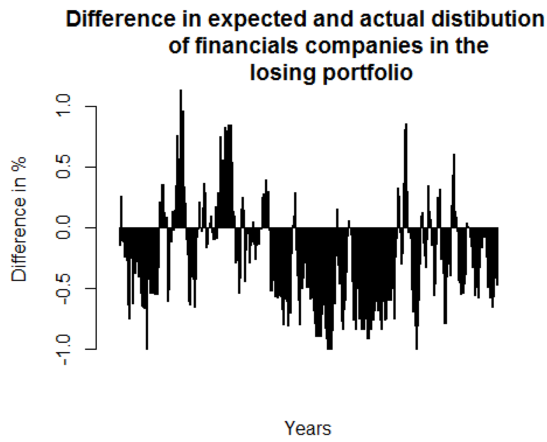
0.5
1.0
Difference in %


Difference in expected and actual distibution
of financials companies in the
losing portfolio
Difference in %
-1.0
-0.5
0.0
0.5
1.0
Years

9 Appendix C: Momentum returns before and after the effect were documented

Table 10: Momentum returns before and after the effects were documented

The table underneath shows the momentum and industry momentum returns on OSE before and after the effects were documented. The underneath figures is based on a dataset from OSE from 1985-2010. The mean is the average monthly return of following a 6-month ranking and holding (industry) momentum strategy. The standard deviation is the monthly standard deviation and the min and max columns show the highest and lowest returns achieved during one month.

Panel A show the figures for the individual stock momentum strategy. This effect were first documented in 1993, and the table shows that the momentum returns were approximately equal before and after its discovery.

Panel B show the figures for the industry momentum strategy. This was first documented in 1999, and the table show that the momentum returns are slightly lower after 1999, but that the effect have been persistent even after its discovery.

Panel A: Momentum returns before and after 1993

Momentum returns	N	Mean	St. Dev	Min	Max
Before 1993	96	0.01268	0.024	-0.053	0.069
After 1993	216	0.01333	0.026	-0.045	0.131

Panel B: Industry momentum returns before and after 1999

Industry momentum returns	N	Mean	St. Dev	Min	Max
Before 1999	168	0.015	0.037	-0.113	0.144
After 1999	144	0.010	0.048	-0.127	0.223