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Anchor and Adjust

An inquiry into the 52-Week High and Momentum Investing on the Oslo Stock Exchange in the period 1990 - 2019

Erik Holst & Kristian Vadla Sletten

Supervisor: Jørgen Haug

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Abstract

The phenomenon that stocks with relatively high (low) returns in recent months continue to exhibit relatively high (low) returns in the following months – commonly referred to as momentum - is one of the greatest puzzles within the field of empirical asset pricing. We demonstrate that momentum has been present on the Oslo Stock Exchange over the period 1990 through 2019. And by replicating the focal parts of the paper *The 52-Week High and Momentum Investing* by George & Hwang we show that stocks with a high (low) price level, measured as nearness to their 52-week high price, are associated with high (low) future returns. We further demonstrate that this measure is less dependent on past returns than past returns are on this measure to predict future returns. We thus conclude that price level is a more important determinant of momentum effects than are past price changes in our Norwegian stock sample.

Preface

This thesis is written as the final part of the Master of Science in Economics and Business Administration at NHH – Norwegian School of Economics. Writing this paper has been both challenging and rewarding, two words that accurately describes the programme at NHH in its entirety.

Our thesis sheds new light on stock market anomalies on the Oslo Stock Exchange and we believe it will be of interest for both future research and market practitioners.

We thank our supervisor Jørgen Haug for his useful comments as well as for excellent teaching in previous semesters.

Lastly, we thank our significant others for bearing with us during times of frustration in the process of developing this paper.

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1 Introduction

Momentum within finance refers to a continuation in stock returns, which stands in contrast to the efficient market hypothesis proposed by Fama (1970) as its presence suggests that stock returns are serial-correlated. Since the focal momentum paper of Jegadeesh & Titman[1] were published in 1993 there has been an abundance of research documenting the effect across international markets, time periods and asset classes. Consequently, the early notions that the anomaly is a result of data snooping is well disregarded.

It is generally accepted in the scientific community that momentum trading strategies deliver anomalous returns on paper. The central postulations underpinning the existence of momentum is that individuals tend to underreact and overreact to news, and as such, stock prices move gradually towards and beyond its fair price while the efficient market hypothesis would suggest an immediate jump to the fair price. There is no clear consensus in literature exactly which biases individuals suffer from. Early research suggested that individuals suffer from anchoring biases and are reluctant to bid a stock with a high (low) price relative to its historical prices further beyond the current price. George & Hwang (2004) thus hypothesised that, if individuals suffer from anchoring biases, current price level of stocks relative to their price history should perform better in explaining momentum, which they found to be true on their US stock sample. The authors measured the price level of a stock relative to its history as nearness to its highest price observed over the prior year. As such, stocks near or at (far from) its 52-week high were presumed to have a high (low) price level. Given their findings, they argued that price level is a more important determinant of momentum effects than are past price changes and anchoring biases appeared to be the most likely explanation for momentum in their sample.

With regards to the Norwegian market, Absalonsen & Vas (2014) demonstrate that momentum has been present, while Von Ubisch (2015) show that there is a relation between nearness to the 52-week high and future returns. With this thesis, we aim to conduct similar analyses before we extend on it by examining whether price level is a more important determinant of momentum effects compared to past returns. Formally, we define the following three hypotheses that will be tested in this thesis; (I) Momentum is present on the Oslo Stock Exchange, (II) there is a relation between nearness to the 52-week high and future stock returns, and (III) price level is a more

[1] According to Ang (2014) momentum appeared in the literature with Levy (1967) but was largely ignored until the work of Jegadeesh & Titman (1993).

important determinant of momentum effects than are past price changes. The Norwegian stock sample used to answer these hypotheses extend from 1990 trough 2019.

We test **(I) whether momentum is present on the Oslo Stock Exchange** by back testing the relative strength strategy of Jegadeesh & Titman (1993). Each month stocks are sorted in a descending order according to their return over recent months. We buy the top 30% and sell the bottom 30% to construct a self-financing position which are to be held in subsequent months following the formation date. We demonstrate that following this strategy is highly profitable in our stock sample and by regressing its returns against common factors we obtain large and statistically significant abnormal returns, and thus infer that momentum has been present on the Oslo Stock Exchange in the period 1990 trough 2019.

By back testing the 52-week high strategy proposed by George & Hwang (2004) we test **(II) whether there is a relation between nearness to the 52-week high and future returns.** Each month stocks are sorted in a descending order according to a sort variable computed as the current price for stock i divided by the highest price for stock i observed over the prior year. We construct a self-financing portfolio by buying the top 30% and selling the bottom 30%. The profits to this strategy are large, statistically significant and anomalous relative to common factors. We conclude that there is a relation between price level and future returns. In other words, stocks with relatively high (low) prices compared to its own price history exhibit relatively higher (lower) returns in the months following the portfolio formation date.

We explore **(III) whether price level is a more important determinant of momentum effects compared to past returns** by following the methodology in George & Hwang (2004). In short, this methodology involves conducting a Fama & MacBeth (1973) style cross-sectional regression analysis allowing us to assess the abnormal returns to the strategies while controlling for the other strategy. We demonstrate that abnormal returns are substantially larger and more statistically significant to the 52-week high strategy compared to the relative strength strategy after controlling for the other strategy. Our results suggest that the relative strength strategy are more dependent on extreme price levels than the 52-week high strategy are on extreme past returns to generate abnormal returns. Thus, consistent with George & Hwang (2004) we conclude that price level is a more important determinant of momentum effects compared to past price changes.

Personally, we find momentum to be an intriguing topic. Financial newspapers and websites constantly publish the company names of stocks that have performed best and worst in recent times, as well as stocks that hit their 52-week highs and lows. If the market does not react rational to such information this provide the potential to gain anomalous returns for enlightened investors. We believe that our study provides valuable empirical information on the attractiveness of momentum as a factor for any investor considering tilting their portfolios towards such factor exposure. In addition, we deem it important to provide an additional out-of-sample robustness test of the focal results presented in George & Hwang (2004) to further generalize their findings.

The rest of this thesis is structured as follows. Section 2 provides a review of the momentum papers we find to be most relevant and inherently presents relevant theory. Section 3 describes our data and the adjustments made to the data prior to the analyses. Section 4 presents our empirical methodology, and section 5 presents the results from testing the hypotheses. In section 6 we discuss some of the most apparent limitations of this paper and we provide suggestions for further research. Section 7 concludes the thesis.

2 Theory and Literature Review

The purpose of this section is to provide an overview of momentum literature as well as to gain a better understanding of momentum. In section 2.1 we explain more thoroughly what is meant by momentum, with focus on the paper of Jegadeesh & Titman (1993). Section 2.2 elaborate on the proposed explanations for momentum which appears to be those with most support in newer literature. We also conduct a brief review of relevant asset pricing theory. Lastly, section 2.3 presents the paper of George & Hwang (2004).

2.1 Momentum

Momentum is often referred to as the phenomenon that winner stocks continue to win and loser stocks continue to lose. More precisely, stocks with high (low) returns relative to other stocks continue to display relatively high (low) returns. Jegadeesh & Titman (1993, Jegadeesh & Titman hereafter) were first to show this on a US stock sample in the paper "*Returns to buying winners and selling losers*". They demonstrated that a zero-cost portfolio constructed each month by buying (selling) stocks with the best (worst) performance over intermediate look back periods[2] (3 to 12 months), and holds this position over intermediate holding periods (3 to 12 months) were a highly profitable strategy on their US stock sample covering the period 1965 to 1989. When the profits remained unexplained by the capital asset pricing model the authors argued that the effect is anomalous and occurs because of a continuation in stock returns. Their main argument for why it occurred were that security prices underreacted to good (bad) news, and as such, the prices converge only gradually towards it fair price.

Since the publication of the paper of Jegadessh & Titman there has been a growing body of literature documenting the effect across countries and asset classes. Rouwenhorst (1998) documented statistically significant abnormal returns to the strategy in 11 out of 12 European countries in the period 1980 to 1995, including Norway. Fama & French (2012) provide more evidence of momentum in international markets by studying data from 23 countries across four regions. Momentum were present in all countries with exception of Japan. Asness, Moskowitz & Pedersen (2013) conduct a comprehensive study on momentum across markets and asset classes. The authors documented consistent momentum profits in all studied markets with regards to

[2] Commonly referred to as the formation period.

both equities and government bonds. As such, the anomaly is persistent and as put nicely by Fama & French (2008); "*The premier anomaly is momentum […]*".

The Efficient Market Hyphotesis

The persistence of momentum challenges the very core of the efficient market hypothesis (EMH hereafter). At its weakest form, the EMH simply states that stock prices reflect all information that can be derived by examining market trading data such as the history of past prices and hence past returns. Technical analysis should be fruitless (Bodie, Kane & Marcus, 2018). Damodaran (2015) provide an intuitive explanation of EMH from an alternative angle. If markets are efficient then the market price is the best estimate of true value. This does not imply that the market price is true at every point in time, all it requires is that errors in the market price are unbiased. Specifically, deviations from the true price are random and uncorrelated with any observable variable. As such, if deviations from the true price are random no group of investors should be able to consistently find over – or undervalued stocks using any investment strategy, which stands in clear contrast to the persistence of momentum.

Time-Series Momentum

It is important to distinguish the type of momentum discussed in this paper from time-series momentum. Jegadeesh & Titman referred to their strategy as a "relative strength" trading strategy. The strategy will select the stocks that have performed relatively best (worst) compared to every other stock in the cross-section, which by definition is stocks with relative strength (weakness) compared to the rest of the stocks in the market. Thus, it is a cross-sectional momentum strategy. On the other hand, the time-series momentum strategy proposed by Moskowitz, Ooi & Pedersen (2012) will look at a stock and buy (sell) the stock if it has performed relatively well (poorly) compared to its own return history. It is intuitive that these two-alternative momentum concepts are closely related and the existence of cross-sectional momentum implies the existence of time-series momentum as defined by Moskowitz et al. (2012), and vice-versa. From a practical investment – and empirical testing point of view, however, the strategies are vastly different.

2.2 Explanations of Momentum

Proposed explanations for the persistence of momentum broadly falls into two categories, rational or irrational explanations. The explanations can be rational and consistent with EMH in the sense that it is compensation for risk or that there exist some limits to arbitrage making it risky and/or costly to arbitrage away mispricing in the market. It should initially be noted that is not obvious how limits to arbitrage relates to EMH. On the contrary, irrational, behavioural based explanations for momentum suggests that there exist hard-wired behavioural biases among investors preventing them from making rational choices leading to momentum.

2.2.1 Risk

In the following we elaborate on the risk based explanations of momentum. We first conduct a brief review on relevant factor theory[3] before we discuss how this theory can be related to momentum.

Factor Theory

The volatility of an asset can be decomposed into an idiosyncratic part, which describe price changes that occur because of firm specific news, and a systematic part, which refers to price changes that occur because of events that affect the aggregate market. Modern asset pricing theory largely builds around the postulation that because idiosyncratic risk is diversifiable, the only relevant risk for an investor in the pricing of assets is systematic risk. Different assets have different exposure to systematic risk, however, and investors will obtain their required return by discounting the expected future value of an asset´s cash flow at a rate determined by the risk of the cash flow as determined by systematic risk. Put simply, expected return $E(r_i)$ for a portfolio or an asset i can in theory be determined by the risk-free rate rf in addition to the risk-premium determined by the asset´s exposure to systematic risk;

$$E(r_i) = rf + B_{i,1}E(f_1) + B_{i,2}E(f_2) + \ \dots + B_{i,K}E(f_K)$$

where $B_{i,k}$ is the beta or sensitivity of asset i with respect to factor k and $E(f_k)$ is the expected risk premium of factor k. The capital asset pricing model (CAPM hereafter) developed collectively by Sharpe (1964), Lintner (1965) and Mossin (1966) assume that the only factor is the market factor;

$$E(r_i) = rf + B_i(E(r_m) - rf)$$

where $(E(r_m) - rf)$ denotes the expected return of the market portfolio $E(r_m)$ in excess of the risk-free rate rf. In other words, the expected risk premium of the market portfolio. CAPM

[3] The general factor theory presented here is based on Ang (2014).

defines bad times as times when the overall stock market performs poorly and if an asset i performs worse relative to the market in bad times $B_i > 1$ investors will be compensated with higher returns than the market over the long run.

There is a strong theoretical foundation underlying CAPM, though empirics demonstrate that it is insufficient to explain variability in returns in the cross-section motivating the work of Ross (1976) to extend on CAPM by including additional factors[4]. However, once extending on CAPM it is not obvious which factors f_K to include and why these factors should represent systematic risk. Relevant factors are often determined by empirical observations[5]. Banz (1981) demonstrated that small firms provide higher risk adjusted returns than large firms over the long run. This anomaly is usually referred to as the size factor. The inclusion of the size factor in factor models comes from the notion that small firms perform worse than large firms in bad times as these firms are, in short, more sensitive to market conditions and perform worse during bad times. Fama & French (1993) found that stocks with high book-to-market (value stocks) outperforms stocks with low book-to-market (growth stocks), typically referred to as the value factor. Ang (2014) explain that stocks with high book-to-market are riskier because during bad times they are burdened with unproductive capital. They wish to cut back in capital but cannot sell their specialized manufacturing equipment. They have high adjustment costs. Stocks with low book-to-market on the other hand can easily divest because a great bulk of their capital is human capital. Hence, value stocks provide higher premiums as they are fundamentally riskier compared to growth stocks. They perform worse during bad times.

It is well documented that "common" factors such as the previously mentioned market, size and value factors are, for the most part, unable to fully explain returns to momentum zero-cost portfolios from previously conducted research which, by definition, makes momentum a phenomenon (Fama & French, 2008). However, there is a plethora of research attempting to identify some omitted factors, that may represent priced risk, to partially or fully explain the existence of momentum. In the following we describe the research which appears to be that with most support in recent literature.

[4] Once extended on CAPM the factor models are typically referred to as multifactor models within the field of arbitrage pricing theory (APT). It is worth noting that CAPM builds on an equilibrium assumption, while multifactor models build on a non-arbitrage assumption. Ross (1976) is the seminal paper on multifactor models. We find a thorough derivation of the assumptions underlying CAPM and multifactor models to be outside the scope of this paper.

[5] Carhart (1997) proposed the inclusion of a momentum factor to test funds loading on momentum.

Business Cycle Risk

Researchers postulate that momentum persists because of business cycle risk. By using a conditional factor model including macroeconomic variables Chordia & Shivakumar (2002) showed on their US stock sample that momentum abnormal returns are eradicated once controlled for these factors. The authors argued that momentum payoffs are attributable to cross-sectional differences in expected returns that vary over time. They concluded that this raises the bar for the behavioural based explanations of momentum making the reasonable assumption that these macro factors represent priced risk.

By replicating the methodology of Chordia & Shivakumar (2002) in international markets, Griffin, Ji & Martin (2003) demonstrate that their conclusions only hold true within the US but generally not in other markets. Moreover, the authors implemented an unconditional factor model by including the variables unexpected inflation, changes in expected inflation, term spread and changes in industrial production, and found that these factors were unable to explain momentum profits internationally and in the US. The authors argued that their findings do not support the view that momentum profits are compensation for investors holding portfolios with high business cycle risk. In a more recent study covering the period 1972 to 2011 on the US market by Asness et al. (2013), modest links are found between momentum and macroeconomic variables such as the business cycle, consumption and default risk.

Systematic Crash Risk

Systematic crash risk is also closely related to the business cycle. Daniel & Moskowitz (2016) demonstrated that momentum strategies "crash" following times of market stress and high volatility. Grundy & Martin (2001) showed that this occurs because when the market has fallen significantly over the formation period, stocks that performed relatively well will be low (market) beta stocks, and stocks that performed relatively poorly will be high beta stocks. Hence, the portfolio of winners (losers) will consist of low (high) beta stocks following a trough. When the market rebounds relatively quickly a momentum strategy will crash as losers outperforms the winners because of the difference market betas between the long – and short portfolio. Similarly, Barroso & Santa-Clara (2015) demonstrate that returns from momentum strategies display large negative skewness and excess kurtosis, and recent literature suggest that investors dislike lower tail sensitive assets (Kelly & Jiang, 2014). With this backdrop, Ruenzi & Weigert (2018) included a crash factor in unconditional factor models. In short, the crash factor was constructed to be a zero-cost portfolio with a long (short) position in stocks with high (low) crash sensitivity. By augmenting standard factor models with this crash factor the abnormal returns to US and international momentum zero-cost portfolios were significantly reduced. The authors thus argued that at least a substantial part of momentum profits represent a risk premium for its exposure to systematic crash risk.

2.2.2 Behavioural

Research suggests that momentum persists because individuals do not correctly incorporate information. The most common theories with regards to the behavioural aspect is that investors tend to underreact or overreact, or both underreact and overreact to information. Following the the paper of Jegadeesh & Titman economists developed behavioural models to explore the relation between investor psychology, security markets and momentum. The models build on some assumptions and the authors show that the models are able to generate momentum patterns in returns. The dominant papers are that of Barberis, Schleifer & Vishny (1998), Daniel, Hirshleifer & Subrahmanyam (1998), Hong & Stein (1999) and Hong, Lim & Stein (2000). It should be noted that there is no clear consensus in existing literature exactly which psychological behavioural biases are dominant in causing momentum.

