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The 52-Week High as a Reference Point in Trading Behaviour

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Abstract

Using Oslo Stock Exchange market data from 1991 to 2010, a portfolio based on the current price's nearness to the 52-week high price yields returns comparable to and partly independent of a past performance based momentum portfolio. This suggests that the 52-week high may contribute to an explanation of price momentum, more specifically by being used as an arbitrary reference point or anchor in trading decisions. Empirically, increased nearness to the 52-week high is associated with lower share turnover and demand, possibly causing a temporary underreaction in stock prices and price momentum as this underreaction is corrected over time.

Sammendrag

En portefølje på Oslo Børs markedsdata fra 1991 til 2010 basert på prisens nærhet til siste års kurstopp gir en avkastning som er sammenlignbar med og delvis uavhengig av en momentum-portefølje basert på tidligere avkastning. Dette kan tyde på at siste års kurstopp kan bidra til å forklare momentum i aksjepriser, ved at denne fungerer som et vilkårlig referansepunkt eller anker i investeringsbeslutninger. Empirisk er økt nærhet til årlig kurstopp forbundet med lavere handelsvolum og etterspørsel, som kan føre til en midlertidig underreaksjon i aksjepriser og momentum etter hvert som prisene blir korrigert.

Høgskolen i Oslo og Akershus, Fakultet for samfunnsfag
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May 29, 2015

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Using Oslo Stock Exchange market data from 1991 to 2010, a portfolio based on the current price's nearness to the 52-week high price yields returns comparable to and partly independent of a past returns based momentum portfolio. This suggests that the 52-week high may contribute to an explanation of price momentum, more specifically by being used as an arbitrary reference point or anchor in trading decisions. Empirically, increased nearness to the 52-week high is associated with lower share turnover and demand, possibly causing a temporary underreaction in stock prices and price momentum as this underreaction is corrected over time.

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Contents

1 Introduction

Quantities and other pieces information rely on context to provide meaning. The way in which a problem is contextually situated or framed will usually have an impact on the decision that is reached. Often, relevant benchmarks are readily available but what if they are not? Various reference points undoubtedly play a role in people's assessment of alternatives, though some may be more or less valid than others. When in lack of relevant information, or when such information is available but too difficult or time-consuming to adquately process, we are prone to rely on benchmarks of questionable validity.

This thesis is concerned with one such reference point, specifically the highest price of a stock over the past 52 weeks. This statistic is regularly quoted in various newspapers and online so it is very likely that it would get some attention from investors. But does it actually influence decision-making, and does this affect market outcomes such as prices and trading volume?

George and Hwang (2004) document that the current price's nearness to the 52-week high predicts future returns and explains profits from momentum investing. Following a similar approach on Oslo Stock Exchange trading data (OSE), I find that a portfolio based on the nearness to the 52-week high yields returns comparable to a portfolio based on the Carhart (1997) past returns momentum factor. In the case of this study, and in contrast to George and Hwang (2004), the momentum (Carhart 1997) portfolio yields superior returns over the 52-week high portfolio however. Still, double sorting the portfolios i.e. sorting by one criterion on a subset determined by the other criterion, yields results suggesting that the strategies are mutually independent to some extent. Thus, price momentum may be partly driven by the current price's nearness to the 52-week high.

As an explanation for the 52-week high momentum strategy profits, George and Hwang (2004) propose an "anchoring" effect. Investors use the 52-week price high as an arbitrary reference point when considering new information and deciding whether to buy, sell or hold an asset. As the price approaches the 52-week high following good news, investors become increasingly reluctant to bid up the price even if it is justified by new information, temporarily suppressing a price increase. Conversely, as bad news pushes the price far from the 52-week high, there is a temporary reluctance to sell. Subsequently, the information prevails leading to a market correction and price continuation.

To test this hypothesis, I conduct Fama-McBeth (1973) regressions on share turnover and a proxy for demand with the nearness to the 52-week high as an explanatory variable. Results indicate that increased nearness to the 52-week high is associated with generally lower turnover and a net selling pressure, consistent with the anchoring hypothesis. At increasingly lower price levels in relation to the 52-week high, there is a progressive increase in turnover which is contradictory to what is expected. This may suggest an assymmetrical anchoring effect with regard to prices near and far from the 52-week high respectively. Alternatively, the higher turnover may be caused by other, competing forces.

The remaining text is structured as follows: The next section reviews the most relevant earlier research. The data used is described in section 3. Section 4 describes the empirical analysis and results. Section 5 discusses empirical results and how they relate to previous research. Section 6 concludes.

2 Related Research

George and Hwang (2004) study momentum in the US stock market[1]. Compared to the momentum strategies of Jegadeesh and Titman (1993) as well as Moskowitz and Grinblatt (1999), they find that a portfolio strategy based on nearness to the 52-week high yields superior returns. George and Hwang's results have been tested on several markets. In the most comprehensive work, Liu, Liu and Ma (2011) show that George and Hwang's results are robust internationally. The 52-week high momentum strategy is profitable in 18 of the 20 countries studied, though profits are significant only in 10. Interestingly, Norway is among the countries where profits are not significant. On the other hand, results by Liu et al. (2011) suggest a correlation between the different investing strategies. Momentum strategies based on past returns tend to work in the same countries as

[1]All stocks at the Center for Research on Security Prices (CRSP)

momentum strategies based on nearness to the 52-week high. Previous analysis of the OSE trading data document the existence of momentum returns (Ødegaard 2013, Nygaard 2011, Korneliussen and Rasmussen 2014). While Liu et al. (2011) obtain their data for all 20 markets studied from Datastream, this thesis utilizes data directly supplied by OSE which should be of equal or higher quality. As such, further inquiry might be warranted.

As the 52-week price high is a readily available piece of information, this represents something of a challenge to the Efficient Market Hypothesis (EMH). According to EMH, markets are assumed to be semi-strong form efficient most of the time. Thus prices should reflect all publicly available information. The 52-week high is certainly a publicly available piece of information and it should already be reflected in current prices, and have no power to predict future prices.

As described in the introduction, George and Hwang suggest the 52-week high as having an anchoring effect as a likely explanation for the 52-week high strategy momentum profits. The use of arbitrary reference point in decisions under uncertainty has been documented in experimental studies conducted by Tversky and Kahneman (1974) who refer to the phenomena as an adjustment and anchoring bias. In the most well known case, separate groups were asked to give an estimate of the percentage of African states in the United Nations. Prior to answering, a wheel of fortune with values from zero to 100 was spun in the presence of the subjects. Outcomes on the wheel of fortune systematically influenced the subjects' responses. Lower outcomes resulted in comparably lower estimates and vice versa.

A number of other studies have looked into the 52-week high and related reference points in trading behaviour[2]. By taking into account the time dimension,

[2]Proximity to the 52-week high as having an effect on decision-making has also been documented in other settings. Heath, Huddart and Lang (1999) find that option exercise activity among corporate employees roughly doubles when the stock price exceeds the 52-week high. In the context of mergers, both targets and bidder use the 52-week high as well as other price peaks in their decision making leading to prices clustering around these price peaks (Baker, Pan and Wurgler 2012). Furthermore, when the offer price exceeds the 52-week high, the likelihood of a deal is increased

Bhootra and Hur (2013) find that stocks which have attained the 52-week high in the recent past outperform stocks which have attained the 52-week high in the distant past. The 52-week high may function as a reference point at market level, not only for individual stocks. Li and Yu (2012) find that nearness to the Dow 52-week high as a proxy for underreaction, and nearness to the Dow historical high as a proxy for overreaction[3], predict future returns on an aggregate level.

A study by Huddart, Lang and Yetman (2009) show that trading volume and returns increase when a stock crosses its previous 52-week high or low. This may potentially be at odds with the anchoring explanation by which we generally would expect lower trading volumes when the stock price is very close to or very far away from the 52-week high. Huddart et al. (2009) cite Barber and Odean's (2008) limited attention bias as the explanation most consistent with their results. In short, this theory states that as investors have limited attention, high or unusually performing stocks will be more easily noticed and, in turn, traded by investors. This could lead to increased buying pressure and an overreaction in prices in the short term.

