Investor Behavior and Asset Pricing Anomalies

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Abstract

This dissertation investigates the behavior of investor classes and their effect on returns, liquidity, and informational efficiency around momentum-related asset pricing anomalies.

Chapter 1 explores the role of household and institutional investor net buying in amplifying and suppressing the returns to momentum-related anomalies. Using trade level data from the NASDAQ OMXH (Finland), trades made by households and institutional investors are identified. Using this data, we show that households slow the integration of positive information into stock prices, resulting in an increase in long run non-mean-reverting momentum. Winner stocks heavily purchased by households in the momentum formation period subsequently outperform winner stocks heavily purchased by institutions during the formation period. The enhanced momentum returns appear to be driven by the tendency of households to insufficiently incorporate news into prices. On the other hand, institutional buying appears to drive prices closer to their fundamental value.

Chapter 2 investigates the cause of volume spikes and post-event returns observed at the 52 week high (George and Hwang, 2004; Huddart et al.,

2009). We argue that these effects are driven by the anchoring of individual investors to the 52 week high price, which drives disposition effect related sales. Our findings indicate that households submit uninformed limit orders to sell at and around the 52 week high price. This effect is magnified with stock- and market-level volatility and for those stocks where the 52 week high has not been recently breached; in both of these cases, anchoring is likely to be heightened. This anchoring behavior provides liquidity, which institutional investors appear to capitalize upon.

Chapter 3 explores the effect of individual investor anchoring at the 52 week high on stock liquidity and informational efficiency. Using intra-day trade and quote data, we find that liquidity increases as the 52 week high approaches, peaking on the 52 week high day. Uninformed liquidity provision, as measured by a reduction in bid-ask spreads and increased depth in the limit order book, weakens informational efficiency/price impact for stocks at the 52 week high. The reduction in price impact cements the idea that momentum and 52 week high returns are driven by the dampening of price discovery by households in winner stocks (Hong and Stein, 1999).

To my mother and father

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Statement of originality

This is to certify that to the best of my knowledge, the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

Joshua Della Vedova

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Introduction

In this dissertation, we explore the relation between investor class trading and momentum-related asset pricing anomalies. Prior research has investigated the role of individual investors in price formation and asset pricing anomalies (Grinblatt and Han, 2005; Kaniel et al., 2008; Odean, 1999). The aim of this thesis is to help understand how investor behavior affects asset pricing anomalies, and vice versa. A specific focus of the thesis is the 52 week high, which provides a signal to investors that the stock is at its peak value over the previous year. We argue that individual investors are more likely than institutional investors to rely on this signal, and, based on their tendency to realize gains, are more likely to sell than buy at the 52 week high, and prefer to use limit orders than market orders when doing so. It is the systematic behavior of individuals that drives the so-called '52-week high effect' (George and Hwang, 2004), where stocks tend to drift upwards, momentum-style, after reaching the 52-week high. We highlight the role of individuals in exacerbating this effect, as they tend to dampen the impact of positive news in winner stocks. We also explore how institutional investors are able to take advantage of the uninformed supply of liquidity from individuals' sell limit orders.

The dissertation is separated into three chapters exploring the different aspects of momentum-related asset pricing anomalies. First, we explore how investor classes (households, financial institutions, and domestic institutions) intensify and suppress momentum-related anomaly returns. We see that household net buying of stocks during the anomaly formation periods cause a dampening of news and subsequent momentum returns.

Second, we investigate how anomalies drive investor behavior. Observing the trades between households and institutions, we see that households anchor their limit order selling to the 52 week high and this directly intensifies future abnormal returns.

Third, we extend our analysis to explore the liquidity and price impact dynamics around anomalies. We identify strong liquidity buildup at the 52 week high. This buildup significantly reduces informational efficiency and helps support our previous result that the momentum-related anomaly returns are caused by uninformed investors dampening price impact.

In the first chapter, we test the theory of Hong and Stein (1999) that momentum is driven by a dampening of news that results in greater post-event non-mean-reverting momentum. We build off the expectation that households dampen price discovery (Shive, 2012) and institutions promote market efficiency (Boehmer and Kelley, 2009). We therefore test whether high levels of household buying leads to an intensification of momentum-related anomaly returns. We examine four well known momentum-related anomalies: Jegadeesh and Titman (1993) momentum, Novy Marx (2012) intermediate momentum, George and Hwang (2004) 52 week high and Bhootra and Hur (2013) recency rate.

Our data set allows us to examine investor behavior by classes (households, foreign institutions, and domestic institutions) at the trade level (Grinblatt and Keloharju, 2000). Using the complete trade-level data from the NASDAQ Helsinki OMXH, we construct monthly investor class net buying metrics. We show that household net buying during the anomaly ranking period (one to six months prior) directly intensifies the size of the lead six month returns for three of the four anomaly measures. In contrast, institutional net buying significantly dampens and partially reverses the anomaly returns.

We next test for the existence of mean reversion in the momentum returns, out to two years. We observe that household-driven momentum continues for up to 24 months without mean reverting. This suggests that household (institutional) trading causes a delay (promotion) to the diffusion of information in prices, resulting in greater (lesser) momentum returns, supporting the theory of Hong and Stein (1999).

In Chapter 2, we continue our analysis by investigating the effect of momentum-related anomalies on investor behavior. We examine the trading between individual and institutional investors around a prominent anomaly anchor - the 52 week high (George and Hwang, 2004). The 52 week high is a notable feature of financial markets (Baker et al., 2012; Driessen et al., 2011) and a potential anchor for investor behavior. Motivated by the tendency of individuals to anchor to non-value-relevant information, we examine the extent to which individual investors are responsible for the volume spikes at the 52 week high (Huddart et al., 2009), their order submission strategies, and how this behavior leads to post 52 week high momentum-like returns (George and Hwang, 2004).

Continuing our analysis of the trade level data used in Chapter 1, we generate daily measures of between-groups (household and institution) trading (trade imbalance) and market order usage (taking rate) to observe investor behavior at the 52 week high. We identify that on days when stocks open at the 52 week high, households sell 50% more frequently than they buy. Supporting our findings, households display prospect theory (Kahneman and Tversky, 1979), anchoring (Tversky and Kahneman, 1992), and disposition effect (Odean, 1998; Shefrin and Statman, 1985) tendencies. On top of a 50% increase in selling activity at the 52 week high, individual limit order usage increases by approximately 10%. These effects are exacerbated if the 52 week high has not been reached for the prior 14 days or in cases of high stock and market volatility, where individuals are more likely to rely on anchors to make decisions.

The limit order selling by individuals appears to be primarily responsible for the momentum-like returns seen after the 52 week high (George and Hwang, 2004). Stocks that have been heavily sold with limit orders exhibit greater post-event abnormal returns compared to stocks sold with low levels of limit orders. Our findings support the prior research that individual investors cluster limit orders (Kelley and Tetlock, 2013) at attention-grabbing nominal prices (Bhattacharya et al., 2012) and help create market distortions. Our results support that the 52 week high momentum returns are driven by household provision of uninformed liquidity, which dampens the effect of trading by informed institutional investors and leads to post-event drift.

In Chapter 3, we build upon our previous findings that households cluster limit order sells to the 52 week high. We investigate this phenomenon at the intra-day trade and quote level to understand how this anchoring behavior affects liquidity and informational efficiency (price impact of trades) at the 52 week high.

We first explore the liquidity dynamics at the 52 week high, investigating multiple measures of transaction costs and depth-based liquidity metrics. Supporting our prior findings, we see the 52 week high is positively related to liquidity provision at the best price and up to five levels of depth, particularly on the ask/sell side. There is a monotonic increase in liquidity as stocks approach their 52 week high. Looking at the 52 week high day, there is a 40% reduction in spreads and a 30% greater provision of limit order sells for stocks, relative to average.

We next test the effect of the uninformed liquidity clustering at the 52 week high. The increase in uninformed liquidity results in a decrease in informational efficiency, as measured by price impact. This dampening of price impact helps to support the findings in Chapter 1, that momentum-related anomaly returns are driven by a dampening of news integration (Hong and Stein, 1999). We note a 'V' shaped path that liquidity and informational efficiency follow as the stock approaches, hits, and recedes from the 52 week high. This increase in price impact is robust to past returns and provides insight into the way nominal price barriers can affect informational efficiency, information disclosures and market efficiency.

Overall, this dissertation provides an important contribution to understanding how investor behavior affects returns, liquidity, and informational efficiency within equity markets. We contribute to the literature by highlighting how households amplify momentum returns by under-reacting to news, as well as their anchoring behavior that provides liquidity for institutional investors to trade on it.

Chapter 1

Investor Behavior and Momentum

1.1 Introduction

This chapter explores the role of investor class trading regarding the existence and attenuation of momentum-related anomalies. Directly observing the behavior of individual investors, this study builds on the theoretical findings of Hong and Stein (1999) and the empirical work of Da et al. (2014) to examine how high household ownership and their under-reaction to news and/or expectation errors lead to an intensification of momentum-related anomalies. This momentum intensification is non-mean-reverting, providing evidence that high household buying leads to an underreaction to news and thus greater anomaly returns in the subsequent period.

Second, intra-day trading data is used to examine institutional investor behavior and momentum-related anomalies. Institutional holdings provide a stabilizing effect to the market (Boehmer and Kelley, 2009), thus reducing and partially reversing the intensity of anomaly returns. This study examines four well known momentum-related anomalies: Jegadeesh and Titman (1993) (JT) momentum, Novy-Marx (2012) (NM) intermediate momentum, George and Hwang (2004) 52 week high (52WH) and Bhootra and Hur (2012) recency rate (RR).

The study uses the full and complete trade data set from 1995-2011 on the NASDAQ Helsinki OMXH to measure how investors create variations to the four momentum-related anomaly returns. Aggregate class-level net directional trading measure, the net buy ratio (NBR), is constructed to determine which category of investors (households, domestic institutions, or foreign institutions) is buying or selling during portfolio formation (ranking) periods. Conditional on a stock being categorized as a 'winner' or 'loser' by the anomaly construction rule, this study then examines whether aggregate investor category trading affects subsequent momentum anomaly returns. For instance, under the JT momentum specification, stocks are sorted into terciles of past returns, then further sorted by investor category net-buying during the formation period. This yields a set of stocks that are anomaly winners with high household NBR during the formation period, and anomaly winners with high household selling during the formation period.

Next, tests are performed to determine whether the realized momentum returns are higher for those stocks heavily purchased, rather than sold, by households in the formation period. Based on the fact that these high household NBR-winners would not have been as informationally efficient as other stocks (Boehmer and Kelley, 2009), we expect higher subsequent returns for stocks in this portfolio than winners in the low household buying portfolio.

The study demonstrates that household buying during the anomaly ranking period is directly related to increasing the size of three of the four anomaly measures. High tercile household net buying leads to an average monthly increase in the portfolios of the JT momentum measure of 2.5%, the 52WH of 1.5% and RR of 1.9% for 6 months forward. This supports the expectation that households have a dampening effect on news, and thus, high household ownership results in greater anomaly returns.

An opposite stabilizing effect is observed for institutional investors, in which their net buying dampens (for domestic institutions) or partially reverses (for foreign institutions) anomaly returns. High buying by foreign institutions during the anomaly ranking period leads to statistically and economically significant reduction in three of the four anomaly returns. There is a reduction in the JT momentum measure of 2.5%, NM momentum of 3% and the 52WH measure of 1.0% for 6 months forward.

The momentum returns are robust and non-mean-reverting. When looking two years forward there is no mean reversion among stocks when high household buying occurs. This supports our finding that household investors cause a slower diffusion of news (Hong and Stein, 1999) and underreaction to positive news by households (Birru, 2015).

The study contributes to the literature on the time varying nature of anomalies, and investor class behavior on information diffusion. First, it builds upon the extensive work into the causes of variation in anomaly returns (Antoniou et al., 2013; Chordia et al., 2014), in particular the role of investor behavior and momentum (Edelen et al., 2016; Hur et al., 2010; Hvidkjaer, 2008). Hur et al. (2010) discuss the potential destabilizing effects of small trades, in doing so they overreach of their identification. This study is able to employ far more clear identification of investor class trading, by doing so we can connect the trades of households directly to the increase of anomaly returns. On the other hand, **?**) is able only to observe the changes in holdings of institutions quarter to quarter. This is a much lower resolution proxy for institutional trading, we add clarity to the literature by revealing that it is not so much institutional holdings, but rather institutional net buying that promotes informational efficiency and reduces the extreme returns to momentum-like anomalies.

Secondly, this study contributes to the literature on the role of class trading and return predictability. It builds off prior studies (Kaniel et al., 2008) and shows the importance of household trading on future returns. Overall, this study expands on the work of Hong and Stein (1999) and Da et al. (2014) by showing that household investors delay, and institutions speed up the diffusion of news that intensifies momentum returns.

This paper proceeds as follows. Section 1.2 discusses the anomaly and investor behavior literature and Section 1.3 presents the hypothesis development. Section 1.4 introduces the data and the method used to measure investor behavior. Section 1.5 outlines the empirical design and reports the key findings. Section 1.6 concludes.

1.2 Literature review

1.2.1 Momentum

In essence, momentum is the tendency for past returns to predict future returns. Momentum is present in multiple asset classes, countries (Chui et al., 2010) and can been seen using a variety of measurement periods (Asness et al., 2013). Jegadeesh and Titman (1993) were the first to discover the ability for past returns to predict future returns. They create a zero cost long-short momentum strategy, in which they buy the highest 30% of stocks and sell the lowest 30% of stocks based on past six month return; they show investors can consistently earn zero cost returns of approximately one percent per month during the subsequent six month holding period.

$$JTMomentum_{i,t} = \sum_{t=-1}^{-6} \frac{price_{i,t} - price_{i,t-1}}{price_{i,t-1}} \tag{1.1}$$

1. Investor Behavior and Momentum

Momentum is a prominent feature of equities markets. Griffin et al. (2003) explore the role of momentum in global markets, finding it to be a reliable and economically significant predictor of returns. Fama and French (2012) continue this global exploration; they note that momentum is a better predictor of returns internationally than unique country specific stock market predictors. Chui et al. (2010) identify the noteworthy exception to momentum, demonstrating that momentum is not present within stock markets with low levels of investor individuality, such as Japan, Korea, Taiwan, and Turkey[1].

Momentum is present in assets markets beyond just equities. Chan et al. (2000) reports the profitability of the long-short momentum strategy with country to country stock indexes. A similar feature is present within commodity futures (Shen et al., 2007). Asness et al. (2013) bring these findings together, uncovering momentum (and the value anomaly) in stocks, equity index futures, government bonds, currencies, and commodity futures.

Given its ubiquitous presence within asset markets there has been further research into the underlying cause of momentum, be it rational, behavioral or a combination. The cause of the momentum, as stated by Jegadeesh and Titman (1993) in support of the rationale of Thaler and Benartzi (1985), is that long term overreaction to information causes prices to be bid well above their fair value. Moreover, (Jegadeesh and Titman, 1993) model includes the rationale of Tversky and Kahneman (1974) represen-

[1]Their rationale is that countries with low levels of cultural individuality display lower or no returns to the momentum strategies. They suggest that a high level of individualism is related to overconfidence and self attribution bias, which help drive momentum returns.

tativeness heuristic and conservatism; this causes individuals to expect high performing stocks/firms to continue to perform well, thus investors adopt a belief and subsequently bid up the stock price. Overbidding of stock price could be a likely explanation of momentum if high return momentum stocks perform poorly (i.e mean revert) after their momentum returns have been observed (6-24 months following).

There is a significant evidence in the literature providing potential and varying explanations regarding the source of momentum. First, cross-sectional dispersion in expected returns would result in risky stocks that perform well in one period to continue to perform well. This has been tested by controlling for risk using the single factor Capital Asset Pricing Model (CAPM) (Sharpe, 1964) as was done by Jegadeesh and Titman (1993) to no effect. Momentum is still positive and significant when including the Fama and French (1993) 3 factors (Jegadeesh and Titman, 2001). Thus, it is unlikely that cross-sectional variations in risk explain the presence of momentum.

Researchers have attempted by explain momentum as the over and under reaction to news by investors. The Hong and Stein (1999) model suggests that information undertakes a slow diffusion through a market. This is due to investor under reaction to news, leading to return continuation up to six months after the news is released. This theory is tested by Hong et al. (2000) who find that momentum works better among small stocks that are expected to have fewer market participants following the stock. They show that analyst coverage is greater among poor performers and that negative firm-specific information diffuses more gradually among the public than positive news. The findings that bad news results in drift is further supported by Chan (2003) and

Jiang and Zhu (2017), with the latter suggesting large shocks to prices are proxying for large information shocks and these stocks produce positive subsequent return continuation three to six months forward. More recent theoretical work supports the claim that word of mouth diffusion of information, with the existence of momentum and contrarian traders, results in an information dissemination regime that causes momentum-like returns (Andrei and Cujean, 2017). Da et al. (2014) finds that investors are less sensitive to continuous information disclosures relative to large discrete disclosures. This sensitivity results in an under-reaction to news released in small bundles and as such increased momentum returns. Birru (2015) suggests that as stocks increase in price investors are less sensitive to positive news. This underreaction and expecational error causes a dampening of prices and subsequent momentum returns. Individuals have a tendency to under-react to new information, in a process known as conservatism (Edwards, 1996). Barberis et al. (1998) models the behavior of investors and observes they have a tendency to overreact to price information and underreact to fundamental information. This process results in non mean-reverting momentum style returns.

Grinblatt and Han (2005) suggest that momentum is the result of the disposition effect (Shefrin and Statman, 1985). This sees investors selling down stocks, which have accumulated capital gains, thus causing positive news to more slowly be integrated into prices during the holding period, therefore making reversals less likely. This explanation is conditioned such that prospect theory/mental accounting investors are prominent owners of the stock.

An alternative behavioral explanation relates to the hot hand fallacy and herding by investors. Ayton and Fischer (2004) explore the role of the hot hand fallacy, namely its the tendency for individuals to rely on recent results to predict future results. The hot hand fallacy creates herding behavior, in which investors flock towards high performing stocks or anchor their behavior towards high performing investors. Herding behavior has been observed by institutional investors, in which their lag behavior has driven future behavior (Sias, 1997, 2004). Herding is expected to result in an overbidding of stocks above their fair value, creating momentum like returns with subsequent mean reversion.

A key insight of the news and investor based explanation of momentum is that investors should either overreact to news or herd to high performers (both leading to overbidding), resulting in momentum with subsequent mean reversion. Alternatively, investors could underreact to news or display disposition effect tendencies (dampen price) and create momentum without mean reversion. Each potential explanation is conditioned on the existence of rational or prospect theory style investors in the market. As such, it is expected that greater ownership by households should result in higher momentum returns.

1.2.2 Intermediate momentum

A primary contention of the JT momentum is the measurement period. An alternative measure to the 6-1 JT momentum has been introduced by Novy-Marx (2012). He states that momentum is primarily driven by a firms intermediate performance between the prior 12 month to prior seven months rather than the traditional prior six month JT momentum.

$$NMMomentum_{i,t} = \sum_{t=-7}^{-12} \frac{price_{i,t} - price_{i,t-1}}{price_{i,t-1}} \tag{1.2}$$

The Novy-Marx (2012) 12-7 month strategy selects stocks based on their average monthly price performance between month $t-12$ to month $t-7$. He found this intermediate horizon strategy was significantly more profitable than the recent horizon long-short momentum strategy. This intermediate momentum is present in U.S. and international equities, as well as currency and commodities. He shows that NM momentum has far more predictive utility than the traditional 6-1 month JT momentum measure; he notes that the JT momentum strategy was very profitable in the 1950s and 1960s, however it has been less profitable in recent times. Novy-Marx (2012) believes the firm's, rather than the security's, intermediate financial performance is the cause of momentum.

NM addresses the issue of lack of inquiry into the consideration of both the ranking period and the holding period when measuring and identifying momentum.Novy-Marx (2012) states that this intermediate ranking period is particularly effective at predicting returns in large capitalization and highly liquid stocks, which tend to be held more heavily by institutions. This intermediate momentum supports the findings of Chordia and Shivakumar (2002); they suggest momentum arises as a result of lagged macroeconomic variables causing delayed returns to prices. This research is continued by Chordia and Shivakumar (2006) who show that momentum captures the systematic component of earnings momentum, of which the momentum portfolios are significantly related to future macroeconomic activities [2]. A relation between industrial performance and momentum is reported by Liu and Zhang (2008); they note that winner momentum stocks have larger factor loadings than loser momentum stocks when it comes to the growth rate of industrial performance, which is priced at the cross-section. Overall, the Novy-Marx (2012) finding is consistent with macro-economic information being slow to innovate into prices, and thus momentum should not be mean-reverting. As NM momentum is thought to be caused by industrial performance it is less likely to be driven by investor behavior.

1.2.3 The 52 week high

Nominal prices and price ranges (highs and lows) can have significant effects on investor expectations and future returns (Birru, 2015). Grinblatt and Keloharju (2001*b*) were among the first researchers to explore the effect of past stock price range on investor behavior. In their study of investor level trading, they report that individuals were sensitive to a stock's price relative to its historical all-time high. Grinblatt and Keloharju (2001*b*) notes that individual investors are more likely to sell stocks near their historical high, displaying both anchoring (Kahneman, 1992) and disposition effect behavior (Shefrin and Statman, 1985).

The importance of share price range was developed further by George and Hwang

[2]These macro economic variables include: changes in GDP, industrial production, consumption, labor income, inflation, and treasury note returns (Chordia and Shivakumar, 2006).

(2004), who introduce the 52WH price as a source of return predictability.

$$52WeekHighRatio_{i,t} = \frac{Price_{i,t}}{High_{i,t}} \tag{1.3}$$

where $High_{i,t}$ is the highest price the share has traded for over the past year (365 calendar days, 252 trading days), while $Price_{i,t}$ is the current price at time t for stock i. The ratio therefore represents the nearness in percentage terms of the stock's current price to its 52WH price. They use a similar zero cost long-short strategy to Jegadeesh and Titman (1993), buying stocks in the 30% nearest and selling those 30% furthest from the 52WH price and by doing so they observe zero cost returns for the lead six months. George and Hwang (2004) observe that a share's nearness to 52WH is a better predictor of future returns than past returns, i.e. momentum. The 52WH maintains its predictive utility even if the stock has not experienced extreme past returns (near or far from the 52WH).

This predictive power of the 52WH has been shown in global markets. Liu et al. (2011) uncover it in 18 of the 20 international equities markets they explore; in addition, they observe the 52WH is robust to short term momentum and accumulated capital gains. In contrast to momentum, the causes of the 52WH as a source of predictability have been relatively limited [3], instead focusing on other areas of finance, such as its role in mergers and acquisitions (Baker et al., 2012), or on option volatility (Driessen et al., 2011).

Bhootra and Hur (2013) extend the findings of George and Hwang (2004) to reveal

[3] A more thorough exploration of the causes of the 52 week high are examined in Chapter 2.

that distance in terms of days, rather than just nearness in price to the 52WH, as a significant driver of stock returns. They discover that shares that are closer, in days, to the 52WH day outperform those further away. Testing RR within the long-short portfolio strategy, they observe that the long-short portfolio produces a positive return of 0.70% per month during the holding period.

$$RecencyRate_{i,t} = 1 - \frac{t_i - t_{i,52WHMAX}}{364} \tag{1.4}$$

where $t_i - t_{i,52WHMAX}$ is the difference between t and the last day in which the price of stock i reached or breached the 52WH. Therefore, the measure reflects the number of days as a fraction of a year since the stock reached its 52WH price.

RR is a measure that looks to explain the existence of momentum via the role of recency bias (Murdock, 1962) [4]. Bhootra and Hur (2013) suggest that the 52WH ratio is a poor anchor as investors process the strength of anchor based on its nearness or farness on a time basis rather than just value basis. This analysis on recency bias is consistent with earlier theories and experimental evidence (Kahneman, 1992; Kahneman and Tversky, 1986) that suggests anchors are more prominent if they are based on recent/proximal information rather than distant/distal information. As with the 52WH, there has been relatively sparse inquiry into the RR and its underlying cause. The most convincing explanation comes from the attention effect (Barber and Odean, 2007); that is when stocks have recently been at their 52WH they are more likely to be newsworthy

[4]Murdock (1962) uses a serial recall task within a laboratory setting to test the effect of memory recall on the position of numbers. He observes a horizontal asymptote from the primacy to the recency effect. This suggests that serial recall is greater for recent observations and decays backwards.

to investors for non-informational reasons. As with JT momentum, both the 52WH and RR are likely to be caused by investor behavior, particularly households. As such it is reasonable to believe that high household ownership is likely to intensify the returns to the long-short anomaly strategies.