The idea behind how momentum can be attributed to behavioural biases can initially be explained by a two-periodic framework. At time t good (bad) news arrive and the stock price increase (decrease), but not sufficiently high to justify the fundamental news because the market underreacts to the news. At time $t + 1$ the market corrects their priors, which is consistent with profits to momentum strategies as it buys (sells) stocks with highest (lowest) returns in recent months, for which it is reasonable to postulate should be stocks for firms where good (bad) news has recently arrived. Moreover, Jegadeesh & Titman and a range of other studies demonstrate that momentum profits reverse over the long run. In other words, the zero-cost momentum portfolio yield negative returns when exceeding intermediate holding periods. This is consistent with the overreaction hypothesis, that when the market corrects their initial underreaction they overreact, yielding additional profits to momentum strategies over the intermediate-term. This overreaction causes stock prices to revert towards its fair price over the long run.

In Barberis et.al´s model (1998) investors underreact to news because of *conservatism*, meaning that individuals are slow to change their beliefs in the face of new evidence. They overreact because they suffer from *representativeness*. Representativeness heuristic is used when making judgement about the probability of an event under uncertainty. Investors assume the probability of a stock going in a certain direction by judging it relative to its performance in the past. They assume that stocks for companies that have performed well (poorly) will continue to perform well (poorly).

Hong & Stein (1999) demonstrate in their model that an underreaction in security prices can occur if private information travel slowly among investors. In other words, their model relies on "bounded rational" investors who have limited information (Ang, 2014). Hong et.al (2000) thus postulated that stocks with slower information diffusion should exhibit stronger momentum, which they tested by performing sorts on size following the hypothesis that news for small stocks gets out more slowly. Indeed, they found that small stocks exhibit stronger momentum. The authors further made the reasonable postulation that private news should travel slowly among stocks with low analyst coverage. They controlled for size as this is likely to be correlated with the degree of analyst coverage, and demonstrated that stocks with low analyst coverage display stronger momentum.

In Daniel et.al´s (1998) model momentum occurs because investors overreact to news. They are *overconfident* and overestimate their ability to forecast firms´ future cash flows. Investors also suffer from *self-attribution*. They attribute successes to their own skill and failures to bad luck. These investors observe positive signals on some stocks which confirms their initial view, and they attribute it to their own skill, leading to overconfidence. Based on increased overconfidence they overreact and push up the prices.

Another important phenomenon that can explain an underreaction with regards to momentum is the *disposition effect* proposed by Grinblatt & Han (2005). The disposition effect states that individuals are risk averse in the domain of gains and risk loving in the domain of losses. Investors will hold on to their losing stocks for too long and not sell to realize their losses. Hence, there is not enough sell pressure to immediately move the stock price down to its fair price implying an underreaction. On the other hand, a lack of buy pressure occurs because investors will tend to sell their winning stocks too early to realize their gains.

George & Hwang builds their 52-week high paper upon the theory that investors exhibit anchoring biases. Investors are reluctant to bid a stock price that is high (low) even higher (lower). George & Hwang thus argues that if momentum is largely driven by anchoring biases price levels should perform better in explaining momentum, which is discussed further in section 2.3.

Herding refers to the phenomenon that individuals tend to follow the trend or the "herd". More specifically, investors tend to copy the behaviour of other investors (Bikhchandani & Sharma, 2000). In an early paper by Nofsinger & Sias (1999) it is argued that overreactions can occur because of herding if a sufficiently high number of investors tilt their portfolios towards a given stock or industry.

2.2.3 Limits to Arbitrage

EMH suggests that in the event of mispricing arbitrageurs will immediately ensure that the price moves to its fair price. The textbook definition of arbitrage involves a costless investment that generates riskless profits (Bodie et al., 2018). It is obvious that an investment in the stock market is rarely risk-free as well as costless. However, if we define that an arbitrage opportunity arises with mispricing, then the limits to arbitrage concept can help gain intuition as to why momentum is persistent. Korajczyk & Sadka (2004) explain that, while limits to arbitrage do not explain the underlying causes for the existence of seemingly profitable momentum strategies, they may be sufficient for their persistence.

Noise Trader Risk

Gray & Vogel (2016) use the existence of *noise trader risk* as an argument for the persistence of momentum. Noise traders trade frequently, and they trade on intuition and gut rather than fundamentals. Gray & Vogel (2016) explain that this causes stock prices to move around a lot more than they should, making it risky for investors to exploit “arbitrage” opportunities. De Long, Schelifer, Summers & Waldmann (1990) show that arbitrageurs will reduce their investment in a mispriced security in the presence of noise trader risk. The authors argue that arbitrage trading will be reduced if the arbitrageurs are risk-averse or invest for clients.

Relative Performance Measures

Gray & Vogel (2016) note that many investment professionals are evaluated over the short-term, and they are evaluated based on relative performance measures such as the information ratio;

$$Information\ Ratio = \frac{Return - Benchmark\ Return}{Tracking\ Error}$$

Where *return* is the obtained return for the portfolio and *benchmark return* is the return of the benchmark the professional is evaluated against. *Tracking error* is the standard deviation in the return difference between the portfolio and the benchmark. In short, allocations to what is perceived to be mispriced assets may have a severe impact on short-term tracking error if these positions are volatile, which may be undesirable for those who the professional is hired on behalf of, even though tracking error would decrease and abnormal returns increase over the long run.

Transaction Costs

Some researchers argue that momentum persists because of transaction costs. There is also a link to liquidity. First, large allocations towards illiquid stocks is infeasible and additionally comes with larger transaction costs making it unattractive for an arbitrageur. High transaction costs are especially true for the short side of the trades as there generally is an asymmetric relationship between the cost of buying – and short selling stocks. Moreover, there may be short selling constraints preventing investors from initialising short positions (Korajczyk & Sadka, 2004). Hence, these market frictions may be a contributing factor as to why arbitrageurs choose to not - or are unable to eradicate the existence of momentum. Following this logic, the momentum profits documented in literature may largely be "paper profits", though this does not contribute to explain why there should be a predictable pattern with regards to stock prices and returns (Grundy & Martin, 2001). It should ultimately be mentioned that research suggest momentum profits persists after accounting for transaction costs (Asness et al., 2013).

2.3 The 52-Week High

2.3.1 The Paper of George & Hwang (2004)

In this thesis, we ultimately test whether price level is a more important determinant of momentum effects compared to past price changes. The paper, which we base our methodology on, *The 52-Week High and Momentum Investing* by George & Hwang (2004, George & Hwang hereafter) found that nearness to the 52-week high dominates and improves upon the forecasting power of past returns for future returns. Their study is conducted on the US market with data from 1963 to 2001. The authors develop what they refer to as a "52-week high strategy" that, each month, buy (sell) stocks that are close to (far from) their highest price observed over the prior year, and holds the portfolios over intermediate holding periods (3 to 12 months). As such, the strategy is similar to the relative strength strategy of Jegadeesh & Titman, though it defines "relative strength" in a different manner.

It should be noted that George & Hwang compare the performance of three alternative momentum strategies in their paper. The relative strength strategy of Jegadeesh & Titman, their proposed 52-week high strategy and additionally, the industrial momentum strategy of Moskowitz

& Grinblatt (1999). The industrial momentum strategy select in each month stocks from the industries that have delivered highest and lowest returns in recent months. In short, Moskowitz & Grinblatt (1999) found that the relative strength strategy was significantly less profitable once controlled for industrial momentum. The authors argued that industry momentum is the source of much of individual stock momentum, in the sense that much of its profits arise either from industry related risk or behavioural biases such as underreactions to industry specific information. Due to unsatisfactory industry data on OSE industrial momentum is largely omitted from this thesis[6]. We thus focus our discussions on individual stock – and 52-week high momentum in the following.

George & Hwang demonstrate that selecting stocks on nearness to the 52-week high is more profitable compared to selecting stocks on past returns. They formally compare the performance of the two sort variables in a regression where they control for the other measure allowing them to estimate returns to what they refer to as "pure" relative strength - and 52-week high portfolios. Their results illustrate that much of individual stock momentum can be explained by stocks that are close to (far from) its 52-week high, and that returns to the 52-week high are larger and more statistically significant. The authors thus argue that the 52-week high measure is superior in forecasting future returns, and they further argued that price level is a more important determinant of momentum effects than are past price changes.

2.3.2 The Anchoring and Adjustment Bias

George & Hwang proposed the explanation for the superiority of the 52-week high measure that investors are reluctant to buy (sell) stocks where the price is perceived to be high (low) even when the fundamentals of the given firm warrants it. When the information prevails, the price moves up (down) resulting in a momentum-like effect Essentially, the weird feeling of buying (selling) when the chart is at a peak (low) prevents stocks from reaching fundamentals (Gray & Vogel, 2016). George & Hwang explained that this is consistent with the "anchoring and adjustment bias" documented by Kahneman, Slovic & Tversky (1982). This bias suggest that individuals use a focal point (anchor) as a reference or starting point. In our case, investors compare the current price to previous price levels – the anchor - and conclude that the price is too high (low) even though the fundamentals of the given firm do not support this view, and they thus initially underreact to information.

[6] This is discussed further in section 6.

2.3.3 Alternative Literature

Since the publication of the paper of George & Hwang a growing body of literature has adopted their approach across several markets. Marshall & Cahan (2005) provide the first out-of-sample test on the Australian stock market and found the 52-week high strategy to outperform the relative strength strategy. Du (2008) arrive at the same conclusion on international stock indices. On the contrary, Bornholt & Malin (2011) found the relative strength strategy to outperform the 52-week high strategy in developed and emerging markets, moreover, the 52-week high strategy were not profitable in emerging markets. Liu, Liu & Ma (2011) conducts a comprehensive study on the topic across 20 markets in different countries, including Norway. The strategy was profitable in 18 out of the 20 markets, but only statistically significant in 10. With regards to Norway, the strategy was profitable but statistically insignificant on their stock sample from 1982 to 2006. Generally, the authors found no clear evidence that one strategy dominated the other when evaluating all markets in conjunction.

3 Data

This section presents the data we have collected and describes the adjustments made to the data prior to the analysis.

3.1 Stock Sample

Our stock sample is retrieved from *Børsprosjektet* which is a website containing financial market data related to Norwegian markets, available for students at NHH[7]. We initially impose two data filters. The stock sample contain information on stocks listed at both Oslo Axess and the Oslo Stock Exchange. We limit our analyses to stocks listed on the Oslo Stock Exchange (OSE hereafter) and hence remove stocks listed at Oslo Axess. Moreover, we limit our analyses to ordinary shares which in *Børsprosjektet* is associated with the tickers "Ordinary Shares" and "A Shares". There is a negligible amount of "B Shares" and because there is ambiguity to whether or not B shares can be considered to be ordinary shares, we choose to exclude them from the analysis. After imposing these initial filters our dataset contain information on 639 unique stocks that have been listed on the exchange over a thirty-year period from and including January 1990 through December 2019.

We download both monthly and daily data. From the monthly data, we utilise the following variables in this paper; stock prices (*Last*), stock prices adjusted for stock splits and dividends (*AdjLast*) and the number of shares issued (*SharesIssued*). Each observation in the dataset is associated with a ticker (*SecurityId*) which is unique for each stock, and this variable thus links information to the stock that it belongs to. Further, *Last* is multiplied with *SharesIssued* to arrive at the market capitalization of stock i in month t. Using *AdjLast* we compute simple nominal returns. We generally work with monthly data in this thesis.

We download daily data on adjusted stock prices and turnover (*OffShareTurnover*) for the same time period. Daily data on adjusted stock prices is used to identify the 52-week high price, and the variable *OffShareTurnover* is used for data filtering as explained in the following section. Table 1 reports summary statistics of relevant variables prior to data filtering.

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Table 1: Summary Statistics of Unfiltered Data

The table presents summary statistics for all Ordinary Shares and A Shares listed on the Oslo Stock Exchange in the period Jan 1990 through Dec 2019. *Last* is the last available closing price. *AdjLast* is the last available closing price adjusted for stock splits and dividends. *Return* is the simple nominal return computed using *AdjLast*. *SharesIssued* is the number of shares issued. *MarketCap* is the stock's market capitalization (in million) obtained as the product of *Last* and *SharesIssued*. *OffShareTurnover* are the number of shares officially traded in the period.

Panel A: Monthly Data

Variable	N	Mean	SD	Min	Max
Last	60 407.00	80.53	182.52	0.02	3 960.00
AdjLast	60 407.00	17 068.13	711 550.58	0.02	49 019 626.08
Return	60 280.00	0.01	0.18	-0.96	8.20
SharesIssued	60 461.00	133 070 069.40	416 120 303.97	0.00	20 272 457 825.00
MarketCap	60 407.00	6 375.15	27 053.10	0.00	631 352.13

Panel B: Daily Data

Variable	N	Mean	SD	Min	Max
AdjLast	1 289 344.00	17 138.28	709 961.75	0.02	49 589 621.73
OffShareTurnover	1 290 318.00	673 183.20	5 713 191.75	0.00	1 576 555 064.00

3.2 Data Processing

It is normal in empirical asset pricing literature to remove penny stocks as they may have microstructure related issues and exaggerated returns. For instance, Jegadeesh & Titman and George & Hwang exclude stocks traded below USD 5. For our Norwegian stock sample, Ødegaard (2020) recommends removing observations where stocks trade below NOK 10 and the total market capitalisation of the stock are below NOK 1 million. We generally follow his recommendation however, filtering out observations below NOK 10 would have a significant impact on the sample size. To mitigate the impact of exaggerated returns while maintaining the sample size we lower the criterion to NOK 5, which still has a relatively large impact on the sample size. As momentum focuses on relative performance between stocks and as long as it is possible to construct diversified portfolios it is not vital to have very broad cross-sections to infer that the anomalies exist, and we generally believe it is important to have a robust stock sample. However, to answer hypotheses 3 we need to maintain the sample size if we want to increase the precision of the results[8]. We also believe that NOK 10 is an excessively strict bound that could exclude several stocks that fall below the bound because of poor performances during recessions and

[8] With narrower cross-sections, it is more likely that the 52-week high – and relative strength portfolios will consist of the same stocks. Because we ultimately aim to assess their performance when controlling for the other measure having to few stocks can reduce the precision of the results.

troughs, for instance the 2008 financial crisis or the 2014 oil price crash. We argue that choosing a strict lower bound may make returns upwards biased as the strong performance of stocks leading up to recessions would be included, while the poor performance of stocks in recessions and troughs would be excluded.

In this thesis, we construct portfolios which are to be held a given number of months ahead, preventing us from filtering on observations if we do not want to induce biases to the results. To understand why, assume that a stock has been sorted into a portfolio, and the stock trades at a price slightly above NOK 5. Assume further that the stock´s price falls below NOK 5, implying that we exclude return calculations from the stock in the remaining months that the portfolio will be held. Because the portfolios we construct may have different characteristics with regards to market capitalization and share price, and because our hypotheses will be answered by evaluating portfolio returns, filtering on observations could lead to a misleading illustration on the differences in portfolio returns. To circumvent this issue, we require that a stock satisfies the filtering criterions at the portfolio formation date to be sorted into a portfolio. This methodology is in line with Jegadeesh & Titman (2001)

Furthermore, Ødegaard (2020) recommends removing observations for stocks that have experienced less than 20 trading days to ensure a more liquid stock sample. Utilising the daily data and the variable *OffShareTurnover* we follow his recommendation and exclude these observations. Lastly, we exclude observations where a stock does not have any shares issued as measured by the *SharesIssued* variable as these stocks will intuitively have zero return and no price. Note that filtering on observations with regards to the latter filters do not induce the biases commented on in the previous paragraph, as these criterions will only be unsatisfied at the beginning of a stock´s time-series. Table 2 presents the average number of stocks in the investment universe each year before and after imposing the respective data filters. Table A.1 in Appendix A reports summary statistics of the filtered dataset.

Table 2: Evolution in Number of Stocks in the Investment Universe each Year

The table presents the evolution of the average number of stocks in the investment universe each year on the Oslo Stock Exchange before and after imposing a given data filter. "Total stocks" is the total number of *Ordinary Shares* and *A Shares* on the exchange. "MarketCap" presents the number of stocks left after imposing the filter that the stock must have a total market capitalization higher than NOK 1 million. "Last" presents the number of stocks left after imposing the filter that a stock must trade at a price higher than NOK 5. "Trading Days" presents the number of stocks left after filtering out observations for stocks that have experienced less than 20 trading days. "Shares Issued" presents the number of stock left after removing observations where a stock does not have any shares issued.

