Investor Behavior at the 52 Week High

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Abstract

This study uncovers how household investors intensify the 52 week high (52WH) effect: increased volume and momentum-like returns at the 52WH price. Using daily household and institutional trading, we find that households sharply increase their, limit order, sells at the 52WH price. This behavior is indicative of anchoring as it is robust to past returns, and intensified by market uncertainty and salience of the 52WH. This uninformed limit order selling at, and prior to, the 52WH leads to a doubling of the unconditional 52WH anomaly returns. The post-event returns are to the benefit of institutions who act as counter parties.

⋆For their helpful comments we thank, Henk Berkman, Justin Birru, Barbara Bliss, Ruchith Dissanayake, Mark Grinblatt, David Hunter, Petko Kalev, Markku Kaustia, and Andrew Urquhart. We wish to thank the seminar participants at the 30th Australasian finance and banking conference, the 8th Financial markets and corporate governance conference, the 2018 University of Melbourne seminar series, the 2018 University of Queensland seminar series, the 2018 European Financial Management Association annual meeting, the 2018 Financial Management Association annual meeting, the 2018 FIRN annual meeting, and the 2019 American Finance Association annual meeting.

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1. Introduction

The 52 week high price, the highest price a stock has traded for over the prior 365 days, is one of the key pieces of information communicated by the financial press. Perhaps the most salient trading cue for an individual, the 52 week high price can be found on the front page of a Google search, directly under a stock's closing price. Prior research has found increased trading volume near the 52 week high (Huddart et al., 2009), as well as subsequent price continuation (George and Hwang, 2004). We refer to this phenomenon as the 52 week high (52WH) effect. Despite the 52WH effect being robust, the underlying mechanism is not yet known.

There are several proposed causes of the 52WH effect, which stem primarily from individual investor behavior. The key potential explanations are related to the disposition effect, anchoring bias, and expectational errors. First, stocks near the 52WH may be carrying high levels of capital gains overhang (Grinblatt and Han, 2005), and thus as stocks approach the high and accumulate gains they induce selling behavior among prospect theory/disposition effect investors (Hur et al., 2010; An, 2016; Wang et al., 2017). Such investors are keen to sell near the 52WH as the stock is, on aggregate, in the domain of gains (Shefrin and Statman, 1985).

Second, the day of the 52WH may act as a salient attention-grabbing anchor (Aragon and Dieckmann, 2011; Yuan, 2015). For example, 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 disproportionately held by individuals.[1] As the 52WH is widely reported by news outlets, websites, and brokers, it is a prominent anchor for households to refer to. Much like past returns (Barber and Odean, 2007), the 52WH will likely be observed by individuals seeking to sell their holdings.

[1] Tversky and Kahneman (1974) notes 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 volatility. Peng and Xiong (2006) suggest that, due to limited attention, investors will prioritize certain anchors and attention-grabbing events over others.

Third, errors in return expectations may be amplified at the 52WH. In accordance with this, Birru (2015) uncovers that the return forecasts of both analysts and professional investors are driven down for stocks near the 52WH. The error is evidenced by the lowering of analyst price-targets and the increase in earnings surprises as the 52WH is approached. Thus, investors may prefer to sell stocks near the 52WH as they believe that future returns are likely to be lower based on erroneous analyst reports and their own lowered skewness expectations (Blau et al., 2020). In combination of the above factors, there is ample evidence that household investors play a key role in the 52WH effect.

In this paper, we uncover how the preference for individual investors to anchor to the 52WH with limit order selling contributes to, and intensifies, the 52WH effect - volume spikes and post-event predictability. To investigate these phenomena, we use investor-account level data on all trades from the clearinghouse of the Nasdaq Helsinki exchange. This data set allows us to classify traders (institutions or individuals) and executed order types (limit order or market order)[2], at and around the 52WH price. From this, we can see which party is demanding (via a market order) or supplying liquidity (via a limit order) with the corresponding trade price and quantity. The data offers significant advantages over other data sets on the US market, which are comparatively less comprehensive/granular, include only a sub-sample of the market (Odean, 1998), aggregate the data at the weekly level (Kaniel et al., 2008) or use trade size to estimate investor identity (Hvidkjaer, 2008).

Our results shed light on the mechanism through which household anchoring, disposition effect, and expectational errors drive the 52WH effect. We highlight how institutional investors directly benefit from the willingness of individuals to supply liquidity at the 52WH.

First, we document that the 52WH acts as a significant anchor to individual investors; as stock prices approach the 52WH we see an exponential increase in household selling. On an average day, the trade imbalance between households and institutions is 0%; neither group

[2]Similar data is used in other studies to investigate the trading behavior of individual investors solely (Grinblatt and Keloharju, 2001; Linnainmaa, 2010) and with institutions (Stoffman, 2014).

is a net buyer or seller. However, for stocks in the immediate vicinity of the 52WH, we observe a monotonic increase in selling from households to institutions. A stock that opens the day within 3% of the 52WH exhibits a net trade imbalance of −12%. In other words, for every 100 trades between households and institutions when the stock is within 3% of the 52WH, households are the selling party on 56 occasions. When the stock opens at the 52WH (100% of the 52WH price), the net trade imbalance shifts to −31% (i.e., households sell in approximately 65 of every 100 trades). We thus argue that the equity volume spikes identified by Huddart et al. (2009) represent the large-scale transfer of ownership from household to institution.