A different explanation for momentum returns is that investors either are subject to "disposition" effect (Grinblatt and Han 2005) and prematurely sell their stocks to realize gains. The disposition effect relies on two cognitive biases as building blocks, Prospect theory (Kahneman and Tversky 1979) and Mental accounting (Thaler 1999). Prospect theory states that utilities are perceived as gains and losses relative to a reference point rather than total wealth. The value or utility

[3]Models incorporating both under- and overreaction in prices seem to be even more exposed to criticism than other behavioural finance work. Examples of such models include Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999). Fama (1998) argues that while a lot of the behavioural finance literature attempt to construct models that are able to unify empirically observable under- and overreaction in prices, the most likely reason for this pattern is chance. Under- and overreaction seems, in the long run, to be fairly evenly distributed, much as predicted by EMH. Lacking the long term reversal or overreaction pattern, George and Hwang's results represent a potentially bigger challenge to EMH than the aforementioned studies. While Fama (1998) argues that most market anomalies are captured by the three-factor model (Fama and French 1992), he concedes that short-term price continuation is not.

function for the decision maker is concave on the positive side and convex on the negative side. Thus, utility or value is diminishing by real gains or losses on both sides of zero. This entails risk averse behaviour on the positive side mirrored by risk seeking behaviour on the negative side. Mental accounting refers to investors tendency to divide their assets into separate mental accounts rather than treating them as part of the same portfolio. Instead of taking the entire portfolio into account when making sell or hold decisions, a disposition effect/mental accounting investor would consider the state of each individual asset in comparison to some reference point.

Usually, the reference point by which losses or gains is measured is modelled as the aquisition price (see for example Frazzini 2006, Grinblatt and Han 2005, Nygaard 2011). Other evidence (Gneezy 2005) suggests that reference points may adjust over time. For example, the aquistion price may have less meaning if much time has passed since purchase, leading the investor to consider other reference points. Yuan (2015) show that market-wide attention-grabbing events when the stock market is high, such as record levels for the Dow index, induce investors to sell their stocks, which has a negative impact on prices and may contribute to price underreaction and continuation.

3 Data

The empirical analysis is based on equities trading data at the Oslo Stock Exchange from 1991 to 2010. Founded in 1819, the Oslo Stock Exchange facilitates the only regulated securities market in Norway today. In 1980 the total market value was NOK 16.5 billion while by 2013 this had grown to NOK 1,806 billion. Historically, and presently, the exchange has been dominated by government-controlled companies such as Norsk Hydro, Telenor and Statoil. Another feature of the Exchange is the dominance of energy and shipping industries.

The data consists of share transactions for all listed companies, for every trading day from January 2, 1991 to December 31, 2010. Each entry includes information for a specific security on bid and offer prices, daily open, high, low and last prices, both raw and adjusted for splits as well as the daily volume weighted average price. A cumulative dividend factor is reported to facilitate further price adjustment for dividend. In addition, information is given on turnover, number of shares issued and security, company and industry identifiers. In total the data contains about 1.04 million entries. Table 1 displays the number of companies, securities and total market capitalization by the end of each year over the sample period.

Not all stocks are traded on every trading day. In the event of no trade for a stock, the last closing price is carried forward. This facilitates sample continuity and calculation based on accurate timeframes since missing values otherwise would have been skipped or ignored in the analysis. Imputation of the last previous price is moreover likely to have minimal effect on most analyses conducted, as zero change in price equals zero return. In the event of no trade, the last price is also the one presented to investors in various media. Insofar as price changes and levels influence trading behavior, this is actually the relevant price whether trading recently have taken place or not.

Data entries are identified by both a firm and security identification number. A few firms have more than one class of shares to differentiate between the voting rights of the owners of the respective share owner [4]. For the purpose of the thesis, I use security rather than firm ID, otherwise ignoring that different securities might be issued by the same firm. As the analysis largely deals with investors perception of the stock price relative to the 52-week high, using individual securities rather than firms seems more appropriate. It is not likely that the exclusion of additional share classes for the firms in question would significantly affect the results in any way.

[4]The number of firms with two, three or even four share classes is steadliy decreasing over the sample period. From 1991-1995 the average number of firms with more than one share class was 23. For 1996-2000, 2001-2005 and 2006-2010 the corresponding numbers was 15, 6 and 4 respectively

Table 1: Sample Statistics

This table displays the number of companies, securities and total market capitalization at the end of each year over the sample period.Total market capitalization is calculated as the sum over all securities unadjusted price times number of shares outstanding.

End-Year	Number of Companies	Number of Securities	Total Market Cap (Billion NOK)
1991	111	143	58.4
1992	123	159	60.8
1993	135	169	96.8
1994	150	181	121.9
1995	168	184	150.1
1996	185	202	188.2
1997	223	242	284.5
1998	244	264	237.5
1999	243	259	346.2
2000	245	258	465.3
2001	231	243	577.7
2002	217	224	441.3
2003	207	214	662.3
2004	201	205	905.6
2005	231	235	1310.9
2006	250	255	1821.8
2007	281	285	2081.3
2008	273	276	959.4
2009	255	260	1502.3
2010	230	233	1717.1

4 Empirical Analysis

The empirical analysis is divided into three parts. Subsection 4.1 describes portfolio construction and results. Subsections 4.2 and 4.3 present regression analyses on turnover and net buying pressure respectively. Methodological descriptions and considerations are introduced as they are required for the different subsections.

4.1 Factor Portfolios

In order to investigate the data for momentum trends, I construct two factor portfolios. These are the PR1YR factor (Carhartt 1997) and a portfolio based on the current price's nearness to the 52-week high (George and Hwang 2004). The PR1YR factor is similar to the Jegadeesh Titman (1993) momentum strategy in that it is based on past returns strategy somewhat simpler as it does not incorporate overlapping portfolios.

For each factor portfolio two versions are constructed. One is based on the full sample while the other is based on a sample in which securities with a market capitalization equal to or below the lowest decile (approx. NOK 73 million) over the sample period is filtered out. This is to examine to what extent results are driven by very small cap securities, as earlier reseach has indicated that some market anomalies may vary systematically with size (Fama and French 2008).

4.1.1 PR1YR Factor Portfolio Construction

In order to construct the PR1YR factor portfolio the the split adjusted last price each month is extracted and further adjusted the for cumulative dividend. In the case of no actual trade on this day for the security in question, the last trading price is carried forward. From the monthly prices, continuously compounded returns for each security is calculated as the natural logarithm of the product of the price at time t divided by the price in the previous period, $ln(\frac{P_t}{P_{t-1}})$. In the event of no price change between periods for a security, either because trading continued at the same price of no trading that day, the return equals zero. Measurement by continuously compounded returns is chosen over simple returns due to the relative ease of calculating cumulative return, which are necessary at later stages in the factor construction the regressions further on. The cumulative return from time t-2 to t-12 for each security each month is then calculated. Securities listed less than 13 months cannot be evaluated by this criterion and are therefore excluded from the sample. At the end each month $t-1$, the securities are then arranged by cumulative return from high to low and divided into three sub-portfolios. As the securities are sorted by cumulative returns, the imputation of the last trading price mentioned above, should have no effect on return calculations or which portfolio a security is designated to. The winner sub-portfolio contains the top 30% of the unique securities and the loser sub-portfolio contains the bottom 30%. In the case that the number of unique securities in the winner portfolio would be a fraction, the number is rounded according to normal rounding rules. The loser sub-portfolio always contain the same number of unique securities as the time-corresponding winner portfolio. The middle sub-portfolio is the remaining 40%. The PR1YR portfolio returns at each month is the equal weighted average monthly continuously compounded returns of the securities in the winner portfolio minus the same for the loser portfolio at time t. This models a self-financing portfolio where a long position the top performing 30% of the securities in the market is acquired from the exceeds of going short the bottom performing 30%. Performance, measured by past cumulative returns $t-2$ to $t-12$, is assessed and the portfolio is rebalanced each month. The month $t-1$ is skipped to account for the bid-ask bounce, a common procedure in the momentum literature (Jegadeesh and Titman 1993, Grinblatt and Han 2005, George and Hwang 2004).