Year	Total Stocks	MarketCap >NOK 1M	Last >NOK 5	Trading Days >=20	Shares Issued >0
1990	121	117	115	113	113
1991	113	109	107	107	107
1992	113	108	97	90	90
1993	115	111	103	95	95
1994	132	128	122	117	117
1995	138	136	128	126	126
1996	146	146	139	138	138
1997	170	169	163	162	162
1998	210	209	194	188	188
1999	206	205	181	180	180
2000	191	191	174	174	174
2001	191	191	158	157	157
2002	182	182	132	132	132
2003	168	168	119	119	119
2004	161	161	131	130	130
2005	179	179	153	153	153
2006	201	200	179	179	179
2007	218	218	202	201	201
2008	214	212	179	179	179
2009	195	192	139	139	139
2010	184	182	138	138	138
2011	180	177	132	132	132
2012	173	169	123	123	123
2013	166	164	124	124	124
2014	162	160	126	126	126
2015	162	162	121	121	121
2016	162	162	121	121	121
2017	165	165	133	133	133
2018	169	169	141	141	141
2019	172	172	141	141	141

3.3 Factors and Risk Free-Rate

We download data on the risk-free rate as well as the size, value and liquidity factor mimicking portfolio returns for the period 1990 to 2020 from Ødegaard (2020) website[9]. The interest rate is the NIBOR rate. The rates are forward looking and are the interest rate for borrowing one month from the given date. Using Norwegian data, the size (SMB) and value (HML) factors is constructed as in Fama & French (1993). The liquidity (LIQ) factor is constructed as in Næs, Skjeldtorp & Ødegaard (2009) equal to the difference between the portfolio with highest liquidity and the portfolio with lowest liquidity sorted on bid-ask spread.

We construct our own equally weighted market portfolio consistent with the weighting scheme that will be used in the constructed portfolios related to the analyses. We also impose the same data filters to ensure consistency between our investment universe and that of the market portfolio. The market portfolio will primarily act as the market factor in factor regressions. In month t the return to the market portfolio is equal to the sum of returns of all stocks in the cross-section divided by the number of stocks in related cross-section.

[9] Link to website: https://ba-odegaard.no/financial_data/ose_asset_pricing_data/index.html

4 Methodology

In the following we present the empirical methodology applied to answer the three hypotheses. Section 4.1 describes the relative strength strategy of Jegadeesh & Titman which lay the foundation for inferring that momentum is present on OSE. Section 4.2 describes the 52-week high strategy of George & Hwang, used to test whether there is a relation between nearness to the 52-week high and future returns. In section 4.3 we describe more thoroughly how we evaluate the performance of the portfolios that will be constructed for the two strategies. Lastly, section 4.4 presents the methodology applied to test whether there is evidence to conclude that price level is a more important determinant of momentum compared to past returns in our sample.

4.1 Relative Strength Portfolios

To test for momentum, we perform what is essentially a univariate portfolio analysis on the relation between past – and future stock returns, though we focus on the hedge portfolio equal to the difference between the portfolio with highest returns in recent months and the portfolio with lowest returns in recent months. Jegadeesh & Titman refers to the methodology as a "relative strength trading strategy". To increase the robustness of our results we will initially back test a total of 16 different relative strength strategies as in Jegadeesh & Titman, JxK, where J denotes the formation period and K denotes the holding period. In the following we describe the construction of the portfolios and the assumptions made.

At the beginning of each month we compute a sort variable which is equal to the obtained return[10] for stock i from and including month $t - J$ through $t - 1$, where $J = (3,6,9,12)$. Stocks are sorted in a descending order on the value of the sort variable each month. In line with George & Hwang (2004) we set our breakpoints at the 30th and 70th percentiles[11]. The upper 30% is the high portfolio, while the lower 30% is the low portfolio. The relative strength strategy takes a long (short) position in the high (low) portfolio (high-low) each month. The portfolios are assumed to be held for K months after the portfolio formation date, where $K = (3,6,9,12)$. As implied, the high (low) portfolio is long (short) stocks with the highest (lowest) return over the previous J months. The portfolios we construct are equally weighted and note that because positions are initialised every month and the portfolio is held for K months, the total return of the high and

[10] Using simple nominal returns this is computed as the cumulative return over the months.

[11] The breakpoints are set such that the upper and lower 30% contain the same amount of stocks, though negligible deviations may occur because of standard rounding rules applied.

low position in isolation is at time t the average of the return of K portfolios held, each initialised in one of the previous K months. On a further note, our portfolio return time series extends from February 1990 and ends in December 2019 for all strategies JxK, implying that we utilise J months prior to February 1990 to construct the J Month sort variable for the starting date in our sample. As is the convention in literature we require a stock to have J months of observations preceding the portfolio formation date to be included in the sort, which is not the case for stocks listed throughout the time series. Further, we do not require a stock to have K months of observations after the portfolio formation date to be included in the sort. If a stock is delisted while held in a portfolio we calculate portfolio return by equally weighing the remaining stocks.

The focal momentum paper of Jegadeesh & Titman sort stocks into equally spaced deciles, while we follow George & Hwang and sort stocks into terciles to ensure a replication of their methodology. According to Bali, Engle & Murray (2016) the more stocks sorted into a portfolio may make the relation between the sort – and outcome variable harder to detect given that a relation exists. This is because if a relation exists and the return of the portfolios increase monotonically with increasing values of the sort variable, the return of the high and low portfolio should be closer with broader portfolios. On the other hand, Bali et al. (2016) explain that more stocks sorted into each portfolio increases the accuracy of the estimate of the true mean value as there is greater diversification and less noise. The choice of tercile portfolios is also motivated by our notion that we require relatively broad portfolios to achieve precision when answering hypothesis 3.

Lastly, we follow George & Hwang and use equally weighted portfolios as this provide information on the performance of the average stock. Value weighted portfolios could be tilted towards the performance of only a few stocks, and thus also infer the possibility that positions are undiversified. The OSE is dominated by a few large stocks[12] and we thus argue that equally weighted portfolios are best suited for the empirical work in this thesis and also ensures a replication to that of George & Hwang. We further argue that value weighted portfolios would be optimal in a paper assessing the tradability of the strategies that we back test because equally weighed portfolios require frequent rebalancing to maintain equal weights. As this thesis is more empirical we will only focus our discussions on results where portfolios are equally weighted.

[12] Ødegaard (2020) demonstrates that the time-series of return from a value weighted market portfolio is dominated by only a handful of stocks on OSE.

4.2 52-Week High Portfolios

To assess whether there is a relation between nearness to the 52-week high price and future returns we perform an analysis which only differ from the relative strength strategy by the sort variable. The construction of the portfolios is based on the paper of George & Hwang and the authors refer to the methodology as a "52-Week High Strategy*"*.

At the beginning of each month all stocks are sorted in a descending order on nearness to their 52-week high price. This sort variable is computed as the current adjusted price[13] of stock i divided by the highest adjusted closing price observed for stock i during the prior 52 weeks, which we approximate as the previous 252 trading days[14]. The variable will take a maximum value of 1 when the current price is the highest price over the prior 52-weeks. The breakpoints are set at the 30[th] and 70[th] percentile in line with George & Hwang. As implied, the high (low) portfolio consists of stocks that are closest to (furthest from) their 52-week high price. In other words, the stocks in the high (low) portfolio are at a high (low) price level compared to the prior year. The portfolios are held for K months and the high-low zero-cost position lays the foundation for inferring that there is a relation between price level and future returns on OSE. With exception of the sort variable the 52-week high portfolios follow the same assumptions as portfolios sorted on past returns. Furthermore, note that the formation period is constant at 12 (J =12) for 52-week high portfolios while $K = (3,6,9,12)$ as before. Hence, there are four different 52-week high strategies that will be evaluated, $12xK$.

4.3 Portfolio Evaluation

4.3.1 Raw Returns

As is normal in literature we initialise the analyses by examining the profitability of the strategies that we back test. There are 16 different relative strength strategies JxK, and four different 52-week high strategies $12xK$ that will be evaluated to increase the robustness of the results. For all strategies, we report the average monthly return in excess of the risk-free rate (excess return hereafter) for the high, low and high-low[15] portfolio together with Newey & West (1987)[16]

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[13] Price adjusted for stock splits and dividends *(AdjLast)*.
[14] We use daily data to identify the highest closing price over the previous year.
[15] Note that the high-low portfolios are independent of the risk-free rate as it is both long and short the rate.
[16] Newey & West (1987) adjusted t-statistics are used to account for the possibility of autocorrelation and heteroscedasticity with regards to the standard errors. We calculate the number of lags required for the estimation as the integer part of the following formula proposed by Bali et al. (2016); $4(T/100)^{2/9}$ where T is the length of the time-series, resulting in five lags.

adjusted t-statistics testing the null hypothesis that high-low return equals zero. If there has been profits to the strategies on OSE in our sample period, the high-low average monthly return should be statistically distinguishable from zero[17].

4.3.2 Risk Adjusted Returns

To formally infer that momentum and 52-week high momentum is present on OSE we regress the time-series of portfolio returns against common factors to hedge out factor exposure. We perform the tests relative to three factor models; CAPM, the Fama & French three factor model (FF3 hereafter) and the Fama & French three factor model augmented with the liquidity factor of Næs et al. (2009, FF3+LIQ hereafter). The FF3+LIQ regression specification is:

$$R_t = a_t + b_1 MKT_t + b_2 SMB_t + b_3 HML_t + b_4 LIQ_t + e_t$$

Where R_t is the excess return of the given portfolio in month t, MKT_t denotes the market factor given by the excess return of the market portfolio in month t. SMB_t and HML_t is the return of the size and value factor respectively in month t and LIQ_t is the return of the liquidity factor. The factor mimicking portfolio returns for the Norwegian stock market is constructed as explained in section 3. By excluding the liquidity factor the model reduces to FF3 and by additionally excluding the value and size factor the model reduces to CAPM. The intercept, a_t denotes the alpha or abnormal return of the portfolio. In other words, it is the return to the portfolio that cannot be explained by included factors and its coefficient for the high-low portfolios should generally be statistically significant if we are to infer that the phenomena has been present on OSE. For the high, low and high-low portfolios we report alphas and Newey & West (1987) adjusted t-statistics relative to all tested models. We also report factor loadings (slope coefficients) to gain additional insights.

It should be clarified that we will not perform the factor regressions for all tested strategies. That is, for all formation – and holding periods JxK. We will work with the formation – and holding period combination that is proven to be the best performer as measured by high-low raw returns for the two strategies respectively. We assume that results obtained from this strategy is relatable to other formation – and holding periods. This assumption is not uncommon in existing literature, both Jegadeesh & Titman and George & Hwang focuses their discussions around their best performing strategy as measured by raw returns. Moreover, we do not find it necessary – nor

[17] We set the level of significance to the magical threshold of 5% with regards to the p-value, implying a t-stat at or above 1.96.

convenient to constantly work with 20 different strategies if we initially document robust profits to several different combinations of formation – and holding periods.

4.3.3 The January Effect

In addition to the main model, we will examine the profits and abnormal returns when excluding January from the return calculations following George & Hwang to account for the empirically documented "January effect". Ødegaard (2020) show that market returns are significantly higher in January compared to the rest of the months for the Norwegian market. Empirics argue that this occurs because investors sell their worst performers in December to realize their losses resulting in a tax-benefit. When the calendar year rolls over, investors buy back these stocks in the hope of gains in the upcoming year (Givoly & Ovadia, 1983; Reinganum, 1983; Roll, 1983). Controlling for the January effect should thus improve upon the profits related to shorting past losers, as these are the worst performers in recent months. We ultimately aim to compare the performance of the two strategies, and the January effect may have an asymmetric impact on the two strategies given its presence.

4.4 Comparison – Fama & MacBeth (1973) Style Regression

We are interested in formally assessing whether price level is a more important determinant of momentum compared to past returns on our Norwegian stock sample covering the period 1990 trough 2020. For this purpose, we follow the methodology proposed in George & Hwang and conduct a Fama & MacBeth (1973, Fama-MacBeth hereafter) style cross-sectional regression analysis.

The regression was developed by George & Hwang. The dependent variable R_{it} is the return to stock i in month t. The independent variables are dummy variables indicating whether stock i is held either in the long or short portfolio for one of the two strategies respectively in month t. As such, the coefficients on the dummy variables measure the contribution of the given strategy to the month t return of stock i after controlling for the other strategy. The regression specification can be expressed as[18];

[18] George & Hwang (2004) also includes dummy variables for the industrial momentum strategy of Moskowitz & Grinblatt (1999) which we do not control for in this thesis. Moreover, George & Hwang (2004) includes the independent variable R_{it-1} to mitigate the impact of bid-ask bounce on the coefficient estimates as the authors skip one month between the formation – and holding periods.

$$R_{it} = b_{0jt} + b_{1jt}Size_{i,t-1} + b_{2jt}JTH_{i,t-j} + b_{3jt}JTL_{i,t-j} + b_{4jt}GHH_{i,t-j} + b_{5jt}GHL_{i,t-j} + e_{it}$$

The independent variables are dummy variables equal to 1 if stock i is sorted into the high or low portfolio as classified by the two alternative strategies respectively in month $t-j$. We use the notation JTH and JTL for Jegadeesh & Titman´s high - and low relative strength portfolios respectively. Similarly, we use the notation GHH and GHL for George & Hwang´s high - and low 52-week high portfolios. Moreover, we follow George & Hwang and control for firm size in the cross-section by including the independent variable $Size$ computed as the natural logarithm of market capitalization[19].

As mentioned earlier, the return to the high – or low position is in month t the return of K portfolios held, each initialised in one of the previous K months. Thus, our methodology involves estimating K regressions each month. Assume that the holding period is three months for the purpose of explanation ($K = 3$). In each month, we run the regression above three times for $j = 1, j = 2$ and $j = 3 = K$. We thus end up with three slope coefficients for each dummy variable where each measures the return to a single portfolio initialised in month $t-j$ after controlling for size and the other momentum measure. The excess return to the total position in month t for the high or low portfolios as classified by one of the two strategies can thus be obtained by taking the average of these three slope coefficients. We end up with one estimate each month and hence a time-series of estimates. By taking the difference between the estimates related to the dummy variables we obtain a time-series for the zero-cost high-low portfolio. We regress the time-series of estimates against factor models to hedge out factor exposure, as we are mostly interested in comparing their performance in predicting returns that are not priced by our common factors. In other words, the momentum part of the returns.

We report the alphas obtained by regressing the time-series of estimates against factor models together with Newey & West (1987) adjusted t-statistics. George & Hwang interprets the slope coefficients related to the dummy variables as the average monthly return to a "pure" high - or low portfolio as classified by one of the two strategies. For instance, our obtained estimate related to the relative strength high portfolio can be interpreted as the abnormal return to a pure high relative strength portfolio that has hedged out the effect of size and the other momentum measure. In other words, it is the return to the portfolio after controlling for the other momentum measure and size. Thus, the analysis is suitable for comparing the magnitude of the abnormal

[19] Taking the natural logarithm of market capitalization is normal in empirical asset pricing literature as market capitalization display a high level of skewness (right skewed) in the cross-section Bali et al. (2016).

returns to the strategies after controlling for the other strategy. For instance, if we find that the pure relative strength high-low portfolio is associated with much larger abnormal returns than the pure 52-week high portfolio, then this suggests that the abnormal part of the returns related to the relative strength strategy is relatively less dependent on the price level being close to or far from its 52-week high. Hence, we can examine which of the two sort variables is dominant, and thus which of returns and price level that is the most important determinant of momentum effects in our sample.

5 Analysis

This section presents the results of our analyses. We start by examining whether momentum has been present on OSE with regards to the standard measure of momentum proposed by Jegadeesh & Titman in section 5.1. Subsequently, we explore whether there is a relation between nearness to the 52-week high and future stock returns, formally documented by George & Hwang. Ultimately, in section 5.3 we aim to assess whether there is evidence to conclude that price level is a more important determinant of momentum effects compared to past returns.

The first two sections 5.1 and 5.2 are rather similar in the sense that we perform the same tests. Each of the section starts with an assessment of whether the respective strategies are profitable, before we discuss their abnormal returns relative to common factors. Subsequently we conduct robustness tests to examine the sensitivity of the results. Lastly, we compare our results to other studies on the Norwegian market. In the final section when answering hypothesis 3 – section 5.3 – we briefly compare the results to George & Hwang instead of studies on the Norwegian market as a similar analysis have never, to our knowledge, been performed on OSE.

5.1 Hyphotesis 1 - The Existence of Momentum on the Oslo Stock Exchange

5.1.1 Profits to Relative Strength Strategies

Jegadeesh & Titman sorted stocks into portfolios on past returns each month and bought the portfolio with highest past returns and sold short the portfolio with lowest past returns and held the portfolios over intermediate holding periods. Such strategies were highly profitable indicating that stocks with relatively high (low) returns in recent months' exhibit relatively higher (lower) returns in the following months, which breaks with EMH as it suggests that stock returns are predictable. Table 3 presents a replication of table I panel A in Jegadeesh & Titman. We report the average monthly excess return to the high, low and high-low portfolios sorted on returns over the previous J months. The portfolios are held for K months after the portfolio formation date.