1.2.4 Time varying anomaly returns

Momentum has been found in multiple asset classes, over multiple periods, however not over every period. There are numerous studies investigating the variable intensity and consistency of momentum and to a lesser degree, other anomaly returns. Daniel and Moskowitz (2016) observe the disappearance in momentum following periods of very poor market-wide performance. When market performance is poor, such as the global financial crisis, and market volatility is high, momentum ceases to exist. Antoniou et al. (2013) suggest that when sentiment is high and investors are optimistic there is a slower integration of negative news and an overreaction to positive signals, both leading to an increase in momentum performance. Avramov et al. (2016) explore the effect of liquidity on the time-varying nature of momentum. They argue that despite the decrease in momentum over the prior decade, it is significantly more profitable following periods of high liquidity. Yao (2012) provides strong evidence to support momentum reversals during January (the end of the United States financial year). He observes momentum reversals - long momentum stocks performing poorly and short momentum stocks performing well. This is due to non tax-exempt investors flipping their commonly observed disposition effect tendencies, with clear tax incentivized trading (selling losers for capital loss purposes) in the month prior.

Outside of JT momentum, and the other three Fama and French (1993) factors (MKT, SMB and HML)(Asness et al., 2013), there has been relatively fewer inquiries into the time-varying nature of the other momentum-related anomalies. The lack of inquiry into other anomalies may be due to momentum's robustness and high Sharpe ratio relative to other anomalies (Barroso and Santa-Clara, 2015). Mclean and Pontiff (2016) find that the returns of more than 100 anomaly measures significantly drop once anomalies are made public knowledge through the publication of research. Beyond the longer term variations shown for momentum, Birru (2018) observes a clear day of the week effect for a series of anomalies. He reports that anomalies with a short speculative leg perform best on Monday (when investor mood is low), while anomalies that have a long speculative leg perform best on Friday (when mood is high)[5]. Despite the scant literature on time variation of the other anomalies, there is clear reason to believe that there is time and market-state variability, particularly in regards to investor behavior, in the momentum-related anomalies.

1.2.5 Investor behavior and return predictability

Chordia et al. (2002) demonstrates that investor trading affects stock prices, namely lagged and contemporaneous order imbalance is strongly linked to market wide returns. There is, however, conflicting evidence regarding the direction and size of the effect of investor class trading and future returns. Kaniel et al. (2008) report that individual

[5]This finding is consistent with the psychology literature on the intra-week variations in mood. Using twitter data, Golder and Macy (2011) report that mood varies throughout the week, rising from its floor on Monday to reach a peak on Fridays and Saturdays.

investors buying and selling tends to push returns in the direction of their trades. This is conditioned on their observation that individual investors have a tendency to buy (sell) stocks that have recently performed poorly (well). Han and Kumar (2013) suggest individuals have a tendency to buy stocks with lottery-like characteristics that tend to underperform relative to the market.

As with individual investors, the results of institutional trading tend to be mixed. Campbell et al. (2009) using trade and quote data to infer institutional investment, find that institutional trading experiences short term losses, potentially indicative of liquidity costs and medium term gains. This observation that institutional trading drives the direction of returns may be due to institutions being informed regarding future announcements (Campbell et al., 2009; Hendershott et al., 2015). Boehmer and Kelley (2009) argue that institutional holdings cause stocks to be more price-efficient and move at a random walk.

The reason that institutional investors drive returns may be due to the likelihood that institutions are more informed ex ante compared to household investors. Kumar (2009) argue that individual investors are more likely to rely on behavioral biases within stocks that are difficult to price. This includes but is not limited to: anchoring (Kahneman, 1992), such as with the 52WH, the recency effect (Jarvik, 1951) as with RR; and the hot hand fallacy (Ayton and Fischer, 2004) and/or the disposition effect (Shefrin and Statman, 1985) with momentum. The direction of investor bias can be strongly predicted, as put forward by Shefrin and Statman (1985), in which investors are more likely to sell winners and hold winners.

The role of investor class trading and its effect on price predictability is challenging to research due to the difficulty of acquiring matched trade data for either institutional or household investors. The most prominent measure of institutional investment is the 13F U.S. quarterly institutional holdings data[6]. As it covers the entire US market, its usage has been quite prominent in financial research (Ivashina and Sun, 2011).

Household trading has been examined in small subsets (66,000 household investors) in the US market by Barber and Odean (2000). Internationally, the universe of French (Barrot et al., 2016), German (Baltzer et al., 2019), Taiwanese (Bhattacharya et al., 2012) and Finnish (Grinblatt and Keloharju, 2000) investor trading data is available and has been used in financial research. Alternatively, researchers have relied on trade size as a proxy for individual investor behavior. Hvidkjaer (2008) using small trades as a proxy for trading, shows that stocks that had experienced intense small-volume selling outperform those that were intensely bought in small-volumes.

There is a small number of studies investigating the role of investor behavior on time varying anomaly returns. Hur et al. (2010) undertook an investigation into the role of individual investors on momentum. Using small trades (less than $5,000) as a proxy for individual investor behavior they find that momentum is stronger in stocks traded heavily in small bundles. In addition, Edelen et al. (2016) explore the role of institutional investor ownership at a quarterly level and a series of market and accounting anomalies and note that institutions tend to buy overvalued stocks and do not push the direction

[6]SEC Form 13F is a quarterly report filed with the US Securities and Exchange Commission (SEC) by institutions, such as pension funds and hedge funds. that have at least $100 million in equity assets under management. The SEC subsequently publishes this data, thus leading to its popularity in research.

of prices. These prior studies have significant issues with their behavior metrics as they use a rough proxy for behavior (trade bundle size) or they measure trading too infrequently (quarterly holdings).

Overall, the prior research can benefit from a more thorough analysis of the role of individual investor ownership and the way their tendency to underreact to news (Hong and Stein, 1999) can intensify momentum returns. In addition, in line with the claims of Boehmer and Kelley (2009), more research into how institutions improve market efficiency is required.

1.3 Hypothesis development

The literature offers a suitable foundation to explore the role of investor class trading, at a much more granular level, on anomaly returns. First, prior studies have relied on firm size or small trade bundles as a proxy for household trading. This study directly measures the stock trading by class during the formation and holding period of the anomalies. Secondly, prior studies used very low frequency data (quarterly) to identify trading by institutions. In contrast, with the greater level of granularity in the data, it is possible to comprehensively explore the role that investor class behavior plays on the diffusion of news and, how this leads to the intensifying and suppressing of the momentum-related anomalies: JT momentum, NM momentum, the 52WH, and RR.

Hypothesis 1: H1 - Household buying increases the intensity of anomaly returns:

Prior research shows that momentum is driven by a slow diffusion of news (Da et al., 2014; Hong et al., 2000; Hong and Stein, 1999). Individual investors, that tend to be inattentive or prospect theory style, are more likely to underreact or misinterpret news causing a dampening of prices, relative to fair value. High individual ownership in a stock is likely to intensify this effect and thus strengthen subsequent momentum returns. As the data used in this study facilitates examination at the trade level, it is possible to directly test this hypothesis. The expectation is that, if the anomalies are driven by investor underreaction to news, greater buying by households in a stock will lead to greater anomaly returns. As this underreaction will not lead to overbidding, these momentum returns will not mean revert in subsequent periods.

Hypothesis 2: H2 - Institutional trading suppresses the intensity of anomaly returns):

Building on the research of Boehmer and Kelley (2009) that institutional investors improve market efficiency, it is possible to directly observe the trades of institutional investors to detect their role in reducing the strength of anomaly returns. The expectation is that institutional investor ownership will result in more informationally efficient stocks, that react and update to news more quickly. Therefore institutional buying will dampen anomaly returns in the subsequent period. This hypothesis will add support to the earlier findings that institutional ownership restricts the returns to anomalies and promotes market efficiency.

1.4 Data and metrics

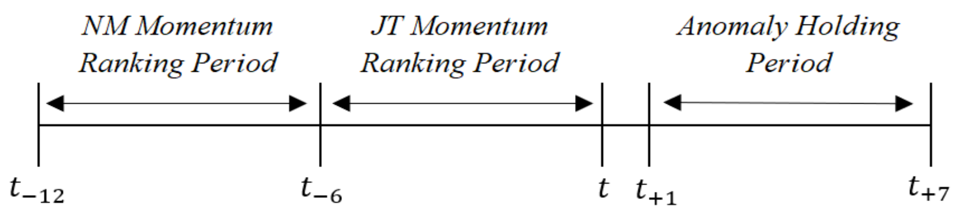
1.4.1 Data

The trade data set in this study is acquired from matched trades on the Helsinki NASDAQ OMXH (OMXH). The data is obtained from the Nordic Central Securities Depository (NCSD). The data set contains the official record of trades: including identifiers that designate investor class (households, domestic institutions, foreign institutions, and other) on both sides of the trade in addition to, stock price and stock quantity. The trade data set is the raw daily trades from 1 January 1995 to 31 December 2011 on the OMXH. The trade data is aggregated from the intra-day trade level to a monthly level designating the three key investor classes, household, foreign institutions, and domestic institutions. Other classes such as charities and not-for-profits were excluded as they are a relatively small fraction of the market and/or they are unlikely to be sensitive to anomalies. This data has been used in previous studies on return predictability and investor behaviour (Grinblatt and Keloharju, 2000; Grinblatt et al., 2012).

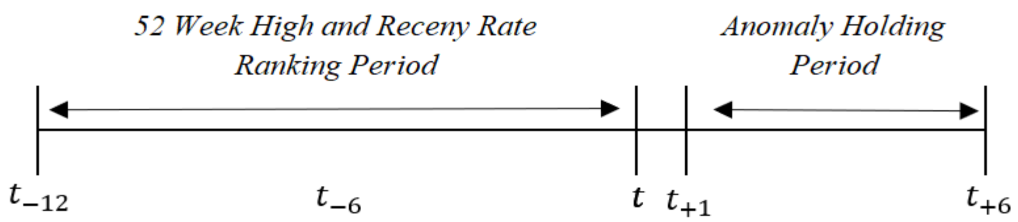
The stock and market characteristics are sourced from the Wharton Research Data Services (WRDS) Compustat data set. The data set includes the end of month prices and aggregated volumes for the OMXH. The merged sample includes the top 100 OMXH stocks based on market capitalization at the end of the sample. This sample selection is informed by Grinblatt and Keloharju (2000) to ensure the results are not biased by small, illiquid stocks.

1.4.2 Anomaly and behavior metrics

The anomalies explored in this study are detailed in Section 1.2. Namely, the price-run anomalies are JT momentum and NM momentum and the price-range anomalies are the 52WH and RR. This study relies on their source papers for the method of calculation, as reported in equations 1.1 1.2, 1.3 and 1.4. The anomalies are calculated on a rolling monthly basis. For the anomalies a month is skipped between the anomaly ranking periods and the holding periods to prevent the effect of the bid-ask bounce (Asness et al., 2013). Figure 1.1 displays the specifications of the ranking and holding periods for each of the anomalies.



(a) Price-run anomaly ranking and holding periods



(b) Price-range anomaly ranking and holding periods

Figure 1.1: Anomaly ranking and holding periods

This figure illustrates how the respective price-range anomalies (Jegadeesh and Titman (1993) JT momentum and Novy Marx (2013) NM momentum) and price-run anomalies (52 week high and recency rate) portfolios are timed and measured.

To measure the rate and direction of trade by class, this study uses a novel measure of class trading, NBR. This measure reports the average relative buying of stock i on day t by each of the three respective investor classes c (households, foreign institutions, and domestic institutions) for the six months prior.

$$NetBuyRatio_{i,t,c} = \sum_{i=1}^{n} \frac{VBuys_{i,t,c} - VSells_{i,t,c}}{VBuys_{i,t,c} + VSells_{i,t,c}}, \tag{1.5}$$

where $VBuys_{i,t,c}$ is the volume of buys and $VSells_{i,t,c}$ is the volume of sells in stock i in month t by investor class c. Intuitively, this measure offers a ratio of the relative direction of trade in a given stock by households, foreign institutions and domestic institutions each month, respectively. The value of the NBR is bounded between -1 and $+1$, where larger positive values indicate a greater proportion of buying relative to selling by the respective investor class in the given month. Using a ratio prevents extreme observations from skewing the results which could be an issue using a nominal measure. Within group trading is netted out against one another, thus this measure is a variation of the trade measure used by Stoffman (2014) and Han and Kumar (2013).

1.5 Results

The empirical approach is as follows: we first calculate the behavior metrics for households and institutions. To test the unconditional results of the anomalies we undertake monthly tercile sorts (low, med, high) of stocks into anomaly portfolios over the ranking period and report the effect on returns and investor behavior in the holding period. To test the effect of investor classes on anomaly returns we next undertake double sorts, first into terciles on one of the four anomalies, and then on ranking period investor NBR, and report the lead returns. Following this, we regress the behavior and anomaly measures against lead returns. Finally, in order to test for mean reversion, we plot the cumulative returns for 24 months for each of the long legs of the anomalies based on past investor class high and low net buying.

1.5.1 Descriptive statistics

Table 1.1 reports the descriptive statistics for the stock and investor behavior in the sample, equally weighted. The mean monthly return is 0.81% over the sample, suggesting the market is trending upwards during the period. The average firm size is 1.94 billion euros, larger than the median firm size of 295 million euros.

Table 1.1: Descriptive statistics

This table reports the descriptive statistics for the main stock characteristics and investor behavior metrics for the sample. For each metric, we report the mean, standard deviation (std dev), 25th quartile, median, and 75th quartile of the monthly values. Average lead return is the average monthly return for the current month. Market capitalization is the price*shares outstanding in tens of million euros. Investor class net buy ratio (NBR) is the (class buys - class sells)/ (class buys + class sells) for the current month for each of the investor classes: households, foreign institutions and domestic institutions. Class volume is the ratio of total volume traded by classes: households, foreign institutions, and domestic institutions, respectively. The sample covers the period of 1 January 1995 to 31 December 2011.

	Mean	Std Dev	25th quartile	Median	75th quartile
Average lead return	0.815	6.635	-2.557	0.47	4.054
Market capitalization (10mil euros)	194.776	987.277	9.207	29.459	100.564
Household NBR	0.017	0.282	-0.132	0.011	0.171
Foreign institution NBR	-0.021	0.291	-0.076	-0.002	0.036
Domestic institution NBR	-0.028	0.223	-0.091	0.000	0.092
Household volume	0.207	0.280	0.021	0.064	0.279
Foreign institution volume	0.349	0.359	0.059	0.166	0.690
Domestic institution volume	0.445	0.403	0.000	0.470	0.869

The mean NBR is slightly higher for households at 0.01 than either foreign or domestic institutions at -0.02. Given NBR is a ratio, this difference in NBR by class is not necessarily indicative of a change in ownership over the sample. The most substantial investor class is the domestic institutions, accounting for 45% of the monthly volume over the sample, followed next by foreign institutions with 35% and lastly households with 20% of the volume.

To ensure the independence of each of the anomaly measures we report the Pearson's correlation coefficients between the measures in Table 1.2. Interestingly, we see a very small correlation between the JT and NM momentum measures (0.05). As expected by Bhootra and Hur (2012) we see the largest correlation between 52WH and RR (0.623).

Table 1.2: Price predictability anomaly correlations

This table reports the Pearson correlations of the four key price predictability anomalies across the sample. JT momentum is the average monthly return for stock i over the period $t-1$ to $t-7$. NM momentum is the average monthly return for the period $t-7$ to $t-13$. The 52 week high ratio is the ratio between the stock's current price and its 52 week high price. Recency rate is a ratio measure of the number of days since the stock last reached its 52 week high as a proportion of a year. The sample covers the period of 1 January 1995 to 31 December 2011. The p statistics are reported in brackets below. The coefficients, ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

	JT momentum	NM momentum	52 week high ratio	Recency rate
JT momentum	1			
NM momentum	0.052***	1		
	(0.001)			
52 week high ratio	0.606***	0.384***	1	
	(0.001)	(0.001)		
Recency rate	0.350***	0.350***	0.623***	1
	(0.001)	(0.001)	(0.001)	

1.5.2 Portfolio sorts

The initial analysis is to test the effect of the anomalies on both returns and investor behavior. This is to support the efficacy of the anomalies in the Finnish market. We first undertake sorts of stocks by month into tercile ranks (low, med, high) for each of the 4 anomalies, as per Jegadeesh and Titman (1993). In Table 1.3 we report the effect of the anomalies on lead 3 and 6 month average returns and NBR during the holding period for each class.

Panel a reports the results of the price-run anomalies and Panel b reports the price-range anomalies. The high tercile anomalies lead to positive returns in excess of low anomaly returns. The strongest of the average lead 3 month returns are JT momentum (1.08%) and RR (1.14%), which are a better predictor than NM momentum (0.94%) and the 52WH (0.836 %). We do not see negative returns to the short legs of the anomalies; instead they underperform relative to the long leg. This may be due to the relatively strong market performance from 1995 to 2011 wherein the long-short strategies would still produce zero cost returns as per Jegadeesh and Titman (1993).

Table 1.3: Single sort portfolios by price-run and price-range predictability anomalies

This table reports the results for single sorts into terciles (low, med, high) on a monthly basis by the price predictability measures JT Momentum, NM Momentum, 52 week high ratio and recency rate (as defined earlier). In addition, we report the results for returns and investor behavior of the monthly tercile sorts, by the average net buy ratio (NBR) over the ranking period for households, foreign institutions and domestic institutions, respectively. The test variables, namely 3 month lead return and 6 month lead return are the average monthly returns for the given portfolio for 3 and 6 months forward, respectively Investor class NBR is the (class buys - class sells) / (class buys + class sells) for the current month for each of the investor classes: households, foreign institutions and domestic institutions. The sample covers the period of 1 January 1995 to 31 December 2011.

	JT momentum			NM momentum		
Panel a: price-run anomalies						
	Low	Med	High	Low	Med	High
3 month lead return	0.587	0.777	1.081	0.676	0.835	0.944
6 month lead return	0.585	0.909	1.183	0.820	0.941	0.921
Household NBR	0.091	0.007	-0.046	0.022	0.014	0.015
Foreign institution NBR	-0.033	-0.017	-0.013	-0.022	-0.021	-0.021
Domestic institution NBR	-0.040	-0.033	-0.013	-0.025	-0.032	-0.029

	52 week high			Recency rate		
Panel b: price-range anomalies						
	Low	Med	High	Low	Med	High
3 month lead return	0.667	0.940	0.836	0.471	0.834	1.141
6 month lead return	0.720	0.964	0.990	0.666	0.810	1.204
Household NBR	0.084	0.027	-0.058	0.042	0.038	-0.029
Foreign institution NBR	-0.023	-0.019	-0.021	-0.032	-0.014	-0.017
Domestic institution NBR	-0.038	-0.028	-0.020	-0.037	-0.030	-0.018

We next look at the effect of the anomalies on investor behavior during the holding period. Households trade inversely to JT momentum, with an NBR of 0.09, indicative of buying, for the low tercile, and an NBR of -0.04, indicative of selling, for the high tercile. This supports the recent findings of Baltzer et al. (2019) that households tend to buy JT losers and sell JT winners. This is predicted in part by both Shefrin and Statman (1985) and Grinblatt and Han (2005) as these stocks are past winners, and as such, households are likely to display disposition effect tendencies and sell down these stocks. A similar contrarian behavior is present for both the 52WH and RR. NM momentum does not drive investor behavior, supporting our expectation that it neither arises from, nor is it driven by investor behavior.

In order to test the role of investor behavior on anomaly returns we undertake double sorts (Bhootra and Hur, 2013). We first sort stocks by one of the four anomalies into terciles (low, med, high) during the ranking period and then sort stocks monthly into terciles (low, med, high) based on their average lagged 6 months investor class NBR and report their lead 6 month average returns. For example, a stock can be in the high JT momentum portfolio and high household NBR (high household buying) from which we report their average monthly return in the holding period. Table 1.4 reports the double sort results for household investors. Panel a reports the anomaly returns for low and medium household NBR. Panel b reports the anomaly returns for high household NBR and the difference in the long leg of the anomalies for high versus low household NBR, thus reporting the marginal effect of household buying on the long leg of the anomaly.

To support hypothesis 1, we expect to observe high household NBR intensify anomaly returns, particularly on the long leg. In Panel b, it is clear that high household NBR results in significant increases in anomaly returns for the high–low portfolio of JT momentum (+1.15%), the 52WH (+0.91%) and RR (+1.17%) for the lead 6 month average monthly return. Outside of NM momentum, household buying has a very strong effect on the long leg of the anomaly returns.

Table 1.4: Double sorts portfolios by household ownership and price predictability anomalies

This table reports the average monthly lead returns for a 6 month period for the double sorts. Firstly, the stocks are sorted on a monthly basis into terciles based on their household average net buy ratio (NBR) (low, medium and high) for the prior 6 months then secondly into terciles (low, med and high) based on the prior JT momentum, NM momentum, 52 week high ratio and recency rate during the ranking period, respectively (as defined earlier). It also reports the net average 6 monthly returns for high anomaly minus low anomaly for each of the respective anomalies based on prior NBR. Panel a reports the values for the low and medium household NBR terciles. Panel b reports the values for high household NBR terciles. In addition, Panel b reports the results of the high - low NBR for the high leg of the anomaly, which is the difference in returns between the high anomaly in the high NBR tercile (high net buying) and the high anomaly for the low NBR tercile (high net selling), reflecting the marginal effect of household NBR on high anomaly portfolios. The sample covers the period of 1 January 1995 to 31 December 2011. The t statistics are reported in brackets below the coefficients ***, **, *, indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel a: low and med household NBR

	Low household NBR				Med household NBR			
	Anomaly rank				Anomaly rank			
	Low	Med	High	High - Low	Low	Med	High	High - Low
JT momentum	0.412**	0.566***	0.805***	0.394	0.391***	0.840***	1.070***	0.679***
	(2.278)	(4.876)	(6.51)	(1.798)	(2.636)	(6.141)	(6.809)	(3.145)
NM momentum	0.759***	0.823***	0.451***	-0.308	0.729***	0.778***	0.860***	0.131
	(4.967)	(6.909)	(3.28)	(-1.395)	(4.425)	(5.738)	(6.077)	(0.597)
52 week high	0.550***	0.733***	0.608***	0.058	0.445***	0.839***	1.031***	0.586***
	(2.815)	(5.738)	(5.494)	(0.254)	(2.618)	(6.222)	(7.709)	(2.713)
Recency rate	0.782***	0.529***	0.639***	-0.143	0.510***	0.632***	1.195***	0.685***
	(4.978)	(3.761)	(5.553)	(-0.676)	(3.467)	(4.39)	(7.901)	(3.272)

Panel b: high household NBR and high less low NBR

	High household NBR				
	Anomaly rank				
	Low	Med	High	High - Low	H-L NBR for high anomaly
JT momentum	0.643***	1.099***	1.800***	1.156***	0.762***
	(5.096)	(8.158)	(7.026)	(4.049)	(2.681)
NM momentum	1.037***	1.040***	1.064***	0.026	0.335*
	(5.295)	(7.536)	(7.694)	(0.114)	(1.663)
52 week high	0.654***	1.193**	1.567***	0.913***	0.855***
	(4.689)	(7.298)	(8.618)	(3.904)	(3.873)
Recency Rate	0.690***	0.883***	1.863***	1.173***	1.316***
	(4.941)	(6.07)	(8.98)	(4.592)	(5.322)

We next look at the effect of household buying on improving the returns to the long portfolios. Panel b reports the high household NBR less low household NBR for the high anomaly (indicative of the effect of the marginal effect of household ownership on the long leg of the anomaly) for each of the four anomalies. For the long leg of the anomalies we observe a strong effect of household buying. The marginal effect of high household NBR is economically and statistically significant for all but NM momentum. The marginal effect of high household ownership on the long leg of the anomalies is 0.762% for JT momentum, 0.85% for the 52WH and 1.13% for RR. These results clearly support the prior findings of Hur et al. (2010) and hypothesis 1, suggesting household investment intensifies anomaly returns.