4.1.2 Nearness to the 52-Week High Factor Portfolio Construction

The 52-week high portfolio is constructed on the same sample and in the same way as the PR1YR-factor in all respects apart from the sorting criterion. While for the PR1YR-factor, securities are sorted according to past cumulative returns, securities in the 52-week high portfolio are sorted by the nearness to the security's maximum price over the past year calculated as $\frac{P_{t-1}}{high_{t-1}}$. The dividend and splits adjusted price, P, for each security each month is divided by the maximum adjusted daily price over the last year approximated as 251 trading days. At each month, the securities are then sorted from high to low by the 52-week high ratio at time $t-1$. Thus the portfolio returns, winner minus loser, are the average continuously compounded returns the following month, that is at time t.

4.1.3 Portfolio Results

Table 2 reports the average continuously compounded monthly returns. Contrary to the results of George and Hwang (2004) and Liu et al (2011), the portfolio strategy based on past returns yield superior returns over the strategy based on nearness to the 52-week high, although both display relatively high returns. Another common feature is that most of the portfolio returns are driven by shorting the loser stocks.

The results of the portfolios constructed on the filtered samples reveal a somewhat different pattern. Whereas the winner portfolios are comparable to the unfiltered portfolios, the loser portfolios are much closer to zero. This yields lower returns overall as the profits from shorting the losers is diminished. Hence, a considerable amount of momentum profits are gained from shorting very small cap securities. For the portfolios on the filtered sample, most of the returns are driven by the winner sub-portfolios.

The differences between the winner and loser portfolios for both strategies are significantly different from zero. This confirms, in statistical terms, that portfolio returns are dependent on the sorting criteria. It is extremely unlikely that the portfolio returns are not, at least in part, determined by the previous sorting.

As the high returns of the momentum portfolios might be associated with increased risk, some standard risk metrics are reported. All portfolios except the 52WH portfolio on the filtered sample have Sharpe ratios, calculated as average return divided by standard deviation of return, that are higher than a market factor (RMRF), which has a Sharpe ratio at 0.20[5]. The 52WH portfolio returns generally

[5] Fama and French (1992) risk factors (RMRF, SMB and HML) for the OSE are borrowed from Professor Bernt Arne Ødegaard's homepage: http://www1.uis.no/ansatt/odegaard/.

have somewhat higher standard deviations leading to lower Sharpe ratios.

The winner minus loser portfolio returns are also regressed on the Fama and French (1992) risk factors. The alpha coefficients may be interpreted as abnormal or risk adjusted return. Interestingly, alphas are higher than average returns for all portfolios, in part resulting from negative correlation with risk factors (see Appendix for factor coefficients). Although the 52WH portfolio returns have somewhat higher volatility than the PR1YR returns and the market factor, it does not seem that momentum returns can be solely explained by increased risk.

Table 2: Portfolio Monthly Returns

The table displays average monthly returns for the PR1YR (Carhart 1997) and the 52-week high (George and Hwang 2004) portfolio strategies respectively. The winner portfolios are the top performing 30% percent of the stocks in month t as ranked by either cumulative returns months $t-2$ to $t-12$, (PR1YR) or the price's nearness to the 52-week high price, $\frac{P_{t-1}}{high_{t-1}}$, (52WH). The loser portfolios are the lowest performing 30% of the stocks. Results are displayed both for the full sample of securities and for a sample where the decile with the lowest market capitalization is excluded. Monthly returns (Winner - Loser) are the equally weighted average continuously compounded returns for that month for selected stocks. Stocks are sorted and selected at the end of each month $t-1$. Sharpe ratios are calculated as the winner minus loser portfolio return divided by its standard deviation. Also reported are alphas or intercepts yielded by regressing the winner minus loser portfolios on the Fama and French (1992) risk factors, RMRF, SMB and HML. T-stats for tests of difference from zero are reported in parentheses.

Portfolio	Winner	Loser	Winner - Loser	Sharpe Ratio	3-Factor Alpha
$PR1YR$	0.89%	-1.22%	2.11% (5.65)	0.38	2.59% (7.02)
$PR1YR_{excl.dec10}$	1.10%	-0.24%	1.34% (3.69)	0.25	1.77% (4.93)
$52WH$	0.65%	-1.17%	1.82% (4.03)	0.27	2.82% (7.90)
$52WH_{excl.dec10}$	0.84%	-0.19%	1.02% (2.37)	0.16	1.96% (5.89)

Figure 1 shows the cumulative returns of both factor portfolios over time. Consistent with loser stocks accounting for the largest contribution, we see that the steepest increase occurs in the aftermath of financially troublesome events such as the dotcom-bubble in 2001 and the credit crisis starting in 2008, hinting that the short side of the strategies may be associated with some risk. Sustained mispricings in the market requires limits to (riskless) arbitrage (Shleifer and Vishny 1997). Otherwise they would be quickly eliminated. Going short in a bet on a bubble to burst might be risky as there is no guarantee that the market will correct itself within a reasonable amount of time. During the internet bubble for example, many investors perceived stocks to be overvalued but were nonetheless unwilling to take bets against these mispricings while some of those who did suffered massive losses (Brav, Heaton and Rosenberg 2004). Aside from these time intervals, returns are more moderate although generally positive. Interestingly, the 52-week high strategy catches up with the PR1YR during the 2001-2003 period but otherwise yield lower returns.

While, returns may seem high, it should be kept in mind that transaction costs are not taken into account. Transaction cost analysis is not trivial partly due to the long timeframe involved. The number of stocks replaced each month as determined by the sorting criteria could potentially vary a lot leading to considerable transaction costs. In Liu et al. (2011), the analysis suggests that the 52-week high investing strategy is not significantly profitable once transaction costs are taken into account. There is otherwise an ongoing debate in the literature as to whether momentum is actually financially exploitable in practice, after transaction costs are deducted (Barroso and Santa-Clara 2015). As the main focus here is to investigate whether past return and/or nearness to the 52-week high predict future returns rather than presenting a money-making scheme, further analysis of transaction costs is not considered a priority.

4.1.4 Portfolio Double Sorts

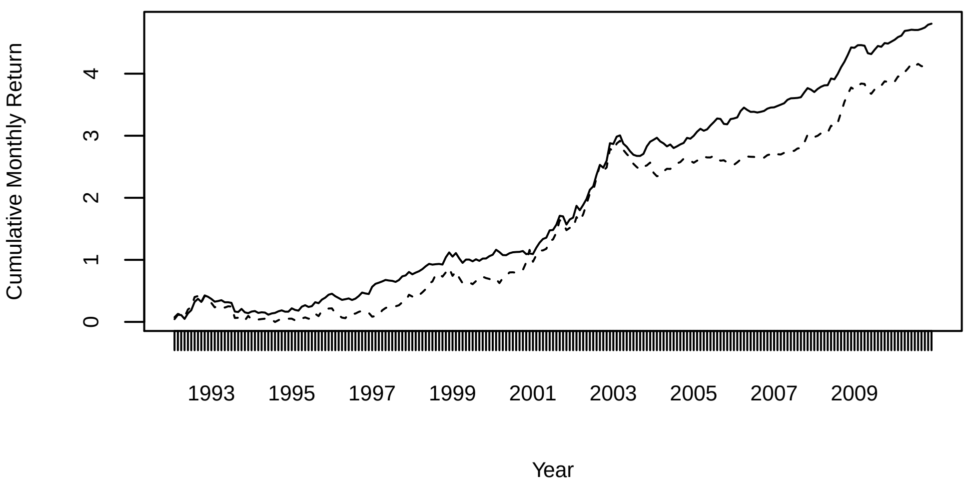
An important question is whether the 52-week high has power to predict future returns independent of the PR1YR factor. In order to disentangle the effects of the sorting criteria from each other, I conduct a double sorting of the portfolio returns.