The table demonstrates economically large average monthly returns to the zero-cost portfolios regardless of the length of the formation and holding periods. The high portfolio has thus exhibited higher returns in the K months after the formation date compared to the low portfolio, on average, for all formation – and holding period combinations. High-low returns are also, for

Table 3: Profits to Relative Strength Portfolios

At the beginning of each month stocks are sorted in a descending order on return over the previous J months. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted. The table presents the average monthly excess return for the high and low portfolios held for K months, in addition to the return from a zero-cost portfolio that takes a long (short) position in the high (low) portfolio - high-low. The numbers in parentheses are Newey & West (1987) consistent t-statistics estimated for the high-low portfolio using five lags. The returns are computed from a time-series extending from Feb 1990 through Dec 2019.

J		K =	3	6	9	12
3	High		0.73 %	0.70 %	0.64 %	0.62 %
3	Low		-0.26 %	-0.14 %	-0.08 %	-0.03 %
3	High-Low		0.99 %	0.84 %	0.72 %	0.65 %
			(3.83)	(3.93)	(3.60)	(3.44)
6	High		0.81 %	0.76 %	0.73 %	0.63 %
6	Low		-0.25 %	-0.12 %	-0.09 %	0.00 %
6	High-Low		1.07 %	0.89 %	0.82 %	0.63 %
			(3.74)	(3.36)	(3.26)	(2.69)
9	High		0.96 %	0.85 %	0.71 %	0.61 %
9	Low		-0.22 %	-0.12 %	-0.05 %	0.02 %
9	High-Low		1.18 %	0.97 %	0.76 %	0.59 %
			(3.75)	(3.20)	(2.64)	(2.19)
12	High		0.85 %	0.70 %	0.59 %	0.50 %
12	Low		-0.20 %	-0.01 %	0.02 %	0.05 %
12	High-Low		1.05 %	0.71 %	0.57 %	0.45 %
			(3.14)	(2.19)	(1.84)	(1.52)

the most part, statistically distinguishable from zero at the 5% threshold. We note that the best performing strategy select stocks on their previous nine-month return and hold the portfolios for three months after the formation date, delivering an average monthly high-low return of 1.18% (t-stat = 3.75). Albeit economically large at 0.57% (t-stat = 1.84) and 0.45% (t-stat = 1.52) respectively, the 12x9 and 12x12 strategies do not deliver statistically significant high-low returns. We can thus not conclude that the observed continuation in returns do not occur by chance in our stock sample for these strategies when we set the required level of significance to the 5% level. It is worth observing that the low portfolios exhibit strikingly small average monthly excess returns ranging from -0.26% to 0.05%. This is striking provided that risky assets should provide risk premiums according to modern portfolio theory. Hence, we can conclude that the relative strength strategy performs well in predicting loser stocks in our sample. Their returns are not only small relative to the high portfolio, but negative.

Our findings suggest that buying winners and selling losers have been highly profitable on OSE in the period 1990 to 2020. To get a better sense of how profitable, note that a 1.18% average monthly return associated with the 9x3 strategy corresponds to 14.16% annually, which is rather striking from a self-financing portfolio. Figure B.1 in appendix B plots the cumulative excess return of a NOK 1 investment into the high, low and high-low 9x3 portfolio. If an investor were to buy the low portfolio in February 1990 and hold the position until the end of December 2019, the investor would gain approximately -84% in cumulative excess return. On the contrary, an investment into the high portfolio delivers a cumulative excess return of 1 619% over the sample period. A NOK 1 investment into a portfolio that delivers the same return as the high-low portfolio provide a cumulative return of 4.083%.

From table 3 we observe that the profitability of the high-low portfolios tends to decline with the length of the holding period. That is, the longer the portfolios are held following the formation date, the less profitable the strategy is. This implies that the returns are largest the first few months after the formation date before they decline. This is consistent with Jegadeesh & Titman, though our pattern is much more distinct. If we make the rather unreasonable assumption that the profits are attributable to underreactions to news, this suggests that investors correct their priors relatively quick after the arrival of information. Given the variation in profits between the choice of formation – and holding periods our results imply that the timing of the measurement of the sort variable as well as the length the portfolios is held play a role in both the magnitude and significance of the profits. As the 12x9 and 12x12 strategies are insignificant, past returns over the previous twelve months are only positively correlated with returns until and including six months in the future.

In appendix B Table B.1 we report profits to momentum strategies when excluding January from the return calculations. Consistent with the existence of a January effect on OSE, high-low returns are substantially larger and more statistically significant. We note that all strategies are statistically significant when January is excluded. The best performer 12x9 deliver an average monthly high-low return of 1.40% (t-stat = 4.39). Returns from both the long and short sides of the trades are impacted in the sense that returns are smaller, though the effect is clearly larger for the short side as expected.

The results reported here are consistent with an intermediate momentum effect on OSE over our sample period. Stocks with relatively high (low) returns are associated with higher (lower) returns in the following months and the results are statistically significant. Moreover, momentum is generally robust to different formation – and holding periods on the exchange, and we note that excluding January significantly improves upon profits to momentum investing in our sample.

5.1.2 Factor Model Alphas

We are generally disinclined to infer that momentum is present on OSE as it is defined before testing whether the high-low portfolio is able to generate statistically significant alpha relative to common factors. Table 4 reports alphas, factor loadings and corresponding t-statistics relative to CAPM, FF3 and FF3+LIQ for the best performing strategy as measured by raw returns – the 9x3 strategy[20]. We first note that the high-low portfolio deliver statistically significant alphas relative to all tested models, which underpins the existence of a continuation in returns that cannot be explained by common factors. Hence, the momentum phenomenon has been present on OSE in the sample period 1990 trough 2019. Relative to CAPM we observe a high-low alpha of 1.48% (t-stat = 5.34). Relative to FF3 and FF3+LIQ the high-low portfolio deliver alphas of 1.48% (t-stat = 5.24) and 1.44% (t-stat = 5.05) respectively. Thus, momentum is robust to these different factor model specifications. There are no noteworthy impacts on the alphas by augmenting CAPM with the size, value and liquidity factors.

The table illustrates that the high portfolios are associated with lower market betas compared to the low portfolios. As such, there are more market risk in the low portfolio. Consequently, the high-low portfolio has negative market betas relative to all factor models. When systematic risk is measured according to CAPM we observe a high-low beta of -0.29 (t-stat = -3.74). These negative market betas suggest that the relative strength strategies are more profitable as measured by raw returns when the market performs poorly. Jegadeesh & Titman report their market beta to be negative at -0.08 relative to CAPM. Thus, on their US stock sample the high and low portfolio have similar market risk, which stands in contrast to our findings. While equal in direction, our high-low market betas are larger in magnitude.

It is important to note that momentum on OSE is confined to the short side of the trades. That is, the high portfolios do not deliver statistically significant alphas relative to all tested models. This implies that the high portfolio does not deliver a continuation in returns larger than its factor exposure. On the contrary, the low portfolios provide negative and statistically significant alphas suggesting a strong continuation in returns with regards to past loser stocks. It is not surprising that these alphas are negative and significant given the negative raw returns associated with the short side of the trades. On the US market Jegadeesh & Titman find that both sides of the trades

[20] Alphas and factor loadings when excluding January can be observed in Appendix B Table B.2. High-low alphas are larger when January is excluded.

Table 4: Risk Adjusted Relative Strength Returns and Factor Loadings

The table presents the results from regressing the time-series of relative strength returns against factor models. At the beginning of each month stocks are sorted in a descending order on return over the previous nine months. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted and they are held for three months after the formation date. High-low is a portfolio taking a long (short) position in the high (low) portfolio each month. The table consists of three sections.

Explanations of Sections: "CAPM" presents the intercept (alpha) and slope coefficients by regressing portfolio returns against the market factor. "FF3" augments CAPM with the size (SMB) and value (HML) factors of Fama & French (1993). "FF3+LIQ" augments FF3 with the liquidity factor (LIQ) of Næs et al. (2009).

General: The market factor is equally weighted and constructed from our filtered stock sample. The time-series of returns extend from Feb. 1990 through Dec. 2019. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. See section 3 in this paper for a further description of the factor mimicking portfolio returns.

Portfolio	Alpha	MKT	SMB	HML	LIQ
		CAPM			
High	0.18 %	0.90			
	(1.23)	(19.96)			
Low	-1.26	1.19			
	(-7.31)	(28.94)			
High-Low	1.44%	-0.29			
	(5.18)	(-3.74)			
		FF3			
High	0.19%	0.90%	-0.00	-0.10	
	(1.34)	(21.26)	(-0.08)	(-1.93)	
Low	-1.29%	1.20	0.04	0.00	
	(-7.23)	(28.81)	(0.94)	(0.08)	
High-Low	1.48%	-0.30	-0.04	-0.11	
	(5.34)	(-3.92)	(-0.53)	(-1.17)	
		FF3+LIQ			
High	0.16%	0.85%	0.10	-0.08	-0.17
	(1.11)	(22.34)	(1.93)	(-1.68)	(-3.25)
Low	-1.28%	1.21	0.01	-0.00	0.04
	(7.00)	(29.42)	(0.18)	(-0.06)	(0.57)
High-Low	1.44%	-0.36	0.09	-0.08	-0.21
	(5.05)	(-5.17)	(0.86)	(-0.84)	(-1.91)

contribute to momentum relative to CAPM, though more recent literature on US stock samples tend to find that momentum is strongest for the short side of the trades Asness et al. (2013).

5.1.3 Robustness Tests

Our results with regards to the existence of momentum on OSE are rather unambiguous. However, we perform two robustness tests. We first examine the pervasiveness of momentum when controlling for size, before we perform a sample split and examine the sensitivity of momentum to different time periods.

Controlling for Size

The purpose here is to assess the robustness of momentum on OSE to firm size. Research suggests that momentum is strongest for small stocks for which it is reasonable to assume are harder to trade because of less liquidity and other microstructure related issues (Fama & French, 2008). Though we have imposed data filters related to market capitalization, the OSE is still dominated by several relatively small stocks. We follow Fama & French (2008) and examine the pervasiveness of momentum on OSE by performing sorts on size. Each month we sort stocks into terciles in a descending order according to their market capitalization, before each small, middle and large group are sorted into terciles in a descending order according to their return over the previous nine months. With regards to the first sort each portfolio contains the same amount of stocks for simplicity, though arguments could be made for alternative breakpoints because of skewness displayed by market capitalization. In the second sort, we set the breakpoints at the 30^{th} and 70^{th} percentile. The portfolios are held for three months following the formation date. We report the results in table B.3 in appendix B and we note that the high-low portfolio deliver economically large and statistically significant returns and alphas within the high and middle size groups, and thus conclude that relative strength momentum is robust to size on OSE. In line with Fama & French (2008) we find that momentum is weakest among the small group and in our case its profits are not statistically significant[21]. This stands in contrast to the arguments that momentum is strongest for small stocks.

Sample Split

By conducting a sample split we test whether momentum on OSE is confined to any specific time periods or extreme outliers and to gain additional insight on momentum. Table 5 reports excess returns and factor model alphas relative to FF3 for equally spaced time periods within the full sample period. We note that the latest period in the stock sample from 2010 to 2020 delivers high-low average monthly excess return and alpha of 1.87% (t-stat = 4.02) and 2.20% (t-stat = 4.14) respectively. The prior period from 2000 through 2010 provide high-low return and alpha of 1.52% (t-stat = 2.93) and 1.81% (t-stat = 4.32). We observe again that the abnormal return from the high-low portfolio is attributable to shorting past losers. The earliest period in the stock sample from 1990 through 2000 does not deliver statistically significant high-low excess return or

[21] The alphas within the small size group are statistically significant.

Table 5: Relative Strength Returns and Alphas for Different Time Periods

The table presents momentum excess returns and alphas for three different time periods in addition to the main model. At the beginning of each month stocks are sorted in a descending order on return over the previous nine months. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted and the portfolios are held for three months after the formation date. High-low is a portfolio taking a long (short) position in the high (low) portfolio each month. The table consists of two sections.
Explanation of Sections: "Excess Return" presents the average monthly excess returns computed from the time-series. "Alphas Relative to FF3" presents the intercept from regressing portfolio returns against the market, size and value factors – the Fama & French three factor model.
General: The market factor used in the factor regressions is equally weighted and constructed from our filtered stock sample. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. See section 3 in this paper for a further description of the factor mimicking portfolio returns.

	1990 - 2020	1990 - 2000	2000 - 2010	2010 - 2020
		Excess Return		
High	0.96%	0.69%	1.14%	1.06%
Low	-0.22%	0.54%	-0.38%	-0.81%
High-Low	1.18%	0.15%	1.52%	1.87%
	(3.75)	(0.26)	(2.93)	(4.02)
		Alphas Relative to FF3		
High	0.19%	0.04%	0.25%	0.31%
	(1.30)	(0.16)	(1.00)	(1.26)
Low	-1.29%	-0.42%	-1.56%	-1.89%
	(-7.19)	(-1.66)	(-6.01)	(-5.82)
High-Low	1.47%	0.46%	1.81%	2.20%
	(5.26)	(1.03)	(4.32)	(4.14)

alpha. As such, we do not find evidence that the high portfolio outperforms the low portfolio, implying that momentum is non-existent in this period. We note that, albeit insignificant, the high-low alpha in the period 1990 to 2020 is economically large at 0.46% (t-stat = 1.03).

Additional insights can be obtained by considering figure 1 below, where we plot a 12-month rolling arithmetic average of portfolio returns. As can be seen, the high 12-month average outperforms its low portfolio for the most part. We attribute the insignificant return and alpha in 1990 to 2000 to the period around 1993, where we observe that the low portfolio clearly outperforms the high portfolio. It is also interesting to note that the low portfolio tends to move at or above the high portfolio following recessions and troughs. This is consistent with the time-varying market beta documented by Grundy & Martin (2001) which causes momentum crashes

Figure 1: 12-Month Rolling Average of Relative Strength Portfolio Returns

At the beginning of each month stocks are sorted in a descending order on return over the previous nine months. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted and held for three months after the formation date. High-low is a portfolio taking a long (short) position in the high (low) portfolio. The figure presents a 12-month rolling arithmetic average of excess portfolio returns. The plot starts in Feb 1991 from where 12 months of prior observations is available.

and motivated the crash factor of Ruenzi & Weigert (2018). In other words, the plot suggests that the low portfolio consists of stocks with higher beta following recessions and troughs compared to the high portfolio, which causes it to outperform the high portfolio in market upswings.

From the same figure, figure 1, we observe that the high portfolio clearly outperforms the low portfolio following the 2014 oil price crash, which largely explain the relatively large profits and alphas to the high-low portfolio in the period 2010 to 2020. According to Næs et al. (2009) the oil price is not priced risk on OSE and the alphas are thus not biased from an obvious omitted risk factor. Chen, Cheng & Demirer (2017) found that momentum payoffs could be predicted by oil return volatility on the Chinese market and argued that momentum profits is driven by time-varying investor sentiment. Moreover, they argued that their findings suggested the oil market dynamics can contribute to stock market inefficiencies. We find it reasonable that uncertainty with regards to the oil price may have an impact on investor sentiment and market efficiency on OSE given that all stocks on OSE have, arguably, either direct or indirect exposure to the oil price. Hence, we argue that high volatility with regards to the oil price may be a contributing factor to explain the large returns and alphas following the 2014 oil price crash.

To further build on the prior discussion, table B.4 in appendix B presents the company names of the top 20 most frequent stocks sorted into the high and low portfolio when the sort variable is the prior nine-month return. We note that the low portfolio is heavily tilted towards stocks with direct exposure to the oil price, while the high portfolio show no such tilt towards any particular industry. Because the low portfolio exhibits strongest momentum, our results can be reconciled with industrial momentum proposed by Moskowitz & Grinblatt (1999), that momentum exhibited by industries can explain a lot of individual stock momentum. As mentioned, we do not control for industrial momentum in this thesis and can thus not exclude the possibility that an industrial momentum strategy would perform better in predicting future returns compared to individual past returns or the 52-week high.

5.1.4 Comparison of Results with Studies on the Norwegian Market

To our knowledge there are no peer-reviewed studies on momentum related to OSE conducted in recent years, and we thus compare our results to previous master theses[22]. Absalonsen & Vas (2014) reports of a statistically significant high-low 9x3 return of 1.64% (t-stat = 5.37) over the period 2004 to 2013 when tercile portfolios is used. As can be seen from table 5 we report a high-low return of 1.52% (t-stat = 2.93) for the period 2000 to 2010 which is most comparable. The profits are thus similar in magnitude though we note that they report higher t-statistics. A possible reason may be that they only include stocks that have been listed their whole sample period resulting in 90 stocks. Our results are thus fairly in line with those of Absalonsen & Vas (2014) given the differing stock sample. The authors also note that high-low profits tend to decline with the length of the holding period, and that abnormal returns are driven by the short side of the trades when evaluating their alphas obtained by regressing quintile portfolio returns against CAPM. We can thus with greater confidence argue that this conclusion in our paper is not a consequence of the use of tercile portfolios.