Second, we find a sharp increase in the use of limit order by households when selling near the 52WH. Conditional on selling, household limit order usage rises from 50% of all household orders when prices are at 97% of the 52WH, to 59% of household orders when at the 52WH price, compared to a baseline of 46% of household orders on non-52WH days. Thus, the 52WH results in an abnormal increase in liquidity provision by households. This supports the finding that uninformed investors prefer to place limit orders when selling (Kaniel and Liu, 2006), and their tendency to cluster limit orders around attention-grabbing or novel prices (Bhattacharya et al., 2012). Our result stands in contrast to the findings of Bian et al. (2018), who observed that individuals increase market order usage (prefer immediacy) as prices increase. On the other hand, we corroborate the findings of Linnainmaa (2010) and Kelley and Tetlock (2013), who document that individuals tend to place latent, unsupervised limit orders at prices that they plan to trade a stock in the future, which in this case offers liquidity to institutional investors.

Stoffman (2014) notes that when institutions and individuals engage in trade with each other, prices move and individuals tend to be on the losing side.Consistent with this finding, Fong et al. (2014) identifies that orders submitted through discount broker channels (presumably, those of individuals) are less informative than those of full-service brokers. As such, we argue that household tendencies to use limit orders when selling, exacerbated at the 52WH, contributes to the continued under-performance of individual investors (Barber et al., 2008).

Third, we find that household selling and limit order use is exacerbated when the 52WH is a more prominent trading cue. For example, when the stock is at a 'new' 52WH (i.e., has not been at the 52WH for seven or more days), net selling by households accounts for close to 70% of their daily trades, and limit orders are employed in 67% of their sells. In addition to supporting the anchoring explanation for the 52WH of Huddart et al. (2009), the result is consistent with the disposition effect (capital gains overhang) explanation of Grinblatt and Han (2005), as new 52WH days offer higher profit-taking opportunities for individuals. The 52WH is also likely to be a more salient anchor in periods of market-wide uncertainty (Kumar, 2009). While households exhibit increased buying in the cross section of stocks during periods of high uncertainty (which we measure using the top tercile of EuroVIX), a stock being at the 52WH does not undergo net household buying. At the 52WH, we also find that households use 11% more limit orders to sell during periods of high uncertainty relative to periods of low uncertainty. The increased household limit order provision arises despite liquidity becoming more expensive (due to increased spreads and adverse selection risks) during periods of high uncertainty.

To remedy the concern that the day of the 52WH is simply a point of high prices or prior returns, rather than a unique event, we undertake a 15-day event study centered on the 52WH day. We show that the 52WH day is the focal point of the high household selling and limit order execution. We observe a 'V' shape pattern in trade imbalance and limit order sales surrounding the 52WH day, after which household behavior returns to pre-52WH day levels. These results are robust to past momentum and stock-specific factors. We repeat the event study for the days in which the stock price reaches the respective 52WH quartile points (0.25, 0.5, 0.75 and 1 (i.e the 52WH)) to test if investors undertake similar anchoring behavior at other values along the 52WH ratio. We detect no evidence of anchoring outside of the 52WH price, supporting its uniqueness to individual investors.

Last, we uncover that limit order selling by individuals significantly contributes to the return continuation following the 52WH. In addition to the 52WH return predicted by George and Hwang (2004), we find that stocks that are in the highest quartile of limit order selling at the 52WH day return an additional 0.8% over the subsequent 90 days, increasing to 1.4% at the 180-day horizon. The post-52WH return is further driven by stocks with high (top-quartile) levels of household limit order selling in the five days leading up to the 52WH day. This build-up of household liquidity results in a marginal 2.1% return at the 180 day level in excess of a regular 52WH. Thus, stocks that households heavily sell, with limit orders at and prior to the 52WH day, generate returns of more than twice those of the 52WH unconditionally. We find these effects when looking at both raw returns and cumulative abnormal returns out to 180 days. We argue that the post-52WH price drift is partly driven by household provision of liquidity, which is capitalized on by institutional investors that benefit from the observed momentum-like return continuation (Edelen et al., 2016).

In summary, we contribute to the literature by identifying a significant contributor to the 52WH effect (volume spikes and post-event returns) as disposition effect and anchoring behavior of individual investors. The preference for households to use limit orders to sell, as identified in prior literature, is sharply increased at the 52WH. Accordingly, stocks with particularly high levels of limit order sales by households at the 52WH earn abnormally positive post-event returns. Together, the tempting opportunity to sell at the 52WH leads to premature and uninformed sells by households, at which point the trading advantage can be taken by institutional investors. Therefore, this paper uncovers another source of the poor performance of individual investors (Barber and Odean, 2000).

This paper proceeds as follows. Section 2 introduces the data and the method used to identify the 52WH and measure investor behavior. Section 3 reports the key findings and discusses their significance in relation to the literature. Finally, Section 4 presents a summary of the results and offers an outline for future research.