At each month, stocks are first sorted by one of the sorting criteria and separated into the top 30%, middle 40% and bottom 30%. Then, stocks inside the top

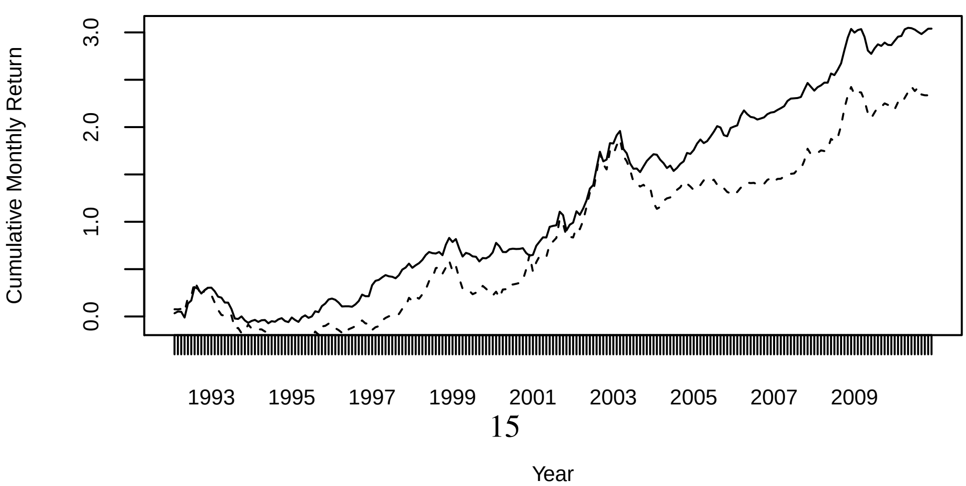
Figure 1: Factor Portfolio Monthly Cumulative Return

The figure displays the cumulative monthly return over time for the factor portfolios. The solid line shows the cumulative return of the PR1YR portfolio where stocks are sorted by the cumulative past return from $t-2$ to $t-12$. The dashed line shows the cumulative return of the 52-week high portfolio where stocks are sorted by the current price's nearness to the 52-week high. In panel A, portfolio returns are calculated on the full sample. Panel B displays portfolio returns on a sample where the where the lowest market capitalization decile is excluded

Panel A: Full Sample



Panel B: Sample Excluding Market Cap Decile 10



and bottom 30% respectively, are sorted again but this time by the other criterion. The purpose is to determine whether there still is a difference between winner and loser sub-portfolios when stocks are sorted within a group determined by the other criterion. If one strategy was wholly dependent on the other, the within-sorting should yield no difference in returns. Results of double sorting are displayed in table 3.

Winner portfolios have higher returns than loser portfolios in all pairwise comparisons. All differences are highly statistically significant except from the 52-week high winner within the PR1YR winner. This suggest that the strategies are independent of each other to some extent. Upward trending stocks are likely to have both high cumulative returns and a 52-week high ratio of one or near to one. An issue with these double sorts is that the number of securities for some months is as low as 40. Double-sorted portfolios for these months have only 12 individual securities. Considering the high correlation between the portfolio sorting criteria this number may be too small to adequately disentangle the portfolios from each other. As such, the statistic tests of winner loser differences may not represent conclusive evidence.

4.2 The 52-Week High and Share Turnover

This section expands on the previous analysis of portfolio returns by introducing turnover, defined as trading volume divided by number of shares outstanding. Are there systematic differences in turnover dependent on the prices nearness to the 52-week high? The main motivation for this subsection, is to shed light on the explanation proposed by George and Hwang with 52-week high as an anchor. An implication of the hypothesis is a greater reluctance to trade when the price is very near or very far from the 52-week high. If investors are more reluctant to bid the price of a stock at the stock price approaches the 52 week high or sell as the price moves far away from this point, we might expect lower turnover at the extremes of the ratio i.e. close to 1 and zero.

Huddart, Lang and Yetman (2009) present evidence that volume increases

Table 3: Pairwise Comparison of PR1YR and 52-Week High Portfolios

This table displays the results of double sorts of portfolios based on the full sample of securities. In panel A stocks are first sorted by the PR1YR criterion, that is cumulative returns from months $t-12$ to $t-2$. Winner and loser portfolios are the top and bottom performing 30% stocks respectively. Then, within the winner and loser portfolios, stocks are sorted again but this time by the nearness to the 52-week high calculated as $\frac{P_{t-1}}{high_{t-1}}$, where $high$ is the maximum price over the past 251 days. Winner and loser portfolios of the within-sorting are similarly the top and bottom performing 30% respectively. In panel B stocks are sorted in the same way only first by nearness to the 52-week high and then by cumulative returns from months $t-12$ to $t-2$. T-stats for tests of difference from zero are reported in parentheses.

Panel A		
Portfolios sorted by PR1YR	Portfolio sorted by 52-Week High	Avg. Monthly Return
Winner	Winner	0.81%
	Loser	0.25%
	Winner - Loser	0.56% (1.39)
Loser	Winner	-0.59%
	Loser	-2.16%
	Winner - Loser	1.57% (2.52)

Panel B		
Portfolio sorted by 52-Week High	Portfolios sorted by PR1YR	Avg. Monthly Return
Winner	Winner	1.36%
	Loser	-0.21
	Winner - Loser	1.57% (4.51)
Loser	Winner	-0.63%
	Loser	-2.41%
	Winner - Loser	1.78% (3.20)

when a stock crosses the upper or lower boundaries of its previous trading range. While unable to assign definitive trading direction or trader type to specific transactions, their results suggest that the increased volume is largely due to purchases by small investors. Several explanations are discussed though the authors put forth Barber and Odean (2008) and the idea of bounded rationality and attention-grabbing stocks as the most likely reason. In a world of almost infinite investment opportunities, investors have a hard time processing all the information and assessing all possible alternatives. Instead, there is a tendency to rely on short-cuts in trading or investment decisions. Stocks that more easily catches the attention of investors are traded more frequently. Stocks outside of their previous price range are more easily noticed by investors and get traded relatively more often.

A different explanation is offered by the disposition effect (Shefrin and Statman 1985, Grinblatt and Han 2005, Frazzini 2006). Prices are at very high levels in relation to the 52-week high could incite investors to sell (Yuan 2015). This would also imply an increase in turnover at very high price levels, though likely to primarily be driven by seller-initiated rather than buyer-initiated trading.

This part of the analysis utilizes weekly observations to facilitate comparison with with previous research, in particular Huddart et al. (2009). Furthermore, weekly observations possess the advantage of having sufficient granularity to accurately capture market dynamics while, compared to daily data, being less influenced my market-immanent phenomena such as bid-ask bounce (Grinblatt and Han 2005). As an added test of robustness of sorts, I nonetheless get qualitatively similar results from regressions on daily data.

Descriptive statistics are displayed in table 4. Turnover (TO_t) is calculated as the sum of the weeks official trading volume divided by the average number of shares issued for that week. The key explanatory variable, $52WH_{t-1}$, is the weekly individual stock price at time $t-1$ divided by the daily maximum price over the previous 52 weeks, approximated as 251 trading days, $\frac{P_{t-1}}{high_{t-1}}$. This yields a number between 0 and 1 where 1 is the most frequent value. Both mean and median are found relatively high on the ratio. This, and other independent variables, are lagged to the end of the previous week to model the appropriate causal direc-

Table 4: Summary Statistics for Turnover Regression Model Variables

This table displays summary statistics for variables used in the regression

$$TO_t = a + b_1 r_{t-1} + b_2 r_{t-2:t-52} + b_3 LNSIZE_{t-1} + b_4 PSPR_{t-1} + b_5 52WH_{t-1} + b_6 52WH^2_{t-1} + e.$$

TO_t is the official number of shares traded of a specific security over the week t divided by average number of shares outstanding for that security that week. $52WH_{t-1}$ is nearness to the 52-week high for the specific security at the end of week $t-1$ calculated as $\frac{P_{t-1}}{high_{t-1}}$, where $high$ is the maximum price over the past 251 days. $LNMCAP_{t-1}$ is the natural logarithm of the market capitalization at the end of week $t-1$ calculated as the unadjusted stock price multiplied by the number of shares outstanding. $PSPR_{t-1}$ is the proportional bid-ask spread at the end of week $t-1$, calculated as $\frac{P_A - P_B}{P_M}$, where P_A is the lowest asking price price, P_B is the highest bidding for that day and P_M is the average of the two. r_{t-1} is the stock's return for week $t-1$ and $r_{t-2:t-52}$ is the cumulative return from week $t-52$ through $t-2$.