In their master thesis Lenschow & Svae (2015) examines for momentum on OSE over the period 1996 to 2015 by sorting stocks into decile portfolios each month. The authors report a high-low 9x3 average monthly return of 1.32% (t-stat = 4.00). Over the whole sample period we report a high-low return of 1.18% (t-stat = 3.75) which is rather similar. Their use of decile portfolios is the likely explanation for why they report marginally higher returns.

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[22] To our knowledge the latest peer-reviewed study was conducted by Rouwenhorst (1998) who use Norwegian data from 1978 trough 1995. The author document a statistically significant high-low return of 0.99%.

All studies we have come across report that momentum on OSE is constrained to the short side of the trades and that returns tend to decline with the length of the holding period. Additionally, the low portfolio has higher exposure to systematic risk compared to the high portfolio (Absalonsen & Vas, 2014; Abusdal & Brodin, 2008; Kloster-Jensen, 2006; Lenschow & Svae, 2015). Although we deviate from the norm by using tercile portfolios we find no critical deviations from our results in previously conducted research on momentum with Norwegian stock samples.

5.1.5 Conclusion on the Existence of Momentum

Momentum refers to the phenomenon that stocks with relatively high (low) returns continue to exhibit relatively high (low) returns. By following the relative strength strategy of Jegadeesh & Titman we demonstrate that the high-low portfolio sorted on past returns has been highly profitable and the result is robust to different formation – and holding periods. Thus, we demonstrate that high-low profits are not driven by data snooping. By regressing portfolio returns against common systematic risk factors we obtain economically large and statistically significant high-low alphas relative to all tested models. We do not find evidence that past winners exhibit a continuation in returns beyond its expected return, and thus infer that the economically large and statistically significant high-low alphas is a consequence of momentum exhibited by stocks with the lowest return in recent months. From the behavioural based explanation of momentum proposed by Jegadeesh & Titman this suggests that the market tend to underreact and/or overreact to bad news and not to good news. We demonstrate that the strategy deliver higher high-low returns and alphas outside of January, consistent with a January effect on OSE. Additionally, we postulate that the momentum strategy tends to crash following recessions and troughs consistent with the time-varying beta documented by Grundy & Martin (2001). Momentum is robust to size but not to different time periods. We do not find evidence that momentum has been present in the period 1990 to 2000. When evaluating the whole sample period in conjunction, however, the results are rather unambiguous and we are confident in inferring that momentum has been present on OSE over the period 1990 trough 2019.

5.2 Hyphotesis 2 – The Relation Between the 52-Week High and Future Returns

Having confirmed that there is a relation between past – and future returns on OSE, we proceed by testing whether there is a relation between nearness to the 52-week high – price level, and future returns. George & Hwang argue that investors suffer from anchoring biases and are reluctant to buy (sell) stocks that have a high (low) price relative to their respective price histories, which they measure as nearness to the 52-week high. Ultimately, fundamental news is incorporated into the stock prices and anomalous returns may be earned once the market corrects their priors.

5.2.1 Profits to 52-Week High Strategies

Analogous to the previous analysis we start this analysis by examining the profits to the 52-week high strategy for different holding periods. In table 6 we report the average monthly excess return to the high, low and high-low portfolios sorted on nearness to the 52-week high price each month, which are held for K months after the portfolio formation date. We first note that the high-low portfolio delivers economically large average monthly returns ranging from 0.61% to 0.95%. The table demonstrates that the best performing strategy is the one where the portfolios are held for three months with an average monthly return of 0.95% (t-stat = 2.69) which is also statistically distinguishable from zero. Portfolios held for six and nine months are also statistically significant at the 5% threshold with high-low returns of 0.76% (t-stat = 2.16) and 0.68% (t-stat = 1.96) respectively. With a high-low return of 0.61% (t-stat = 1.83) the portfolios held for the longest holding period that we evaluate, twelve months, are not statistically significant although it is economically large. In line with portfolios sorted on past returns we observe that high-low returns are declining with the length of the holding period, suggesting that 52-week high momentum is strongest for shorter periods after the portfolio formation date.

Table 6: Profits to 52-Week High Portfolios

At the beginning of each month stocks are sorted in a descending order on nearness to the 52-week high price computed as the current price divided by the highest price observed over the prior year. The top (bottom) 30% constitutes the high (low) portfolio. The table presents the average monthly excess return for the high and low portfolios held for K months, in addition to the return from a zero-cost portfolio that takes a long (short) position in the high (low) portfolio - high-low. The numbers in parentheses are Newey & West (1987) consistent t-statistics estimated for the high-low portfolio using five lags. The returns are computed from a time-series extending from Feb 1990 through Dec 2019.

J	K =	3	6	9	12
12 High		0,73 %	0,65 %	0,59 %	0,55 %
12 Low		-0,22 %	-0,11 %	-0,09 %	-0,05 %
12 High-Low		0,95 %	0,76 %	0,68 %	0,61 %
		(2,69)	(2,16)	(1,98)	(1,83)

Figure C.1 in appendix C plots the cumulative performance of a NOK 1 investment into the high, low and high-low portfolios held for three months. Over the thirty-year period we evaluate the high portfolio provide a cumulative excess return of 826% while the low portfolio delivers a cumulative excess return of -87%. A zero-cost investment with a long (short) position in the high (low) portfolio delivers a cumulative return of 1 500% over the sample period. While a cumulative return of 1 500% is striking from a zero-cost portfolio, we initially note that it is significantly lower than what we document with regards to portfolios sorted on past returns as presented in the prior analysis.

Table 7 reports the results when January is excluded. In line with George & Hwang, results with regards to the 52-week high are highly sensitive to whether or not January is included in the return calculations. The best performing strategy of George & Hwang delivers a high-low return of 1.23% (t-stat = 7.06) when January is excluded. When January is included, their high-low portfolio provides an average monthly return of 0.45% (t-stat = 2.00), which is barely statistically significant at the 5% threshold. Our results are comparable as we obtain an average monthly high-low return and t-stat when January is included and excluded at 0.95% and 1.36% respectively for the portfolios held for three months. We further note that, when January is excluded, all high-low portfolios deliver statistically significant profits.

Table 7: Profits to 52-Week High Portfolios - Excluding January

At the beginning of each month stocks are sorted in a descending order on nearness to the 52-week high price computed as the current price divided by the highest price observed over the prior year. The top (bottom) 30% constitutes the high (low) portfolio. The table presents the average monthly excess return for the high and low portfolios held for K months when January is excluded, in addition to the return from a zero-cost portfolio that takes a long (short) position in the high (low) portfolio - high-low. The numbers in parentheses are Newey & West (1987) consistent t-statistics estimated for the high-low portfolio using five lags. The returns are computed from a time-series extending from Feb 1990 through Dec 2019.

J	K =	3	6	9	12
12 High		0.66%	0.57%	0.51%	0.46%
12 Low		-0.70%	-0.57%	-0.55%	-0.50%
12 High-Low		1.36%	1.14%	1.05%	0.96%
		(3.71)	(3.07)	(2.85)	(2.71)

5.2.2 Factor Model Alphas

Having demonstrated that 52-week high strategies are highly profitable, we further test whether these profits can be explained by conventional risk factors when working with the portfolio held for three months. Table 8 reports alphas and factor loadings[23] relative to CAPM, FF3 and FF3+LIQ. We observe that high-low alphas are economically large and statistically

[23] Table C.1 in appendix C reports alphas and factor loadings when excluding January.

Table 8: Risk Adjusted 52-Week High Returns and Factor Loadings

The table presents the results from regressing the time-series of 52-week high returns against factor models. At the beginning of each month stocks are sorted in a descending order on nearness to the 52-week high price computed as the current price divided by the highest price observed over the prior year. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted and held for three months after the formation date. High-low is a portfolio taking a long (short) position in the high (low) portfolio each month. The table consists of three sections.

Explanations of Sections: "CAPM" presents the intercept (alpha) and slope coefficients by regressing portfolio returns against the market factor. "FF3" augments CAPM with the size (SMB) and value (HML) factors of Fama & French (1993). "FF3+LIQ" augments FF3 with the liquidity factor (LIQ) of Næs et al. (2009).

General: The market factor is equally weighted and constructed from our filtered stock sample. The time-series of returns extend from Feb. 1990 through Dec. 2019 on the Oslo Stock Exchange. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. See section 3 in this paper for a further description of the factor mimicking portfolio returns.

Portfolio	Alpha	MKT	SMB	HML	LIQ
			CAPM		
High	0.15 %	0.69			
	(1.19)	(21.14)			
Low	-1.32%	1.31			
	(-7.33)	(31.74)			
High-Low	1.47%	-0.62			
	(5.49)	(-9.28)			
			FF3		
High	0.20%	0.69	-0.06	-0.03	
	(1.50)	(22.14)	(-1.55)	(-1.09)	
Low	-1.38%	1.31	0.07	-0.02	
	(-7.42)	(31.39)	(1.42)	(-0.34)	
High-Low	1.57%	-0.63	-0.13	-0.02	
	(5.62)	(-9.69)	(-1.73)	(-0.28)	
			FF3+LIQ		
High	0.18%	0.67	-0.02	-0.02	-0.07
	(1.38)	(22.39)	(-0.33)	(-0.78)	(-1.42)
Low	-1.38%	1.31	0.09	-0.01	-0.02
	(-7.30)	(28.07)	(1.33)	(-0.27)	(-0.27)
High-Low	1.57%	-0.63	-0.10	-0.01	-0.04
	(5.48)	(-9.41)	(-0.99)	(-0.18)	(-0.39)

distinguishable from zero which infers a relation between price level and future returns that remain unexplained by conventional factors. Relative to both FF3 and FF3+LIQ we observe high-low alphas of 1.57% with t-statistics of 5.62 and 5.48 respectively. The high-low alpha is smaller relative to CAPM at 1.47% (t-stat = 5.49). We note that only the short side of the transactions generate significant alphas suggesting that stocks close to its 52-week high do not deliver abnormal returns in the months following the portfolio formation date.

Further note that the high portfolio has rather strikingly small market betas, for instance 0.69 (t-stat = 21.14) relative to CAPM, which largely explain the economically large and negative market betas of the high-low portfolio. Relative to CAPM we observe a high-low beta of -0.62 (t-stat = -

9.28). These findings are consistent with the documentation of Driessen, Lin & Van Hermert (2013). On a US stock sample covering the period 1963 through 2008 the authors explore, among other things, market betas of portfolios consisting of stocks that approach – and breaks through their 52-week high price. In short, the authors provide statistically significant evidence that stocks' market beta decrease when prices approach its 52-week high. According to the theories of Kahneman et al. (1982) the 52-week high serves as a resistance level, and Driessen et al. (2013) predicted that stock prices should be less sensitive to market conditions when approaching this threshold. Although we are unable to detect statistically significant alphas for the long side of the trade this strongly suggests that there are some underlying behavioural factors that can, perhaps, explain the economically small market beta of the high portfolio. It should be mentioned that George & Hwang, and other studies in general, does not report their factor loadings which prevents us from comparing our market betas to theirs.

5.2.3 Robustness Tests

We evaluate the robustness of the relation between price level and future stock returns parallel to our previous analysis. Table C.2 in appendix C presents the results from a bivariate sort, sorting first on size then on the 52-week high measure. We find that the 52-week high is robust to size, and weakest among the group of small stocks. Within this sub sample of stocks the average monthly high-low raw return is economically large but statistically insignificant, though its risk adjusted returns are statistically distinguishable from zero.

Table 9 below reports average monthly returns and alphas relative to FF3 over three different time periods. We note that 52-week high momentum is not present in the first period of the stock sample from 1990 to 2000, and that high-low returns and alphas are largest in the final period from 2010 to 2020. Interestingly, in the final period both the long and the short side of the transactions generate abnormal returns relative to FF3 given the statistical significant alphas related to both the high – and low portfolio.

We also plot a 12-month rolling arithmetic average of portfolio returns, this time in appendix C Figure C.3 The plot is rather similar to that where portfolios are sorted on past returns. The 52-week high strategy tends to crash following recessions and troughs. Moreover, we note from table C.3 in appendix C that the low portfolio is tilted towards companies for stocks with direct exposure to the oil price. As such, the discussions related to our previous analyses where portfolios are sorted on past returns largely also holds true for portfolio sorted on the 52-week

Table 9: 52-Week High Returns and Alphas for Different Time Periods

The table presents 52-week high excess returns and alphas for three different time periods in addition to the main model. At the beginning of each month stocks are sorted in a descending order on nearness to the 52-week high price computed as the current price divided by the highest price observed over the prior year. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighed and held for three months after the formation date. High-low is a portfolio taking a long (short) position in the high (low) portfolio. The table consists of two sections.

Explanation of Sections: "Excess Return" presents the average monthly excess returns computed from the time-series. "Alphas Relative to FF3" presents the intercept from regressing portfolio returns against the market, size and value factor – the Fama & French three factor model.

General: The market factor used in the factor regressions is equally weighted and constructed from our filtered stock sample. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. See section 3 in this paper for a further description of the factor mimicking portfolio returns.

	1990 - 2020	1990 - 2000	2000 - 2010	2010 - 2020
		Excess Return		
High	0.73%	0.39%	0.77%	1.00%
Low	-0.22%	0.55%	-0.32%	-0.93%
High-Low	0.95%	-0.16%	1.08%	1.93%
	(2.69)	(-0.25)	(1.60)	(4.58)
		Alphas Relative to FF3		
High	0.20%	-0.04%	0.16%	0.47%
	(1.50)	(-0.16)	(0.78)	(2.06)
Low	-1.38%	-0.39%	-1.68%	-2.05%
	(-7.42)	(-1.38)	(-6.15)	(-7.28)
High-Low	1.57%	0.35%	1.85%	2.52%
	(5.62)	(0.74)	(4.89)	(5.43)

high measure. This is an indication that the two strategies will tend to sort into portfolios many of the same stocks, which is intuitive given that stocks with highest (lowest) returns in recent months should also relatively often be stocks that are near (far from) its 52-week high.

5.2.4 Comparison of Results with Studies on the Norwegian Market

There are, to our knowledge, two studies exploring the relation between nearness to the 52-week high and future returns on OSE. Liu et al. (2011) study the 52-week high strategy in 20 different stock markets across different countries. With regards to the Norwegian market, the authors use a sample of 210 stocks over the period 1982 through 2006. In line with this paper they set the breakpoints at the 30^{th} and 70^{th} percentile. The authors report a high (low) return of 1.82% (1.30%). Further, the high-low portfolio delivers a statistically insignificant return of 0.52% (t-stat = 1.33). For the period 1990 to 2000, which is most comparable, our high-low portfolio delivers an average monthly return of 0.35% (t-stat = 0.74). Still, our high (low) portfolio delivers an average monthly return of -0.04 (-0.39) which differ substantially from their findings. It should be noted that the authors work with portfolios held for six months, while we mostly work with portfolios held for three months. Given the different stock sample, time period and assumptions it is hard to make any conclusive statements about why our results differ from theirs. As we have demonstrated, profits to 52-week high momentum are sensitive to different time periods which is the likely explanation. With regards to the Norwegian market the authors do not report results from factor regressions.

In his master thesis, Von Ubisch (2015) explores 52-week high momentum over the period 1991 trough 2010 on OSE. The author use a stock sample similar to ours, however, do not initially impose any data filters. The author reports a high-low return of 1.82% (t-stat = 4.03) and FF3 alpha of 2.82% (t-stat = 7.90) respectively. In line with our findings the high-low alpha is much higher than the high-low raw return, though our results differ both in magnitude and significance when we evaluate the sub periods 1990 to 2000 and 2000 to 2010 in conjunction from table 9. Von Ubisch (2015) also tests the results against imposing the data filter that the bottom decile is removed from the sample each month when stocks are sorted in a descending order on market capitalization. This should make our samples more comparable as we, in this thesis, exclude penny stocks. After imposing the filter the author report high-low return and FF3 alpha of 1.02 (t-stat = 2.37) and 1.96% (t-stat = 5.89) respectively which is somewhat similar to our documentation over the period 1990 to 2010. The most interesting similarity between our and his study is, however, that he reports a highly negative market beta for the high-low portfolio at -0.79. The author does not report the market betas for the high and low portfolios in isolation. Although our results deviate in magnitude and significance from that of Von Ubisch (2015) there are no contradictions between our results.