2. Data and metrics

To explore how households trade around the 52WH, this study investigates the behavior of individual investors on the NASDAQ Helsinki. The study combines three data sets: investor-level trade data from Euroclear Finland, trade and quote data from HEX and stock level data from Thomson Reuters Datastream database and VSTOXX. First, the investor behavior data is acquired from Euroclear Finland.[3] This data set contains the official records of trades, including price and quantity as well as identifiers that designate trader group identity (households, financial institutions, non-financial corporations, government agencies, non-profit institutions, and foreigners). We remove government agencies, non-profit institutions and foreigners leaving the data set with households and institutional investors. The data include the raw intra-day trades from 1 January 2000 to 31 December 2009[4] on the NASDAQ Helsinki. The data are aggregated to the daily level by group and trading is split into either household or institutional trades; this allows us to observe the interaction between investor classes, as performed by Stoffman (2014). Within-group trading (i.e., household with household) is removed from the main sample, as it is not possible to extract trade direction or trade type from these observations, as well as the Stoffman (2014) claim that within-group trading does not affect prices.

Second, to identify the order submission type, we use the HEX microstructure data. The data is the original supervisory records which contains the complete order submission history for the NASDAQ Helsinki. The records include the price, quantity and time of each respective order, which can be classified as a limit or market order using the Lee and Ready (1991) algorithm. As per Linnainmaa (2010), we combine the Euroclear data with the HEX data to identify the investor class, price, quantity, time and order type of each executed

[3]The Euroclear is responsible for clearing and settlement of all trades within Finland. Finland has a direct holding system in which all holdings are registered with Euroclear, therefore the data is highly accurate and reflective of the entire market. Refer to Stoffman (2014) for a more comprehensive discussion of the data.

[4]The sample ends in 2009 as the Euroclear no longer provides intra-day trading between institutions but rather aggregates the trades due to netted clearing at day's end. Thus, post 2010, we are unable to identify between group trading statistics with the same accuracy.

trade.

Third, in addition to the trade data, we merge the price, volume, and share characteristics obtained from Thomson Reuters Datastream database, and the VSTOXX European volatility index (VIX) value obtained from STOXX for the sample period. The Finnish and U.S. equities markets are similar in their limit order structure with a call market at open and close. The investor trade data conforms to similar literature by Kumar and Lee (2006).

The main advantage of the data is that it includes all trades rather than a sub-sample, which is regularly used in investor behavior studies (Barber and Odean, 2000); as a result, the data comprises millions of investors, thus far stronger identification of market-wide behavior than prior studies. The investors in our sample also exhibit disposition effect trading (Grinblatt and Keloharju, 2000) and anchor to their purchase price, as is the case in the US market (Ben-David and Hirshleifer, 2012), among other behavioral factors. Thus, the behavior of the Finnish investors in the sample is likely to reflect the behavior of U.S. and global investors.

2.1. 52 week high and investor behavior metrics

The focus of the study is on both the 52WH ratio and the 52WH day itself. The 52WH ratio is the ratio of the current stock price to the maximum daily closing price over the previous year. A stock's 52WH RATIO is defined as follows:

$$\text{52WH RATIO}_{i,t} = \frac{\text{PRICE}_{i,t}}{\text{HIGH}_{i,t}} \tag{1}$$

where $\text{PRICE}_{i,t}$ is the stock's price at the close of day t, while $\text{HIGH}_{i,t}$ is the highest daily closing price for stock i over the past year $(t - 365, t)$, where t is measured in calendar days. The ratio therefore represents the nearness, in percentage terms, of the stock's current price to its 52WH price. In addition to the 52WH ratio, we examine investor behavior on days in which the stock's price opens at, or near, the HIGH which we refer to as the 52WHMAX.

To measure the rate and direction of trading between households and institutions, we use a measure of trade imbalance (TRADEIMB) to estimate the relative buying of stock i on day t by households when trading with institutions.

$$\text{TRADEIMB}_{i,t} = \sum_{i=1}^{n} \frac{\text{VOL\_BUYS}_{i,t} - \text{VOL\_SELLS}_{i,t}}{\text{VOL\_BUYS}_{i,t} + \text{VOL\_SELLS}_{i,t}}, \tag{2}$$

where $\text{TRADEIMB}_{i,t}$ is the household's trade imbalance in stock i on day t, $\text{VOL\_BUYS}_{i,t}$ is the volume of buys and $\text{VOL\_SELLS}_{i,t}$ is the volume of sells in stock i on day t by households. Intuitively, this measure offers a daily ratio of the relative direction and intensity of trade in a given stock between households and institutions. The value of $\text{TRADEIMB}_{i,t}$ is bound between -1 and $+1$, where larger positive values indicate a greater share of buying by households relative to institutions. For example, a TRADEIMB of -0.5 corresponds to households selling two units for every one they are purchasing of a given stock on a given day. As this includes only between-group trading, we do not report the corresponding measure for institutions.