Statistic	N	Mean	St. Dev.	Min	Max
TO_t	211,447	0.012	0.079	0.000	25.727
$52WH_{t-1}$	181,932	0.752	0.233	0.001	1.000
$LNMCAP_{t-1}$	210,984	20.320	1.713	13.638	27.232
$PSPR_{t-1}$	193,768	0.054	0.104	0.0001	1.999
r_{t-1}	211,953	0.003	0.084	−0.974	4.133
$r_{t-2:t-52}$	182,212	−0.030	0.667	−6.804	3.349

tion.

A number of control variables which might conceivably have an effect on turnover are also included. Size, represented by market capitalization, is an established risk factor in stock return research and might influence turnover as well since price and volume should be linked. Due to the distribution being heavily skewed to the right, I take the natural logarithm to mitigate the potential effects of outliers and obtain a more evenly distributed variable.

The proportional bid-ask spread, $PSPR$, at the end of week $t-1$ is included as a control variable. Following Chordia, Roll and Subrahmanyam (2000), this is calculated as the bid-ask spread normalized by the bid-ask midpoint, $\frac{P_A - P_B}{P_M}$, where P_A is the lowest asking price price, P_B is the highest bidding for that day and P_M is the average of the two. The bid-ask spread is likely to have an impact on trading volume (Griffin, Nardari and Stulz 2007). Trading volume and bid-ask spread both carry information about the liquidity of a stock. In controlling for bid-ask spread the intention is to isolate liquidity related factors that might have bearing on turnover.

Additionally, I include controls for return for the previous week as well as weeks $t-2$ to $t-52$. Earlier studies strongly indicate that recent and past returns are postitively related to trading volume so it is reasonable to control for this (see for example Statman, Thorley and Vorvink 2006, Griffin et al. 2007, and Glaser and Weber 2009). The previous week's return, r_{t-1}, may also capture some of the effect of news or economic shocks thereby to some extent accounting for rational drivers of turnover.

Given the anchoring hypothesis, we would expect lower turnover at the extremes of the $52WH$ ratio. This assumes that traders are increasingly unwilling to buy as the price approaches the 52-week high and increasingly unwilling to sell when the price is pushed far away from the 52-week high. To capture this possible non-linear relation between turnover and the 52-week high ratio, the latter is also included as a second degree term. The following model is estimated by means of

Fama-MacBeth (1973) cross sectional regressions.

$$TO_t = a + b_1 r_{t-1} + b_2 r_{t-2:t-52} + b_3 LNSIZE_{t-1} + b_4 PSPR_{t-1} + b_5 52WH_{t-1} + b_6 52WH^2_{t-1} + e. \tag{1}$$

Fama-Macbeth (1973) estimation entails performing one cross sectional ordinary least squares regression for each time period. Regression coefficients are then averaged over the number of time periods. The advantage of this relative to standard panel estimation that is corrects for cross sectional correlation in the residuals whereas conventional panel methods do not share this quality. The method is also considered to be suitable for data with a relatively large number of time periods compared to the number of individuals (Soulakis 2008) as is the case here.

Table 5 reports regression results. All independent variables are statistically significant. Specification 1 show that, when controlling for past returns, size and proportional bid-ask spread, the linear relation between the $52WH$ and turnover is negative. However, a similar model (specification 2) but with the inclusion of the $52WH^2$ regressor, indicate a convex relation. The top (lowest) point of a polynomial variable is calculated as $\frac{-a}{2b}$ where a is the fist degree and b the second degree term. A positive (negative) sign for the product indicate a bottom (top) point (Wooldridge 2013). Thus, the $52WH$ has a bottom point at 0.91. Turnover is decreasing as the $52WH$ increases up to this point and then rising. According to this model, when the $52WH$ variable is at maximum, i.e. 1, turnover is about at the same level as at the $52WH$ level of 0.8. At lower values on the $52WH$ ratio, turnover is higher. Unreported specifications with third and fourth degree terms included, indicate that a roughly U-shaped relation but with the bottom point skewed towards the upper end of the $52WH$ represents the better model fit.

Past returns are positively correlated with turnover. Last week's returns have a larger impact on than the returns over the last year. Relative changes in market capitalization are positively correlated with turnover, indicating that larger firms have a higher portion of their shares trading at a given moment in time. As expected there is a negative relation between the the bid-ask spread and turnover in the following period. Control variables have generally smaller coefficients than the $52WH$ variable. It is particularly interesting that nearness to the 52-week high

Table 5: Turnover Regression Results

This table displays the results of the regression
$TO_t = a + b_1 r_{t-1} + b_2 r_{t-2:t-52} + b_3 LNSIZE_{t-1} + b_4 PSPR_{t-1} + b_5 52WH_{t-1} + b_6 52WH^2_{t-1} + e.$
Specification 1 is estimated without the inclusion of the $52WH_{t-1}$ and $52WH^2_{t-1}$ regressors. In specification 2 the $52WH_{t-1}$ regressor is introduced and specification 3 displays the full model described above. TO_t is the official number of shares traded of a specific security over the week t divided by average number of shares outstanding for that security that week. $52WH_{t-1}$ is the nearness to the 52-week high for the specific security at the end of week $t-1$ calculated as $\frac{P_{t-1}}{high_{t-1}}$, where $high$ is the maximum price over the past 251 days. $LNMCAP_{t-1}$ is the natural logarithm of the market capitalization at the end of week $t-1$ calculated as the unadjusted stock price multiplied by the number of shares outstanding. $PSPR_{t-1}$ is the proportional bid-ask spread at the end of week $t-1$, calculated as $\frac{P_A - P_B}{P_M}$, where P_A is the lowest asking price price, P_B is the highest bidding for that day and P_M is the average of the two. r_{t-1} is the stock's return for week $t-1$ and $r_{t-2:t-52}$ is the cumulative return from week $t-52$ through $t-2$. Standard errors are reported in parentheses.

	Dependent variable:		
	TO_t		
	(1)	(2)	(3)
r_{t-1}	0.021**	0.041***	0.044***
	(0.009)	(0.009)	(0.008)
$r_{t-2:t-52}$	−0.002	0.004	0.010***
	(0.002)	(0.003)	(0.002)
$LNMCAP_{t-1}$	−0.0003**	0.0004***	0.001***
	(0.0001)	(0.0001)	(0.0001)
$PSPR_{t-1}$	−0.070***	−0.064***	−0.063***
	(0.003)	(0.003)	(0.003)
$52WH_{t-1}$		−0.039***	−0.173***
		(0.004)	(0.017)
$52WH^2_{t-1}$			0.095***
			(0.014)
Constant	0.017***	0.035***	0.077***
	(0.002)	(0.003)	(0.006)
Observations	166,733	166,494	166,494
R^2	0.239	0.266	0.321
Note:	*p<0.1; **p<0.05; ***p<0.01		

may have a larger influence on turnover than past returns.

In the sample, there are four extreme values ranging from 9 to 25, all tied to one specific securitiy inside a four week time frame. This is likely related to some special event and perhaps not representative for trading behaviour in general. At these data points, turnover values are associated with very low 52-week high ratio scores. Regression results are in principle similar when preforming the same regression without these outliers although the curvature of the $52WH$ coefficients are affected slightly. Also the low point is pushed to a value of 1.04 which suggest a negative relation with turnover for all possible $52WH$ levels. In addition, I compare small and large cap stocks by estimating models on each subsample where large cap stocks is defined as having a market capitalization value at median or higher in the full sample. Again, results are largely similar although the curvarure and low points vary somewhat. For the small cap stocks the bottom point is at 0.81 on the $52WH$ ratio so turnover is increasing after this point. The coefficients for variables r_{t-1} and $LNMCAP_{t-1}$ are not significant in estimation on this sample. In case of the estimation on large cap stocks, the relation to turnover is negative for all possible $52WH$ levels though the negative relation is dampened as the price approaches the 52-week high.