To test hypothesis 2, namely that institutions dampen anomaly returns, we undertake a similar double sort to 1.4. In Table 1.5, we first sort stocks by the price-run and price-range anomaly terciles, and next sort by foreign institution NBR during the ranking period and report the average lead 6 month returns. In Panel b, we observe the effect of high foreign institutional buying on the anomaly returns. High foreign institution buying leads to a disappearance in the returns for the *long less short* portfolio for all the anomalies. Moreover in Panel a, we observe that when foreign institutions are selling the long less short strategy is profitable for JT momentum (0.95%) and the 52WH (0.56%). This supports the findings of Boehmer and Kelley (2009) that a reduction in institutional ownership increases market distortions.

Last, we observe the marginal effect of high less low NBR for the long anomaly legs. We see that high NBR leads to both JT momentum (-1.194%) and 52WH (-0.832%) becoming negative. This contrasts with our earlier household findings and clearly supports Edelen et al. (2016) who reports institutional holdings reduce the intensity of anomaly returns.

Table 1.5: Double sorts portfolios by foreign institution ownership and price predictability anomalies

This table reports the average monthly lead returns for a 6 month period for the double sorts. Firstly, the stocks are sorted on a monthly basis into terciles based on their foreign institution average net buy ratio (NBR) (low, medium and high) for the prior 6 months then secondly into terciles (low, med and high) based on the prior JT momentum, NM momentum, 52 week high ratio and recency rate during the ranking period, respectively (as defined earlier). It also reports the net average 6 monthly returns for high anomaly minus low anomaly for each of the respective anomalies based on prior NBR. Panel a reports the values for the low and medium foreign institution NBR terciles. Panel b reports the values for high foreign institution NBR tercile. In addition Panel b reports the results of the high - low NBR for the high leg of the anomaly, which is the difference in returns between the high anomaly in high NBR tercile (high net buying) and the high anomaly for the low NBR tercile (high net selling), reflecting the marginal effect of foreign institution NBR on high anomaly portfolios. The sample covers the period of 1 January 1995 to 31 December 2011. The t statistics are reported in brackets below the coefficients ***, **, *, indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel a: low and med foreign institution NBR

	Low foreign institution NBR				Med foreign institution NBR			
	Anomaly rank				Anomaly rank			
	Low	Med	High	High - Low	Low	Med	High	High - Low
JT Momentum	0.774***	1.150***	1.731***	0.957***	-0.047	0.695***	1.055***	1.102***
	(5.259)	(8.557)	(8.684)	(3.861)	(-0.295)	(5.457)	(7.063)	(5.051)
NM Momentum	1.568***	1.157***	0.939***	-0.628**	0.345***	0.601***	0.781***	0.436**
	(7.983)	(8.493)	(6.654)	(-2.595)	(2.102)	(4.565)	(5.448)	(2.028)
52 week high	0.763***	1.520***	1.320***	0.558**	0.106	0.518***	1.106***	0.999***
	(4.818)	(9.3)	(8.266)	(2.442)	(0.594)	(3.966)	(9.193)	(4.678)
Recency rate	1.271***	0.809***	1.521***	0.250	0.005	0.472***	1.162***	1.157***
	(8.321)	(5.706)	(8.063)	(1.021)	(0.035)	(3.046)	(8.962)	(5.927)

Panel b: high foreign institution NBR and high less low NBR

	High foreign institution NBR				
	Anomaly rank				
	Low	Med	High	High - Low	H-L NBR for high anomaly
JT Momentum	0.854***	0.609***	0.617***	-0.237	-1.194***
	(6.509)	(4.834)	(4.235)	(-1.21)	(-4.836)
NM Momentum	0.576***	0.883***	0.635***	0.059	0.687***
	(3.683)	(7.113)	(4.767)	(0.292)	(3.606)
52 week high	0.816***	0.746***	0.542***	-0.274	-0.832***
	(5.426)	(5.727)	(4.332)	(-1.397)	(-4.025)
Recency rate	0.561***	0.795***	0.725***	0.164	-0.086
	(4.155)	(6.002)	(5.323)	(0.851)	(-0.373)

To continue the investigation of hypothesis 2, in Table 1.6 we repeat the above double sort analysis for domestic institutions. There is limited support for the role of domestic institution trading and variation in anomaly returns. There is little directional evidence, in contrast to the findings of the prior two classes. The clearest evidence of their stabilizing effect is presented in Panel a, where we report the medium domestic institutional NBR portfolio. We observe that when domestic institutions are neither buying nor selling, the long less short anomaly portfolios produce the greatest returns. Panel b reports the marginal effect of high less low domestic institution NBR on the long leg of the anomalies. We see that they are all economically and statistically insignificant.

Table 1.6: Double sorts portfolios by domestic institution ownership and price predictability anomalies

This table reports the average monthly lead returns for a 6 month period for the double sorts. Firstly, the stocks are sorted on a monthly basis into terciles based on their domestic institution average net buy ratio (NBR) (low, medium and high) for the prior 6 months then secondly into terciles (low, med and high) based on the prior JT momentum, NM momentum, 52 week high ratio and recency rate during the ranking period, respectively (as defined earlier). It also reports the net average 6 monthly returns for high anomaly minus low anomaly for each of the respective anomalies based on prior NBR. Panel a reports the values for the low and medium domestic institution NBR terciles. Panel b reports the values for high domestic institution NBR terciles. In addition panel b reports the results of the high - low NBR for the high leg of the anomaly, which is the difference in returns between the high anomaly in the high NBR terciles (high net buying) and the high anomaly for the low NBR tercile (high net selling), reflecting the marginal effect of domestic institution NBR on high anomaly portfolios. The sample covers the period of 1 January 1995 to 31 December 2011. The t statistics are reported in brackets below the coefficients ***, **, *, indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel a: low and med domestic institution NBR

	Low domestic institution NBR				Med domestic institution NBR			
	Anomaly Rank				Anomaly Rank			
	Low	Med	High	High - Low	Low	Med	High	High - Low
JT Momentum	0.690***	0.818***	1.276***	0.587***	0.213	0.716***	0.968***	0.755***
	(5.23)	(6.544)	(6.185)	(2.397)	(1.408)	(5.662)	(6.709)	(3.615)
NM Momentum	1.053***	0.737***	0.986***	-0.067	0.475***	0.798***	0.630***	0.155
	(6.102)	(5.668)	(6.854)	(-0.302)	(3.043)	(6.069)	(4.59)	(0.744)
52 Week High	0.741***	0.917***	1.053***	0.312	0.237	0.807***	0.836***	0.598***
	(5.166)	(6.12)	(6.691)	(1.434)	(1.351)	(6.866)	(6.45)	(2.784)
Recency Rate	0.749***	0.833***	1.160***	0.412*	0.303**	0.496***	1.078***	0.774***
	(5.134)	(6.158)	(6.788)	(1.825)	(2.051)	(3.566)	(7.898)	(3.956)

Panel b: high domestic institution NBR and high less low NBR

	High domestic institution NBR				
	Anomaly Rank				
	Low	Med	High	High - Low	H-L NBR for High Anomaly
JT Momentum	0.612**	0.862**	1.116**	0.504*	-0.083
	(3.789)	(6.707)	(7.163)	(2.245)	(-0.321)
NM Momentum	0.931**	1.027**	0.783**	-0.148	-0.081
	(4.876)	(8.196)	(5.544)	(-0.623)	(-0.412)
52 Week High	0.651**	0.901**	1.073**	0.422**	0.110
	(3.796)	(5.98)	(8.133)	(1.932)	(0.53)
Recency Rate	0.833**	0.682**	1.119**	0.286	-0.126
	(5.827)	(4.39)	(7.505)	(1.353)	(-0.559)

Overall, the double sort results clearly support hypothesis 1, namely that household trading drives anomaly returns, particularly on the long leg. This continues to support the role of households on news dampening. There is considerable evidence to support hypothesis 2, namely that institutions, in this case foreign institutions dampen anomaly returns. The importance of investor behavior on JT momentum and price-range anomalies is an interesting finding as it shows investors are sensitive to these anomalies and their trading is significant in driving their returns.

These results highlight the stabilizing effect of the largest investors in the market, domestic institutions. When they don't trade heavily anomalies intensify. It is also interesting to note the relative absence of the role of investor behavior on NM momentum. This supports the discussion of Novy-Marx (2012) who states this measure is driven by firm-industrial performance rather than investor behavior or market conditions.

1.5.3 Multivariate analysis

Having established the importance of investor behavior on anomaly returns, we next tease out the effect of these by regressing the investor and anomaly factors against lead return.

$$\begin{aligned} Return_{i,t} = b_0 + b_1 AnomalyRank i,t + b_2 InvestorNBR_{i,t,c} \\ + b_3 HighInvestorNBR_{i,t,c} * HighAnomaly_{i,t} + MKT + \epsilon_{i,t} \end{aligned} \tag{1.6}$$

where $Return_{i,t}$ is the average of the lead 6 month return of stock i at time t. $AnomalyRank_{i,t}$ is a tercile ranking [0, 1, 2] for each of the four anomalies at time

t for the respective stocks i. $InvestorNBR_{i,t,c}$ is the NBR for each investor class c (household, foreign institution and domestic institution) for stock i at time t. MKT is the Fama and French (1993) European market factor. The other European Fama French factors were not included due to their limited validity within the Finnish market. The standard errors are clustered at year level. In addition the models include fixed effects at the year and firm level.

Table 1.7 reports the results from estimation of the above regression specification for the price-run anomalies. Model I reports the baseline anomaly returns, while Models II, III and IV report the effect of household, foreign institution and domestic institution trading on anomaly returns respectively.

In Table 1.7, Models I-IV report the effect of investor behavior and JT momentum on returns. There is clear evidence of the efficacy of household buying to predict positive future returns unconditionally. There is continual support for hypothesis 1, as household buying improves momentum returns; the interaction of high (tercile) household NBR and high JT momentum results in an average return of 2.48% per month.

In Model III we observe that foreign institutional buying dampens and/or reverses the long leg of anomaly returns. High foreign institution buying leads to negative returns unconditionally. The interaction of high institutional trading and high JT momentum results in economically and statistically significant -2.54% return per month. In Model IV we continue to see that domestic institution's NBR drives returns unconditionally and does not have a significant effect on anomaly returns.

In Table 1.7, Models V-VIII report the effect of investor behavior and NM momentum on future returns. NM momentum is not a significant driver of future returns, nor is it influenced by investor behavior under this specification. When foreign institutions display high NBR, the long leg of NM momentum is predictive of negative future returns (-2.98%). The regression results continue to support the lack of importance of investor behavior on NM momentum. The findings suggest that investors of all classes are more sensitive to returns over the prior 6 months (JT momentum) rather than 7-12 months prior (NM momentum), indicative of myopia (Benartzi and Thaler, 1995) .

Table 1.7: Regression of stock returns on price-run anomalies and investor behavior

This table reports average coefficient estimates from the monthly cross-sectional regressions for the sample. The dependent variable is the monthly stock returns for months $t+1$ to $t+7$. Anomaly rank is a tercile ranking [0,1,2] of the given stock based on it price-run (JT momentum or NM momentum) anomaly value during the ranking period ($t-12$ to t). Class NBR is the net buy ratio (class buys - class sells)/ (class buys + class sells) for households (HH), foreign institutions (FI) or domestic institutions (DI) in stock i for the current month. High class NBR is an indicator variable, which equals one if the stock at time t is the top quartile for NBR over the prior six months. High anomaly is an indicator variable, which equals one if the stock is in the top quartile for the given anomaly. MKT is the Fama and French European market factor. All models include year and firm fixed effects and cluster the standard errors at the year level. The sample includes the top 100 stocks on the NASDAQ OMXH based on market capitalization over the period 1 January 1995 to 31 December 2011. The p statistics are reported in brackets below the coefficients, ***, ** and * indicate significance at the 1%, 5%, and 10 % levels, respectively.

	Anomaly: JT momentum				Anomaly: NM momentum			
	I	II	III	IV	V	VI	VII	VIII
Intercept	0.542**	0.281*	0.769**	0.533**	0.761***	0.635***	0.973***	0.725***
	(0.000)	(0.022)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Anomaly rank	0.209***	0.276***	0.204***	0.207***	-0.004	0.007	-0.005	0.007
	(0.000)	(0.000)	(0.001)	(0.001)	(0.994)	(0.899)	(0.924)	(0.905)
HH NBR		0.102***				0.058		
		(0.008)				(0.120)		
High HH NBR* High anomaly		2.482***				1.422		
		(0.005)				(0.136)		
FI NBR			-0.117***				-0.111**	
			(0.001)				(0.002)	
High FI NBR* High anomaly			-2.543***				-2.998***	
			(0.002)				(0.000)	
DI NBR				-0.003				0.005
				(0.920)				(0.881)
High DI NBR* High anomaly				0.083				0.093
				(0.598)				(0.577)
MKT	0.038***	0.038***	0.038***	0.043***	0.034***	0.033***	0.033***	0.038***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year F.E	y	y	y	y	y	y	y	y
Firm F.E	y	y	y	y	y	y	y	y
N	12600	12600	12571	12440	12030	12030	12017	11917
R-sq	0.031	0.042	0.051	0.031	0.012	0.021	0.045	0.023

We continue the analysis in Table 1.8 for the price-range anomalies. Model I reports the baseline anomaly returns, while II, III, and IV report the effect of household, foreign institution and domestic institution trading on anomaly returns, respectively. There is a continuation of strong anomaly returns associated with high household buying. High household NBR interacted with high 52WH or RR results in an increase in average monthly returns of 1.47% and 1.91%, respectively. In support of hypothesis 2, we continue to see foreign institutions dampening anomaly returns. By inspecting the coefficients of high institutional trading and high 52WH anomaly returns we show that foreign institutions dampen the 52WH by -0.96 % per month. Domestic institution trading results in negative but insignificant co-efficients. This stabilizing role of domestic institutions offers additional support to benefits of institutional ownership.

Table 1.8: Regression of stock returns on price-range anomalies and investor behavior

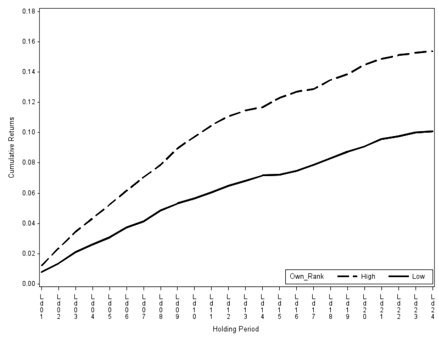
This table reports average coefficient estimates from the monthly cross-sectional regressions for the sample. The dependent variable is the monthly stock returns for months $t+1$ to $t+7$. Anomaly rank is a tercile ranking [0,1,2] of the given stock based on it price-range (52 week high or recency rate) anomaly value during the ranking period ($t12$ to t). Class NBR is the net buy ratio (class buys - class sells)/ (class buys + class sells) for households (HH), foreign institutions (FI) or domestic institutions (DI) in stock i for the current month. High class NBR is an indicator variable, which equals one if the stock at time t is the top quartile for NBR over the prior six months. High anomaly is an indicator variable, which equals one if the stock is in the top quartile for the given anomaly. MKT is the Fama and French European market factor. The sample includes the top 100 stocks on the NASDAQ OMXH based on market capitalization over the period 1 January 1995 to 31 December 2011. All models include year and firm fixed effects and cluster the standard errors at the year level. The p statistics are reported in brackets below the coefficients, ***, ** and * indicate significance at the 1%, 5%, and 10 % levels, respectively.

	Anomaly: 52 week high				Anomaly: Recency rate			
	I	II	III	IV	V	VI	VII	VIII
Intercept	0.608***	0.378***	0.821***	0.555***	0.628***	0.452***	0.863***	0.572***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Anomaly Rank	0.144**	0.200***	0.173***	0.159**	0.124**	0.165***	0.145**	0.129**
	(0.021)	(0.002)	(0.006)	(0.011)	(0.042)	(0.008)	(0.018)	(0.037)
HH NBR		0.0902**				0.0724		
		(0.019)				(0.054)		
High HH NBR* High anomaly		1.472**				1.905***		
		(0.040)				(0.008)		
FI NBR			-0.124***				-0.130***	
			(0.001)				(0.000)	
High FI NBR* High anomaly			-0.960*				-0.160	
			(0.090)				(0.827)	
DI NBR				0.010				0.015
				(0.775)				(0.664)
High DI NBR* High anomaly				-0.034				-0.196
				(0.815)				(0.165)
MKT	0.038***	0.038***	0.038***	0.043***	0.038***	0.037***	0.038***	0.043***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year F.E	y	y	y	y	y	y	y	y
Firm F.E	y	y	y	y	y	y	y	y
N	12687	12686	12644	12508	12695	12694	12652	12515
R-sq	0.021	0.035	0.032	0.031	0.021	0.036	0.031	0.032

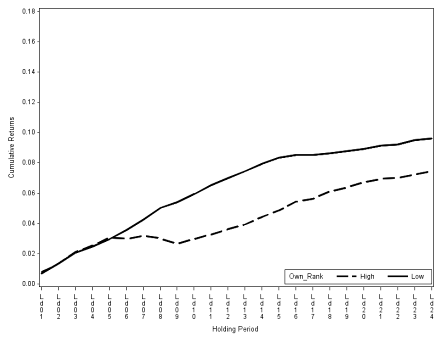
1.5.4 Further analysis: post holding period

To better explain the rationale behind why household buying drives anomaly returns we test for the existence of mean reversion beyond the holding period. We plot the lead 24 month cumulative return (CR) (skipping month 1, as per Jegadeesh and Titman (1993)) for each of the long legs of the anomaly terciles for high and low investor NBR terciles. If overbidding is the cause of the anomalies we should observe mean reversion occurring after the holding period (Jegadeesh and Titman, 1993). In contrast, if the anomalies occur as a result of a dampening of news the price should continue to rise to the fair value level (Hong and Stein, 1999).

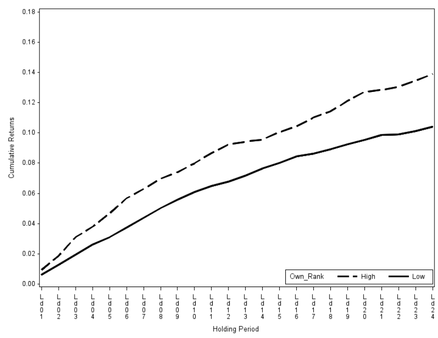
Figure 1.2, reveals that high household NBR (dashed line) results in a strong positive holding period drift for the high anomaly terciles out to the 12 month period. Out to 12 and 24 months, the 12 month CR for JT momentum for high household NBR is approximately 17%, which is economically much larger than the 9% seen for the low household NBR. Despite the greatest return occurring during the first 6 months there is no sign of mean reversion out to 24 months, but rather return-continuation. This return continuation is particularly strong for high household NBR anomalies. This finding is the case with all but NM momentum which continues to be unaffected by investor behavior. We fail to see mean reversion in the anomalies, this suggests that investor driven momentum returns is not a result of overbidding but rather a dampening of news (Hong et al., 2000; Hong and Stein, 1999).



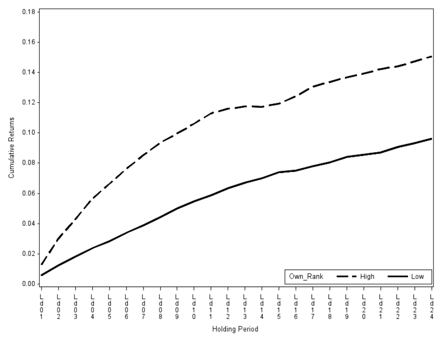
(a) JT momentum



(b) NM momentum



(c) 52 week high

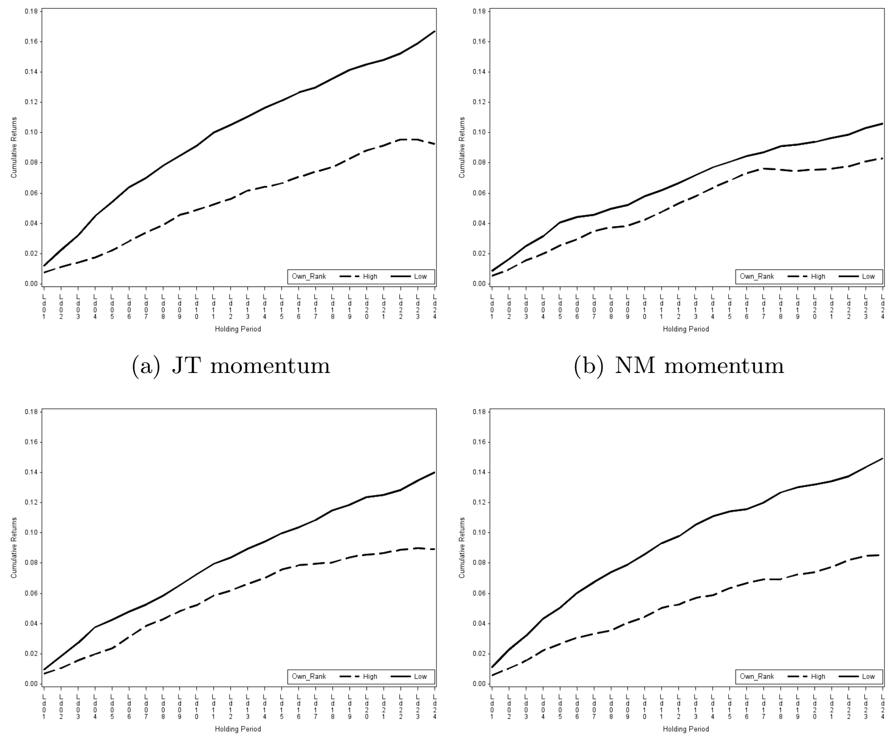


(d) Recency rate

Figure 1.2: 12 month cumulative returns for high anomaly portfolios for high and low household net buying during ranking period

The plots show the cumulative returns (CR) for the top tercile anomaly portfolios for the anomalies: Panel a - JT momentum, Panel b - NM momentum, Panel c - the 52 week high and Panel d - recency rate. These are sorted based on the average monthly household net buy ratio (NBR) from t_{-7} to t_{-1}, of which the high and low are plotted. The top tercile of household NBR is represented by the dashed line whereas the bottom tercile household NBR is represented by the full line for each of the respective high tercile anomaly portfolios. The sample covers the period of 1 January 1995 to 31 December 2011.

In Figure 1.3 there is an almost perfect inverse symmetry for foreign institutions compared to households. High foreign institution net buying leads to a a reduction in lead 12 month CR relative to low foreign institution NBR, 0.11% as compared to 0.14%. We see a similar effect for all but NM momentum, in which we see no effect of trading. High foreign institution buying leads to a quicker flattening of returns, further supporting that price discovery is more efficient in stocks held by institutions and as such large momentum returns are less likely.



(a) JT momentum

(b) NM momentum

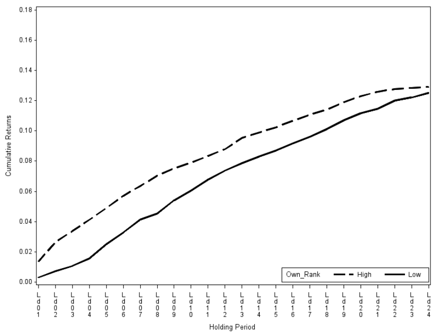
(c) 52 week high

(d) Recency rate

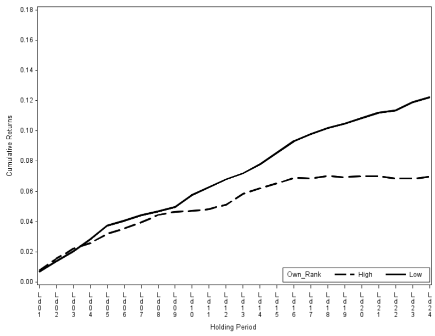
Figure 1.3: 12 month cumulative returns for high anomaly portfolios for high and low foreign institution net buying

The plots show the cumulative returns (CR) for the top tercile anomaly portfolios for the the anomalies: Panel a - JT momentum, Panel b - NM momentum, Panel c - the 52 week high and Panel d - recency rate. These are sorted based on the average monthly foreign institution net buy ratio (NBR) from t_{-7} to t_{-1}, of which the high and low are plotted. The top tercile of foreign institution NBR is represented by the dashed line whereas the bottom tercile foreign institution NBR is represented by the full line for each of the respective high tercile anomaly portfolios. The sample covers the period of 1 January 1995 to 31 December 2011.