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, taking rate sells (TRS) to determine the relative number of market order sells relative to total sell orders by households.

$$\text{TRS}_{i,t} = \frac{\text{MARKET\_ORDERS}_{i,t}}{\text{MARKET\_ORDERS}_{i,t} + \text{LIMIT\_ORDERS}_{i,t}}, \tag{3}$$

where $\text{MARKET\_ORDERS}_{i,t}$ is the volume of executed market orders sells while $\text{LIMIT\_ORDERS}_{i,t}$ is the volume of executed limit order sells by households in stock i at day t when the counterparty are institutions. The measure $\text{TRS}_{i,t}$ takes values between 0 and 1, with smaller magnitudes indicating a stronger preference for limit orders when selling. For example, a TRS of 0.4 means that households are executing six limit order sells for every four market order sells of a given stock on a given day. We also report BETWEEN_TURNOVER which is the ratio of household to institutional volume relative to total volume, as well as INSTO_TURNOVER and HH_TURNOVER which is the ratio of institution to institution and household to household volume relative to total volume, respectively.

3. 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; we report these in Table 1. We see that, across the sample, the TRADEIMB between groups is near zero; thus on any given day, households on aggregate are neither net buyers nor sellers to institutions. Next, we observe the household tendency to use limit orders to sell, as measured by TRS. The mean TRS is 0.52, which (by being greater than 0.50) shows that households are slightly more likely to use market order when selling to institutions in general. The proportion of volume from between group trades, BETWEEN_TURNOVER, is 54%; therefore, the interaction between households and institutions will likely have consequential effects on the market. Next, INSTO_TURNOVER (institutional trades with institutions) accounts for just 14% of turnover, while HH_TURNOVER (household trades with households) accounts for approximately 30% of all volume, which is similar to the rate found by Kumar and Lee (2006) in the U.S. market (approximately 24%).

[Begin Table 1 here]

3.1. The 52 week high ratio

Our first analysis is to determine the general effect of the 52WH price on household trading behavior. To do so, we sort stocks into deciles based on their 52WH RATIO, ascending from furthest to nearest the 52WHMAX. Table 2 and Figure 1 report the metrics for household behavior (TRADEIMB and TRS) sorted into deciles of nearness to the 52WH. Stocks closer to the 52WH exhibit negative TRADEIMB, indicating that households are net sellers, and TRS values of less than 0.5, indicating that households are more likely to use limit orders when selling. The stocks in decile 10 (closest to the 52WH) show a TRADEIMB of -0.248, which indicates that households are the selling party in 62.5 of every 100 trades between households and institutions. When selling, the TRS value of 0.462 for decile 10 stocks indicates that households use market orders on 46.2% of occasions (or use limit orders on 53.8% of occasions). In contrast, stocks far from the 52WH exhibit positive TRADEIMB and values of TRS greater than one-half. Moreover, there is a monotonic decrease in TRADEIMB by decile of nearness to the 52WH. Thus, there is a greater magnitude of net selling by households the closer the stock is to the 52WH. Order types when selling favor limit orders for the top two deciles of nearness to the 52WH, otherwise households exhibit a slight preference for market orders.

Table 2, panel b, reports the near 52WH decile is a statistically significant 41.1% lower than the far 52WH decile in TRADEIMB, indicating substantially higher selling by households to institutions. This supports the expectation of Grinblatt and Han (2005) whereby the likelihood that households will sell a stock increases as it begins to accumulate capital gains by increasing in price. The difference in the top two deciles (Near - 9) shows a drop of 0.122 in TRADEIMB (a near 100% change), supporting the notion that proximity to the 52WH exacerbates the household willingness to sell to institutions.

[Begin Table 2 here]

In Table 2, panel b, we also find a statistically significant decrease in the value of TRS for both the Near - Far deciles, an 8.4% decrease, and the Near - 9 deciles, a 3% decrease. As the TRS is relatively stable across the 52WH deciles up until the 52WH, the findings provide preliminary support for the expectation that households use limit orders to anchor their selling to the 52WH price. This stands in contrast to the results of Bian et al. (2018), who find that households increase their use of market orders as a stock's price rises.

3.2. The 52 week high day

Having observed that individual investors are sensitive to the general effect of the 52WH RATIO, we next explore investor behavior on the days in which the stock opens at, or within, specific percentage ranges near the 52WH price. If the 52WH is an important cue for individual investor decision making, we expect its anchoring influence to increase as the exact 52WH price approaches. In Table 3, we report the investor behavior metrics (TRADEIMB and TRS) and mean-comparison tests for stocks above 95% of the 52WH RATIO. In Table 3, panel a, we report TRADEIMB for increasing thresholds of the 52WH RATIO, with rows of the panel indicating stock-day combinations of a 1% band. For instance, the row labeled [0.95, 0.96) highlights stocks trading between 95 and 96% of their 52WH price, which exhibit a mean trade imbalance of −0.076. As the proximity to the 52WH increases, the value of TRADEIMB declines monotonically, ultimately reaching −0.311 for firms at the 52WH (at 1.00 × 52WH RATIO). The convex pattern we observe in TRADEIMB as the threshold narrows demonstrates the influence of the anchor 52WH price.

To test significance of the difference in the TRADEIMB metrics by percentage bands, Table 3, panel b, reports the results of pairwise comparisons of TRADEIMB by 52WH RATIO. This allows us to determine (for example) whether the TRADEIMB for stocks between 0.96 and 0.97 × 52WH (estimated as −0.104) is significantly different from that at other percentage bands of the 52WH RATIO. The results indicate that the differences observed in TRADEIMB at the thresholds of [0.99, 1.00) × 52WH are significant relative to those at the thresholds of [0.98, 0.99) × 52WH or lower. There is similarly significance when comparing stocks opening at the 52WH (1.00) with those that open within 1% of, but not at, the 52WH (−0.123). The 52WH itself is significantly lower in TRADEIMB than all percentage bands <1.00, thus the 52WH provides additional impetus for investors to sell in excess of high nominal prices generally.