Overall, results indicate low turnover at price levels close to the 52-week high and vice versa. This is somewhat contradictory to what we initially would expect with regard to the anchoring hypothesis proposed by George and Hwang (2004). Increased reluctance to buy a stock as it is approaching the 52-week high or sell as the price is moving very far from the 52-week high implies lower turnover at $52WH$ extremes. This would be most consistent with a nonlinear concave relation. Turnover is generally low at high price levels, consistent with the anchoring hypothesis. On the other hand, the negative relation is dampened as the price approches the 52-week high as reflected by the conxex relation, and there is a slight increase in turnover as the price reaches levels very close to the 52-week high. The anchoring hypothesis offers no explanation for this. On the lower end of the $52WH$, turnover is generally high and progressively increasing at lower price levels, which is not consistent with what we would expect given the anchoring hypothesis.

Athough I do not explicitly estimate turover at price levels outside the previous price range as is done by Huddart et al. (2009), a $52WH$ value of 1 implies that the price has risen above its previous 52-week high. Using a set of dummy variables for price decile increments relative to the 52-week high, they find a negative relation to turnover for all increments, but a higher turnover as the price comes into contact with or rises above the 52-week high or low. Although my model uses a polynomial term rather than a dummy structure, this is somewhat similar to the nonlinear relation I find where turnover is increasing at price levels very close to the 52-week high. My results differ in that turnover seems to be gradually increasing at lower price levels relative to the 52-week high. Even at the 52-week high turnover is, according to my results, still comparably low.

As noted above Huddart et al. (2009) cite Barber and Odean (2008) and limited attention bias coupled with particular attention grabbing stocks as having an impact on buying behaviour. Supposedly the increased volume is, for the most part, a result of increased buying activity from private investors. This might help explain why there is a turning point towards increased turnover at price levels close to the 52-week high. Conversely, very low price levels might have an attention-grabbing effect. Given that the anchoring hypothesis predicts a reluctance to sell at very low price levels relative to the 52-week high, these stocks could be perceived as underpriced. Still, price levels around or just below the mean value on the $52WH$ ratio are also associated with turnover at the same level as when the price is at the 52-week high. It is hard to see any attention-grabbing quality about these.

The slight increase in turnover at price levels very near the 52-week high may be consistent with a disposition effect with the 52-week high as the reference point, following previous research indicating that record price levels increase the likelohood of investors selling their shares (Yuan 2015, Grinblatt and Keloharju 2001). High price levels push investors into a more risk adverse state thereby motivating selling in order to close gains.

At high price levels, the relation between nearness to the 52-week high is consistent with the anchoring hypothesis in that turnover generally is comparably low. In contrast, turnover is progressively increasing at lower price levels. The anchoring hypothesis offers no explanation for this. In the next section I attempt to evaluate the hypothesis further by inspecting the relation between the nearness to the 52-week high and a proxy for net buying pressure. This might also shed light on whether an increase in turnover at high price levels is driven by buying attention or a disposition type effect with the 52-week high as reference point.

4.3 The 52-Week High and Net Buying Pressure

Results in the prevoius section were somewhat ambiguous with regard to the anchoring hypoethesis and other possible explanations for price momentum associated with the current price's nearness to the 52-week high. In this section a slightly different angle is explored by looking into the relation between the nearness to the 52-week high and a proxy for relative buying or selling pressure.

At price levels close to the 52-week high, the anchoring hypothesis implies reduced demand, dampening the effect of news on the price and leading to price continuation (George and Hwang 2004). At low price price levels far from the 52-week high, the hypothesis predicts a reluctance to sell, i.e. reduced supply. A similar demand and supply pattern in relation to the nearness to the 52-week high is consistent with disposition effect type trading behaviour. A shown by Yuan (2015), market-wide attention-grabbing events, such as record levels for the Dow-index and front-page news articles about the stock market lead investors to sell their holdings and realize gains. Although some selling activity might also be motivated by a desire to rebalance a diversified portfolio to a set of predermined weights. At low price levels the disposition effect predicts, similar to the anchoring hypothesis, a reluctance to sell. If relatively high turnover at price levels near the edges or outside previous price ranges is driven by limited attention coupled with an attention-grabbing stocks effect (Huddart et al. 2009, Barber and Odean 2008), we would expect to se higher demand at the very high and very low price levels and lower demand in between.

As a proxy for the relative buying or selling pressure for a stock each day, I make use of the difference between the VWAP statistic, which is provided in the original dataset for each stock-day, and the midpoint between the most agreeable bid and ask prices that day. VWAP is the volume weighted average price and captures the average price of all transactions that day, calculated as

$$P_{VWAP} = \frac{\sum_j P_j Q_j}{\sum_j Q_j}, \tag{2}$$

where P_j is the price and Q_j the quantity of the discrete trade j. Net buying pressure, NBP, is calculated for each day as $P_{VWAP} - \frac{P_A - P_B}{2}$, where P_A is the best (i.e. lowest) asking price price and P_B is the best (highest) bidding price for that day.

If the VWAP is higher than the bid-ask midpoint for a stock, the volume weighted average price is closer to the asking price than the bidding price. Accordingly, there is a relative willingness to bid up the price, suggesting net buying pressure. Conversely, if the VWAP is lower than the midpoint, the majority of trading is at prices closer to the bidding price, suggesting a comparative eagerness to sell. A positive sign indicates net buying pressure while a negative sign indicates net selling pressure. My approach is somewhat reminiscent of Bollen and Whaley (2004) who instead define net buying pressure as the difference between buyer and seller motivated contracts each day. Since I do not have data on whether transactions are are buyer or seller initiated, I use the VWAP statistic instead. As the most favourable bid and ask prices are likely contain information about actual trading intent, this should be a reasonable proxy for net buying or selling pressure on an aggregate level.

For ease of comparison with other empirical results, the analysis is carried out on weekly data. In the regression the sum of the net buying pressure proxy over the last week is used as the dependent variable. Regression on the average daily net buying pressure over the week rather than the sum yield very similar results.

There are heavy outliers on both sides of zero. Almost all outliers belong to one specific security while the rest are distributed among four other securities. I trim away the most extreme cases by filtering out values over the 99.95th below

Table 6: Summary Statistics for Net Buying Pressure Regression Variables

This table presents summary statistics for the variables used in the regression

$$NBP_t = a + b_1 r_{t-1} + b_2 r_{t-2:t-52} + b_3 LNMCAP_{t-1} + b_4 52WH_{t-1} + e.$$

NBP_t is a proxy variable for net buying pressure, calculated each day as $\frac{\sum_j P_j Q_j}{\sum_j Q_j} - \frac{P_A - P_B}{2}$, where P_j is the price and Q_j the quantity of the discrete trade j. P_A is the best (i.e. lowest) asking price price and P_B is the best (highest) bidding price and then summarized over the week t. $52WH_{t-1}$ is nearness to the 52-week high for the specific security at the end of week $t-1$ calculated as $\frac{P_{i,t-1}}{high_{i,t-1}}$, where $high$ is the maximum price over the past 251 days. $LNMCAP_{t-1}$ is the natural logarithm of the market capitalization at the end of week $t-1$ calculated as the unadjusted stock price multiplied by the number of shares outstanding. r_{t-1} is the stock's return for week $t-1$ and $r_{t-2:t-52}$ is the cumulative return from week $t-52$ through $t-2$.

Statistic	N	Mean	St. Dev.	Min	Max
NBP_t	212,781	−0.389	12.028	−596.194	363.143
$52WH_{t-1}$	181,746	0.752	0.233	0.001	1.000
r_{t-1}	211,741	0.003	0.084	−0.974	4.133
$r_{t-2:t-52}$	182,026	−0.030	0.667	−6.804	3.349
$LNMCAP_{t-1}$	210,754	20.320	1.713	13.638	27.232

the 0.05th percentile. Together this accounts for 0.1% of the sample size. Summary statistics of regression variables are displayed in table 6.