5.2.5 Conclusion on the Relation Between the 52-Week High and Future Returns

The main postulations put forth by George & Hwang is that a strategy that buy (sell) stocks that are close to (far from) its 52-week high price deliver abnormal returns because individuals suffer from anchoring biases. Consistent with these postulations we document economically large and statistically significant profits to such a strategy on OSE, and the results are generally robust to different holding periods. The profits are substantially larger when accounting for the empirically documented January effect. By regressing high-low returns against conventional factors we obtain economically large and statistically significant alphas. Interestingly, we find that the long side of the trades are associated with strikingly low market betas consistent with that of Driessen et al. (2013). Moreover, we do not find abnormal returns to the long side of the transactions in general, though we do find significant alphas when evaluating the period 2010 trough 2019 in isolation. Our obtained results are robust to size, but we do not find statistically significant abnormal returns in the first period of the sample from 1990 to 2000. Nevertheless, when considering the whole sample period our results are strongly supportive of the view that there is a relation between price level and future returns. We thus conclude that a relation between nearness to the 52-week high price and future returns have been present on OSE over the period 1990 trough 2019.

5.3 Hyphotesis 3 – Price Level as the Determinant of Momentum Effects

In the previous sections of the report we demonstrate that that there is a relation between past – and future stock returns on OSE, as well as a relation between nearness to the 52-week high price and future returns and the results are robust. These profits and abnormal returns are rather similar, which is intuitive postulating that stocks with high (low) returns during the formation period should also relatively often be stocks that are closer to (further from) its 52-week high, and vice versa. Still, their profits and alphas are not identical. In this section of the report, we aim to formally assess whether price level is a more important determinant of momentum effects compared to past returns on OSE by the means of the Fama-MacBeth regression analysis described in section 4. The focus of the analysis lie on the high-low risk-adjusted returns, as this provide information on the performance of the sort variables in generating returns that are not compensation for systematic risk as measured by our factor models.

Subsection 5.3.1 presents the results from the Fama-MacBeth regressions, where we compare their performance when controlling for the other strategy and size. In subsection 5.3.2 we perform robustness tests before we briefly compare our results to that of George & Hwang in subsection 5.3.3. Subsection 5.3.4 concludes the analysis related to hypothesis 3.

5.3.1 Fama-MacBeth Results

To formally test whether price level is a more important determinant of momentum effects compared to past returns, we conduct the Fama-MacBeth regression analysis as described in section 4, where we control for the respective momentum measures and size. Table 11 reports the estimates obtained by hedging out factor exposure from the time-series of slope coefficients. We examine the strategies that are held for three months, and with regards to the relative strength strategy, the portfolios are constructed using the nine-month prior returns as the sort variable. The focus lie on the bottom two rows, which reports the abnormal returns to the pure high-low portfolios. The table illustrate that the pure 52-week high portfolio deliver abnormal returns of 1.31% (t-stat = 5.19) and 1.37% (t-stat = 5.29) relative to CAPM and FF3 respectively when January is included. Alphas are substantially smaller and less statistically significant for the pure

Table 11: Fama-MacBeth Results for 52-Week High *12x3* and Relative Strength *9x3*

Each month between Feb 1990 and Dec 2019, 3 (j = 1,…,3) cross-sectional regressions are estimated for the 52-week high 12x3 and relative strength 9x3 strategies:

$$R_{it} = b_{0jt} + b_{1jt}Size_{i,t-1} + b_{2jt}JTH_{i,t-j} + b_{3jt}JTL_{i,t-j} + b_{4jt}GHH_{i,t-j} + b_{5jt}GHL_{i,t-j} + e_{it}$$

where R_{it} and $Size_{i,t}$ are the excess return and the market capitalization of stock i in month t. $JTH_{i,t-j}$ ($JTL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to the nine month prior return in month $t-j$, and zero otherwise. $GHH_{i,t-j}$ ($GHL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to nearness to the 52-week high in month $t-j$, and zero otherwise. The coefficient estimates of a given independent variable are averaged over j = (1,…3). The numbers in the table is the intercept of a regression with the time-series of the given average as the dependent variable and systematic risk factors as independent variables to hedge out factor exposure. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. "Jan.Incl" presents the results when January is included and "Jan.Excl" presents the results when January is excluded. The market factor in the regressions is equally weighted and constructed from our filtered stock sample. See section 3 in this paper for a description of the size and value factors which is part of the Fama & French three factor model (FF3).

	Jan. Incl		**Jan. Excl**	
Coefficient	CAPM Alpha	FF3 Alpha	CAPM Alpha	FF3 Alpha
Intercept	1.00%	0.07%	0.61%	-0.15%
	(2.49)	(0.22)	(1.33)	(-0.4)
Size	-0.23%	-0.08%	-0.16%	-0.05%
	(-3.75)	(-1.72)	(-2.48)	(-0.93)
JTH	0.54%	0.47%	0.52%	0.45%
	(2.94)	(2.85)	(2.7)	(2.63)
JTL	-0.20%	-0.16%	-0.21%	-0.17%
	(-1.13)	(-0.86)	(-1.22)	(-0.96)
GHH	0.41%	0.42%	0.44%	0.44%
	(3.44)	(3.35)	(3.72)	(3.66)
GHL	-0.90%	-0.95%	-1.07%	-1.08%
	(-4.38)	(-4.54)	(-5.24)	(-5.22)
JTH-JTL	0.74%	0.63%	0.73%	0.63%
	(2.86)	(2.48)	(2.78)	(2.45)
GHH-GHL	1.31%	1.37%	1.51%	1.53%
	(5.19)	(5.29)	(6.13)	(5.98)

relative strength portfolio at 0.74% (t-stat = 2.86) and 0.63% (t-stat = 2.48). When January is included, our results suggest that the relative strength strategy is more dependent on extreme price levels than the 52-week high are on extreme past returns to generate abnormal returns in the months following the formation date.

The difference between the abnormal returns are larger outside of January. The pure 52-week high portfolio deliver alphas of 1.51% (t-stat = 6.13) and 1.53% (t-stat = 5.98) relative to CAPM and FF3. The pure relative strength portfolio deliver alphas of 0.73% (t-stat = 2.78) and 0.63% (t-stat = 2.45), half the size of the 52-week high.

We also perform this test for the formation – and holding period combination most studied in George & Hwang. The portfolios are held for six months following the portfolio formation date, and the relative strength portfolios are constructed using six month prior returns. We report these results in Appendix D, table D.1. The difference is smaller when comparing these strategies. The 52-week high delivers 0.86% (t-stat = 4.02) and 0.86% (t-stat = 4.06) in abnormal returns relative to CAPM and FF3. The relative strength deliver alphas of 0.56% (t-stat = 2.84) and 0.54% (t-stat = 2.83). Outside of January, the difference is larger. Relative to CAPM the pure 52-week high portfolio deliver an alpha of 0.99% (t-stat = 4.53) while the pure relative strength portfolio deliver an alpha 0.57% (t-stat = 2.81). These results also illustrate that the 52-week high outperforms the relative strength once the other strategy is controlled for.

By definition, the 52-week high looks back 12 months. We follow George & Hwang and examine whether the length of the look-back period contributes to the dominance of the 52-week high. The results can be viewed in appendix D. Table D.2 reports the results for the 52-week high 12x3 and relative strength 12x3, and Table D.3 reports the results for the 52-week high 12x6 and relative strength 12x6. We find that the 52-week high outperforms the relative strength from these strategies as well. In line with George & Hwang, the dominance is stronger. Moreover, with a 12-month look-back period for both strategies, the pure relative strength portfolio is not statistically significant with exception of when January is included and systematic risk is measured according to CAPM. This suggests that, with this look-back period, all profitable positions in stocks as measured by risk adjusted returns for the relative strength strategy are also close to or far from its 52-week high. In other words, portfolios sorted on past returns are fully dependent on the price being high (low) relative to its price history to generate abnormal returns.

The results presented here are strongly supportive of price level being a more important determinant of momentum effects on OSE. The abnormal returns to the pure 52-week high portfolio are substantially larger and more statistically significant than those to the pure relative strength high-low portfolio and the results are robust to different formation – and holding period combinations. Our results imply that, portfolios sorted on past returns have relatively less explanatory power on future abnormal returns once controlled for whether the stocks are close to (far from) its 52-week high. In other words, abnormal returns are substantially lower to stocks with extreme past returns that are not close to (far from) its 52-week high, compared to when they are close to (far from) its 52-week high. On the contrary, the 52-week high largely maintains its abnormal returns. As such, if the stock is close to (far from) its 52-week high, stocks need not have experienced extreme past returns to generate large abnormal returns in subsequent months.

Hence, our results suggest that price level is a more important determinant of momentum effects than are past price changes.

5.3.2 Robustness Tests

We perform additional robustness tests to further validate our results. Parallel to our previous analyses we conduct a sample split, and divide the sample period into three equally spaced time periods. We report the results for the pure high-low portfolios in table 12 below. Interestingly, we find that the pure relative strength portfolio outperforms the pure 52-week high portfolio in the first period, although both strategies are insignificant. As such, it could be argued that the results are not robust to time, though we do not find it constructive to make this argument given the lack of statistical significance to both strategies We note that the 52-week high portfolio outperform the relative strength portfolio in both periods from 2000 to 2010 and from 2010 to 2020, and the dominance is especially clear in the period 2000 to 2010. We thus argue that the results are robust to different time periods within the full sample period.

Table 12: Fama-MacBeth Results for Different Time Periods

The Fama-MacBeth regression described in section 3 is conducted for three different time periods, and the table presents the abnormal returns to the "pure" high-low relative strength and 52-week high portfolios. The table consists of two panels.

Explanations of panels: Panel A presents results when the portfolios are held for three months, and the sort variable related to the relative strength strategy (JT) is the nine-month prior return. Panel B presents results when the portfolios are held for six months, and the sort variable related to the relative strength strategy (JT) is the six-month prior return.

General: The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. The factor model used in the factor regressions is the Fama & French three factor model. See section 3 for a description of the factors.

Panel A: 12x3 (GH) and 9x3 (JT)

Portfolio	1990-2020	1990-2000	2000-2010	2010-2020
JTH - JTL	0.63%	0.50%	0.39%	1.10%
	(2.48)	(1.11)	(0.92)	(2.36)
GHH - GHL	1.37%	0.29%	1.99%	1.84%
	(5.29)	(0.66)	(4.06)	(6.52)

Panel B: 12x6 (GH) and 6x6 (JT)

Portfolio	1990-2020	1990-2000	2000-2010	2010-2020
JTH - JTL	0.52%	0.46%	0.34%	0.90%
	(2.83)	(1.32)	(1.02)	(2.83)
GHH - GHL	0.86%	0.16%	1.21%	1.29%
	(4.06)	(0.45)	(2.83)	(4.68)

We also test our results against different variations in data filters as these may have an asymmetric impact on the different strategies. Specifically, we remove the filter that a stock must have at least 20 trading days to be sorted into a portfolio and the filter that a stock must trade above NOK 5.

We also test the results by setting the filter to the proposed threshold of Ødegaard (2020) which is NOK 10. We report high-low alphas relative to FF3 in table 13 for these different variations in data filters. We note that the results are robust to all selected variations in data filters. Interestingly, the pure relative strength portfolio does not deliver statistically significant alpha when imposing a stricter limit on share price (Last > 10).

Table 13: Fama-MacBeth Results for Variations in Data Filters

The table presents abnormal returns to "pure" high-low relative strength and 52-week high portfolios for selected variations in data filters. The returns are obtained by the Fama-MacBeth regression analysis described in section 3. "Last > 10" states that a stock must trade higher than NOK 10 to be sorted into a portfolio. "Last (0)" removes all filters with regards to share price. "Turnover (0)" removes all filters with regards to turnover. The table consists of two sections.

Explanations of Sections: Panel A presents results when the portfolios are held for three months, and the sort variable related to the relative strength strategy (JT) is the nine-month prior return. Panel B presents results when the portfolios are held for six months, and the sort variable related to the relative strength strategy (JT) is the six-month prior return.

General: The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. The factor model used in the factor regressions is the Fama & French three factor model. See section 3 for a description of the factors.

Panel A: 12x3 (GH) and 9x3 (JT)

Portfolio	Main Model	Last > 10	Last (0)	Turnover (0)
JTH - JTL	0.63%	0.49%	0.71%	0.62%
	(2.48)	(1.83)	(2.39)	(2.44)
GHH - GHL	1.37%	1.35%	1.08%	1.37%
	(5.29)	(5.71)	(3.74)	(5.26)

Panel B: 12x6 (GH) and 6x6 (JT)

Portfolio	Main Model	Last > 10	Last (0)	Turnover (0)
JTH - JTL	0.54%	0.48%	0.64%	0.54%
	(2.83)	(2.52)	(3.1)	(2.81)
GHH - GHL	0.86%	0.69%	0.90%	0.86%
	(4.06)	(3.25)	(3.62)	(4.06)

Lastly, George & Hwang skips a month between the formation – and holding periods to account for short-term mean reversion documented by Jegadeesh (1990) and Lehmann (1990). Short-term mean reversion refers to the phenomenon that stock returns tend to have a negative cross-sectional relation with returns over the next week or month (Bali et al., 2016). We have largely omitted this from our analysis, and we argue that our results with regards to hypotheses 1 and 2 should be sufficiently robust to such a minor change in portfolio construction. We have thus chosen to perform the analyses using a rather standard approach and not skip a month between the formation and holding periods. However, because we now compare the performance of the two sort variables this phenomenon may impact one of the strategies more than the other if it is present on OSE. We would expect it to have larger impact on the relative strength strategy as it selects stocks on returns. Thus, we test the sensitivity of the results to skipping a month between the formation – and holding periods. We follow George & Hwang and include the independent variable $R_{i,t-1}$ in the Fama-MacBeth regressions, which is the one month lagged excess return for stock i to control for bid-ask bounce. We report the results from this regression analysis in table 14 below, and we do not find the results to be sensitive to skipping a month between the formation – and holding periods. However, we note that the abnormal returns to the pure high-low portfolios are somewhat closer once accounting for short-term mean reversion, consistent with the notion that it should have a larger impact on the relative strength strategy as it selects stocks on returns. Interestingly, we note that the coefficient estimate on $R_{i,t-1}$ is negative after hedging out factor exposure, which is consistent with short-term mean reversion.

Table 14: Fama-MacBeth Results Accounting for Short-Term Mean Reversion

Each month between Feb 1990 and Dec 2019, 3 (j = 2,…,4) or 6 (j = 2,…,7) cross-sectional regressions are estimated for the 52-week high and relative strength strategies:

$$R_{it} = b_{0jt} + b_1 R_{it-1} + b_{2jt} Size_{i,t-1} + b_{3jt} JTH_{i,t-j} + b_{4jt} JTL_{i,t-j} + b_{5jt} GHH_{i,t-j} + b_{6jt} GHL_{i,t-j} + e_{it}$$

where R_{it} and $Size_{i,t}$ are the excess return and the market capitalization of stock i in month t. $JTH_{i,t-j}$ ($JTL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to the nine or six month prior return in month $t-j$, and zero otherwise. $GHH_{i,t-j}$ ($GHL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to nearness to the 52-week high in month $t-j$, and zero otherwise. The coefficient estimates of a given independent variable are averaged over j = (1,…3) or j = (1,…,6). The numbers in the table is the intercept of a regression with the time-series of the given average as the dependent variable and systematic risk factors as independent variables to hedge out factor exposure. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. "12x3 (GH) and 9x3 (JT)" refers to portfolios held for three months and the relative strength strategy uses the prior nine months as the sort variable. "12x6 (GH) and 6x6 (JT)" refers to portfolios held for six months and the relative strength strategy uses the prior six months as the sort variable.

	12x3 (GH) and 9x3 (JT)		**12x6 (GH) and 6x6 (JT)**	
Coefficient	CAPM Alpha	FF3 Alpha	CAPM Alpha	FF3 Alpha
Intercept	1.05%	0.09%	1.63%	0.69%
	(2.34)	(0.25)	(3.99)	(2.04)
R_{it-1}	-0.66%	-1.11%	-1.77%	-2.31%
	(-0.67)	(-1.14)	(-2.15)	(-2.92)
Size	-0.23%	-0.09%	-0.29%	-0.15%
	(-3.57)	(-1.73)	(-4.82)	(-3.09)
JTH	0.41%	0.36%	0.36%	0.33%
	(2.21)	(2.09)	(2.58)	(2.61)
JTL	-0.35%	-0.29%	-0.20%	-0.24%
	(-1.95)	(-1.50)	(-1.46)	(-1.66)
GHH	0.38%	0.43%	0.22%	0.23%
	(3.23)	(3.36)	(2.20)	(2.14)
GHL	-0.73%	-0.82%	-0.53%	-0.54%
	(-3.29)	(-3.65)	(-2.78)	(-2.86)
JTH-JTL	0.76%	0.65%	0.56%	0.57%
	(3.01)	(2.55)	(2.81)	(2.85)
GHH-GHL	1.11%	1.25%	0.75%	0.77%
	(4.6)	(4.65)	(3.31)	(3.42)

5.3.3 Comparison of Results with George & Hwang

Our results are qualitatively consistent with that of George & Hwang in the sense that we find the pure 52-week high portfolio to outperform the pure relative strength portfolio as measured by risk adjusted returns. And in line with their study, our results suggest that price level is largely the driver of momentum abnormal returns. However, George & Hwang argues that their 52-week high strategy is also the more profitable strategy as measured by raw returns given their findings. We do not find this to be the case in our sample. When including January our high-low 52-week high portfolio deliver an average monthly return of 0.95% when we do not control for the other measure, while the relative strength strategy delivers 1.18%. Outside of January their average monthly returns are similar. As such, the relative strength strategy may be preferable for an investor interested in maximizing his return over the long-run, although the 52-week high strategy generally deliver higher risk-adjusted returns. We argue that our study is more empirical and not suitable for making statements about which strategy or factor is superior, though we believe the findings can be useful for investors. Lastly, Gray & Vogel (2016) demonstrate on the US market that the 52-week high strategy is only more profitable as measured by raw returns once stocks are sorted into terciles. When deciles are used, the high-low relative strength portfolio were superior in raw returns in their sample.