[Insert Table 3 here]

Continuing the investigation into the effect of the 52WH RATIO on investor behavior, in

Table 3, panel c, we report average values of TRS by percentage bands of the 52WH price. For prices below a 52WH RATIO of 0.98, individuals exhibit a slight preference towards using market orders to sell (as TRS values are greater than 0.5). A dramatic decline in the use of market orders to sell is observed for stocks trading above a 52WH RATIO of 0.99, at which point TRS drops below 0.467.

Table 3, panel d, tests the differences between TRS values for the percentage bands of the 52WH RATIO. The results show that there is a significantly higher tendency to use limit orders when selling for stocks trading above a 52WH RATIO of 0.97 (compared with days when the stock is below this value). The significance of the two bottom-right entries of Table 3, panel d (-0.031 and -0.055), as prices move from 52WH RATIOs of 0.98 to 0.99 to 1.00, indicates that there is an exponential pattern to the increasing use of limit orders with proximity to the 52WH. The anchoring effect of the 52WH thus not only appears to impact the decision to sell by individuals, but their order submission strategies.

The results corresponding to Table 3, panels b and d, are shown graphically in Figure 2. We plot the difference in TRADEIMB and TRS for stocks with a 52WH RATIO in excess of 0.95 (in 1 % bands) and those with a 52WH RATIO below 0.95 (as reported in the first columns of panels b and d of Table 3). The convex pattern in the two metrics is apparent and supports the role of anchoring in excess of the disposition effect.

[Insert Figure 2 here]

We further test if making the 52WH more prominent increases its usage as an anchor by households. We do this by introducing, similarly to Huddart et al. (2009), a NEW52WH. We explore the idea of the new 52WH by identifying stocks that are within 1% of (or at) the 52WH price (i.e., [0.99, 1.00]) and have not been within 1% of the 52WH in the last 7, or 14, calendar days. For example, we recognize the NEW7 if a stock opens the day within 1% of the 52WH price and has not been within 1% of the 52WH price within the prior 7 days. This allows for a distinction between high-momentum stocks that are continually increasing in price and forming consecutive 52WH prices (as indicated by 52WHMAX) and those that have just broken through and established a NEW52WH.

In Table 4, we report descriptive statistics for TRADEIMB and TRS, and the results of the pairwise comparison tests between Non 52WH days; days at which the stock is within 1% of the 52WH (52WHMAX) and the NEW52WH specifications (NEW7 and NEW14). In support of our expectation, we see that the TRADEIMB is lower for the NEW7 (-0.393) and the NEW14 (-0.313) relative to the 52WHMAX (-0.192). When comparing directly in Table 4 panel b, all measures of the 52WH day are statistically significant and negative relative to Non 52WH days. NEW7 and NEW14 both exhibit greater magnitudes of household selling (more negative TRADEIMB, -0.202 and -0.122, respectively) than the average 52WH day.

We next test the effect of the NEW52WH on TRS within Table 4, panels c and d. We uncover a strong increase in household limit order selling at all specifications of the 52WH relative to Non 52WH days. A stock being at the 52 week high for some time increases the tendency for households to use limit orders to sell. For example, on the NEW7, market orders account for 33.7% (limit orders account for 66.3%) of household sales. In Table 4, panel d, we observe the marginal effect of newness on the 52WH through the pairwise comparison tests. The increase in the proportion of limit orders used when selling is significant for both NEW7 and NEW14, relative to the average 52WH (TRS of -0.115 and -0.097, respectively). Thus, the increased salience from a NEW52WH (one that has not occurred for a week or more) intensifies household selling, with limit orders. This supports the result of Huddart et al. (2009), who showed that the longer the time since the 52WH, the greater the trading volume.

[Insert Table 4 here]

When prices are more uncertain, individuals are more likely to rely on cues or signals to make their trading decisions(Tversky and Kahneman, 1992; Kumar, 2009). We take the 20-day moving average of the market-wide volatility index (VIX) to determine if general uncertainty marginally affects the household behavior metrics, TRADEIMB and TRS. Taking the entire time period from 2000-2009, we sort across trading days by the EuroSTOXX volatility index (labeled simply as VIX) into terciles, which we define as LOWVIX, MEDVIX and HIGHVIX.[5] Table 5 reports descriptive statistics and pairwise comparisons for stocks within 1% of the 52WH price, conditional on the VIX tercile. For example, stocks that are at the 52WH during a day which is in the highest tercile of VIX are labeled as HIGHVIX 52WH MAX.

In Table 5, panels a and b, we do not find a significant change in TRADEIMB for stocks at the 52WH during periods of HIGHVIX, relative to the other two periods. There is a slight increase in the tendency of households to sell in MEDVIX periods, compared with LOWVIX periods (a difference of -0.028), although it appears that market-wide uncertainty does not systematically increase the selling behavior of individuals at the 52WHMAX.