In addition to the 52-week high ratio, I include controls for past returns over the last week and over the last year. Past returns could conceivably affect buy-sell pressure dynamics. On the positive side, past returns could incite limited attention biased investors, or investors following some momentum strategy, to buy the stock or prospect theory/mental accounting style investors to sell in order to realize gains. On the other hand, negative returns could induce selling pressure as a consequence of attempts to stop losses or reduce selling pressure due to investors' reluctance to realize losses as per the disposition effect. Recent past returns also represent the best available data at my disposal to capture the effect of economically significant events. As the nearness to the 52-week high is likely to be highly correlated with past returns, it is furthermore necessary to control for this in order to isolate any effect of the price level relative to the 52-week high.

I also include the logarithmic transformation of market capitalization as a proxy for size. It is not theoretically clear as to which side size might push buy-sell pressure dynamics, but it might be an important control nonetheless. Private investors own a higher fraction of small firms than large. At the same time, several studies (for example Nygaard 2011, Barber and Odean 2008) argue that private investors are generally more susceptible to cognitive biases. At the same time, private ownership is more widespread among small cap stocks than large. Consequently, cognitive biases like the reliance on arbitrary reference points like the 52-week high might have a larger impact on small cap stocks trading although this is generally more of an assumption than an established empirical result in the literature. The following model is estimated using Fama-McBeth (1973) cross sectional regressions.

$$NBP_t = a + b_1 r_{t-1} + b_2 r_{t-2:t-52} + b_3 LNMCAP_{t-1} + b_4 52WH_{t-1} + e \quad (3)$$

Table 7 reports regression results. Specification 1 is estimated without the $52WH$ variable. In specification 2, we see that higher levels on the 52-week high ratio is significantly associated with negative net buying pressure or net selling pressure. The coefficient is nearly of the same magnitude as returns over the last week. As the price level increases more trading occurs at prices closer to the bidding price. Conversely, recent returns are positively correlated with NBP, implying trading at prices closer to the asking price as returns increase. This effect is magnified and more significant after the inclusion of the $52WH$ variable. Intermediate term past returns are positively correlated with selling pressure. This is consistent with the disposition effect explaining momentum profits (Grinblatt and Han 2005). Interestingly, after the inclusion of the $52WH$ variable, the coefficient for intermediate past returns is no longer significant and reduced in magnitude. The $LNMCAP$ variable is positively correlated with buying pressure in both specifications.

Similar to the regression on turnover in the previous section, a different specification with the inclusion of a second degree term of the 52-week high ratio is attempted to check for a possible nonlinear relation between the 52-week high and net buy pressure. In this specification, neither the first nor the second degree term are significant suggesting a linear relation is the better model fit.

I also perform regression on an untrimmed sample to check if the the trimming described above have an effect on the results. The estimation is sensitive to the removal of outliers with regard to inference. When outliers are included in the regression, only the $LNMCAP$ variable is significant, although coefficient signs for all independent variables are identical to the estimation on the trimmed sample. Still, as the outliers are extremely concentrated around very few securities, they are not very representative for the full sample. Hence, it seems reasonable to exclude them from the analysis.

The reported model has a relatively small R^2 and it cannot be ruled out that it is suffering from a lack of control variables. Macroeconomic factors is one area that springs to mind. Unfortunately, this is not available in my data and falls ouside the scope of this analysis. Some caution in the interpretation of the results is probably warranted.

Overall, results suggest a relative eagerness to sell or reluctance to buy at higher price levels relative to the 52-week high and vice versa, consistent with both the anchoring hypothesis. The hypothesis explaining higher turnover by in-

Table 7: Net Buying Pressure Regression Results

This table displays results of estimating the model

$NBP_t = a + b_1 r_{t-1} + b_2 r_{t-2:t-52} + b_3 LNMCAP_{t-1} + b_4 52WH_{t-1}$+e.

NBP_t is a proxy variable for net buying pressure, calculated each day as $\frac{\sum_j P_j Q_j}{\sum_j Q_j} - \frac{P_A - P_B}{2}$, where P_j is the price and Q_j the quantity of the discrete trade j. P_A is the best (i.e. lowest) asking price price and P_B is the best (highest) bidding price and then summarized over the week t. $52WH_{t-1}$ is nearness to the 52-week high for the specific security at the end of week $t-1$ calculated as $\frac{P_{t-1}}{high_{t-1}}$, where $high$ is the maximum price over the past 251 days. $LNMCAP_{t-1}$ is the natural logarithm of the market capitalization at the end of week $t-1$ calculated as the unadjusted stock price multiplied by the number of shares outstanding. r_{t-1} is the stock's return for week $t-1$ and $r_{t-2:t-52}$ is the cumulative return from week $t-52$ through $t-2$. Standard errors are reported in parentheses.

	Dependent variable:	
	NBP_t	
	(1)	(2)
r_{t-1}	0.919*	1.775***
	(0.540)	(0.554)
$r_{t-2:t-52}$	$-$0.376***	$-$0.054
	(0.063)	(0.110)
$LNMCAP_{t-1}$	0.139***	0.158***
	(0.015)	(0.016)
$52WH_{t-1}$		$-$1.814***
		(0.268)
Constant	$-$3.376***	$-$2.324***
	(0.309)	(0.336)
Observations	181,156	180,857
R^2	0.020	0.026
Note:	*p<0.1; **p<0.05; ***p<0.01	

creased buying activity directed at attention-grabbing stocks at higher price levels relative to the 52-week high, is not supported by these results. Instead, as high price levels relative to the 52-week high are associated with selling pressure, a slight increase in turnover is more consistent with disposition effect type behavior.

5 Discussion

Earlier research indicate that the current price's nearness to the 52-week high may have an effect on trading behaviour and, in turn, market outcomes such as trading volume and return. In the literature, several possible explanantions are considered. While the precise mechanisms causing variation in volume and price continuation may differ, the explanations have in common that the 52-week high is getting attention from investors and that this attention and the perceived significance of this figure is influencing trading decisions. The various explanations and their characteristics with regard to expected willingness to trade, proxied by turnover, and net buying pressure are summarized in table 8.

In order to inspect whether there is price momentum associated with the nearness to the 52-week high, separate from previously documentet momentum (Jegadeesh and Titman 1993, Carhart 1997), I construct and compare corresponding portfolios. Results indicate correlation between the 52-week high and PR1YR momentum factors, but also that they work independently of each other to some extent. Sorting the portfolios within or depentent on each other still yield meningfull differences in returns in most cases. It is a suspicion that the number of securities in the sample may be less than ideal for disentangling the two portfolios from each other.

Similar to George and Hwang (2004), I find that the 52-week high strategy yields significant monthly returns. In my case a considerable part of the returns are driven by very small cap stocks. George and Hwang (2004) do not report portfolio results for separate size categories, so it is not clear whether their results share this quality. In the OSE sample the 52-week high portfolio is dominated by

Table 8: Empirical Results and Explanation Candidate Consistency

This table summarizes key characteristics of the main hypotheses and explanations for price continuation discussed. The lowest entry presents the corresponding stylized empirical results.

Hypothesis or explanation	**Expected relative turnover or willingness to trade**	**Expected domination of net buying or selling pressure**	**Associated price continuation mechanism**
Anchoring on the 52-week high	Lower as the price moves towards the 52-week high ratio extremes	Selling pressure at high price levels, buying pressure at low price levels relative to the 52-week high	Underreaction
Limited Attention/Attention grabbing stocks	Higher at the 52-week high and low	Buying pressure at current price to 52-week high ratio extremes	Overreaction
Disposition effect with the 52-week high as reference price	Higher at high price levels, lower at low price levels relative to the 52-week high	Selling pressure at high price levels, buying pressure at low price levels relative to the 52-week high	Underreaction
Overconfidence	Generally high	No clear expectation	Overreaction
Stylized empirical results	Generally lower when the price moves towards the 52-week high, and vice versa, but a slight increase when very close to the 52-week high	Selling pressure at high price levels, buying pressure at low price levels relative to the 52-week high	Not empirically determined.

the PR1YR cumulative return portfolio, while in George and Hwang (2004) the 52-week high strategy generally dominates momentum portfolios based on past returns. My results also differ from those of Liu et al. (2011) which do not find significant profits in the Norwegian market, though it is hard to directly compare the results, in past because their sample runs from 1982 to 2006. Both George and Hwang (2004) and Liu et al. (2011) employ a more complex strategy of multiple overlapping portfolios, which also complicates direct comparison of results.