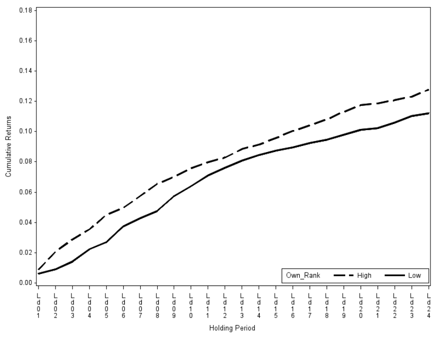
Last, in Figure 1.4 we see little or no effect of high or low net buying by domestic institutions on the profitability of the long anomaly portfolios. This finding is consistent with earlier findings that domestic institutions do not create fluctuations to anomaly returns.



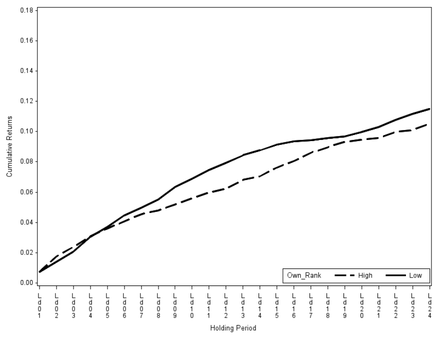
(a) JT momentum



(b) NM momentum



(c) 52 week high



(d) Recency rate

Figure 1.4: 12 month cumulative returns for high anomaly portfolios for high and low domestic institution net buying

The plots show the cumulative returns (CR) for the top tercile anomaly portfolios for the the anomalies: Panel a - JT momentum, Panel b - NM momentum, Panel c - the 52 week high and Panel d - recency rate. These are sorted based on the average monthly domestic institution net buy ratio (NBR) from t_{-7} to t_{-1}, of which the high and low are plotted. The top tercile of domestic institution NBR is represented by the dashed line whereas the bottom tercile domestic institution NBR is represented by the full line for each of the respective high tercile anomaly portfolios. The sample covers the period of 1 January 1995 to 31 December 2011.

1.6 Conclusion

This study uses a rich set of trade data to explore the role of investor class trading on momentum-related anomaly returns. The findings support the theory that momentum is a result of investor underreaction to news (Da et al., 2014; Hong and Stein, 1999). We find stocks that are heavily bought by households significantly increase the returns to the long portfolio of JT momentum, the 52WH and RR anomalies. There is a clear stabilizing effect of institutional investment (Boehmer and Kelley, 2009) on anomaly returns. High buying by foreign institutions leads to a reversal in the long leg of three of the four anomaly portfolios. Moreover, domestic institutions dampen anomaly returns causing the long less short trading strategy to be non profitable.

The finding that households drive momentum is not consistent with an overreaction effect, but rather a news dampening effect as it continues out to at least 18 months after the anomaly formation period. Last, the lack of importance of investor behavior regarding the variation in NM momentum returns supports the expectation of Novy-Marx (2012) who suggests it is driven solely by industrial performance and not investor behavior, as with the other three anomalies (JT momentum, 52WH and RR).

Future analysis into the role of investor behavior regarding other anomalies is likely to reveal similar effects. The finding that NM momentum is not influenced by investor behavior suggests that anomalies may vary in their ability to grab the attention of investors (Barber and Odean, 2007; Da et al., 2014; Mclean and Pontiff, 2016). Thus, further examination into why investor classes are drawn to certain anomalies may be a rich area of future study.

Chapter 2

Investor Behavior at the 52 Week High

2.1 Introduction

This chapter, explores the trading of individual investors with institutional investors around a salient and prominent anchor, the 52 week high (the 52WH, henceforth) (George and Hwang, 2004; Huddart et al., 2009). For an investor with prospect theory preferences (Kahneman and Tversky, 1979), the 52WH represents a signal to sell, as the stock is likely to be in the domain of gains (Shefrin and Statman, 1985), and provides an anchor for the highest past price (Kahneman, 1992). However, the 52WH does not represent value-relevant information in a weak-form efficient market. Thus, this selling pressure by household investors at the 52WH dampens upward price movement (George and Hwang, 2004; Grinblatt and Han, 2005), leading to subsequent but delayed return continuation.

This chapter examines the extent to which individual investors are responsible for the 52WH effect, their order submission strategies, and how they contribute to subsequent return drift. Using clearinghouse-level data from Finland (Grinblatt and Keloharju, 2001*a*), which allows the identification all trades made by individuals and institutions, this study explores between-group trading for 100 stocks over the period 2004–2009. Several key findings are uncovered.

First, on days when stocks open near the 52WH (specifically, within 3 percent of the 52WH), the individual-institutional trade imbalance (reflecting the net buying of individuals from institutions) is -17.5 percent, compared with 0 percent for days when stocks are not trading at the 52WH. Thus, for a trade between an individual and an institution on the 52WH day, there is a 58.8 percent chance that the individual investor is on the sell side, compared with an even chance for non-52WH days. Thus, this study presents clear evidence that trade at the 52WH involves systematic selling by individuals to institutions. The volume spikes identified by Huddart et al. (2009) therefore likely represent transfers between ownership groups - household to institution.

Second, the 52WH appears to induce limit order submission in this selling by individuals. This supports the findings that uninformed investors generally prefer to place limit orders when selling (Kaniel and Liu, 2006; Linnainmaa, 2010). Individuals also appear to cluster limit orders around attention-grabbing or novel prices (Bhattacharya et al., 2012). The study finds that individuals prefer to use limit orders on 52WH days, when they provide liquidity/use limit orders on 49.5 percent of sell trades, which is significantly higher than the 45.7 percent of sell trades on non-52WH days.

Third, limit order selling by individuals appears to be primarily responsible for the return continuation at the 52WH identified by (George and Hwang, 2004). This study, observes stocks at the 52WH earn 60-day cumulative abnormal risk-adjusted returns of 0.158 percent (0.64 percent p.a). In the 60 days after the 52WH day, we see that high (top-quartile) limit order usage on the 52WH subsumes the return continuation. Thus the 52WH phenomenon, under closer inspection, is driven by household provision of liquidity, which dampens trading by informed institutional investors.

The findings also reveal that these effects are intensified for 'new' 52WHs (when the stock is at the 52WH for the first time in 14 days), where the individual-institutional trade imbalance is -36.3 percent, suggesting that capital gains overhang (Grinblatt and

Han, 2005) further drives selling by individuals. The effects are also stronger during periods of high market volatility, when individuals are more likely to rely on anchors in making their trading decisions (Kumar, 2009).

For robustness, an event study is undertaken, on the 5 days prior to and following the 52WH day, to determine whether the 52WH day itself is the unique point of interest. The results indicate that the 52WH day itself is the focal point of the high household selling and limit order execution, after which investor behavior (both selling and limit order usage) returns to pre-52WH day levels. Overall, the findings using investor-level trade data contribute to the literature on the poor performance of household investors (Barber et al., 2008; Odean, 1998) and the role of anchors in financial markets (Bhattacharya et al., 2012) and provide a clear identification and explanation of both the volume spikes and the post-event returns observed at the 52WH (George and Hwang, 2004; Huddart et al., 2009).

This chapter proceeds as follows. Section 2.2 discusses the related literature and presents the hypotheses. Section 2.4 introduces the data and the method used to identify the 52WH and measure investor behavior. Section 2.5 reports the key findings of the study and discusses their significance in relation to the literature. Finally, Section 2.6 presents a summary of the results of the study and offers an outline for future research.

2.2 Literature review

Prior empirical research exploring individual investor behavior identifies a number of facts. Household investors tend, for example, to be net buyers of stocks that have captured their attention (Barber and Odean, 2007), with institutional investors being the counter-parties in these trades. Households tend to be contrarian investors, particularly in their selling behavior. On average, households sell stocks following positive news announcements and buy stocks subject to negative news (Hirshleifer et al., 2008; Kaniel et al., 2008). Individuals tend to exhibit the disposition effect, which renders them particularly prone to selling winning stocks and holding losers (Odean, 1998). As a result of their trading activity, they underperform the market and institutional investors (Odean, 1999).

Individual investors have also been shown to rely on anchors [7] when making their trading decisions (Bhootra and Hur, 2013; Jegadeesh and Titman, 1993; Li and Yu, 2012). Anchors that have been identified as influencing investor decisions include a stock's purchase price (Shefrin and Statman, 1985; Odean, 1998; Ben-David and Hirshleifer, 2012), its historical high price (Huddart et al., 2009; Li and Yu, 2012), and the 52WH (George and Hwang, 2004). The latter anchor is the focus of this study.

A stock's 52WH ratio is defined as follows:

$$52WeekHighRatio_{i,t} = \frac{Price_{i,t}}{High_{i,t}} \tag{2.1}$$

where $High_{i,t}$ is the highest daily closing price for stock i over the past year $(t - 252, t)$, where t is measured in days, while $Price_{i,t}$ is the current stock price. The ratio therefore represents the nearness, in percentage terms, of the stock's current price to

[7] Anchoring is the tendency of individual to rely heavily on a single piece of information, or a rule of thumb, to influence their decision making (Tversky and Kahneman, 1974).

its 52WH price.

George and Hwang (2004) demonstrate that the 52WH ratio is a significant driver of momentum profits (Jegadeesh and Titman, 1993). Anchoring at the 52WH has also been shown to play a key role in predicting trading volume. Huddart et al. (2009), for instance, find that past price ranges influence investor trading in aggregate and that there are volume spikes when a stock crosses its 52WH price. Baker et al. (2012) highlight the role of the 52WH as a key consideration in the pricing of MA deals.

2.2.1 Causes of the 52 week high effect

There are several proposed causes of the 52WH effect, which stem primarily from individual investor behavior. The key explanations are related to the disposition effect, anchoring bias, and expectational errors.

First, nearness to the 52WH price may proxy for the level of capital gains that investors are holding at any given time, which is also known as the capital gains (An, 2016; Grinblatt and Han, 2005; Hur et al., 2010; Wang et al., 2017). High levels of capital gains overhang induce selling behavior among individual investors, particularly those who are susceptible to the disposition effect. These investors are keen to sell near the 52WH because the stock is, in aggregate, in the domain of gains for investors with prospect theory preferences.

Second, the day of the 52WH may act as a key attention-grabbing anchor (Aragon and Dieckmann, 2011; Yuan, 2015). Huddart et al. (2009) find that trading volume rises sharply when stock prices pass the 52WH threshold. This effect is amplified for smaller stocks, those with more valuation uncertainty, and those with a greater proportion of individual holdings. Tversky and Kahneman (1974) noted that individuals are more likely to rely on heuristics, including anchors, when problems are uncertain, while Daniel et al. (1998) note that behavioral biases are amplified in times of uncertainty. Peng and Xiong (2006) suggest that, due to limited attention, investors will prioritize certain anchors and attention-grabbing events over others. As the 52WH is reported by news outlets and brokers, it is a salient anchor for investors trading stocks. As a result, the 52WH will likely be incorporated by individuals seeking to sell, particularly for stocks that have a degree of valuation ambiguity.

Third, errors in expectations may be amplified at the 52WH (Baker et al., 2012; Birru, 2015) because both analyst and investor return expectations are driven down for stocks near the 52WH, as evidenced by price targets and earnings surprises. Thus, investors may prefer to sell stocks near the 52WH because they believe that future returns are likely to be lower based on erroneous analyst reports and their own skewness expectations. Indeed, recent evidence suggests that stocks trading near the 52WH demonstrate no premium for skewness (Blau et al., 2018), unlike stocks far from the 52WH.

2.2.2 Trade type at the 52 week high

While prior studies have examined the impact of trade at the 52WH, generally finding volume increases and return continuation, there has been little direct investigation into the identification of who is trading at the 52WH. Studies have typically implied that individual selling behavior is responsible for the 52WH effect; however, this has not yet been clearly measured.

Individuals generally prefer to use limit orders for trading. For instance, Black (1986) suggests that uniformed traders place orders based on either an exogenous liquidity requirement or noise that is immaterial to the true fair value of an asset. Due to their lack of private information, individuals are generally considered uninformed investors. Indeed, Baker and Stein (2004) note that the information content of trades can be measured via an individual's willingness to supply liquidity, which households prefer to do.

Building on these findings, Kaniel et al. (2008) show that individuals prefer to place limit orders to earn a 'liquidity premium' from institutional investors seeking execution immediacy. This liquidity premium varies over time with market-wide uncertainty (Nagel, 2012). However, the literature does not appear to address individual order submission behavior being anchored to the 52WH. Several authors (Kelley and Tetlock, 2013; Linnainmaa, 2010) find that individuals tend to place latent, unsupervised limit orders; such orders are placed at prices at which investors plan to buy or sell a stock in the future. This latent price is of crucial importance, as it suggests that individuals could place latent limit orders at key anchors such as the 52WH. Kelley and Tetlock (2013) further recognize individual investors' tendency to use limit orders helps to supply liquidity and immediacy to institutional investors trading via market orders. In addition, Bhattacharya et al. (2012) note that individual investors use limit orders to anchor trades to milestone nominal prices and that individuals anchor to the left-most digit of a price, i.e., \$6.99 versus \$7.00. Sell limit orders are demonstrated to cluster around round numbers, suggesting that individuals anchor to salient price points with liquidity-providing orders.

In contrast, Bian et al. (2018) relate order aggressiveness to prior returns; retail investors on the Shanghai Stock Exchange are more aggressive in submitting sell orders for stocks that have experienced gains. However, a negative quadratic term indicates that investors are less aggressive in selling stocks that experienced strong rather than moderate gains. While this does not provide specific predictions for stocks at the 52WH, it does demonstrate that prior returns appear to influence individuals' order submission strategies.

2.2.3 Trade between individuals and institutions

Individual investors have been shown to generally underperform in their trades (Barber et al., 2008), less attention has been paid to the counter-parties of these trades. Among the exceptions, Stoffman (2014) analyzes the stock trades between 'groups', classified as household and institutional investors. When within-group trading occurred (e.g., households with households), despite it being quite common, there was little price effect. However, when institutions and individuals engage in trade, individuals tend to be on the losing side. For example, when individuals sell to institutions, prices tend to increase at short horizons. Consistent with this, Fong et al. (2014) find that orders submitted through discount broker channels (presumably, those of individuals) are less informative than those of full-service brokers. This effect is particularly pronounced for market orders vis-à-vis limit orders, implying that individuals are likely better off supplying, rather than demanding, liquidity.

2.3 Hypothesis development

In the literature, there appears to be little exploration of the role of investors in causing the observed 52WH effect and the costs associated with this behavior. Thus, by using a rich data set, this study is able to analyze household trading behavior (buying/selling and limit order usage) with institutions and the stock returns following the 52WH. The review of the literature (Section 2.2) gives rise to clear, testable hypotheses:

- **Hypothesis 1:** H1 - Individual investors exhibit strong anchoring to the 52WH price and strong selling behavior at and around the 52WH day.

- **Hypothesis 2:** H2 - Households will be more likely to use limit orders when selling at the 52WH.

- **Hypothesis 3:** H3 - Households anchor more to the 52WH when it is more salient and during uncertain periods, as shown by greater limit order usage.

- **Hypothesis 4:** H4 - Households will suffer as a result of this anchoring behavior in the form of post-event return continuation following the 52WH day.

2.4 Data and metrics

To explore how households trade around the 52WH, this study uses trades obtained directly from the Helsinki NASDAQ OMXH (OMXH). The data come from the Nordic Central Securities Depository (NCSD). This data set contains the official records of trades, including identifiers that designate trader group identity (domestic institutions, foreign institutions, households, and others). The data include the raw daily trades from 1 January 2004 to 31 December 2009 [8] on the OMXH. Filters are applied to include only the top 100 companies based on market capitalization from the end of the sample[9]. Additionally, the data are aggregated to the daily level by group, and trading is then split into either household or institutional trades (this includes foreign institutions, domestic institutions and other investors; see Table 2.1) to observe the interaction between investor classes, as performed by Stoffman (2014). Within-group trading is removed from the main sample, as it is not possible to extract trade direction or trade type from these observations. In addition to the trade data, we merge the price, volume, share characteristics, and European volatility index (VIX) price from Compustat for the sample period.

[8] The sample ends in 2009 as the NCSD no longer provides intra-day trading between institutions but rather aggregates the trades at day's end. Thus, we are no longer able to identify, with the same accuracy, the trade imbalance and taking rate between groups.

[9] Including only the top 100 stocks by market capitalization ensures that the sample is widely held by both institutional and household investors and is not illiquid or thinly traded.

2.4.1 Anomaly and investor behavior metrics

The 52WH ratio is the ratio of the current stock price to the maximum daily closing price over the previous year, as described in equation 2.1. We identify days on which the stock opens at the 52WH as follows. If the 52WH ratio at the current day's open is at or above 97%, then we consider the current day to be a 52WH day. This may capture days for which the stock does not breach the 52WH threshold, but this would be observable to an investor *ex ante*.

To estimate the impact of capital gains overhang (that is, whether investors have likely sold their prior winners), we calculate the *New 52WH*. To do so we categorize a New 52WH if the price has not been at or above the 52WH price in the prior 14 calendar days, following Huddart et al. (2009).[10]

Table 2.1: Allocation of investors to groups

The table shows the allocation of the investor groups to group 1 (households) and group 2 (institutions). The two groups are identified in the data and all trades within groups net to zero, all between groups trades are reported in the subsequent tables and figures.

Group 1: Households	Group 2: Institutions
Households	Foreign institutions
	Domestic institutions
	Trusts
	Others

To measure the rate of 'between-group' trading, we use a novel measure of trade imbalance. This measure reports the relative buying of stock i on day t by households

[10]Subsequent analysis using lags of 30 calendar days showed no significant difference relative to the 14-day lag.

against institutions. It is an extension of the order imbalance measure developed by Chordia et al. (2002) for buying and selling intensity.

$$TradeImbalanceHH_{i,t} = \sum_{i=1}^{n} \frac{VBuysHH_{i,t} - VSellsHH_{i,t}}{VBuysHH_{i,t} + VSellsHH_{i,t}}, \tag{2.2}$$

where $TradeImbalanceHH_{i,t}$ is the household's trade imbalance, and $VBuysHH_{i,t}$ is the volume of buys and $VSellsHH_{i,t}$ is the volume of sells in stock i on day t by households. Intuitively, this measure offers a ratio of the relative direction of trade in a given stock between households and institutions. The value of $TradeImbalanceHH$ is bounded between -1 and $+1$, where larger positive values indicate a greater share of buying by households relative to institutions. As this includes only between-group trading, we do not report the corresponding measure for institutions, which is the opposite-signed value.

Next, we construct measures of order aggressiveness. First, limit orders and market orders are identified using the Lee and Ready (1991) algorithm, based on order execution relative to the midpoint of the bid-ask spread.

We then utilize the Bloomfield et al. (2009) measure *TakingRateHH* to determine the relative amount of market orders to total orders by households. Specifically,

$$TakingRateHH_{i,t,d} = \frac{MarketOrderHH_{i,t,d}}{MarketOrdersHH_{i,t,d} + LimitOrdersHH_{i,t,d}}, \tag{2.3}$$

where $MarketOrdersHH_{i,t,d}$ is the volume of *executed* market orders and $Limit$ $OrdersHH_{i,t,d}$ is the volume of executed limit orders by households in stock i at time

t, and d indicates direction (either buying or selling). The measure $TakingRateHH$ takes values between 0 and 1, where 0 indicates that households traded only using limit orders. The complement of this metric $(1 - TakingRateHH)$ would indicate the the liquidity providing rate of households.

2.4.2 Additional controls

We follow Bian et al. (2018) and include risk and liquidity controls, as they may contribute to the variation in trade imbalance and taking rate. We calculate a stock-specific risk measure (Handa and Schwartz, 1996) as the lagged 20 trading day standard deviation of returns. Stock-specific risk should increase the bid-ask spread and, thus, increase adverse selection risks when using limit orders (Glosten and Milgrom, 1985).

$$Risk_{i,t} = \left(\left(\frac{1}{20-1}\right)\sum_{i=1}^{20}(R_{i,t} - \bar{R}_{i,t})\right)^{1/2}, \tag{2.4}$$

where $\bar{R}_{i,t}$ is the average of the daily return R_i on stock i for the 20 prior trading days. Thus, $Risk_{i,t}$ is the standard deviation of the daily return over the 20 days prior to day t.

The Amihud (2002) illiquidity measure is used as a control for the daily price impact of trades. We compute an average Amihud illiquidity measure, as the lagged 20-day average daily value,

$$Amihud_{i,t} = \sum_{i=1}^{20} \frac{|R_{i,t-1}|}{20 * DVOL_{i,t-1}}, \tag{2.5}$$

where $R_{i,t}$ is the return of stock i on day t, and $DVOL_{i,t-1}$ is the trading volume in euros on day $t - i$. A high Amihud measure is an indicator of low liquidity because it reflects the movements in a stock price for a given level of volume.

2.4.3 Comparison with the U.S.

The Finnish and U.S. equities markets are similar in their limit order structure. The investor trade data conforms to similar literature by Kumar and Lee (2006), including all trades rather than a sub sample, which is regularly used in investor behavior studies (Barber and Odean, 2000) and offers far stronger identification of market wide behavior. The findings of the present study reveal that the average daily household trading in percentage terms exceeds that of the US market, with households a participant in at least 30% of the total daily trading. This result suggests the observed effects may have stronger effects on the Finnish market relative to the U.S. The investors in our sample also exhibit disposition effect trading and anchor to their purchase price (Ben-David and Hirshleifer, 2012), among other factors. Thus the behavior of the Finnish investors is likely to reflect the behavior of U.S. and global investors.

2.5 Results

To observe the effect of the 52WH on investor behavior, it is necessary to first establish benchmarks for the investor behavior metrics across our sample. In Table 2.2 we see that on any given day, the rate of trade imbalance between groups is near zero, suggesting that households neither buy nor sell to institutions over the period. The taking rates for buys and sells are between 0.50 and 0.56. This shows that across the sample, households tend to use market orders when trading with institutions. Additionally, between-group trading accounts for approximately 1/3 of all volume across all size terciles; this is slightly higher than the rate found by Kumar and Lee (2006) in the U.S. market. Households also tend to trade small-cap stocks among themselves (57% of turnover), while institutions tend to trade large stocks among themselves (66% of turnover). This supports prior expectations that households are more active in smaller cap stocks.

Table 2.2: Descriptive statistics by size tercile

This table reports the descriptive statistics for the main investor behavior and stock characteristics. For each daily observation the mean, standard deviation, 25th percentile, median and 75th percentile of the sample sorted into terciles by market capitalization at the end of the sample are reported. Trade Imbalance HH is the daily balance of household trade with institutional investors (I.I). Taking rate sells is the ratio of household market order usage when selling to institutions. Between turnover HH is the ratio of household to institution trade relative to all volume. Within turnover I.I is the ratio of institution to institution trade relative to all volume. Within turnover HH is the ratio of household to household trade relative to all volume. Market capitalization is the price*shares outstanding/100 million. The sample period is from January 2004 to December 2009

Market capitalization	Variable	Mean	Std Dev	25th Pctl	Median	75th Pctl
Small	Trade imbalance ratio HH	-0.010	0.873	-1.000	0.000	1.000
	Taking rate sells HH	0.557	0.430	0.000	0.650	1.000
	Between turnover HH (%)	0.358	0.420	0.000	0.230	0.619
	Within turnover I.I (%)	0.075	0.415	0.000	0.000	0.203
	Within turnover HH (%)	0.567	0.450	0.125	0.558	1.000
	Market capitalization	3.546	2.617	1.713	2.938	4.806
Medium	Trade imbalance ratio HH	-0.049	0.781	-0.904	-0.097	0.791
	Taking rate sells HH	0.543	0.377	0.179	0.564	0.963
	Between turnover HH (%)	0.392	0.372	0.109	0.325	0.588
	Within turnover I.I (%)	0.284	0.463	0.000	0.260	0.645
	Within turnover HH (%)	0.324	0.372	0.033	0.168	0.513
	Market capitalization	18.154	9.590	11.132	15.886	23.242
Large	Trade imbalance ratio HH	-0.027	0.561	-0.442	-0.017	0.380
	Taking rate sells HH	0.524	0.265	0.361	0.524	0.689
	Between turnover HH (%)	0.272	0.849	0.091	0.188	0.357
	Within turnover I.I (%)	0.656	1.087	0.554	0.782	0.895
	Within turnover HH (%)	0.072	0.289	0.003	0.012	0.045
	Market capitalization	409.915	1081.570	64.908	128.403	254.745

2.5.1 The 52 week high ratio

Our first analysis is to determine the general effect of the 52WH price on trading behavior; to do so, we first sort stocks into deciles based on their 52WH ratio, ascending from furthest from to nearest to the 52WH. Table 2.3 and Figure 2.1 depict a clear monotonic decrease in the household trade imbalance ratio as stocks approach the 52WH. This decrease is indicative of higher rates of selling behavior both due to the 52WH ratio and at the 52WH price. The near 52WH decile is as much as 32% points lower than the far 52WH decile in trade. This supports the expectation in Grinblatt and Han (2005) that the likelihood that households will sell a stock increases as it begins to accumulate capital gains. In addition, the *near-9* portfolio shows a 10% increase in the trade imbalance ratio, which indicates that the 52WH price is as an anchor for individuals to sell, in excess of the disposition effect.