We examine TRS conditional on periods of VIX in Table 5, panel c and d. We see a monotonic decrease in TRS for stocks at the 52WHMAX as volatility increases from the low to high VIX tercile. Market-wide uncertainty thus appears to increase the use of limit orders by households when selling at the 52WH. The difference in TRS between LOWVIX and MEDVIX periods is 0.068, with a further 0.044 difference between MEDVIX and HIGHVIX periods. Conditional on selling at the 52WH, individuals are much more likely to use limit orders during periods of high uncertainty. Thus, volatility does not spark an increase in general selling, but it does however result in individuals using limit orders to anchor directly to the price. This finding is also of interest as during periods of uncertainty liquidity provision tends to be more costly, due to either increased spreads or higher adverse selection costs (Linnainmaa, 2010). By providing liquidity in an order book during periods of high uncertainty, households are arguably adding a more valuable option to other traders in the market (Nagel, 2012).

[5] We have taken the entire sample period in determining thresholds for the three VIX-related variables. An alternative approach would be to find an abnormal VIX relative to a rolling average. Our findings are qualitatively similar using such a procedure.

Overall, the initial sorts and pairwise comparisons show strong support for our expectation; households sell (with limit orders) at the 52WH. This behavior becomes significantly stronger if the anchor becomes more salient with both prominence (NEW52WH) and uncertainty (MEDVIX and HIGHVIX).

[Insert Table 5 here]

3.3. Investor behavior regressions

Next, we conduct a series of regressions of household trade imbalance and abnormal household trade imbalance on variables related to the 52WH. To do so, we run regressions examining the tendency of households to sell, with limit orders, at the 52WH. This allows us to examine the influence of the price anchor on household trading decisions. We employ a set of regressions with household trade imbalance (TRADEIMB) from equation 2 and abnormal household trade imbalance (AB_TRADEIMB), which we define as the TRADEIMB less the lagged 90-day stock level TRADEIMB, as dependent variables. The variable AB_TRADEIMB allows us to examine the selling propensity of households relative to the recent activity in the stock, which may be higher than usual due to recent price increases. Our independent variables of interest are 52WHMAX (reflecting the stock being within 1% of the 52WH) and NEW7, alongside HIGHVIX and an interaction between HIGHVIX and 52WHMAX. Respectively, this allows us to investigate whether selling intensity by households is significantly increased at the 52WH, if this selling is exacerbated by a new 52WH, and if household selling activity spikes during periods of market uncertainty, generally and at the 52WH. We include a set of control variables that have been found to influence household selling behavior (Bian et al., 2018), these include past returns, market capitalization, market and firm-specific volatility, and stock price.

$$\begin{aligned}\text{TRADE}_{i,t} = {} & \beta_0 + \beta_1 52\text{WHMAX}_{i,t} + \beta_2 \text{NEW7}_{i,t} \\ & + \beta_3 \text{HIGHVIX}_{i,t} + \beta_4 \text{HIGHVIX}_t \times 52\text{WHMAX}_{i,t} \\ & + \text{Controls}_{i,t} + \epsilon_{i,t},\end{aligned} \tag{4}$$

where the dependent variable $\text{TRADE}_{i,t}$ is a vector of household trade metrics, either: $\text{TRADEIMB}_{i,t}$ is the daily ratio of household net buying with institutional investors in stock i on day t, or $\text{AB\_TRADEIMB}_{i,t}$ is the daily $\text{TRADEIMB}_{i,t}$ less the average 90-day lagged stock level $\text{TRADEIMB}_{i,t}$ in stock i on day t. The independent variables in the regression are as follows: $52\text{WHMAX}_{i,t}$ is an indicator variable with a value of one, if the stock i price opens day t within 1% of the 52WH price, zero otherwise. $\text{NEW7}_{i,t}$ is an indicator variable with a value of one, if the stock i price opens day t within 1% of the 52WH price and has not been at the 52WHMAX in the 7 calendar days prior, zero otherwise. HIGHVIX_t is an indicator variable that has a value of one, if the lag 20 day average EuroVIX index value is in the highest tercile on day t, over the sample, zero otherwise. The regressions include the following controls: $\text{JTMOMHIGH}_{i,t}$ is similar to Jegadeesh and Titman (1993) momentum measure in which it is an indicator variable that has a value of one, if the lagged 90 day stock return is in the highest tercile on day t, zero otherwise. $\text{MKTCAP}_{i,t}$, which is the market capitlization of the stock in 100 millions of euros. VIX_t is the average value for the EuroVIX index for the prior 20 trading days. $\text{PRICE}_{i,t}$ is the closing price of the stock i on day t. $\text{RISK}_{i,t}$ is the lag 20 day average standard deviation of returns in the stock i on day t. The regressions include fixed effects for the firm and year level and the standard errors are clustered as per White (1980).