Overall, results at this stage of the analysis imply that the 52-week high is likely have an impact on trading and stock returns at OSE. Having established this, the next step is to look for plausible reasons to why this might be the case. Momentum profits following the 52-week high strategy suggest an imperfectly functioning market with regard to absorbing information. If current prices did reflect all publicly available information, the momentum effect should not be significant. Prices reflect trading behaviour, so looking into behavioural or cognitive biases represents a logical direction of inquiry. One reason might be that investors are conservative in their assessment of new information causing a temporary underreaction in prices. George and Hwang propose a variant of this line of reasoning where the 52-week high functions as an anchor to which new information is compared. This hypothesis implies a relative reluctance to trade at the extremes of the current price to the 52-week high ratio. As such, looking into trading volume at different price levels is a natural step forward.

My estimated model of turnover at varying 52-week high ratio levels is consistent with this prediction to some degree. At above average price levels relative to the 52-week high, turnover is generally lower and vice versa. Turnover deceases as the price level increases up to a point very close to the 52-week high. Very close to the 52-week high there is a slight increase in turnver. The anchoring hypothesis does not consider what might happen after the price reaches the 52-week high so it does not account for this increase. At low price levels, turnover is also relatively high which is contradictory to the anchoring hypothesis.

Though results may not be directly comparable due to different model designs, my results differ from Huddart et al. (2009) in that turnover is not particularly high when the price is at the 52-week high. Instead, turnover is generally lower when the price is relatively close to the 52-week high. However, most model specifications, and particularly estimations on small cap subsamples, suggest a slight increase in turnover when the price is very near the 52-week high. This may be explained by disposition effect style behaviour with the 52-week high as the reference point. A matching relation, though at market rather than individual stock level, is disclosed in Yuan (2015). Net selling pressure at high price levels indicate that this explanation is a better fit than the attention-grabbing stocks explanation proposed by Huddart et al. (2009) as increased trading activity in this case would be primarily demand driven.

Lower turnover as the price moves towards the 52-week high is consistent with the anchoring hypothesis, while higher turnover at the price moves away is more difficult to explain. As an additional test of the hypothesis, I consider the relation between the nearness to the 52-week high and relative demand. Results of regressions on a proxy for net buying pressure significantly indicate that as the price level in relation to the 52-week high increases, more trading is going on at prices closer to the bidding price implying a relative willingness to sell rather than buy. Different regression specifications indicate that the best fit is a linear model with an increased selling pressure high price levels and buying pressure at low price levels relative to the 52-week high. This is as the anchoring hypothesis would predict.

Overall, the anchoring hypothesis proposed is fairly, but not completely, consistent with empirical results. The relatively high turnover at low price levels remains as somewhat of a puzzle. At the same time shorting loser stocks, i.e. stocks at price levels far from the 52-week high, account for a considerable amount of portfolio returns. Thus, price dynamics at low price levels may be an important element in explaining price momentum. The higher turnover here might suggest that anchoring on the 52-week high works differently at low price levels. Stocks trading at prices far from the 52-week high might be considered relatively cheap and get traded more. Numerous studies present evidence that investors are overconfident in their ability to make trading decisions and trade excessively (see for example Statman et al. 2006, Odean 1999). High turnover has been connected with subsequent poor performance (Lee and Swaminathan 2000). Daniel et al. (1998) explain short term momentum by an initial overreaction in prices which then gradually corrects itself. This overreaction is linked to overconfidence and self-attribution biases. Investors overrate their trading ability and the importance of their available information, particularly if private or analyst-generated information. Still, there is no good reason why investors would be more overconfident at low price levels than high. At this point, I have no means of testing whether higher turnover at low price levels might be caused by overconfidence or other behavioural biases. Instead, this might represent an avenue for further research.

Lastly, the various explanations at play here are not necessarily mutually exclusive. Rather, the empirical results indicate the dominant relations. Regardless of the exact causes or interplay between causes of varying impact, it seems that the 52-week high may have some influence on trading behaviour or a market coordinating function, although the effect is very hard to quantify.

6 Conclusion

In this study I consider possible effects that the nearness to the 52-week high might have on trading behaviour. Through analyses with regard to returns prediction, turnover and net buying pressure I show that the current price's nearness to the 52-week high may seem to have an influence trading behaviour in a number of ways.

A portfolios based on the nearness to the 52-week high yields returns comparable to that of a portfolio based on cumulative returns over the past year. Double sorting the portfolios indicate that portfolio strategies work independently of one another to some extent. Price levels close to the 52-week high is associated with lower turnover and increased selling pressure which may cause a temporary underreaction in prices. At price levels far from the 52-week high there is a relative reluctance to sell. This empirical pattern is consistent with the hypothesis that the 52-week high is used as an anchor. Contrary to expectation, empirical results suggest higher turnover when the price is far from the 52-week high. The theories or hypotheses considered offer no clear and simple explanation for this relation.

There are some limitations nonetheless. Analysis is conducted by using data at market level which means that behaviour is studied in an indirect way. Individual investors' intentions cannot be fully understood. Some parts might have benefitted from additional data on such matters as earnings announcements and other economically meaningful news, macroeconomic factors and the direction of transactions to ascertain relative buying or selling pressure under various conditions. A direction for further research into the 52-week high and other reference points' influence on trading behaviour could be to incorporate data on these factors to more comprehensively test behavioural theoretical assumptions and empirical results.

7 References

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8 Appendix

8.1 Portfolio Risk Adjustment

In this section I look into the potential exposure Fama and French (1992) risk factors on PR1YR and 52WH winner minus loser portfolio returns. This is done by carrying out ordinary least squares (OLS) regressions on the monthly continuously compunded portfolio returns with these risk factors as independent variables.

$$R_{WML,t} = a + RMRF_t + SMB_t + HML_t + e \tag{4}$$

RMFR is the difference between an equal weighted market index and the NIBOR[6] and represents market risk. SMB and HML represent size and value risk respectively. The intercept of the regressions can be interpreted as a risk adjusted or abnormal return. As is shown in table 9, portfolio intercepts are higher than average raw returns reported in section 4.1.3. This result is mainly due to the portfolio returns being negatively correlated to the RMRF factor or market risk. Negative coefficients for risk factor variables can be interpreted as the PR1YR and 52WH portfolios diversifying risk (Barroso and Santa Clara 2015). Another way of looking at it, is that the 3-factor model do not explain returns from the PR1YR and 52WH portfolios very well. If this was the case, intercepts should not be signicantly different from zero.

[6] Norwegian InterBank Offered Rate

Table 9: Fama and French (1992) Risk Factor Regressions

This table displays results of running ordinary least squares (OLS) regressions on the returns of the $PR1YR$ and $52WH$ portfolios based on both full and filtered samples. Standard errors are reported in parentheses.

	Dependent variable:			
	$PR1YR$	$PR1YR_{excl.dec10}$	$52WH$	$52WH_{excl.dec10}$
	(1)	(2)	(3)	(4)
RMRF	-0.325^{***}	-0.323^{***}	-0.804^{***}	-0.786^{***}
	(0.064)	(0.063)	(0.062)	(0.058)
SMB	-0.147^{*}	-0.023	-0.080	0.026
	(0.080)	(0.078)	(0.077)	(0.072)
HML	0.039	-0.019	0.167^{**}	0.129^{**}
	(0.069)	(0.067)	(0.067)	(0.062)
Intercept	0.026^{***}	0.018^{***}	0.028^{***}	0.020^{***}
	(0.004)	(0.004)	(0.004)	(0.003)
Observations	227	227	227	227
R^2	0.108	0.108	0.435	0.460
Adjusted R^2	0.096	0.096	0.427	0.453
Residual Std. Error (df = 223)	0.053	0.052	0.052	0.048
F Statistic (df = 3; 223)	8.996^{***}	8.958^{***}	57.156^{***}	63.392^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$