In conclusion, our results are rather consistent with the main postulations put forth by George & Hwang, and it appears that an anchoring and adjust bias may be a likely explanation for momentum in our sample.

5.3.4 Conclusion on Price Level as the Determinant of Momentum

All tests considered, we find strong evidence that price level is a more important determinant of momentum effects in our sample. Alphas to pure 52-week high portfolios are substantially larger and more statistically significant than those for pure relative strength portfolios. These results suggest that the relative strength strategy are far from able to maintain its anomalous returns after controlling for the 52-week high strategy. On the contrary, portfolios sorted on the 52-week high perform relatively better in maintaining its abnormal returns once controlled for whether the stocks have exhibited extreme high or low returns in recent months. In other words, the relative strength strategy is relatively more dependent on price level than the 52-week high strategy is on past returns to generate future abnormal returns. The results are robust to different combinations of formation – and holding periods, to different time periods, to variations in data filters and to when we account for short-term mean reversion. We thus conclude that price level is a more important determinant of momentum effects than are past price changes in our Norwegian sample.

6 Limitations and Further Research

In the following, we briefly discuss what we find to be the most apparent limitations of this paper and we provide suggestions for further research within the area of momentum on OSE. First, we find the documentation of the economically small market beta of our high portfolio sorted on the 52-week high measure to be intriguing. A further inquiry into the relation between price level and market beta on OSE would be an interesting study, perhaps conducted similar to that in Driessen et al. (2013).

In our view, the most restrictive limitation of this paper is that we do not control for industrial momentum documented by Moskowitz & Grinblatt (1999) and thus, do not arrive at an exact replication of the Fama-MacBeth regression in George & Hwang. As discovered throughout the process of writing this thesis our low portfolios, which exhibit the strongest momentum and 52-week high momentum, are tilted towards stocks for companies with direct exposure to the oil price. This is an indication that the continuation in returns that we document for both strategies may be an industry story rather than an individual stock story. An inquiry into industrial momentum on OSE would be interesting and we believe that, if possible, controlling for industrial momentum may alter some of the conclusions drawn. We have neither had the capacity to implement an additional strategy, nor satisfactory data. Ødegaard (2020) show that there were four industries with more than 42 stocks, one with 26 and six with 14 or less as measured by the GICS[24] industry sectors in 2019. Because the strategy buy (sell) stocks in the best (worst) performing industry each month, such discrepancy in the number of stocks in each industry makes it difficult to back test the strategy and end up with robust results on OSE.

George & Hwang perform additional tests that are outside the scope of this thesis. They demonstrate that the high-low 52-week high portfolios do not exhibit long-term mean reversion. And because they find that price level is largely the main driver of momentum, they argued that intermediate-term momentum and long-term reversals are separate phenomena. This stands in contrast to research at the time suggesting that intermediate-term momentum and long-term reversals are integrated parts in individual's behavioural biases as modelled by Barberis et al. (1998), Hong & Stein (1999), and Daniel et.al (1998). We have not tested for long-term mean

[24] The Global Industry Classification Standard

reversion in this paper and suggest that evaluating long-term mean reversions on OSE for the alternative sort variables to be a topic warranted for further research.

7 Conclusion

The phenomenon that stocks with relatively high (low) returns continue to exhibit relatively high (low) returns – commonly referred to as momentum - is one of the greatest puzzles within the field of empirical asset pricing. We test for the presence of momentum on the Oslo Stock Exchange over the period 1990 trough 2020. Subsequently, we explore whether there is relation between nearness to the 52-week high price and future returns. Ultimately, by replicating the methodology proposed by George & Hwang (2004) we test whether price level, as measured by nearness to the 52-week high, is a more important determinant of momentum effects compared to past returns.

To test for momentum, we sort stocks into tercile portfolios each month based on a descending order on return over intermediate look-back periods and hold the portfolios over intermediate holding periods. We demonstrate that a self-financing portfolio with a long position in the high portfolio and a short position in the low portfolio – the relative strength strategy of Jegadeesh & Titman - delivers statistically significant average monthly returns. By regressing the time-series of returns against common factors we obtain economically large and statistically significant alphas relative to all tested models, which underpins the existence of momentum on the Oslo Stock Exchange over our sample period. The anomaly is robust to size, but not over time. We do not find evidence that the high portfolio has outperformed the low portfolio in the subperiod 1990 to 2000. Moreover, we find that momentum on the Oslo Stock Exchange is constrained to the short side of the trades, as the abnormal returns to the high portfolios are not statistically significant. This implies that stocks with highest returns in recent months do not exhibit a continuation in returns beyond its factor exposure. Nevertheless, our results are unambiguous. Stocks with relatively high (low) return in recent months continue to display relatively high (low) returns in subsequent months on average over our sample period. We thus concluded that momentum has been present on the Oslo Stock Exchange in the period 1990 trough 2019.

Following George & Hwang (2004) we implement their proposed 52-week high strategy to test whether there has been a relation between price level and future stock returns on the Oslo Stock Exchange over the sample period. We sort stocks into tercile portfolios each month based on a descending order on nearness to the 52-week high computed as the current price divided by the highest price observed over the prior year, and hold the portfolios over intermediate holding periods following the formation date. We show that a zero-cost portfolio with a long position in the high portfolio and a short position in the low portfolio delivers statistically significant profits and alphas. The results are robust to size and parallel with the portfolios sorted on past returns, we do not find evidence of a statistical significant relation in the period 1990 to 2000 in isolation. Moreover, the abnormal returns are confined to the short side of the trades when the whole period 1990 to 2020 is evaluated in conjunction. Interestingly, when considering the period 2010 trough 2019 in isolation, we find that both sides of the trades generate anomalous returns. All tests considered, we find a rather unambiguous relationship between price level - as measured by nearness to the 52-week high - and future stock returns on the exchange in the period 1990 trough 2019.

Lastly, we test whether price level is a more important determinant of momentum effects by evaluating the abnormal returns of the tested strategies while controlling for the other strategy in a Fama-MacBeth cross-sectional regression analysis. We demonstrate that factor model alphas associated with the 52-week high strategy are substantially larger and more statistically significant compared to alphas associated with the relative strength strategy. This is especially true outside of January when accounting for the empirically documented January effect. The results are also robust to a sub period analysis, to when we skip a month between the formation and holding periods to account for short-term mean reversions, as well as to different variations in data filters. We thus conclude that price level has been a more important determinant of momentum effects compared to past returns, and the postulations put forth by George & Hwang (2004) thus holds true on the Oslo Stock Exchange.

In conclusion, our thesis find that there has been a relation between past – and future stock returns on the Oslo Stock Exchange, as well as a relation between nearness to the 52-week high price and future stock returns. Our results are also strongly in favour of the hypothesis that price level is a more important determinant of the momentum phenomenon compared to past returns. As such, all three of the defined hypotheses stands to be true in our Norwegian stock sample.

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Appendices

Appendix A: Summary Statistics of Filtered Data

Table A.1: Summary Statistics of Filtered Data

The table presents summary statistics for all Ordinary Shares and A Shares listed on the Oslo Stock Exchange in the period Jan 1990 through Dec 2019 after imposing data filters. *Last* is the last available closing price. *AdjLast* is the last available closing price adjusted for stock splits and dividends. *Return* is the simple nominal return computed using *AdjLast*. *SharesIssued* is the number of shares issued. *MarketCap* is the stock's market capitalization (in million) obtained as the product of *Last* and *SharesIssued*. *OffShareTurnover* are the number of shares officially traded in the period. See section 3 in this paper for a description of the imposed data filters.

Variable	N	Mean	SD	Min	Max
Last	50 152,00	95.47	196.52	5.01	3 960.00
AdjLast	50 152,00	18 267.27	776 303.66	0.15	49 019 626.08
R	50 096,00	0.01	0.16	-0.90	8.20
SharesIssued	50 152,00	106 873 460.27	277 534 638.76	68 633.00	3 574 898 329.00
MarketCap	50 152,00	7 579.48	29 541.40	5.77	631 352.13
OffShareTurnover	48 953,00	7 875 981.79	37 830 097.33	-1 091 137 378.00	1 989 745 188.00

Appendix B – Momentum

Table B.1: Profits to Relative Strength Portfolios Excluding January

The table presents returns when January is excluded from the calculations. At the beginning of each month stocks are sorted in a descending order on return over the previous J months. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted. The table presents the average monthly excess return for the high and low portfolios held for K months, in addition to the return from a zero-cost portfolio that takes a long (short) position in the high (low) portfolio - high-low. The numbers in parentheses are Newey & West (1987) consistent t-statistics estimated for the high-low portfolio using five lags. The returns are computed from a time-series extending from Feb 1990 through Dec 2019.

J		K = 3	6	9	12
3	High	0.55%	0.48%	0.42%	0.37%
3	Low	-0.68%	-0.54%	-0.47%	-0.40%
3	High-Low	1.23%	1.02%	0.89%	0.78%
		(4.66)	(4.64)	(4.32)	(4.02)
6	High	0.63%	0.55%	0.48%	0.38%
6	Low	-0.70%	-0.55%	-0.49%	-0.39%
6	High-Low	1.33%	1.10%	0.98%	0.77%
		(4.67)	(4.12)	(3.82)	(3.21)
9	High	0.76%	0.61%	0.47%	0.38%
9	Low	-0.64%	-0.52%	-0.44%	-0.37%
9	High-Low	1.40%	1.14%	0.91%	0.74%
		(4.38)	(3.69)	(3.05)	(2.63)
12	High	0.62%	0.46%	0.35%	0.27%
12	Low	-0.58%	-0.41%	-0.38%	-0.34%
12	High-Low	1.19%	0.87%	0.73%	0.61%
		(3.49)	(2.58)	(2.24)	(1.98)

Table B.2: Risk Adjusted Relative Strength Returns and Factor Loadings Excluding January

The table presents the results from regressing the time-series of momentum returns against factor models when January is excluded. At the beginning of each month stocks are sorted in a descending order on return over the previous nine months. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted and they are held for three months after the formation date. High-low is a portfolio taking a long (short) position in the high (low) portfolio each month. The table consists of three sections.
Explanations of Sections: "CAPM" presents the intercept (alpha) and slope coefficients by regressing portfolio returns against the market factor. "FF3" augments CAPM with the size (SMB) and value (HML) factors of Fama & French (1993). "FF3+LIQ" augments FF3 with the liquidity factor (LIQ) of Næs et al. (2009).
General: The market factor is equally weighted and constructed from our filtered stock sample. The time-series of returns extend from Feb. 1990 through Dec. 2019. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. See section 3 in this paper for a further description of the factor mimicking portfolio returns.

Portfolio	Alpha	MKT	SMB	HML	LIQ
		CAPM			
High	0.22%	0.89			
	(1.38)	(18.01)			
Low	-1.37%	1.19			
	(-8.32)	(28.10)			
High-Low	1.58%	-0.30			
	(5.73)	(-3.68)			
		FF3			
High	0.21%	0.89	0.00	-0.11	
	(1.43)	(19.40)	(0.03)	(-2.11)	
Low	-1.37%	1.19	0.00	0.00	
	(-8.28)	(28.28)	(0.09)	(0.04)	
High-Low	1.58%	-0.31	0.00	-0.12	
	(5.87)	(-3.84)	(-0.02)	(-1.19)	
		FF3+LIQ			
High	0.17%	0.83	0.11	-0.09	-0.18
	(1.17)	(20.80)	(2.11)	(-1.74)	(-3.31)
Low	-1.37%	1.20	-0.01	0.00	0.02
	(-7.95)	(30.42)	(-0.14)	(-0.01)	(0.26)
High-Low	1.54%	-0.37	0.12	-0.09	-0.20
	(5.53)	(-5.15)	(1.17)	(-0.91)	(-1.79)

Figure B.1: Cumulative Excess Returns of Relative Strength Portfolios

At the beginning of each month stocks are sorted in a descending order on return over the previous nine-months. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted. The figure presents the cumulative excess return for the high and low portfolios held for three months, in addition to the return from a zero-cost portfolio that takes a long (short) position in the high (low) portfolio - high-low. The equally weighted market portfolio in the figure "EW Market" is constructed from our filtered stock sample.

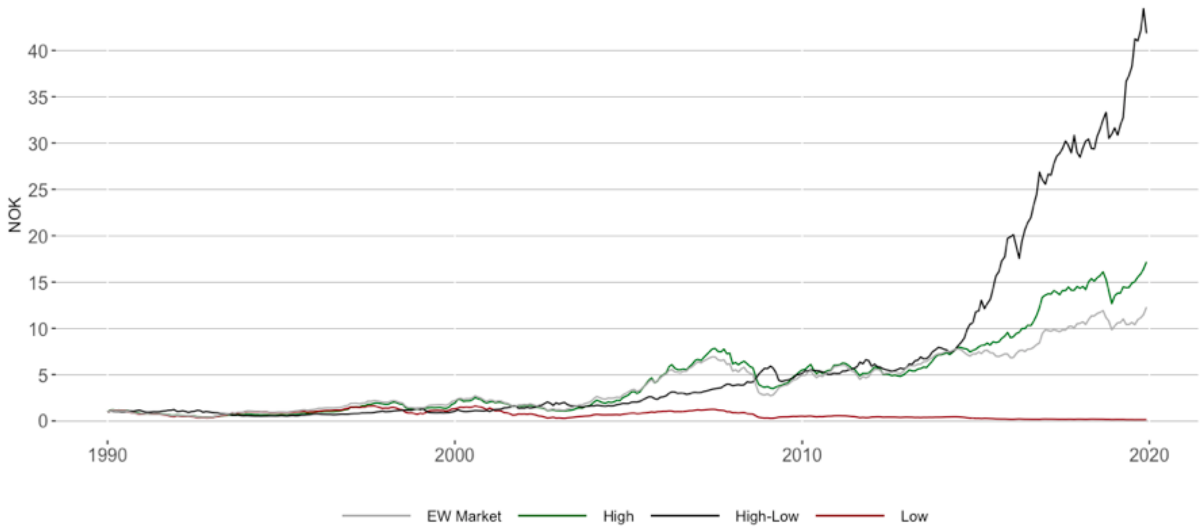

Figure B.2: Return Series of Relative Strength High and Low Portfolios

At the beginning of each month stocks are sorted in a descending order on return over the previous nine months. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted and held for three months after the formation date. The figure presents the return series for these portfolios.

Table B.3: Relative Strength Returns and Alphas within Size Based Sub Samples

The table presents returns and alphas for the relative strength strategy within size based sub samples. At the beginning of each month stocks are sorted into tercile portfolios according to their market capitalization. Each large, medium and small group are then sorted into tercile portfolios in a descending order on return over the previous nine months. The breakpoints at the second sort is set at the 30th and 70th percentiles while there is an equal amount of stocks in each portfolio with regards to the first sort. The high (low) portfolio are stocks in the top (bottom) 30% with regards to the second sort. The portfolios are equally weighted and held for three months after the formation date. High-low is a zero-cost portfolio with a long position in the high portfolio and a short position in the low portfolio. "Excess Return" is the average monthly excess return. "CAPM Alpha" is the intercept from a regression with excess portfolio return as the dependent variable and the market factor as the independent variable. "FF3" augments CAPM with the size and value factors – the Fama & French three factor model.

General: The market factor is equally weighted and constructed from our filtered stock sample. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. See section 3 in this paper for a description of the size and value factors. The time-series extend from Feb 1990 through Dec 2019.

Size	Portfolio	Excess Return	CAPM Alpha	FF3 Alpha
Large	High	0.82%	0.18%	0.27%
	Low	-0.36%	-1.39%	-1.04%
	High-Low	1.19% (3.85)	1.41% (4.84)	1.31% (4.32)
Medium	High	0.82%	0.02%	0.27%
	Low	-0.46%	-1.59%	-1.67%
	High-Low	1.29% (3.17)	1.61% (3.83)	1.93% (5.37)
Small	High	1.07%	0.32%	0.08%
	Low	0.37%	-0.90%	-1.27%
	High-Low	0.70% (1.24)	1.22% (3.01)	1.35% (2.84)

Table B.4: Top 20 most Frequent Companies in High – and Low Relative Strength Portfolios Sorted on Past Nine-Month Return

The table presents the company names of the top 20 most frequent stocks sorted into the high and low portfolios when the sort variable is the prior nine-month return. "High" is stocks with the largest value of the sort variable, and "Low" is stocks with the smallest value of the sort variable.