Table 2.3: Household behavior by nearness to the 52 week high price

Stocks are sorted by day into 52 week high deciles, then report the household between groups trading on a stock by stock basis. Panel a reports the mean daily rate over the sample period 2004-2009 for household trading based on the relevant 52WH decile. Panel b reports the difference between the near minus far decile and the near minus '9' for their respective HH trading. The p statistics are presented in parenthesis, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

	Trade imbalance HH		Taking rate sells HH	
52 week high rank	Mean	Std dev	Mean	Std dev
Panel a: household behavior by 52 week high rank				
1 (Far)	0.095	0.612	0.534	0.314
2	0.078	0.640	0.547	0.315
3	0.043	0.647	0.539	0.315
4	0.012	0.655	0.543	0.314
5	-0.007	0.648	0.544	0.314
6	-0.022	0.652	0.540	0.315
7	-0.035	0.656	0.535	0.318
8	-0.087	0.653	0.524	0.320
9	-0.130	0.652	0.515	0.320
10 (Near)	-0.231	0.628	0.505	0.309
	Mean		Mean	
Panel b: household Mean difference in behavior				
Near - Far	-0.327**		-0.030**	
	(0.001)		(0.001)	
Near - 9	-0.102**		-0.010**	
	(0.001)		(0.051)	

Next, we examine individual investors' sell taking rate, and we observe fairly flat usage of sell limit orders by 52WH decile. Between the 9th and near deciles, we observe a strong increase in household limit order selling. We find a statistically significant increase in limit order usage for both the $near - far$ deciles and the near less 9th deciles. This provides preliminary support for the hypothesis that households anchor their limit order selling to the 52WH price.

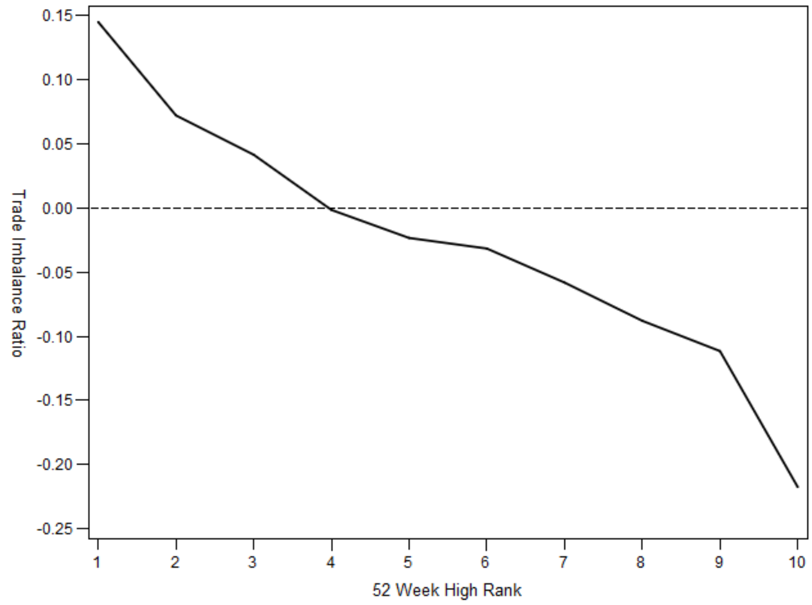


Figure 2.1: Household trade imbalance by 52 week high rank

The figure plots the household average daily trade imbalance ratio with institutions for the top 100 stocks sorted into deciles based on the stocks' current price/52 week high price. 52 week high rank is sorted from 1 (farthest from 52WH price) to 10 (nearest to the 52WH price)

The general effect of the 52WH ratio is that households tend to sell their stocks as they approach the 52WH, and this is consistent with the disposition effect (Shefrin and Statman, 1985) and accumulated capital gains effect (Grinblatt and Han, 2005). Second, this behavior is intensified at the near 52WH decile, which shows that households may anchor their selling behavior to the 52WH price in combination with increased limit order usage to sell down their positions.

2.5.2 The 52 week high day

Having observed that individual investors are sensitive to the general effect of the 52WH ratio, we explore investor behavior on the days during which the stock opens at or within 3% of the 52WH price; we consider this being at the 52WH price/the 52WH day. We also add additional specificity to the 52WH by introducing, similarly to Huddart et al. (2009), a new 52WH. We recognize a new 52WH if the stock has not breached the 52WH price in the 14 days prior to the current 52WH. This allows for a distinction between high-momentum stocks that are continually increasing in price and forming consecutive 52WH days and those that have established and just broken through a new 52WH. Finally, we introduce volatility to determine whether this increases the salience of an anchor as predicted by the literature (Tversky and Kahneman, 1974, 1992).

To explore investor behavior on the 52WH day, we undertake three sorts:

1. Average day vs. 52WH day

2. New 52WH day vs. Old 52WH day

3. Low VIX on the 52WH day vs. High VIX on the 52WH day

Table 2.4: Investor behavior on the 52 week high day

This table presents the results of the daily investor behavior metrics of trade Imbalance ratio , taking rate sells and taking rate buys between household and institutions. The sample covers the 2004 to 2009 period for the top 100 stocks on the NASDAQ OMXH. Panel a firstly sorts stocks by day if they are not at the 52WH and those that are at or within 3% of the 52WH price (at 52WH) at the day's open. We report the investor behavior mean and standard deviation (std dev) metrics and the mean difference. Panel b firstly identifies stocks by day if they are within 3% of the 52WH price and have been at the 52WH within the last 14 trading days (old 52WH) and those that are within 3% of the 52WH and the stock price has not surpassed the 52WH in the past 14 trading days (new 52WH).We report the investor behavior mean and std dev metrics and the mean difference. Panel c firstly sorts stock days into quartiles by the level of EuroVIX. We report the high and low VIX quartile and then identify stocks by day if they are within 3% of the 52WH price. We report the investor behavior mean and std dev metrics and the mean difference. The p values are presented in parenthesis, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

Panel a: average day vs. 52 week high day					
	Average day		52WH day		52WH day - Average day
	Mean	Std dev	Mean	Std dev	
Trade imbalance ratio HH	-0.007	0.738	-0.175	0.685	-0.168**
					(0.001)
Taking rate sells HH	0.543	0.351	0.505	0.327	-0.038**
					(0.001)
Panel b: old Vs new 52 week high					
	Old 52WH Day		New 52WH Day		New - Old 52WH
	Mean	Std dev	Mean	Std dev	
Trade imbalance ratio HH	-0.166	0.687	-0.363	0.623	-0.197**
					(0.001)
Taking rate sells HH	0.507	0.328	0.460	0.302	-0.047**
					(0.001)
Panel c: low vs. high VIX on the 52 week high day					
	Low VIX on 52WH day		High VIX on 52WH day		High - Low VIX
	Mean	Std dev	Mean	Std dev	
Trade imbalance ratio HH	-0.18	0.638	-0.301	0.639	-0.121**
					(0.001)
Taking rate sells HH	0.50	0.297	0.523	0.337	0.023**
					(0.001)

We first report the general effect of the 52WH day, the results of which are presented in Table 2.4, Panel a. The trade imbalance on the 52WH day is, on average, -0.175; this means households are selling 17 percentage points more than they are buying. Households tend to use significantly more limit orders at the 52WH (54% vs. 50% otherwise). This, in combination with the trade imbalance finding, strongly supports the hypothesis that individuals intensify their selling at the 52WH and do so with anchoring-style limit orders.

Having established the general role of the 52WH price on household behavior, we next test the relative effect of the new 52WH against the old 52WH in Table 2.4, Panel b. In support of our hypothesis, we see sharp increases in the household trade imbalance ratio at the new 52WH (-0.363), which is 20% points lower than at the old 52WH. Limit order usage strengthens at the new 52WH: we observe that the sell taking rate significantly drops from the old 52WH rate of 0.50 to the new 52WH rate of 0.46. This finding supports the role of the 52WH as an anchor around which individual investors place latent limit orders in expectation of a 52WH approach or breakthrough (Linnainmaa, 2010). The relative increase in limit orders at the new 52WH suggests that individuals require time to build up their limit order books in advance of the 52WH price (Kaniel et al., 2008).

In Panel c, we introduce market-wide volatility to determine whether the 52WH price as an anchor is strengthened by volatility/uncertainty. We compare stocks at the 52WH in a low-volatility market to those in a high-volatility market. To do so, we sort stocks into quartile portfolios based on the lagged 20 day EuroVIX index price and then sort the stocks that are at the 52WH price. Further supporting our hypothesis, high uncertainty results in enhanced household selling behavior (12 % points) by households. We observe lower usage of limit orders to sell when volatility is high, suggesting that households are less likely to provide liquidity when it is more costly due to either increased spreads or adverse selection costs. Glosten and Milgrom (1985) show that as uncertainty increases, relative spreads and adverse selection risks increase. As such, this finding suggests that individuals are both sensitive to the 52WH as an anchor and sensitive to the adverse selection risks associated with the higher volatility.

2.5.3 Further specifications

To offer further support for our hypotheses, we conduct a series of four OLS regressions for household trade imbalance on the dummy variables for $52WHMax_{i,t}$ and $New52WHMax_{i,t}$ with interactions and control variables for size, price, market volatility, liquidity and risk.

$$\begin{aligned} TradeImbalanceHH_{i,t} = b_0 + b_1 52WHMax_{i,t} + b_2 New52WHMax_{i,t} \\ + b_3 52WHRatio_{i,t} + Interactions + Controls + \epsilon_{i,t} \end{aligned} \tag{2.6}$$

where $TradeImbalanceHH_{i,t}$ is the ratio of household net buying in stock i at time t when trading with institutions. $52WHMax_{i,t}$ is an indicator variable that takes the value of one if the stock i is at the 52WH on day t, zero otherwise. $New52WHMax_{i,t}$ is an indicator variable that takes the value of one if the stock i is at the New 52WH on day t, zero otherwise. $52WHRatio_{i,t}$ is the ratio of the price of stock i at time t to the stock's 52WH price. $TakingRateSellsHH_{i,t}$ is the ratio of sell market orders by households to that of institutions in stock i price at time t. $TakingRateSellsHHlow_{i,t}$ is an indicator variable that takes value one if the household taking rate of stock i at time t is in the lowest quartile, zero otherwise. The interaction variable is equal to one if the stock is both at the 52 week high and is in the highest quartile of limit order selling for the day. The controls include $MktCap_{i,t}$, which is the log market capitalization of stock i at time t; VIX, which is the average EuroVIX for the days $t-20$ to t; $Price$ is the log price of stock i at time t; and the $AmihudMeasure$ and $Risk$ are as defined in equation 2.5 and equation 2.4, respectively.

The results of the above regressions are presented in table 2.5. In model I, we first examine the effect of the 52WH max price and, as expected, observe a strong negative coefficient (-0.158), which is indicative of anchoring at the 52WH. The marginal effect of the new 52WH is a very large increase in household selling, as predicted, and net selling increases by -0.239%; thus, salience increases the strength of the anchor. When controlling for the 52WH ratio, we see that the 52WH ratio has a negative relationship with the trade imbalance and represents an independent source of increased selling by households, most likely proxying for the disposition effect.

Table 2.5: Regression of household trade imbalance on the 52 week high day

This table presents results from the OLS regression 2.6, with trade imbalance ratio as the dependent variable. The 52WH max is an indicator variable with a value of one, if the stock i price opens within 3% of the 52WH price, zero otherwise. The new 52WH max is an indicator variable with a value of 1, if stock i price opens within 3% of the 52WH price and has not been at the 52WH in the 14 calendar days prior, zero otherwise. The $52WHratio$ is the ratio of stock i price at time t relative to the 52WH price. Taking rate sells is the rate of market order usage by households to sell stock i at time t. $Takingratesellslow$ * $52WHmax$ is in indicator variable that has a value of one, if the taking rate sells in stock i are in the lowest quartile on day t and the stock is at the 52WH, zero otherwise. $MktCap$ is the log market capitalization of stock i at time t. VIX is the average value for the EuroVIX index for the prior 20 trading days. The Amihud measure is the lag 20 day average value of the Amihud (2002) measure for stock i. Risk is the lag 20 day average standard deviation of returns in stock i. The t statistics are reported in brackets below the coefficients , ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

	Dep var: household trade imbalance ratio			
	I	II	III	IV
Intercept	-0.052	-0.052	0.154***	-1.411***
	(-1.56)	(-1.57)	(4.52)	(-43.96)
52WH max	-0.158***	-0.148***	-0.092***	-0.167***
	(-25.00)	(-23.04)	(-13.49)	(-25.55)
New 52WH max		-0.239***		
		(-8.50)		
52 week high ratio			-0.296***	
			(-25.67)	
Taking rate sells				-0.005
				(-0.65)
Taking rate sells low * 52 WH max				-0.087***
				(-6.72)
MktCap	-0.006***	-0.006***	-0.004**	0.058***
	(-3.36)	(-3.35)	(-2.19)	(34.23)
VIX	0.005***	0.005***	0.003***	0.006***
	(27.35)	(27.40)	(15.96)	(31.01)
Price	0.026***	0.026***	0.028***	0.005**
	(10.27)	(10.19)	(11.08)	(2.13)
Amihud measure	-0.656***	-0.656***	-0.537***	-3.211***
	(-3.19)	(-3.19)	(-2.62)	(-14.30)
Risk	0.001	0.001	0.001	0.001**
	(1.42)	(1.49)	(1.47)	(2.02)
Obs	88,686	88,686	88,686	88,686
R-Sq	0.0190	0.0198	0.0262	0.0445

Finally, we introduce the interaction variable $RakingRateSellsHH$ $Low_{i,t}$* $52WHmax$. This coefficient indicates that when households use limit orders at the top quartile for the 52WH, it strongly drives a negative trade imbalance. Thus, latent limit order usage is in part responsible for the strong selling behavior that we observe at the 52WH (Linnainmaa, 2010). We find consistent negative coefficients around our 52WH-based variables. The 52WH ratio provides a strong proxy for disposition effect behavior. However, the 52WH max price and the new 52WH exhibit much larger negative coefficients, which reveal the marginal effect of being at the 52WH and it being very salient, respectively. These results are robust to risk and liquidity measures, which suggests that the observed selling behavior is driven by behavioral measures.

To provide further support for our hypothesis that individuals anchor to the 52WH with limit orders, we use the following series of OLS regressions on the dummy variables for the 52WH and the new 52WH with interactions, liquidity and risk controls.

$$\begin{aligned} TakingRateSellsHH_{i,t} = b_0 &+ b_1 52WHMax_{i,t} + b_2 New52WHMax_{i,t} \\ &+ b_3 52WHRatio_{i,t} + Interactions + Controls \\ &+ \epsilon_{i,t} \end{aligned} \tag{2.7}$$

where $TakingRate_{i,t}$ is the ratio of executed sell market orders to total sells for stock i at time t that are executed against institutional investors. Other interaction and control variables are as defined in regression 2.7.

The results for regression 2.7 are presented in Table 2.6. We follow a similar protocol to observe the effect of the 52WH, the new 52WH and the 52WH ratio on household order submission strategy. We first find that the 52WH price causes increased limit order usage by households. We observe an additional effect of the new 52WH, which has a coefficient of -0.047 and indicates that households use approximately 4.5 percentage points more limit orders to sell stocks when the anchor becomes more salient, at the new 52WH. We then report the effect of the 52WH ratio, which is non-significant and does not reduce the effect of the 52WH, thus suggesting that the use of limit orders is more closely related to anchoring at the 52WH rather than to a need to sell down accumulated capital gains. Finally, we introduce the interaction of days when the VIX is in the highest quartile and at the 52WH max price. This causes a small but significant increase in market order usage, thus furthering our previous observation that uncertainty reduces limit order usage generally, most likely due to the adverse selection costs that households have to bear with limit orders. Our controls are consistent across all models, and we find that households use limit orders more in small stocks, a higher price results in more market orders (i.e., as a result of the decline in the relative tick size), and risk increases market order usage, as expected.

Overall, the regressions continue to support our hypotheses. First, households are sensitive to the 52WH as a sell signal, and they sell using limit orders. This selling behavior is also intensified under uncertainty and when the anchor is more salient. Thus, we continue to obtain direct support for the notion that the selling behavior is as a result of latent limit orders placed at the 52WH (Bhattacharya et al., 2012; Kelley and Tetlock, 2013; Linnainmaa, 2010).

Table 2.6: Regression of household limit order selling on the 52 week high day

This table presents results from the OLS regression 2.7, with taking rate sells as the dependent variable. The 52WH max is an indicator variable with a value of one, if the stock i price opens within 3% of the 52WH price, zero otherwise. The new 52WH max is an indicator variable with a value of 1, if stock i price opens within 3% of the 52WH price and has not been at the 52WH in the 14 calendar days prior, zero otherwise. The $52WHratio$ is the ratio of stock i price at time t relative to the 52WH price. $HighVIX$ * $52WHmax$ is an indicator variable that has a value of one, if the EuroVix index value is in the highest quartile, over the past year, on day t and the stock is at the 52WH, zero otherwise. $MktCap$ is the log market capitalization of stock i at time t. $VIX[t-20,t]$ is the average value for the EuroVIX index for the prior 20 trading days. $Price$ is the log price of stock i at time t. $AMIHUD$ is the lag 20 day average value of the Amihud (2002) measure for stock i. Risk is the lag 20 day average standard deviation of returns in stock i. The t statistics are reported in brackets below the coefficients , ***, **, *, indicate significance at the 1%, 5% and the 10% level, respectively.

	Dep var: household taking rate sells			
	I	II	III	IV
Intercept	0.634***	0.634***	0.630***	0.635***
	(37.75)	(37.76)	(36.43)	(37.81)
52WH max	-0.036***	-0.034***	-0.037***	-0.066***
	(-11.53)	(-10.69)	(-11.04)	(-7.24)
New 52WH max		-0.047***		
		(-3.44)		
52 week high ratio			0.006	
			(1.03)	
High VIX *52 WH max				0.002***
				(3.53)
MktCap	-0.004***	-0.004***	-0.004***	-0.004***
	(-4.55)	(-4.55)	(-4.59)	(-4.56)
VIX	-0.001***	-0.001***	-0.001***	-0.002***
	(-15.17)	(-15.15)	(-13.69)	(-15.53)
Price	0.007***	0.007***	0.007***	0.007***
	(5.30)	(5.27)	(5.28)	(5.44)
Amihud measure	0.176	0.176	0.174	0.176
	(1.47)	(1.48)	(1.46)	(1.47)
Risk	0.001**	0.001**	0.001**	0.001**
	(2.24)	(2.28)	(2.24)	(2.25)
Obs	80,283	80,283	80,283	80,283
R-Sq	0.0044	0.0046	0.0044	0.0046

2.5.4 Event analysis: around the 52 week high day

Having identified the importance of the 52WH day, we next explore stock and investor behavior before and after the high. This is done, first, to ensure that the 52WH day itself is the novel event rather than just the approximate time period when the price is high, and second, to investigate the behavior of investors prior to and following the high. Because the 52WH may be relatively predictable as the price rises in the days prior, we expect that investors may begin acting in preparation for the high. Additionally, following the 52WH, investors may respond or adjust their behavior after redeeming their gains on the event date. To undertake the analysis, we employ event study methodology (MacKinlay, 1997) with an event time frame of t_{-5} to t_{+5} trading days around the 52WH price being reached. To extend the previous findings, the trade imbalance ratio and the taking rate are of key importance. Additionally, we include the abnormal return (AR) and cumulative abnormal return (CAR) for the event windows to determine the economic cost of anchoring to the 52WH for households in the short run.

$$AR_{i,t} = R_{i,t} - R_{m,t} \tag{2.8}$$

where $AR_{i,t}$ refers to the AR on stock i at time t, $R_{i,t}$ is the daily return on stock i at time t, and $R_{m,t}$ is the daily return on the OMXH market at time t. $AR_{i,t}$ allows us to determine the return on the stock in excess of the market return.

$$CAR_{i,t} = \sum_{t=1}^{n} AR_{i,t} \tag{2.9}$$

$CAR_{i,t}$ refers to the CAR for stock i from time t to time n. To determine the importance of the event window, we need to aggregate the abnormal returns to draw any conclusions regarding the event of interest. The reported $CAR_{i,t}$ is the equally weighted aggregated AR by stock surrounding the 52WH day event.

Figure 2.2 and Table 2.7 depict both the AR and investor behavior pattern around the new and old 52WH. We first observe the increased selling behavior that is typical of stocks with a high 52WH ratio. In addition, we find that selling peaks at the 52WH day, ranging from approximately -15% to as low as -35% for stocks at the new 52WH, after which selling returns to pre-event levels. We observe a very similar pattern of household limit order selling, whereby limit order selling peaks at the 52WH day and reverts to baseline levels thereafter. This analysis addresses the potential counter-factual that the 52WH is itself just a state of high prices, as we show that household selling and sell limit orders peak at the 52WH day and recede thereafter.

To test the hypothesis that individuals suffer as a result of this anchoring behavior, we identify the AR and calculate the CAR for the pre and post-event periods. We find that the AR rises leading up to the event as is required to meet the 52WH price; this suggests that the stocks reaching the 52WH are doing so in excess of potential market-led rallies. We find that stocks are experiencing significant CAR in the pre-event period at the old and new 52WH of 5.91% and 3.27%, respectively. As expected, individuals are selling down these stocks as the price approaches the 52WH. We observe a significant AR at the event date and CAR over the 5-day forward period for the old 52WH, suggesting that households are missing out on significant post-event-period returns, of as much as 5.5%. This is not the case for the new 52WH, which does not exhibit return continuation on the event day or in the post-event return but rather return reversion. Thus, this finding shows that in the short term, individual investors are in fact not losing out when selling at the new 52WH but only when they sell at the old 52WH.

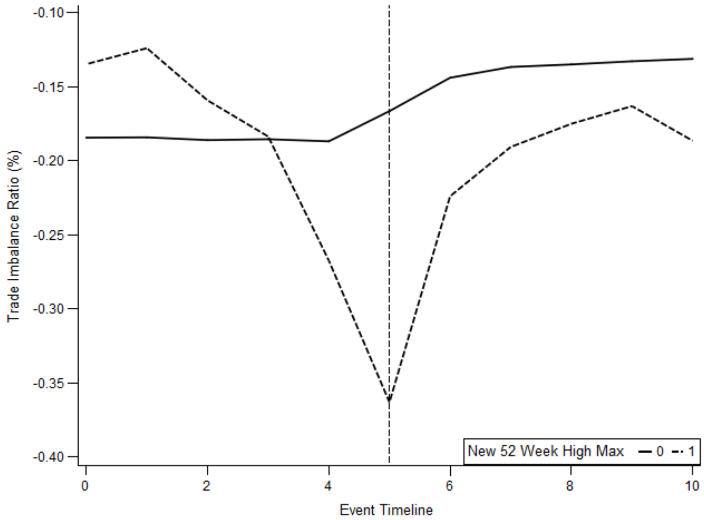
Our hypothesis that households are anchoring to the 52WH, with limit orders, and suffer as a result is clearly supported by the findings. We see that there is a general effect of the 52WH ratio that leads to disposition-effect-style selling. In addition, we find that sell limit orders executed immediately prior to and on the 52WH day cause significant decreases in the trade imbalance ratio. This causes the AR to be relatively weak on the 52WH day. The implication is that investors miss out on significant short-term post-event abnormal returns, which supports the finding of Barber et al. (2008) that prices move against household trading. Individuals, however, do not face lost AR when reacting to the new 52 WH, which is a novel finding. The existence of a new 52WH is much more rare than that of an old 52WH, which suggests that despite this finding, households are, on average, losing out on economic returns.