The results of the regressions are presented in Table 6. In Model I, we examine the effect of the 52WHMAX price on TRADEIMB. The coefficient of −0.212 indicates that household selling increases by 21% when a stock is at the 52WH. This effect holds after controlling for JTMOMHIGH, which identifies high momentum stocks, suggesting that disposition effect style selling is expected, but does not take away from the anchored selling seen at the 52WH. In Model II, we see an intensified impact on household selling when the stock is at a new 52WH. The coefficient for NEW7 of −0.286 is an increase of around 35% from the unconditional value of 52WHMAX from Model I. Thus, newness of the 52WH further drives household selling. In Model III, we find that high levels of the VIX index tend to lead to household buying, but that this effect is offset when stocks are at the 52WH. Thus, we do not observe increased household selling at the 52WH in periods of high VIX relative to periods of lower levels of uncertainty, but the typical household purchasing is reduced by the price anchor. In Models IV-VI, we employ AB_TRADEIMB as the dependent variable within the regression. These tests show that, even relative to stock-specific factors that may drive household trade imbalance, the 52WH influences household selling decisions. Abnormal household selling increases by 13% at the 52WH, relative to non-52WH days from Model IV, for example. We find, overwhelmingly, even when controlling for factors that typically drive the intensity of household selling, the 52WH still represents a crucial decision-making cue.

[Insert Table 6 here]

To determine if households increase their propensity to use limit orders when selling at the 52WH, we repeat the above regression protocols with TRS and AB_TRS as the dependent variables, where AB_TRS is TRS less the average level of limit order usage in a stock over the preceding 90 days.

$$\begin{aligned}\text{LIMIT}_{i,t} = \beta_0 &+ \beta_1 \text{52WHMAX}_{i,t} + \beta_2 \text{NEW7}_{i,t} \\ &+ \beta_3 \text{HIGHVIX}_{i,t} + \beta_4 \text{HIGHVIX}_t \times \text{52WHMAX}_{i,t} \\ &+ \text{Controls}_{i,t} + \epsilon_{i,t},\end{aligned} \tag{5}$$

where $\text{LIMIT}_{i,t}$ is a vector of household limit order selling variables. $\text{LIMIT}_{i,t}$ is either $\text{TRS}_{i,t}$, the ratio of market order sells relative to total sell orders by household for stock i on day t that are executed against institutional investors, or $\text{AB\_TRS}_{i,t}$ the daily $\text{TRS}_{i,t}$

less the average 90-day lagged stock level $\text{TRS}_{i,t}$ in stock i on day t. Other interaction and control variables are as defined in regression equation (4). The regressions include firm and day fixed effects, and adjust standard errors as per White (1980) .

The results for the regressions are presented in Table 7. In Model I, we find that the 52WHMAX results in a significant increase in limit order usage by households (with a coefficient for 52WHMAX of -0.110), supporting the idea that households increase their tendency to use limit orders when selling at the 52WH. Complementary to the findings reported in Table 4, panel c, a stock being at the 52WH leads households to switch from market orders to limit orders when selling. Prior returns, as controlled for with JTMOMHIGH, also increase the tendency for households to use limit orders when selling, but this effect is dwarfed by the 52WH effect. In Model II, we see an even greater tendency to use limit orders when selling at a new 52WH, with an approximate 60% increase (i.e., -0.110 to -0.175) in TRS for NEW7 compared with the 52WHMAX. Household limit orders are particularly likely to be utilized when a new 52WH is reached, consistent with the theory of latent limit order submission (Linnainmaa, 2010). In Model III, we augment the 52WHMAX specification from Model I with an indicator variable for HIGHVIX and an interaction between HIGHVIX and NEW52WHMAX. Both the additional factors increase the level of limit order usage by households. During periods of high uncertainty (when the variable HIGHVIX takes a value of one), households tend to prefer to use limit orders when selling, an effect which is exacerbated by a stock being at the 52WH. Combined, the effect of high levels of uncertainty is to increase the level of limit order usage (although not the tendency to sell, as seen in Table 6).

Within Models IV-VI, we use AB_TRS as the dependent variable. Similar effects as to the corresponding specifications I-III are observed. A stock trading at the 52WH exhibits a substantial increase in the household's use of limit orders when selling, and this effect is particularly pronounced for new 52WHs and in periods of high uncertainty. The findings from Table 7 support the univariate results, showing that households increase their usage of limit orders when selling at the 52WH. Our finding stands in contrast to the findings of Bian et al. (2018), who find that past returns are positively related to the demand for market orders. Our results specifically show that the anchor of the 52WH drives household order submission strategies.

Overall, the investor behavior regressions reinforce the role of individual investors as drivers of the volume spikes at the 52WH. First, households are sensitive to the 52WH as a trading cue, around which they anchor their limit order selling. These results provide evidence that the selling behavior observed by Huddart et al. (2009) at the 52WH is as a result of direct and latent limit orders placed at the 52WH (Linnainmaa, 2010; Kelley and Tetlock, 2013; Bhattacharya et al., 2012).

[Insert Table 7 here]

3.4. Event analysis: around the 52 week high day

Having identified the importance of the 52WH day, we next explore investor behavior in the days before and after the high. We do this for two reasons. Firstly, we aim to ensure that the 52WH day itself is the novel event, rather than just the approximate time period when the price is high. Secondly, it allows us to investigate the behavior of investors prior to, and following, the high. Given the 52WH may be relatively predictable, as the price of a given stock rises in the days prior, we expect that household investors begin acting in anticipation of the 52WH.