Low	High
Goodtech	Tomra Systems
Frontline	Subsea 7
NRC Group	NTS
Jinhui Shipping and Transportation	Atea
Borgestad	Nordic Semiconductor
DNO	DNO
Belships	Tandberg
Bonheur	NRC Group
PGS	Bonheur
Ganger Rolf	AF Gruppen
ContextVision	Schibsted ser. A
Odfjell ser. A	Veidekke
SAS AB	TGS-NOPEC Geophysical Company
Norske Skogindustrier	PGS
Kverneland	Tide
Dolphin Drilling	Byggma
Nordic Semiconductor	ContextVision
Nekkar	Frontline
Solvang	Gyldendal
Q-Free	Royal Caribbean Cruises

Appendix C – The 52-Week High

Table C.1: Risk Adjusted 52-Week High Returns and Factor Loadings Excluding January

The table presents the results from regressing the time-series of 52-week high returns against factor models when January is excluded. At the beginning of each month stocks are sorted in a descending order on nearness to the 52-week high computed as the current price divided by the highest price observed over the prior year. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted and they are held for three months after the formation date. High-low is a portfolio taking a long (short) position in the high (low) portfolio each month. The table consists of three sections.
Explanations of Sections: "CAPM" presents the intercept (alpha) and slope coefficients by regressing portfolio returns against the market factor. "FF3" augments CAPM with the size (SMB) and value (HML) factors of Fama & French (1993). "FF3+LIQ" augments FF3 with the liquidity factor (LIQ) of Næs et al. (2009).
General: The market factor is equally weighted and constructed from our filtered stock sample. The time-series of returns extend from Feb. 1990 through Dec. 2019. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. See section 3 in this paper for a further description of the factor mimicking portfolio returns.

Portfolio	Alpha	MKT	SMB	HML	LIQ
		CAPM			
High	0.24%	0.69			
	(1.83)	(19.98)			
Low	-1.49%	1.31			
	(-8.47)	(30.80)			
High-Low	1.73%	-0.61			
	(6.60)	(-9.06)			
		FF3			
High	0.26%	0.69	-0.03	-0.04	
	(1.95)	(20.64)	(-0.84)	(-1.15)	
Low	-1.51%	1.31	0.03	-0.02	
	(-8.52)	(30.09)	(0.52)	(-0.45)	
High-Low	1.77%	-0.62	-0.06	-0.01	
	(6.59)	(-9.17)	(-0.80)	(-0.21)	
		FF3+LIQ			
High	0.25%	0.67	0.01	-0.03	-0.07
	(1.80)	(20.70)	(0.23)	(-0.82)	(-1.59)
Low	-1.52%	1.30	0.05	-0.01	-0.04
	(-8.29)	(26.28)	(0.88)	(-0.31)	(-0.52)
High-Low	1.77%	-0.63	-0.04	-0.01	-0.03
	(6.39)	(-8.95)	(-0.45)	(-0.16)	(-0.25)

Figure C.1: Cumulative Excess Returns of 52-Week High Portfolios

At the beginning of each month stocks are sorted in a descending order on nearness to the 52-week high price computed as the current price divided by the highest price observed over the prior year. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted. The figure presents the cumulative excess return for the high and low portfolios held for three months, in addition to the return from a zero-cost portfolio that takes a long (short) position in the high (low) portfolio - high-low. The equally weighted market portfolio in the figure "EW Market" is constructed from our filtered stock sample.

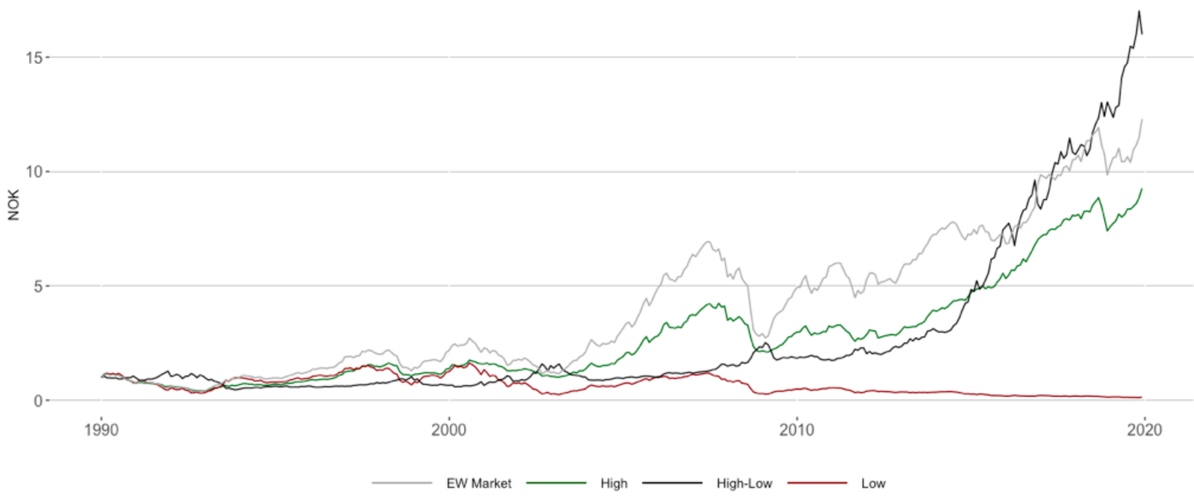

Figure C.2: Returns Series of 52-Week High – High and Low Portfolios

At the beginning of each month stocks are sorted in a descending order on nearness to the 52-week high price computed as the current price divided by the highest price observed over the prior year. The top (bottom) 30% constitutes the high (low) portfolio. The portfolios are equally weighted and held for three months after the formation date. The figure presents the return series for these portfolios.

Table C.2: 52-Week High Returns and Alphas within Size Based Sub Samples

The table presents returns and alphas for the relative strength strategy within size based sub samples. At the beginning of each month stocks are sorted into tercile portfolios according to their market capitalization. Each large, medium and small group are then sorted into tercile portfolios in a descending order on nearness to the 52-week high price computed as the current price divided by the highest price observed over the prior year. The breakpoints at the second sort is set at the 30th and 70th percentiles while there is an equal amount of stocks in each portfolio with regards to the first sort. The high (low) portfolio are stocks in the top (bottom) 30% with regards to the second sort. The portfolios are equally weighted and held for three months after the formation date. High-low is a zero-cost portfolio with a long position in the high portfolio and a short position in the low portfolio. "Excess Return" is the average monthly excess return. "CAPM Alpha" is the intercept from a regression with excess portfolio return as the dependent variable and the market factor as the independent variable. "FF3" alpha augments CAPM with the size and value factors – the Fama & French three factor model.

General: The market factor is equally weighted and constructed from our filtered stock sample. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. See section 3 in this paper for a description of the size and value factors.

Size	Portfolio	Excess Return	CAPM Alpha	FF3 Alpha
Large	High	0.57%	-0.06%	0.17%
	Low	-0.34%	-1.48%	-1.16%
	High-Low	0.93% (2.84)	1.43% (4.97)	1.33% (4.48)
Medium	High	0.97%	0.32%	0.19%
	Low	-0.58%	-1.82%	-1.87%
	High-Low	1.55% (3.74)	2.13% (6.23)	2.06% (5.87)
Small	High	0.91%	0.31%	0.16%
	Low	0.48%	-0.91%	-1.31%
	High-Low	0.43% (0.73)	1.22% (2.70)	1.47% (3.31)

Figure C.3: 12-Month Rolling Average of 52-Week High Portfolio Returns

At the beginning of each month stocks are sorted in a descending order on nearness to the 52-week high price computed as the current price divided by the highest price observed over the prior year. The portfolios are equally weighted and held for three months after the formation date. High-low is a portfolio taking a long (short) position in the high (low) portfolio. The figure presents a 12-month rolling arithmetic average of excess portfolio returns. The plot starts in Feb 1991 from where 12 months of prior observations is available.

Table C.3: Top 20 Most Frequent Companies in High – and Low 52-Week High Portfolios

The table presents the company names of the top 20 most frequent stocks sorted into the high and low portfolios when the sort variable is nearness to the 52-week high price computed as the current price divided by the highest price observed over the prior year. "High" is stocks with the largest value of the sort variable, and "Low" is stocks with the smallest value of the sort variable.

Low	High
Jinhui Shiping and Transportation	Arendals Fossekompani
PGS	Olav Thon Eiendomsselskap
Frontline	Voss Veksel - og Landmandsbank
DNO	Skiens Aktiemølle
NRC Group	Orkla
SAS AB	Tomra Systems
Belships	AF Gruppen
Nordic Semiconductor	Norsk Hydro
ContextVision	Veidekke
Nekkar	DNB
Kverneland	Gyldendal
Goodtech	Rieber & Søn
Dolphin Drilling	Hafslund ser. A
Borgestad	Kongsberg Gruppen
Subsea 7	NTS
Tandberg Data	Storebrand
Software Innovation	Farstad Shipping
Photocure	Wilh. Wilhelmsen ser. A
Norwegian Air Shuttle	Solvang
Aker BioMarine	Tide

Appendix D: Fama-MacBeth Regression Results

Table D.1: Fama-MacBeth Results for 52-Week High *12x6* and Relative Strength *6x6*

Each month between Feb 1990 and Dec 2019, 6 (j = 1,…,6) cross-sectional regressions are estimated for the 52-week high 12x6 and relative strength 9x6 strategies:

$$R_{it} = b_{0jt} + b_{1jt}Size_{i,t-1} + b_{2jt}JTH_{i,t-j} + b_{3jt}JTL_{i,t-j} + b_{4jt}GHH_{i,t-j} + b_{5jt}GHL_{i,t-j} + e_{it}$$

where R_{it} and $Size_{i,t}$ are the excess return and the market capitalization of stock i in month t. $JTH_{i,t-j}$ ($JTL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to the six month prior return in month $t-j$, and zero otherwise. $GHH_{i,t-j}$ ($GHL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to nearness to the 52-week high in month $t-j$, and zero otherwise. The coefficient estimates of a given independent variable are averaged over j = (1,…6). The numbers in the table is the intercept of a regression with the time-series of the given average as the dependent variable and systematic risk factors as independent variables to hedge out factor exposure. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. "Jan.Incl" presents the results when January is included and "Jan.Excl" presents the results when January is excluded. The market factor in the regressions is equally weighted and constructed from our filtered stock sample. See section 3 in this paper for a description of the size and value factors which is part of the Fama & French three factor model (FF3).

	Jan. Incl		**Jan. Excl**	
Coefficient	CAPM alpha	FF3 alpha	CAPM Alpha	FF3 alpha
Intercept	1.82%	0.84%	1.43%	0.65%
	(4.68)	(2.60)	(3.37)	(1.94)
Size	-0.31%	-0.16%	-0.25%	-0.13%
	(-5.32)	(-3.59)	(-3.99)	(-2.83)
JTH	0.36%	0.31%	0.35%	0.30%
	(2.48)	(2.45)	(2.31)	(2.24)
JTL	-0.20%	-0.24%	-0.23%	-0.25%
	(-1.58)	(-1.73)	(-1.75)	(-1.90)
GHH	0.33%	0.32%	0.34%	0.32%
	(3.33)	(3.04)	(3.33)	(3.08)
GHL	-0.52%	-0.54%	-0.66%	-0.64%
	(-2.86)	(-2.92)	(-3.43)	(-3.40)
JTH - JTL	0.56%	0.54%	0.57%	0.55%
	(2.84)	(2.83)	(2.81)	(2.83)
GHH - GHL	0.86%	0.86%	0.99%	0.96%
	(4.02)	(4.06)	(4.53)	(4.48)

Table D.2: Fama-Macbeth Results for 52-Week High *12x3* and Relative Strength *12x3*

Each month between Feb 1990 and Dec 2019, 3 (j = 1,…,3) cross-sectional regressions are estimated for the 52-week high 12x3 and relative strength 9x3 strategies:

$$R_{it} = b_{0jt} + b_{1jt}Size_{i,t-1} + b_{2jt}JTH_{i,t-j} + b_{3jt}JTL_{i,t-j} + b_{4jt}GHH_{i,t-j} + b_{5jt}GHL_{i,t-j} + e_{it}$$

where R_{it} and $Size_{i,t}$ are the excess return and the market capitalization of stock i in month t. $JTH_{i,t-j}$ ($JTL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to the twelve month prior return in month $t-j$, and zero otherwise. $GHH_{i,t-j}$ ($GHL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to nearness to the 52-week high in month $t-j$, and zero otherwise. The coefficient estimates of a given independent variable are averaged over j = (1,…3). The numbers in the table is the intercept of a regression with the time-series of the given average as the dependent variable and systematic risk factors as independent variables to hedge out factor exposure. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. "Jan.Incl" presents the results when January is included and "Jan.Excl" presents the results when January is excluded. The market factor in the regressions is equally weighted and constructed from our filtered stock sample. See section 3 in this paper for a description of the size and value factors which is part of the Fama & French three factor model (FF3).

	Jan.Incl		**Jan.Excl**	
Coefficient	CAPM Alpha	FF3 Alpha	CAPM Alpha	FF3 Alpha
Intercept	1.13%	0.16%	0.68%	-0.09%
	(2.80)	(0.45)	(1.52)	(-0.25)
Size	-0.23%	-0.08%	-0.17%	-0.05%
	(-3.88)	(-1.76)	(-2.56)	(-0.95)
JTH	0.35%	0.27%	0.32%	0.26%
	(1.77)	(1.52)	(1.57)	(1.42)
JTL	-0.26%	-0.27%	-0.16%	-0.16%
	(-1.31)	(-1.27)	(-0.79)	(-0.78)
GHH	0.46%	0.47%	0.50%	0.49%
	(3.70)	(3.60)	(4.07)	(4.02)
GHL	-0.90%	-0.91%	-1.14%	-1.11%
	(-3.95)	(-3.87)	(-5.20)	(-4.94)
JTH - JTL	0.61%	0.54%	0.48%	0.42%
	(2.07)	(1.87)	(1.56)	(1.43)
GHH - GHL	1.36%	1.37%	1.64%	1.61%
	(5.32)	(5.13)	(6.86)	(6.42)

Table D.3: Fama-Macbeth Results for 52-Week High *12x6* and Relative Strength *12x6*

Each month between Feb 1990 and Dec 2019, 6 (j = 1,…,6) cross-sectional regressions are estimated for the 52-week high 12x6 and relative strength 12x6 strategies:

$$R_{it} = b_{0jt} + b_{1jt}Size_{i,t-1} + b_{2jt}JTH_{i,t-j} + b_{3jt}JTL_{i,t-j} + b_{4jt}GHH_{i,t-j} + b_{5jt}GHL_{i,t-j} + e_{it}$$

where R_{it} and $Size_{i,t}$ are the excess return and the market capitalization of stock i in month t. $JTH_{i,t-j}$ ($JTL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to the twelve month prior return in month $t-j$, and zero otherwise. $GHH_{i,t-j}$ ($GHL_{i,t-j}$) is dummy variables equal to 1 if stock i is in the top (bottom) 30% according to nearness to the 52-week high in month $t-j$, and zero otherwise. The coefficient estimates of a given independent variable are averaged over j = (1,…6). The numbers in the table is the intercept of a regression with the time-series of the given average as the dependent variable and systematic risk factors as independent variables to hedge out factor exposure. The numbers in parentheses are Newey & West (1987) adjusted t-statistics estimated using five lags. "Jan.Incl" presents the results when January is included and "Jan.Excl" presents the results when January is excluded. The market factor in the regressions is equally weighted and constructed from our filtered stock sample. See section 3 in this paper for a description of the size and value factors which is part of the Fama & French three factor model (FF3).

	Jan.Incl		**Jan.Excl**	
Coefficient	CAPM Alpha	FF3 Alpha	CAPM Alpha	FF3 Alpha
Intercept	1.68%	0.70%	1.27%	0.49%
	(4.43)	(2.19)	(3.09)	(1.49)
Size	-0.29%	-0.15%	-0.23%	-0.11%
	(-5.17)	(-3.25)	(-3.82)	(-2.47)
JTH	0.30%	0.26%	0.28%	0.23%
	(1.88)	(1.71)	(1.59)	(1.47)
JTL	0.02%	0.00%	0.05%	0.04%
	(0.10)	(0.00)	(0.27)	(0.22)
GHH	0.38%	0.38%	0.40%	0.39%
	(3.46)	(3.30)	(3.49)	(3.42)
GHL	-0.63%	-0.63%	-0.78%	-0.77%
	(-3.31)	(-3.27)	(-4.37)	(-4.19)
JTH - JTL	0.28%	0.26%	0.22%	0.19%
	(1.02)	(0.92)	(0.75)	(0.66)
GHH - GHL	1.01%	1.01%	1.18%	1.16%
	(4.40)	(4.32)	(5.39)	(5.24)