Table 2.7: Abnormal stock returns and investor behavior at the new and old 52 week high.

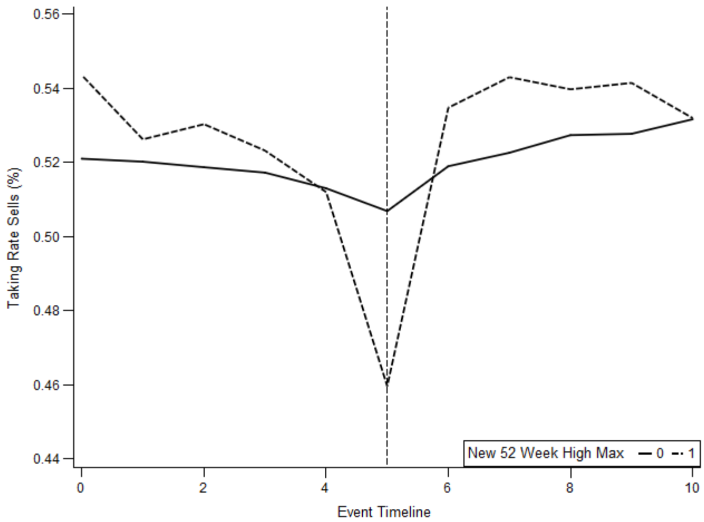
This table reports the statistics for the event study $t_{-5} to t_{+5}$ days around the 52 week high day event. Panel a presents the 5 day lead and lag abnormal return (stock return less market return), household trade imbalance and the taking rate sells of the respective stocks sorted based on whether they are at the new or old 52WH at time T. Panel b reports the cumulative lead and lag abnormal return of stocks at the new and old 52WH as well as the 5 day pre, during and 5 day post event window. The p statistics are presented in parenthesis, ***, **, *, indicate significance at the 1%, 5%, and the 10% levels, respectively.

Panel a: pre- and post 52 week high						
Time	Abnormal returns (%)		Trade imbalance ratio HH		Taking rate sells HH	
	Old 52WH	New 52WH	Old52WH	New 52WH	Old 52WH	New 52WH
t_{-5}	0.987	0.220	-0.184	-0.135	0.521	0.544
t_{-4}	1.025	0.201	-0.184	-0.124	0.520	0.526
t_{-3}	1.228	0.207	-0.186	-0.159	0.519	0.530
t_{-2}	1.280	0.603	-0.185	-0.184	0.517	0.523
t_{-1}	1.341	2.048	-0.187	-0.267	0.513	0.512
t_0	**0.582**	**0.031**	**-0.166**	**-0.363**	**0.507**	**0.460**
t_{+1}	0.650	-0.045	-0.144	-0.224	0.519	0.535
t_{+2}	0.650	0.067	-0.137	-0.191	0.523	0.543
t_{+3}	0.006	-0.135	-0.135	-0.175	0.527	0.540
t_{+4}	0.641	-0.066	-0.133	-0.163	0.528	0.541
t_{+5}	0.645	-0.032	-0.131	-0.186	0.532	0.532

Panel b: cumulative lead and lag abnormal returns			
	Old 52WH	New 52WH	New - Old
CAR pre event window	5.917	3.277	-2.639
			(0.52)
52WH day AR	0.582	-0.031	0.613
			(0.15)
CAR post event window	1.940	-0.275	-2.215*
			(0.07)
Pre - post event CAR	3.976***	3.552***	
	(0.001)	(0.001)	



(a) Trade imbalance ratio



(b) Taking rate sells

Figure 2.2: Investor behavior around new and old 52 week high

The plots identify stocks by day if they are within 3% of the 52WH price and have been at the 52WH within the last 14 trading days (Old 52WH) and those that are within 3% of the 52WH and the stock price has not surpassed the 52WH in the past 14 trading days (New 52WH). Panel a plots the daily average abnormal return for all stocks from the t_{-5} to t_{+5} centering at the 52 week high. Panel B plots the daily average household trade imbalance with institutions for the same period.

We next continue the analysis of post-52WH abnormal returns during the $t+5$ event day window using the following OLS regression specifications.

$$
\begin{aligned}
CAR_{i,t,n} = b_{0,} &+ b_1 52WHmax_{i,t} + b_2 New52WHmax_{i,t} \\
&+ b_3 52WHratio_{i,t} + Investorbehavior + Interactions \\
&+ Controls + \epsilon_{i,t}
\end{aligned}
\tag{2.10}
$$

h hg

$CAR_{i,n,t}$ is the CAR from time t to time n, which is equal to $t+5$, for stock i. The cumulative trade imbalance is the sum of the trade imbalance divided by shares outstanding of stock i over the specified period.

$TradeImbalanceRatioLow_{i,t}$ is an indicator variable that takes the value of one if the stocks are currently in the lowest quartile of daily trade imbalance, zero otherwise. All other interactions and controls are as defined above.

The results of regression 2.10 are presented in Table 2.8. We find that the effect of the 52WH price results in clear post-event alpha. Furthermore, the new 52WH coefficient is not significant, and thus does not lead to any additional returns when controlling for the 52WH. We obtain a similar non-significant coefficient for the 52WH ratio. Thus, the 52WH max price is the sole cause of the post-event 5-day abnormal returns.

We now introduce investor behavior in the form of cumulative trade imbalance [11] and find that much of the positive returns following the 52WH are driven by household selling, but this is not the case prior to the 52WH. This supports the expectation offered

[11] Cumulative trade imbalance is the sum of the household buys - household sells over the given period.

by Kelley and Tetlock (2013) that prices move against household trading. We next observe the effect of sell limit orders on 5-day-lead abnormal returns and, interestingly, find that the taking rate for sells is inversely related to future returns, that is, sell limit orders drive positive returns, while the interaction variable $TakingRateSellsLow * 52WHMax$ shows that very high limit order usage at the 52WH is very strongly related to post-event drift, to the extent that the 52WH Max is no longer significant. This suggests that the underlying cause of the observed 52WH and post-event returns is in large part due to household limit orders: when we control for them, the 52WH effect disappears. This implication may very well explain the underlying cause of the 52WH post-event returns being household limit order selling allowing for the liquidity for post-event drift. Having observed the short-term effect of this anchoring behavior, a longer term exploration of AR drift is required to determine the full economic effect of this behavior on household returns and the role of sell limit orders in causing the longer term 52WH drift (Bhootra and Hur, 2013; George and Hwang, 2004).

Table 2.8: 5 day lead cumulative abnormal returns following the 52 week high

This table presents results from the OLS regression 2.10, with 5 day lead cumulative abnormal returns as the dependent variable. The 52WH max is an indicator variable with a value of one, if the stock i price opens within 3% of the 52WH price, zero otherwise. The New 52WH max is an indicator variable with a value of 1, if stock i price opens within 3% of the 52WH price and has not been at the 52WH in the 14 calendar days prior, zero otherwise. The $52WHratio$ is the ratio of stock i price at time t relative to the 52WH price. $Tradeimbalance$ is the ratio of household buying behavior as a percentage of total household trading in stock i at time t as a percentage of shares outstanding. *cumtradeimbalance* is the cumulative household trade imbalance in stock i as a percentage of shares outstanding for the 5 days prior. $Takingratesells$ is the rate of market order usage by households to sell stock i at time t. $Takingratesellslow$ * $52WHmax$ is in indicator variable that has a value of one, if the taking rate sells in stock i are in the lowest quartile on day t and the stock is at the 52WH, zero otherwise. $MktCap$ is the log Market capitalization of stock i at time t. VIX is the average value for the EuroVIX index for the prior 20 trading days. The t statistics are reported in brackets below the coefficients, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

	Dep var: 5 day lead cumulative abnormal return				
	I	II	III	IV	V
Intercept	0.190***	0.190***	0.188***	0.161***	0.199***
	(7.18)	(7.18)	(6.85)	(6.53)	(6.31)
52WH max	0.018***	0.019***	0.017***	0.011**	-0.001
	(3.16)	(3.28)	(2.78)	(2.08)	(-0.17)
New 52WH max		-0.025			
		(-0.95)			
52 week high ratio			0.004		
			(0.37)		
5 day lag cum trade imbalance				0.002	
				(0.72)	
Trade imbalance				0.007	
				(0.93)	
5 day lead cum trade imbalance				-0.014***	
				(-5.82)	
Taking rate sells					-0.021**
					(-2.05)
Taking rate sells low					-0.015*
					(-1.78)
Taking rate sells low * 52 WH max					0.058***
					(4.45)
MktCap	-0.009***	-0.009***	-0.009***	-0.008***	-0.009***
	(-7.10)	(-7.11)	(-7.11)	(-6.47)	(-6.36)
VIX	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.11)	(-1.11)	(-0.89)	(-0.82)	(-1.00)
Obs	92,093	92,093	92,093	92,093	92,093
R-Sq	0.006	0.006	0.006	0.009	0.009

2.5.5 Drift

Birru (2015) finds that the 52WH acts as a psychological barrier for investors. The result is expectational errors [12] and under-reaction to news at the 52WH. Therefore, for our hypothesis to hold, post-event drift should occur following the 52WH; this will reflect the cost to households in lost returns as a result of anchoring to the 52WH. We have identified the cost at the 5-day-lead period, and we next need to determine the cost of the 52WH anchor to individuals in the form of longer term post-52WH drift. To measure post-event drift, we follow the method of Garfinkel and Sokobin (2006). Following each 52WH event, we sum the firm's AR over a 30- and 60-calendar-day window. We use the 30- and 60-day CAR as the dependent variable in OLS regressions to explore the effect of the 52WH ratio, the 52WH price and the new 52WH on future returns. We include additional interactions at the 52WH and controls for investor behavior, firm size and market volatility.

To test the hypothesis that households suffer from return continuation as a result of anchoring to the 52WH, we use the following OLS regression specification:

$$\begin{aligned} CAR_{i,t,n} &= b_{0,} + b_1 52WHmax_{i,t} + b_2 New52WHmax_{i,t} \\ &\quad + b_3 52WHratio_{i,t} + Investorbehavior + Interactions \\ &\quad + Controls + \epsilon_{i,t} \end{aligned} \tag{2.11}$$

where $Car_{i,t,n}$ is the CAR for stock i over the forward period from t to n. Table 2.10 presents the results from regressions for the 30 and 60 days following the 52WH day.

Consistent with the expectations from prior literature (George and Hwang, 2004),

[12] Expectational errors are the difference between the expectation and actual event; Birru (2015) suggests that investors' expectational errors regarding future returns are particularly high at the 52WH.

we find that the 52WH max price and the 52WH ratio are strongly associated with positive future abnormal returns. The effect of the new 52WH on AR is not present for the 30-day window, but the coefficient becomes negative and significant for the 60-day window. However, it is not large enough to distort the 52WH drift, and it is relatively infrequent; thus, it would not result in any large changes in economic terms.

We introduce cumulative trade imbalance and obtain negative and significant coefficients for the period t_{+1} to t_{+5}. This supports our hypothesis that household investor behavior is costly, to the extent that prices move against it, and influences post-trade movements. This finding supports the prediction of Birru (2015) that households suffer as a result of their expectational errors at the 52WH.

Finally, in Model V and Model X, we find that high limit order usage by households is strongly related to post-event drift for both the 30- and 60-day windows. Similarly to the 5-day CAR, when we include the indicator variable $Takingratesells- \, low * 52WH$, which indicates the highest quartile for limit order usage at the 52WH, we observe strong and positive post-event returns, for both the 30-day and 60-day windows. The addition of this interaction causes the 52WH max price to no longer predict future returns. This finding suggests that the underlying cause of the 52WH anomaly (George and Hwang, 2004) is a result of household limit order selling at the 52WH.

Our findings are robust to our controls. We find that post event returns are strongly related to market capitalization; that is, small firms experience larger positive post-event drift, while market-wide VIX is also significantly related to negative returns. Of key interest is the role of the new 52WH; the results show that it is negatively related to post-event drift, which suggests that these stocks experience less post-event drift. Overall, the new 52WH lessens the extent of the post-event drift. Nevertheless, individuals still suffer as a result of their anchoring behavior over longer periods. Overall, these results explain the large post-event drift found by George and Hwang (2004) as naively being a result of the 52WH; however, upon further investigation, the rationale offered by Kahneman (1992); Kelley and Tetlock (2013); Shefrin and Statman (1985), namely the disposition effect, anchoring and unsupervised limit orders, is clarified: it is in fact households selling, for non-informational reasons, and providing liquidity that allows prices to continue to rise following the 52WH.

Table 2.10: 30 and 60 day lead cumulative abnormal returns following the 52 week high

This table presents results from the OLS regression 2.10, with 5 day lead cumulative abnormal returns as the dependent variable. The 52WH max is an indicator variable with a value of one, if the stock i price opens within 3% of the 52WH price, zero otherwise. The new 52WH max is an indicator variable with a value of 1, if stock i price opens within 3% of the 52WH price and has not been at the 52WH in the 14 calendar days prior, zero otherwise. The $52WHratio$ is the ratio of stock i price at time t relative to the 52WH price. $Tradeimbalance$ is the ratio of household buying behavior as a percentage of total household trading in stock i at time t as a percentage of shares outstanding. $Cumtradeimbalance$ is the cumulative household trade imbalance in stock i as a percentage of shares outstanding for the 5 days prior. $Takingratesells$ is the rate of market order usage by households to sell stock i at time t. $Takingratesellslow$ * $52WHmax$ is in indicator variable that has a value of one, if the taking rate sells in stock i are in the lowest quartile on day t and the stock is at the 52WH, zero otherwise. $MktCap$ is the log market capitalization of stock i at time t. VIX is the average value for the EuroVIX index for the prior 20 trading days. The t statistics are reported in brackets below the coefficients , ***, **, *, indicate significance at the 1%, 5%, and the 10% levels, respectively.

Table 2.10: Continued

	Dep var: 30 day lead CAR					Dep var: 60 day lead CAR				
	I	II	III	IV	V	VI	VII	VIII	IX	X
Intercept	0.924***	0.924***	0.892***	0.957***	1.055***	1.879***	1.880***	1.814***	1.560***	1.712***
	(15.75)	(15.75)	(14.71)	(15.68)	(14.52)	(22.39)	(22.40)	(20.91)	(20.14)	(18.62)
52WH max	0.068***	0.071***	0.057***	0.062***	-0.001	0.158***	0.165***	0.136***	0.122***	-0.005
	(5.34)	(5.50)	(4.16)	(4.77)	(-0.04)	(8.70)	(8.93)	(6.92)	(7.42)	(-0.30)
New 52WH max		-0.079					-0.170**			
		(-1.37)					(-2.07)			
52 week high ratio			0.048**					0.098***		
			(2.05)					(2.94)		
5 day lag cum trade imbalance				0.004					0.001	
				(0.63)					(0.13)	
Trade imbalance				0.010					0.007	
				(0.50)					(0.28)	
Cumulative trade imbalance				-0.013**					-0.014*	
				(-2.09)					(-1.82)	
Taking rate sells					-0.120***					-0.185***
					(-5.18)					(-6.30)
Taking rate sells low					-0.064***					-0.116***
					(-3.36)					(-4.84)
Taking rate sells low * 52 WH max					0.257***					0.489***
					(8.56)					(12.84)
MktCap	-0.045***	-0.045***	-0.045***	-0.046***	-0.047***	-0.092***	-0.092***	-0.092***	-0.076***	-0.077***
	(-15.57)	(-15.58)	(-15.69)	(-15.51)	(-14.56)	(-22.31)	(-22.32)	(-22.47)	(-20.16)	(-18.87)
VIX	-0.001**	-0.001**	-0.000	-0.001**	-0.001**	-0.001**	-0.001**	-0.000	-0.001	-0.001
	(-2.07)	(-2.06)	(-1.13)	(-2.22)	(-2.18)	(-2.03)	(-2.02)	(-0.76)	(-1.28)	(-1.54)
Obs	92,737	92,737	92,737	92,737	92,737	92,737	92,737	92,737	92,737	92,737
R-Square	0.0028	0.0028	0.0028	0.0029	0.0044	0.0058	0.0059	0.0059	0.0050	0.0078

The R^2 values for the models are low, between 0.28% and 0.77%. There are several potential reasons for this. First, we are explaining market-adjusted abnormal returns in a cross-sectional regression. Second, we are explaining individual stock rather than portfolio returns, as is done in Fama and French (1992) style regressions; in the context of this study, portfolios would be inappropriate. Finally, these R^2 values are comparable to those found in previous studies of post-event drift on stock returns (Garfinkel and Sokobin, 2006).

2.6 Conclusion

This study exploits a rich data set from the NCSD to examine how individual investors anchor to the 52WH price, their trade direction, their order submission type and the subsequent cost of this anchoring behavior. The findings are consistent with the literature on the 52WH, anchoring, and the disposition effect.

This study finds that individual investors undertake disposition style investing – selling winners and anchoring behavior around the 52WH price. They do so with latent limit order selling, which is intensified if the 52WH becomes more salient, either due to newness or volatility. This chapter demonstrates through an event study that the 52WH day is in fact the unique point of interest, with investor behavior prior to and following the day occurring as otherwise as expected. This anchoring behavior is not costless: there is strong post-event return continuation at the 5-, 30-, and 60-day time horizons, consistent with momentum-style returns. This behavior directly benefits institutional investors, which are the counter-parties to the observed trades, through this bias, households provide liquidity for institutions to open up momentum positions and generate post-52WH event returns.

Finally, this study contributes to the literature by showing that the underlying cause of the 52WH post-event drift may be that households limit order sells placed at the 52 week high. When controlling for the 52WH, it is clear that it no longer explains future returns; rather, it is the limit order selling by households that provides the liquidity to drive future positive returns. Overall, this evidence contributes to the growing literature on the 52WH, the poor performance of individual investors, and how their behavior affects returns. This study has many implications for future research regarding the role of individual investors as liquidity providers, particularly around anchors and attention-grabbing events.

Chapter 3

Liquidity and Price Impact at the 52 Week High

3.1 Introduction

The previous chapter explored the relationship between return continuation at the 52 week high (52WH) and the use of limit orders by households, revealing that when the stock hits the 52WH in conjunction with high levels of household limit order selling, subsequent positive abnormal returns are realized. However, positive abnormal returns are not realized at the 52WH when low levels of household limit order selling are observed. Thus, it is arguable that the 52WH effect is driven by household liquidity provision.

A currently unexplored area is how the 52WH affects stock-level liquidity, and its corresponding relation with informational efficiency. Linnainmaa (2010) and Kelley and Tetlock (2013) find that liquidity buildup/limit orders can create market distortions. These market distortions are more likely to occur as the 52WH represents a salient price and visible anchor of interest to (particularly uninformed) investors. Birru (2015) suggests the 52WH is a barrier for information integration, and this chapter argues that this barrier is driven by non-informational selling through the channel of household limit orders. The clustering in liquidity should result in a decrease in informational efficiency and help to explain much of the information barrier observed at the 52WH.

Using intra-day trade and quote (TAQ) data to obtain bid-ask spread and depth liquidity measures (depth slope and bid-ask asymmetry, capturing sidedness in order flow) from Goyenko et al. (2009), we find that the 52WH is positively related to liquidity provision at the best price and up to 5 levels of depth. Consistent with liquidity provision expectations, we observe a greater than 40% reduction in the bid-ask spread for stocks at the 52WH, relative to other stocks. This buildup of liquidity is concentrated on the ask side of the book, with corresponding asymmetry in the limit order book as the 52WH approaches, and on the 52WH day. For example at the 52WH, the ask slope becomes 40% steeper and the limit order book 30% more asymmetric, up to the 5th best price, compared to non-52WH stocks.

We build on the finding of Birru (2015), and demonstrate that the informational efficiency of stock prices is much lower at the 52WH due to the influx of uninformed investors. We see that the price impact of trades (Hasbrouck, 1991) is dampened as an excess of liquidity is available at the 52WH. A reduction in measures of price impact (by between 30% and 50%) is observed for stocks on the 52WH day, relative to other days. We also report a 'V' shaped path that both the liquidity and price impact metrics follow as the stock approaches, hits, and rebounds from the 52WH. The profound reduction in price impact is robust to past returns and has important implications regarding the effect of highs and nominal price barriers on informational efficiency, information disclosures and market efficiency.

This study contributes to the literature by exploring the tendency for uninformed investors to cluster their limit orders at nominal prices (Bhattacharya et al., 2012). We argue that the 52WH represents, like round numbers, a strong candidate price for uninformed trading decisions and limit order clustering. Firstly, while round numbers might induce uninformed traders to either buy or sell, the 52WH it is a much clearer signal for investors to sell, leading to greater order clustering by uninformed investors. Secondly, at the 52WH, investors are likely to be in the domain of gains, and those with prospect theory style preferences may be more likely to sell. Fraser-Mackenzie et al. (2015) argue that the round number effect is driven by prospect-theory style preferences. However, round numbers do not necessarily indicate that investors are in the domain of gains, as is likely the case for most investors who decide to sell at the 52WH.

We shed additional light on the use of limit orders by households. Kaniel et al. (2008) show that retail investors prefer to submit limit orders, and are able to earn positive abnormal returns in the short-run as compensation for liquidity provision. Barrot et al. (2016) explain that this is consistent with the general finding that individual investors lose to institutions because most individuals only reverse their trades after the gains from liquidity provision have dissipated. Using Finnish data, Linnainmaa (2010) uncovers losses on limit orders, and gains on market orders, while Stoffman (2014) demonstrates that trades between institutions and households tend to favour institutional investors. However, none of these studies have specifically analyzed trades around the 52WH (or indeed any other liquidity-clustering event).

This chapter builds on Chapters 1 and 2 and offers considerable insight into the role of individual investors and market distortions. Our key finding of uninformed liquidity provision coincides with a steep decline in informational efficiency at the 52WH. This dual finding supports the claim of Boehmer and Kelley (2009) that institutions stabilize and in contrast households destabilize markets. Thus this thesis offers considerable support regarding the role of institutional investors in reducing the importance of anomalies and provides additional evidence to highlight the importance of anchors and the 52WH in markets.

This chapter proceeds as follows. Section 3.2 discusses the prior research. Section 3.3 outlines the hypothesis development, Section 3.4 introduces the data and the method used to measure liquidity and informational efficiency. Section 3.5 outlines the empirical design and reports the key findings and discusses their significance in relation to the literature. Lastly, section 3.6 concludes.

3.2 Literature review

This chapter explores the liquidity and informational efficiency dynamics of stocks as their price approaches and breaches the 52WH. Thus it is key to consider prior research on the 52WH, its role in financial markets, as well as the other causes of market/stock-level liquidity clustering and market/stock-level variations in informational efficiency.

3.2.1 The 52 week high

George and Hwang (2004) highlight the importance of the 52WH and the 52WH ratio as a key anchor and source of return predictability.

$$52WeekHighRatio_{i,t} = \frac{Price_{i,t}}{High_{i,t}} \tag{3.1}$$

where $High_{i,t}$ is the highest price the share has traded for over the past year (252 trading days), while $Price_{i,t}$ is the current price. The ratio therefore represents the nearness in ratio terms of the current price to its 52WH price.

The 52WH is a commonly publicized metric within interactive broker environments and financial news. Its importance has been demonstrated in multiple areas of finance, with its role as a driver of investor behavior partially explained by four key behavioral theories: anchoring (Tversky and Kahneman, 1992), the disposition effect (Shefrin and Statman, 1985), attention (Barber and Odean, 2007) and expectational errors (Birru, 2015). Although not mutually exclusive they all provide a clear psychological rationale into why investors, particularly individuals, are sensitive to the 52WH.

Anchoring at the 52WH has been shown to play a key role on both future returns and investor behaviour. George and Hwang (2004) find that when stocks are trading near their 52WH, they are less sensitive to positive information and more sensitive to negative information. They also point out that the 52WH ratio is a more statistically and economically significant positive predictor of future returns than past return momentum (Jegadeesh and Titman, 1993). The 52WH has also been found to be a key anchor in M&A activities (Baker et al., 2012) and on the behavior of individual investors (see Chapter 2). Anchors are quite prominent in financial markets and have been observed at nominal prices, such as round numbers (Bhattacharya and O'Hara, 2018) and investor's purchase price (Ben-David and Hirshleifer, 2012).

In addition to the role of the 52WH as an anchor, **?**) suggest the 52WH can cause individual investors to exhibit disposition effect style trading, namely to sell winners and hold losers (Shefrin and Statman, 1985). The 52WH can act as the maximum point of accumulated capital gains for investors. Therefore, as the 52WH approaches the probability of selling held assets substantially increases. Similar to the anchoring explanation, the 52WH may result in the slower diffusion of information into prices, as there is an increase in the sell side supply by non-informational sellers [13].

The importance of the 52WH is not just limited to the level of accumulated capital gains, as the 52WH day can act as a key attention grabbing event. Barber and Odean (2007) explore the role of investor attention in stock trading and stock returns, finding that individual investors are more likely to buy/sell stocks that have caught investor's attention. They measured the order imbalance of individual investors' revealing that individuals are more likely to buy attention grabbing stocks. This attention-grabbing effect caused greater buying with the purchased stocks having poorer subsequent performance. Peng and Xiong (2006) suggest that with the existence of limited attention, investors will prioritize certain information/anchors over others. As the 52WH price is a conspicuous piece of information provided by most brokers and financial news sources it is predicted to, and found to, have a significant effect on contemporaneous and future returns, as well as volume and trade imbalance.

Birru (2015) notes that the 52WH acts as a psychological barrier in which investors under react to stock news close to the 52WH. He finds that futures and options, which are not as heavily traded by individual investors, are priced closer to their fair value than the underlying asset, when near the 52WH. In conjunction, Blau et al. (2018) observes that skewness premiums all but disappear at the 52WH, suggesting that investors believe that the 52WH is the upper bound for stock returns. Thus, there is an expectation that investors incorrectly forecast the future price path and thus may prematurely cluster

[13] Non-informational traders are those that are trading for reasons rather than information based, i.e. informed traders. We use the rationale of Black (1986) and denote non-informational traders as those that are trading for liquidity, noise or speculation

their selling towards this upper bound price.

Prior research into the 52WH offers considerable insight into the 52WH effect generally[14], however limited investigation has been undertaken into the market microstructure dynamics around the 52WH. Previous research offers a clear testable hypothesis into the role of the 52WH in attracting uninformed liquidity trades and how this can affect informational efficiency.

3.2.2 Liquidity

The question of liquidity around the 52WH is not well known, and as a result there are two potential and conflicting narratives. First, if individual investors at the 52WH are demanding liquidity to sell down their positions, with disposition effect style tendencies, there could be a drying up of liquidity as investors seek and match counter-parties. This supports Bian et al. (2018), who observe that investors are less likely to use limit orders to sell down winners. Second, if the high acts as an attention grabbing event as suggested by Barber and Odean (2007), there could be increased liquidity at the 52WH in the short term as investors place latent unsupervised limit orders at the anchor price (Kelley and Tetlock, 2013; Linnainmaa, 2010). Linnainmaa (2010) suggests that household investors have a tendency to place unsupervised limit orders. These limit orders can cause limit order execution spikes as they are hit during periods of high volatility or earnings announcements. Thus a thorough investigation of the stock spreads and the shape of the limit order book could provide valuable insights towards resolving this conflict.

[14]For a more comprehensive discussion of the 52WH in other areas of finance see Chapter 2.

3.2.3 Liquidity clustering

Study of the variation and clustering of stock-level liquidity is relatively scarce. Stock-level liquidity can be related to tick sizes (Moulton, 2005), the existence of derivatives (Fedenia and Grammatikos, 1992), nominal (penny and dime) prices (Ikenberry and Weston, 2008) and time of day (McInish and Wood, 1992). These findings are informative, however there is limited discussion into the causes of time varying liquidity at the stock-level. There has also been limited examination of liquidity clustering within asset pricing anomalies.

Prior literature documents the clustering of limit orders around round numbers (Box and Griffith, 2016; Chiao and Wang, 2009; Shiller, 2000) suggests that market participants, in the absence of agreement on fundamental firm value, may use the nearest round number as a trade proxy, while Ball et al. (1985) argue that trade clustering stems from overall valuation uncertainty, consistent with a greater reliance on heuristics for harder-to-value assets. Chiao and Wang (2009) document that limit orders, particularly those submitted by individual investors tend to cluster at integer prices, and that non-marketable orders cluster more than marketable limit orders. Box and Griffith (2016) show that sell limit orders cluster more on round increments as prices are rising. This results in short-run deviations from price efficiency; leading to reduced price impact as informed traders take advantage of excess liquidity. Clustered limit orders mean that traded prices are less likely to reflect fundamental firm value.

Nominal price anchors provide a potential area of exploration. Although purchase price could be a potential anchor (Ben-David and Hirshleifer, 2012), it is inappropriate as there is investor-to-investor variability [15], whereas the 52WH price is shared among stock market participants and thus clustering is more likely. Kuo et al. (2015) argue that limit orders cluster at nominal and round prices as investors use round-numbers as cognitive shortcuts to save energy on 'extensive algorithmic processing'. Consistent with this idea, they find that traders who submit more limit orders at round numbers exhibit worse trading performance. In accordance with this, Bhattacharya et al. (2012) show that there is excessive selling at prices one penny above round number prices, and suggest that the cost of round number biases approaches $1 billion U.S. per year.

3.2.4 Informational efficiency

As a clear influx of investors enter the market at the 52WH for non-informational reasons there is a clear testable conjecture regarding the stock's informational efficiency. If an increase in uninformed investors enter the market, price discovery should suffer, and as such these liquidity based trades should slow the diffusion of information into the market as suggested by Birru (2015).

Informational efficiency and price impact is the ability for market participants to accurately and in a timely fashion incorporate information into stock prices. Informational efficiency varies based on market wide factors such as: trading latency (Riordan and Storkenmaier, 2012), barriers to insider trading (Fishman and Hagerty, 1992), and accounting standardization (Lagoarde-Segot, 2009). Price discovery can be affected at the stock level by the inclusion of a stock into an index (Kaul et al., 2000), cross listing

[15] As the time, date, and price of investor purchases vary, there is insufficient stability of a nominal price in which investors as a group would cluster. This renders purchase price to be an unlikely source of limit order clustering.

(Chang et al., 2013), and institutional investment (Boehmer and Kelley, 2009) among others. Despite some analysis into the stock-level variation of price impact, there is still significant room for exploration into the time-varying nature of stock level informational efficiency.

3.3 Hypothesis development

Building off the prior literature there are clear testable hypothesis regarding the importance of the 52WH on liquidity and informational efficiency. As such, this study predicts that due to the combination of the disposition effect, anchoring, attention and expectation errors, the 52WH, similar to round numbers, will act as a key nominal price in which an increasing number of investors enter the market for non-informational reasons. As the uninformed investors enter the market they increase the amount of liquidity, particularly on the ask (sell) side of the limit order book, causing increased liquidity and lopsidedness in the limit order book.

Hypothesis 1: H1 - Increase in liquidity provision at the 52WH

The increase in non-informational investors will result in an increase in liquidity as the 52WH approaches, reaching a maximum at the 52WH.

In chapter 2 we noted that an increase in household limit order sells resulted in strong post event abnormal returns. We continue to expect that as investors enter the market for non-informational reasons we will see a strong dampening of informational efficiency (Hong and Stein, 1999).

Hypothesis 2: H2 - Reduction in price impact at the 52WH

The increase in liquidity around the 52WH should coincide with a reduction in price efficiency as the investors entering the market are doing so for primarily non-informational reasons, thus dampening the effect of trading on price movements.

3.4 Data and Metrics

The data set used includes the 78 largest stocks by market capitalization on the Helsinki NASDAQ OMXH. This data set includes all the millisecond stamped TAQ data, as well as the depth and price history for the 78 stocks. The data was obtained from the Thomson Reuters Tick History (TRTH) database. The stock price data was obtained from the Wharton Research Data Services (WRDS) Compustat data set. The data set covers the period from 1 January 2000 to 31 December 2014.

This study explores the liquidity, price impact, and informational efficiency of stocks in relation to the 52WH. As such, multiple liquidity and price discovery measurement metrics discussed by Goyenko et al. (2009) and Foucault et al. (2013) are adopted. With the intra-day data set it is possible to use higher speed measures aggregated to the daily level alongside other direct daily measures. The metrics used in this study are detailed in the following subsections.

3.4.1 Liquidity measures: spreads

The liquidity metrics first focus on different measure of the prevailing bid-ask spread as a proxy for liquidity.

$$QuotedSpread_{i,t} = \frac{(Ask_{i,t} - Bid_{i,t})}{m_{i,t}} \tag{3.2}$$

where $Ask_{i,t}$ and $Bid_{i,t}$ are the respective bid and ask prices for stock i at time t, and $m_{i,t}$ is the mid-quote price of the stock i at time t. Quoted spread (Q-spread) reports the round trip cost of a given market order that executes against the current best bid and ask prices. The Q-spread is time-weighted and aggregated at the daily level, as per McInish and Wood (1992).

$$EffectiveSpread_{i,t} = \frac{2q_{i,t}(P_{i,t} - m_{i,t})}{m_{i,t}} \tag{3.3}$$

where $q_{i,t}$ is a trade direction indicator $+1$ is for buyer initiated trades and -1 for seller initiated trades. $P_{i,t}$ is the price for which the trade executes while $m_{i,t}$ is the mid-quote price of the stock i at time t. Effective spread (E-spread) reflects the round cost trip of a liquidity demanding trade (limit order). E-spread is the euro volume-weighted average of the effective spreads for each completed trade within the day.

$$RealizedSpread_{i,t} = (P_{i,t} - m_{i,t+5min})m_{i,t} \tag{3.4}$$

where $q_{i,t}$ is a trade direction indicator, where $+1$ is for buyer initiated trades and -1 for seller initiated trades. $P_{i,t}$ is the price for which the trade executes while $m_{i,t+5min}$ is the mid-quote price of the stock i at time $t + 5$ minutes. Realized spread (R-spread) is aggregated using euro volume weighting for each stock within the day. R-spread is similar to E-spread, insofar as it reflects the round trade cost of a liquidity demanding trade; in contrast, it observes the effect relative to the mid-point 5 minutes following the trade, from which it assumes the price impact has been revealed (Foucault et al., 2013).

3.4.2 Liquidity measures: limit order book depth

The above spread measures provide insight into the liquidity at the prevailing bid and ask. Depth metrics can provide additional information regarding liquidity beyond the first level of quotes. The shape and characteristics of the limit order book demonstrates the ability to trade at subsequent prices and quantities. They are useful in showing the demand and supply for the stocks on given days and how this changes relative to the 52WH.

$$Askslope_{i,t} = \frac{AskDepthAtBest5_{i,t}}{Ask5_{i,t} - m_{i,t}} \tag{3.5}$$

where $AskDepthAtBest5_{i,t}$ is the sum of the quantity of available asks from the 1st to the 5th level by stock i at time t. $Ask5_{i,t}$ is the ask price at the 5th level. This measure reflects the gradient of the ask slope from the mid-quote to the 5th level of ask.

$$BidSlope_{i,t} = \frac{BidDepthAtBest5_{i,t}}{BidPrice5_{i,t} - m_{i,t}} \tag{3.6}$$

where $BidDepthAtBest5_{i,t}$ is the sum of the quantity of available bids from the 1st to the 5th level by stock. $BidPrice5_{i,t}$ is the prevailing ask price at the 5th level. This measure reflects the gradient of the bid slope from the mid-quote to the 5th level of bid. Higher values of the slope metrics reflect a steeper ask or bid slope respectively.

In addition to the gradient of the slopes, the relative asymmetry of depth is an important factor to determine the relative demand and supply of the stock.

$$ScaledDepthDifference_{i,t,x} = \frac{QuoteAsk_{i,t,x} - QuoteBid_{i,t,x}}{QuoteAsk_{i,t,x} + QuoteBid_{i,t,x}} \tag{3.7}$$

where $QuoteAsk_{i,t,x}$ and $QuoteBid_{i,t,x}$ is the respective ask and bid quotes. It represents a scaled level of asymmetry at the prevailing quote to level x. If it is greater than zero it is in the direction of asks and vice versa for bids below zero. It is a useful measure to consider the shape of the limit order book at different levels. We report this at the 1st and 5th levels (x) respectively.

3.4.3 Price impact and the information content of trades

To support the expectation that the 52WH acts a barrier to information integration we explore the informational efficiency of trades. To measure informational efficiency we use two measures: 5 minute simple price impact (simple price impact henceforth) and a more robust permanent price impact.

$$SimplePriceImpact_{i,t} = \frac{2q_{i,t}(m_{i,t+5min} - m_{i,t})}{m_{i,t}} \tag{3.8}$$

where $q_{i,t}$ is a trade direction indicator, +1 for buyer initiated trades and -1 for seller initiated trades. $m_{i,t}$ is the mid-quote price of the stock i at time t. The simple price impact measures the subsequent mid-quote price change five minutes following a trade.

A key consideration of the 52WH is the entrant of new investors trading for non-informational reasons. In line with hypothesis 1, namely trades at the 52WH should be less informed, you expect to see lower price impacts, as measured by simple price impact. A limitation of the simple price impact is that it compounds the price innovations from all trades between the initial trade and the 5 minute mid quote. As a result simple price impact can overstate the effect of a trade on price, particularly for periods of high volume (Foucault et al., 2013).

Due to the limitations of simple price impact measurements this study implements a vector auto-regression (VAR) model (Hasbrouck, 1991) that uses a system of equations modelling signed order flow and log returns. This study utilizes the reduced form VAR to infer the dynamics of the structural model.

$$x_t = u^x + \sum_{i=1}^{60} a_i^r r_{t-i} + \sum_{i=1}^{60} a_i^x x_{t-i} + e_t^x \tag{3.9}$$

$$r_t = u^r + \sum_{i=1}^{60} a_i^r r_{t-i} + \sum_{i=1}^{60} a_i^x x_{t-i} + e_t^r \tag{3.10}$$

where t indexes 1-second intervals, and x_t is signed-dollar-volume of trades in the 1-second interval, t. r_t is the log-mid-quote change in the t-th interval, e_x^t is the unanticipated signed volume, and e_t^r and is a mid-quote innovation not caused by order flow (Foucault et al., 2013).

We operationalize the model using an impulse response function applying an unanticipated shock of volume. The VAR utilizes 60 lags of each variable based on the economic intuition of Comerton-Forde et al. (2016). We apply a 10,000 Euro shock of volume to e_x^t ,the signed volume, and an equivalent price shock to e r_t the mid-quote price, which we refer to as permanent price impact. The VAR determines the relative informational efficiency at different prices of a given stock. The simple price impact and permanent price impact measures are used in unison to test the effect of the 52WH on liquidity, price impact and informational efficiency.

3.5 Results

To test the importance of the 52WH on liquidity and price impact the following empirical approach is undertaken. First, we estimate the liquidity (spread and depth) and price discovery metrics from the intra-day TAQ and depth data. Second, we sort stocks into deciles based on their 52WH ratio and report the effect to liquidity and price impact. Third, we undertake a single sort of stocks at or within 3% of the 52WH and report the mean differences in measures comparing stocks at the 52WH to those that are not. Fourth, we continue to explore the liquidity and informational efficiency at the 52WH via stock day one-stage OLS regressions. Last, to support the importance of the 52WH day, we employ event-study methodology and plot the metrics 5 days prior to and 5 days following the 52WH day.

3.5.1 Descriptive statistics

Table 3.1 reports the descriptive statistics for the stocks, equally weighted, in the sample. The mean (median) firm in the sample has a market capitalization of 2.52b Euros (525m Euros). The mean (median) Q-spread is 95bps (59bps), larger than the R-spread of 51bps (23 bps). The mean simple price impact of a trade is 28bps while permanent price impact has a mean of 17bps. The data is winsorized at the 5th and 95th percentile to prevent data errors and extreme values skewing the results.

Table 3.1: Descriptive statistics

This table reports means, standard deviations, and quartile points (P25, Median, P75) of variables calculated at the stock-day level. Market cap is the price * stocks outstanding in tens of millions of Euros. Volume is the amount of stock units traded by day in millions. Price is the contemporaneous price of the given stock. Quoted Spread is the round trip cost of a given market order that executes against the current best bid and ask prices. Effective spread is the execution cost of a round trip of a liquidity demanding trade. The realized spread is the change in price against the mid-quote five minutes following the trade relative to the mid-quote at time t. The ask and bid slope represent the gradient of the respective slope values to the 5th level relative to the mid-quote at time t for each stock. SDD represents a scaled level of asymmetry at the prevailing quote, 1 and 5 respectively. Simple price impact measures the subsequent mid-quote price change five minutes following a trade. The Permanent price impact reports the results of the VAR for a 10,000 Euro volume shock on returns. The sample comprises the 78 largest, by market capitalization, OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile.

	Mean	Std dev	25th	50th	75th
Stock characteristics:					
Market cap (10 mil Euros)	25.165	114.935	1.505	5.283	14.628
Volume (mil)	0.872	4.88	0.009	0.06	0.351
Price	18.685	20.744	5.187	12.758	24.555
Liquidity and price impact metrics:					
Quoted spread	98.525	102.099	22.715	59.500	134.348
Effective spread	81.465	79.946	22.577	51.281	110.374
Realized spread	51.141	70.855	3.260	23.348	71.219
Ask slope	251.285	440.911	17.744	66.208	236.280
Bid slope	235.623	415.069	15.298	61.529	223.756
SDD 1	0.046	0.244	-0.105	0.033	0.189
SDD 5	0.067	0.232	-0.082	0.047	0.212
Simple price impact	28.765	36.657	5.807	14.486	35.562
Permanent price impact	17.159	35.231	0.155	1.859	13.290

Table 3.2 reports the correlations between all liquidity and price impact measures. To support the validity of the measures, as proxies for liquidity and for efficacy within the study. We observe significant positive correlations among the liquidity metrics and positive correlations between the liquidity and price impact metrics. This supports the expectations of Goyenko et al. (2009) that liquidity is related to informational efficiency.

Table 3.2: Correlations between liquidity and price impact measures

This table reports correlations between liquidity and price impact metrics. Quoted spread is the round trip cost of a given market order that executes against the current best bid and ask prices. Effective spread is the execution cost of a round trip of a liquidity demanding trade. The realized spread is the change in price against the mid-quote five minutes following the trade relative to the mid-quote at time t. The Ask and bid slope represent the gradient of the respective slope values to the 5th level relative to the mid-quote at time t for each stock. SDD represents a scaled level of asymmetry at the prevailing quote, 1 and 5 respectively. Simple price impact measures the subsequent mid-quote price change five minutes following a trade. The Permanent price impact reports the results of the VAR for a 10,000 Euro volume shock on returns. The sample comprises the 78 largest, by market capitalization, OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile. The p-values are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels respectively.

	Quoted spread	Effective spread	Realized spread	Ask slope	Bid slope	SDD1	SDD5	Simple price impact	Permanent price impact
Quoted spread	1								
Effective spread	0.871***	1							
	(0.001)								
Realized spread	0.693***	0.828***	1						
	(0.001)	(0.001)							
Ask slope	-0.351*	-0.316***	-0.245***	1					
	(0.001)	(0.001)	(0.001)						
Bid slope	-0.356***	-0.321***	-0.251***	0.883***	1				
	(0.001)	(0.001)	(0.001)	(0.001)					
SDD1	0.074***	0.077***	0.064***	-0.056***	-0.088***	1			
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)				
SDD5	0.118***	0.105***	0.096***	-0.040***	-0.158***	0.440***	1		
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)			
Simple price impact	0.417***	0.390***	-0.121*	-0.209***	-0.209***	0.040***	0.038***	1	
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		
Permanent price impact	0.489***	0.441***	0.083***	-0.211***	-0.211***	0.050***	0.063***	0.680***	1
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	

3.5.2 The 52 week high ratio

To test our first hypothesis, we examine the general effect of the 52WH ratio on liquidity. We sort the stocks daily into ascending deciles in order to observe the effect of nearness and farness from the 52WH on liquidity. First, by examining the spread metrics (Q-spread, R-spread and E-spread) in Table 3.3 Panel a, we see a clear and significant monotonic slope downwards, indicative of higher liquidity and lower costs of trade, as stocks approach the 52WH. The spread measures effectively halve going from the lowest to highest 52WH decile, with the magnitude of this effect ranging from -56bps for Q-spread to -30bps for R-spread. This reduction in the spreads allows investors to trade market orders more cheaply at the 52WH and in turn their limit orders are less rewarded by receiving a lower spread.

We next assess the liquidity buildup of the bid-ask book and its symmetry by examining the depth measures, in particular the bid slope, ask slope and scaled depth difference at the 1st and 5th level. First, we examine the bid and ask slope up to the 5th level. The ask slope increases (more limit order sell quantity) as it approaches the 52WH and the inverse is observed for the bid slope (less limit order buy quantity). Simply put, this means that stocks near the 52WH have much more liquidity available to buyers - as sellers increase their willingness to provide liquidity to the market, this in effect creates the asymmetric order book.

We next observe the SDD at the 1st and 5th levels. The clearest effect of this asymmetry of the SDD is observed at the 5th level in which we see a significant monotonic shift upwards, from 0.018 to 0.094. Simply put, as stocks approach the 52WH they become more unbalanced in the favor of the ask (sell) side. This increase in the ask side supports prior research that the disposition effect leads investors to increase their selling to realize gains based on past positive returns (Shefrin and Statman, 1985). Given that the disposition effect causes investors to sell for profit realization rather than information reasons it is expected that they are less time-restricted, and thus will use limit orders. These results support the earlier findings in Chapter 2 demonstrating a clear increase in household limit order at and around the 52WH. This study reveals that the 52WH acts as a strong anchor for limit order sells, but does not have the same effect for buys.

Table 3.3: Liquidity and price impact metrics by 52 week high ratio deciles

The table reports the liquidity and price impact metrics sorted into deciles (from low to high) based on their 52 week high ratio. The 52 week high ratio is the ratio between the stocks current price and its 52 week high price (the highest price the stock has traded for over the prior year). Quoted spread is the round trip cost of a given market order that executes against the current best bid and ask prices. Effective spread is the execution cost of a round trip of a liquidity demanding trade. The realized spread is the change in price against the mid-quote five minutes following the trade relative to the mid-quote at time t. Simple price impact measures the subsequent mid-quote price change five minutes following a trade. The Permanent price impact reports the results of the VAR for a 10,000 Euro volume shock on returns. The ask and bid slope represent the gradient of the respective slope values to the 5th level relative to the mid-quote at time t for each stock. SDD represents a scaled level of asymmetry at the prevailing quote, 1 and 5 respectively. In addition, the table reports the high less low value for each metric. Standard errors are clustered at the stock level, the p-values are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The sample comprises the 78 largest OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile.

	Quoted spread	Effective spread	Realized spread	Simple price impact	Permanent price impact
Low	115.002	106.211	63.962	39.096	25.064
2	106.523	96.869	58.728	35.329	23.735
3	98.879	88.351	53.597	32.793	21.006
4	90.041	80.126	48.730	30.174	19.419
5	83.336	73.561	44.195	28.285	17.518
6	79.266	68.696	41.363	26.912	16.233
7	76.172	66.485	40.752	25.271	14.885
8	69.743	61.377	38.122	23.170	12.512
9	61.161	54.566	33.660	21.044	9.929
High	58.624	54.693	33.503	21.034	8.031
High - Low	-56.378***	-51.518***	-30.459***	-18.062***	-17.033***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

	Ask slope	Bid slope	SDD 1	SDD 5
Low	302.649	307.676	0.051	0.018
2	328.489	324.943	0.038	0.031
3	244.254	240.061	0.051	0.049
4	227.750	221.106	0.044	0.051
5	229.965	224.209	0.041	0.054
6	252.539	236.897	0.038	0.063
7	271.913	257.39	0.031	0.064
8	289.448	267.601	0.041	0.076
9	304.631	266.713	0.045	0.095
High	334.203	276.222	0.032	0.094
High - Low	31.553	-31.453	-0.019**	0.075***
	(0.75)	(0.73)	(0.03)	(0.00)

As liquidity increases it is expected to have a positive influence on price discovery and informational efficiency (Glosten and Milgrom, 1985). We next test hypothesis 2 to observe the effect of the 52WH on price impact. In Table 3.3 we report simple price impact, which is a measure of price changes 5 minutes following a trade, and permanent price impact, which is the result of a VAR model which reports the effect on price after we apply a 10,000 Euro shock to signed volume. In support of hypothesis 2 we see a similar monotonic downwards fall in both price impact measures as stocks approach the 52WH. We see a drop in simple price impact by more than half, with simple price impact dropping by a significant 18.062bps and permanent price impact dropping by 2/3rds or -17.03 bps. This is a significant drop in both measures and supports the claim of Birru (2015) that the 52WH acts as a barrier for information integration.

3.5.3 The 52 week high day

The previous section demonstrates the general effect of the 52WH ratio. We next test the specific effect of the 52WH day as an anchor and a cluster of liquidity. We do so by classifying stocks if their price closes within 3% of their 52WH price as being at the 52WH max. We first undertake uni-variate sorts and secondly OLS regressions to explore the role of the 52WH on the liquidity and price impact measures.

Table 3.4: Liquidity and price impact metrics at the 52 week high

The table reports the liquidity and price impact metrics for stocks at the 52 week high and the mean across all days. The 52 week high day is the day in which the stock is within 3% or has surpassed the previous 52 week high price. Quoted spread is the round trip cost of a given market order that executes against the current best bid and ask prices. The Effective spread is the execution cost of a round trip of a liquidity demanding trade. The realized spread is the change in price against the mid-quote five minutes following the trade relative to the mid-quote at time t. Price impact measure the subsequent mid-quote price change five minutes following trade. The Permanent price impact reports the results of the VAR for a 10,000 Euro volume shock on returns. Ask and bid slope represent the gradient of the respective values to the 5th level relative to the mid-quote at time t. Ask (bid) slope is the gradient of the order book up to five levels. SDD represents a scaled level of asymmetry at the prevailing quote, 1 and 5 respectively. In addition, the table reports the mean difference between the mean and the 52 week high for each metric. Standard errors are clustered at stock level, the p-values are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.The sample comprises the 78 largest OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile

	Quoted spread	Effective spread	Realized spread	Simple price impact	Permanent price impact
Mean	106.324	87.084	54.829	30.38	19.044
52 week high max	59.539	54.384	33.368	20.981	8.871
Mean difference	-46.785**	-32.700**	-21.461**	-9.399**	-10.174**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

	Ask slope	Bid slope	SDD1	SDD5
Mean	236.534	227.807	0.048	0.062
52 week high max	320.174	272.123	0.038	0.094
Mean difference	83.640**	44.316	-0.009*	0.032**
	(0.05)	(0.26)	(0.08)	(0.00)

We start by examining the liquidity metrics at the 52WH day in comparison to an average day. In Table 3.4 we see significant decreases in all spread metrics, indicative of strong increases in liquidity at the best prices. Q-spread falls by half (-47bps), as do the other two spread measures. The shape of the ask slope becomes significantly steeper, increasing by 40%. The limit order book, as shown by SDD at the 5th level, displays both a steeper ask slope and a more asymmetric order book - towards the sell side. Thus, this continues to support our first hypothesis that the 52WH day is a strong driver of liquidity, particularly on the sell side.

In support of hypothesis 2, we again see significant declines in informational efficiency at the 52WH day. We see a significant 9.39bps drop in simple price impact and a significant 10.17bps drop in permanent price impact. This continues to support our expectation of the existence of the high liquidity and low information environment at the 52WH. These findings are consistent with the findings of both Linnainmaa (2010), and Bhattacharya et al. (2012) that investors may cluster latent limit orders at nominal price anchors.

We next test the effect of both the 52WH ratio and the 52WH day controlling for expected confounding market microstructure variables. We use a series of OLS regressions looking at the effect of the 52WH variables on the liquidity measures: Q-spread, E-spread and R-spread.

$$\begin{aligned} LiquidityMetrics_{i,t} = \beta_0 + \beta_1 52WHMax_{i,t} + \beta_2 52WHRatio_{i,t} + \beta_3 Price + \\ \beta_4 MarketCap_{i,t} + \beta_5 LagReturn_{i,t} + \beta_6 IdiosyncraticRisk_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.11}$$

Where the $LiquidityMetrics_{i,t}$ are the daily Q-spread, E-spread and R-spread within stock i. The independent variables: $52WHMax_{i,t}$ is an indicator variable [0,1] in which a value of 1 represents the day in which the stock is within 3% or has surpassed the previous 52WH price; and the $52WHratio_{i,t}$ is the ratio between the stocks current price and its 52WH price. The control variables: $Price_{i,t}$ is the contemporaneous price of the given stock i at time t; $MarketCap_{i,t}$ is the price * stocks outstanding in tens of millions of Euros; $LagReturn_{i,t}$ the sum of the daily return for the prior 3 months by stock; and $IdiosyncraticRisk_{i,t}$ is the standard deviation of the daily returns for the prior 3 months by stock.

Table 3.5: Effects of 52 week high on liquidity

This table reports OLS regression estimates using a stock-day panel. Quoted spread is the round trip cost of a given market order that executes against the current best bid and ask prices. The Effective spread is the execution cost of a round trip of a liquidity demanding trade. The Realized spread is the change in price against the mid-quote five minutes following the trade relative to the mid-quote at time t. The 52 week high max is an indicator variable [0,1] in which a value of 1 represents the day in which the stock is within 3% or has surpassed the previous 52 week high price. The 52 week high ratio is the ratio between the stocks current price and its 52 week high price (the highest price the stock has traded for over the prior year). Price is the contemporaneous price of the given stock i at time t. Market Cap is the price * stocks outstanding in tens of millions of Euros. $Lagreturn_{3months}$ is the sum of the daily returns for the prior 3 months by stock. Idiosyncratic risk is the standard deviation of the daily returns for the prior 3 months by stock. Standard errors are clustered at stock level, the p-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The sample comprises the 78 largest OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile

	Dep var:					
	Quoted spread		Effective spread		Realized spread	
Intercept	126.751***	161.583***	109.246***	150.929***	70.171***	91.136***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
52 week high max	-26.237***	-6.831**	-21.001***	-3.231*	-13.135***	-1.421
	(0.00)	(0.03)	(0.00)	(0.10)	(0.00)	(0.39)
52 week high ratio		-60.074***		-64.096***		-36.002***
		(0.00)		(0.00)		(0.00)
Price	-1.478***	-1.209***	-1.224***	-1.011***	-0.863***	-0.711***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Market Cap	-0.091**	-0.155***	-0.065**	-0.122***	-0.039**	-0.075***
	(0.01)	(0.00)	(0.02)	(0.00)	(0.03)	(0.00)
Lag Return	-0.037***	-0.048***	-0.033***	-0.039***	-0.026***	-0.025***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Idiosyncratic risk	3.029***	3.728***	2.425***	2.737***	2.108***	2.025***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs	224269	201001	221384	198832	221337	198794
Adj R-sq	0.148	0.162	0.142	0.162	0.086	0.091

Table 3.5 reports the results of the above regression specification. Supporting hypothesis 1, we see large and significant negative coefficients for the $52WHRatio_{i,t}$ and

$52WHMax_{i,t}$ across all spread measures. As expected, the control variables are significant and in the direction forecast by prior research (Goyenko et al., 2009) and economic intuition. A key insight is the strong role of the 52WH ratio that drives much of the liquidity. By including $LagReturn_{3months}$ we in part address the issues of accumulated capital gains raised by Grinblatt and Han (2005) who suggest that the increased activity/liquidity is as a result disposition effect investors selling down their winning stocks. The relatively small co-efficient of $LagReturn$ is informative as past returns could act as an attentional driver (Barber and Odean, 2007), or as mentioned earlier, bring disposition effect investors into the market. Despite this prediction it is not an economically large driver of the increased liquidity. These results are consistent with and robust to the inclusion of firm and year fixed effects.

Next, using similar OLS regression specifications, we explore the role of the 52WH on depth.

$$\begin{aligned} DepthMetrics_{i,t} = \beta_0 + \beta_1 52WHMax_{i,t} + \beta_2 52WeekHighRatio_{i,t} + \beta_3 Price + \\ \beta_4 MarketCap_{i,t} + \beta_5 LagReturn_{i,t} + \beta_6 IdiosyncraticRisk_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.12}$$

Where the $DepthMetrics_{i,t}$ are: bid spread, ask spread, SDD1, and SDD5 by stock at i time t. The independent variables and controls are as defined earlier.

Table 3.6: Effects of 52 week high on depth

This table reports OLS regression estimates using a stock-day panel. Ask (bid) slope is the gradient of the order book up to five levels. SDD represents a scaled level of asymmetry at the prevailing quote, 1 and 5 respectively. The 52 week high is an indicator variable [0,1] in which a value of 1 represents the day in which the stock is within 3% or has surpassed the previous 52 week high price. The 52 week high ratio is the ratio between the stocks current price and its 52 week high price (the highest price the stock has traded for over the prior year). Price is the contemporaneous price of the given stock i at time t. Market cap is the price * stocks outstanding in tens of millions of Euros. $Lagreturn_{3months}$ is the sum of the daily return for the prior 3 months by stock. Idiosyncratic risk is the standard deviation of the daily return for the prior 3 month by stock. Standard errors are clustered at stock level, the p-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The sample comprises the 78 largest OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile

	Dep Var:							
	Ask slope		Bid slope		SDD1		SDD5	
Intercept	171.9**	168.1	163.2**	201.4*	0.060***	0.069***	0.072***	-0.018
	(0.004)	(0.081)	(0.005)	(0.040)	(0.000)	(0.000)	(0.000)	(0.229)
52 week high max	62.27*	34.31	21.91	5.343	-0.003	0.005	0.039***	0.024***
	(0.028)	(0.218)	(0.344)	(0.824)	(0.500)	(0.294)	(0.000)	(0.000)
52 week high ratio		11.22		-44.66		-0.0190		0.111***
		(0.914)		(0.670)		(0.240)		(0.000)
Price	1.566	1.017	1.768	1.323	-0.007**	-0.007**	-0.006*	-0.005*
	(0.369)	(0.458)	(0.305)	(0.332)	(0.004)	(0.006)	(0.040)	(0.029)
Market Cap	1.352***	2.276***	1.248***	2.157***	-0.002	-0.008**	-0.004	-0.008
	(0.000)	(0.000)	(0.000)	(0.000)	(0.136)	(0.004)	(0.181)	(0.050)
Lag return	0.0888	0.0741*	0.0945*	0.100**	-0.001***	-0.009**	-0.009**	-0.001***
	(0.072)	(0.033)	(0.041)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)
Idiosyncratic risk	-7.056*	-6.040*	-7.101*	-7.376**	0.008***	0.008***	0.004***	0.007***
	(0.040)	(0.016)	(0.027)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
Obs	138873	124908	138872	124908	138870	124908	138875	124909
Adj R-sq	0.210	0.296	0.203	0.303	0.004	0.005	0.008	0.018

In Table 3.6 we see a significant buildup of liquidity on the ask side with positive and significant coefficients at the 52WH max. The increased liquidity we observe earlier is the result of the sell side rather than the buy side. This is further supported by observing the SDD at the 5th level as we see positive and significant results at the 52WH max, which refers to the strong asymmetry towards the ask side in the limit order book. We do not observe a significant effect of the 52WH on the ask slope, which indicates that the liquidity buildup is a result of the increased number of sellers providing liquidity.

We last test hypothesis 2, within the OLS framework, to assess the result of the 52WH on informational efficiency and price impact.

$$\begin{aligned} PriceImpactMetrics_{i,t} = \beta_0 + \beta_1 52WHMax_{i,t} + \beta_2 52WHRatio_{i,t} + \\ \beta_3 Price_{i,t} + \beta_4 MarketCap_{i,t} + \beta_5 LagReturni, t + \beta_6 \\ IdiosyncraticRisk_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.13}$$

Where the $PriceImpactMetrics_{i,t}$ are the daily simple price impact and permanent price impact, as defined in equations 3.8 and 3.10. The independent variables and controls are as defined in regression 3.11.

Table 3.7: Effects of 52 week high on price impact

This table reports OLS regression estimates using a stock-day panel. Simple price impact measure the subsequent mid-quote price change five minutes following trade. Permanent price impact reports the results of the VAR for a 10,000 Euro volume shock on returns. The 52 week high is an indicator variable [0,1] in which a value of 1 represents the day in which the stock is within 3% or has surpassed the previous 52 week high price. The 52 week high ratio is the ratio between the stocks current price and its 52 week high price (the highest price the stock has traded for over the prior year). Price is the contemporaneous price of the given stock i at time t. Market cap is the price * stocks outstanding in tens of millions of Euros. $Lagreturn_{3months}$ is the sum of the daily return for the prior 3 months by stock. Idiosyncratic risk is the standard deviation of the daily returns for the prior 3 months by stock. Standard errors are clustered at stock level, the p-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively. The sample comprises the 78 largest OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile

	Dep var:			
	Simple price impact		Permanent price impact	
Intercept	36.40***	53.87***	25.33***	24.13***
	(0.000)	(0.000)	(0.000)	(0.000)
52 week high max	-6.477***	-1.791*	-5.761***	-3.767***
	(0.000)	(0.012)	(0.000)	(0.000)
52 week high ratio		-23.01***		-3.976
		(0.000)		(0.432)
Price	-0.314***	-0.269***	-0.323***	-0.294***
	(0.000)	(0.000)	(0.000)	(0.000)
Market Cap	-0.025**	-0.0459**	-0.044**	-0.045**
	(0.007)	(0.002)	(0.005)	(0.003)
Lag return	-0.003	-0.008***	-6.870**	-8.551***
	(0.258)	(0.000)	(0.002)	(0.000)
Idiosyncratic risk	0.253	0.544***	23.05*	181.9*
	(0.224)	(0.000)	(0.016)	(0.036)
Obs	221337	198794	199785	187977
Adj R-sq	0.051	0.069	0.069	0.074

Table 3.7 reports the simple price impact, revealing a strong and economically significant reduction in price impact. Interestingly, the 52WH ratio is a larger driver of the reduction in price impact. Looking further into permanent price impact, it is clear that the 52WH Max is the primary driver of the reduction in informational efficiency. The finding that the 52WH acts as a driver of both liquidity and poor informational efficiency supports both our hypotheses and provides considerable insight into the role

of anchors beyond current price.

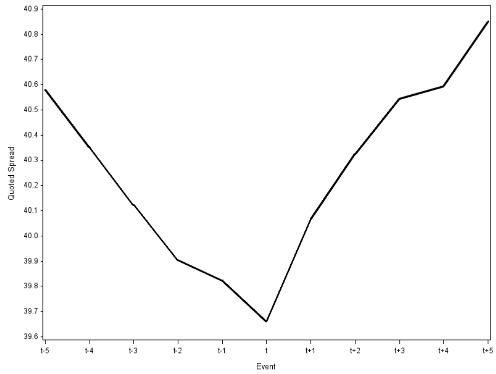
3.5.4 Pre and post 52 week high day

Prior to and following the 52WH it is reasonable to expect liquidity to innovate and potentially cluster at the 52WH day. To explore this possibility we use the event study method of MacKinlay (1997) focusing on the liquidity and price impact metrics (rather than returns) 5 days prior and 5 days following the 52WH day (t).

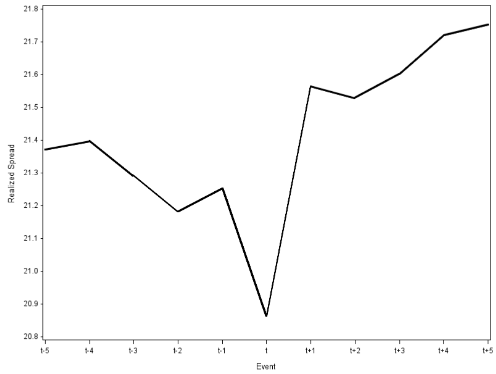
We first plot the mean values of the spread metrics, weighted by price, at time t, around the 52WH day. There is clear 'V' pattern centering on the high day and reverting upwards immediately after the 52WH day.

We next plot the depth measures in Figure 3.2 and see very similar effect for the Ask slope and SDD at the 5th level, supporting the earlier regression results, that find the 52WH day to be a key anchor. Prior to the day, we see a clear buildup of liquidity on the ask side which is taken, thus receding downwards following the high day. We observe a similar effect for SDD5.

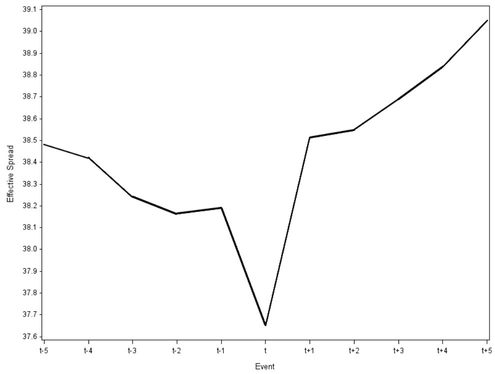
Last, in Figure 3.3, we plot the price impact at and around the 52WH. Providing additional support for hypothesis 2 we observe a similar 'V' shape around the 52WH day. The 52WH day provides a strong barrier to information integration, as a general rule greater liquidity results in greater informational efficiency.



(a) Quoted Spread



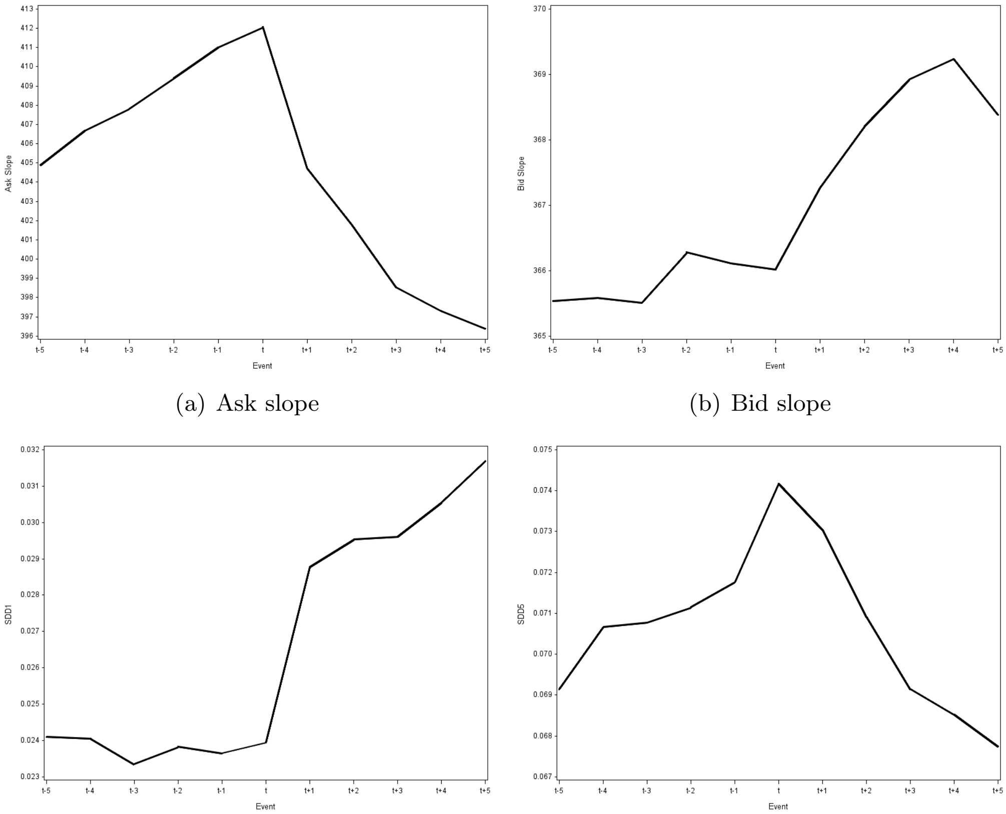
(b) Realized Spread



(c) Effective Spread

Figure 3.1: Spread metrics around the 52 week high day

This figure plots the quoted spread (Panel a) realized spread (Panel b) and effective spread (Panel c) 5 days prior (t_{-5}) to and 5 days following ($_{t+5}$) the 52 week high day (t). The 52 Week High day is the day in which the stock is within 3% or has surpassed the previous 52 week high price. The metrics are weighted by their price at time t. The sample comprises the 78 largest OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile.



(a) Ask slope

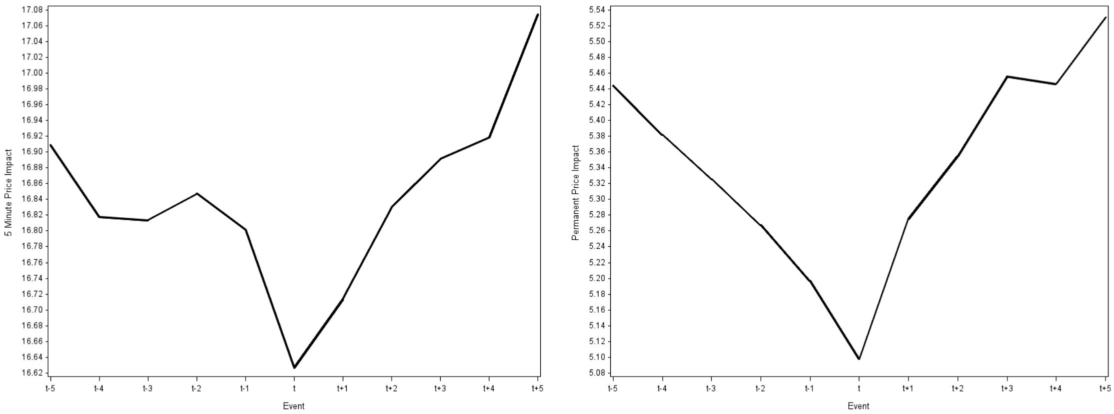
(b) Bid slope

(c) Scaled depth difference 1

(d) Scaled depth difference 5

Figure 3.2: Depth metrics around the 52 week high day

This figure plots the ask slope (Panel a), bid slope (Panel b), scaled depth difference 1 (Panel c), and scaled depth difference 5 (panel d) for 5 days prior (t_{-5}) to and 5 days following ($_{t+5}$) the 52 week high day (t). The 52 week high day is the day in which the stock is within 3% or has surpassed the previous 52 week high price. The metrics are weighted by their price at time t. The sample comprises the 78 largest OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile.



(a) 5 minute price impact

(b) Permanent price impact

Figure 3.3: Price impact metrics around the 52 week high day

This figure plots the 5 minute price impact (Panel a) and permanent price impact (Panel b) 5 days prior (t_{-5}) to and 5 days following ($_{t+5}$) the 52 week high day (t). The 52 Week High day is the day in which the stock is within 3% or has surpassed the previous 52 week high price. The metrics are weighted by their price at time t. The sample comprises the 78 largest OMXH-listed stocks from January 1, 2000 to December 31, 2014. The data is winsorized at the 5th and 95th percentile.

3.6 Conclusion

This study uses intra-day TAQ and depth data to explore the liquidity dynamics at the 52WH and its effect on the price impact of trades. This study reveals large increases in liquidity as the 52WH approaches and at the 52WH price. This comes in the form of a halving of spreads and an almost doubling of the limit order sell quantity up to the 5th level of the limit order book. This liquidity buildup is asymmetric towards the ask side, suggesting investors see the 52WH as an anchor to sell, supporting the findings of Chapter 2. The findings are consistent with the 52WH being a driver of investor anchoring and expectational errors.

This study demonstrates, contrary to the expectations of extant microstructure literature, that the increase in liquidity at the 52WH results in a significant deterioration in informational efficiency. This reduction is indicative of increased trading as a result of non-informational investors entering the market. Looking 5 days prior and following the 52WH this liquidity is focused on the 52WH in a 'V' shaped pattern, highlighting the importance of the 52WH day as an anchor.

These finding have significant implications regarding the time varying and clustering nature of liquidity and how this can affect informational efficiency, particularly around nominal prices. It opens up room for future research into the market microstructure dynamics of many more asset pricing anomalies.

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