To undertake the analysis, we employ an event study methodology with a time frame of $t-7$ to $t+7$ trading days around the 52WH price being reached, specifically when a stock commences a day's trade within 1% of the 52WH. We estimate the coefficients of regressions of TRADEIMB and TRS on 52WHMAX and NEW7 each day from $t-7$ to $t+7$. Figure 3 plots the coefficients of the regressions of investor behavior seven days either side of the 52WH day, with Figure 3, panels a and b, showing the coefficients from the TRADEIMB regressions on 52WHMAX and NEW7, respectively. Figure 3, panels c and d, plot the coefficient from the TRS regressions on 52WHMAX and NEW7, respectively. Ninety-five percent confidence intervals are overlaid on the parameter estimates.

For each day $t + k$ between $k = -7$ and $k = +7$, we run separate regressions of the following type, where $t = 0$ is the day of the 52WH, and $\text{HHTRADE}_{i,t}$ is either TRADEIMB or TRS in stock i on day t

$$HHTRADE^k_{i,t} = \beta^k_0 + \beta^k_1 \text{52WHIND}_{i,0} + Controls_{i,t} + \epsilon^k_{i,t}, \tag{6}$$

where $\text{52WHIND}_{i,0}$ denotes either 52WHMAX or NEW7, and the control variables are as defined in regression equation (4), they include past momentum returns, market capitalization, market volatility, nominal price, and stock volatility. . We include firm and day fixed effects, and adjust standard errors as per White (1980) to produce our confidence interval estimates. The coefficient of β^k_1 is the variable of interest, which we plot in the columns of each panel of Figure 3.

In Figure 3, panel a, we observe a consistent below-average (i.e., less than zero) TRADEIMB at and around the 52WH day. This result remains despite controlling for prior momentum-like returns, which could induce disposition effect style selling. From $t-4$, or four days prior to the 52WH being reached, to the 52WH day, a significant increase in household selling occurs. Following the 52WH day, there is a sharp rebound in TRADEIMB, and household selling is significantly lower on day $t + 1$ than the 52WH day. In Figure 3, panel b, we examine how the TRADEIMB varies around the NEW7. Here, there is a larger jump in household selling from day $t - 1$ to day t, indicative of a larger surprise. The rebound in TRADEIMB following a new 52WH is slower than average, taking an average of three days to return to pre-52WH levels.

We observe a very similar 'V' shaped pattern for household limit order selling (TRS) in Figure 3, panel c. Limit order selling increases in the week leading up to, and peaks at, the 52WH day, reverting within five days post the 52WH to its average level. Limit order selling around a NEW52WH, from Figure 3, panel d, appears as much more of a surprise than for the average 52WH, and only slightly differs from its average level on the immediate day preceding the 52WH. Thus, it is clear that the 52WHMAX and the NEW7 are the unique points of interest rather than our findings reflecting a state of general high nominal prices.

[Insert Figure 3 here]

3.5. Event analysis: 52 week high quartiles

To further remedy the concern that the 52WHMAX is one of many nominal points on the 52WHRATIO that investors anchor to, we undertake a placebo test by considering alternative threshold percentiles of the 52WHRATIO spectrum. This provides a test of whether the observed effect at the 52WH is replicated at 52WHRATIO values of 0.25, 0.50, and 0.75. If investors are motivated to trade at quartiles of the 52WH, then similar findings should be obtained. We plot 14 days of investor behavior around when the exact 52WHRATIO quartiles (0.25, 0.50, 0.75 and 1.00) are reached. We select the quartile points to act as counterfactual to see if investors anchor to different nominal values of the 52WHRATIO. As in the prior regressions, we control for past returns to account for the disposition effect primarily driving the results.

To observe the counterfactual, for each day $t+k$ between $k=-7$ and $k=+7$, we run separate regressions of the following type, where $t=0$ is the day in which the stock is at the precise 52WHRATIO quartile, and $\text{HHTRADE}_{i,t}$ is either TRADEIMB or TRS in stock i on day t

$$HHTRADE^{k}_{i,t} = \beta^{k}_{0} + \beta^{k}_{1}\text{52WHQUARTILE}_{i,t,q} + Controls_{i,t} + \epsilon^{k}_{i,t}, \tag{7}$$

where $\text{52WHQUARTILE}_{i,t,q}$ is an indicator variable which takes a value one, if stock i on day t opens the day at the respective 52WHRATIO quartile q, which are at the specified values (0.25, 0.50, 0.75 or 1). The control variables are as defined in regression equation 4. We include firm and day fixed effects, and adjust standard errors per White (1980). As in regression 6, the coefficient of β_1^k is the variable of interest, which we plot in each panel of Figure 4.

In support of our claim that the 52WHMAX is unique, in Figure 4, panel a, across the period we observe flat and mostly positive coefficients of TRADEIMB for the 0.25, 0.50 and 0.75 52WHQUARTILEs. This is in stark contrast to the behavior of individuals around the '1' 52WHQUARTILE i.e. the 52WHMAX. Figure 4, panel b plots the coefficient of TRADEIMB for each of the 52WHQUARTILEs, in which the results hold when controlling for stock-specific factors and, importantly, past stock gains.

Figure 4, panels c and d, plot the TRS values for the 52WHQUARTILEs. TRS is relatively neutral or marginally positive, indicative of net market order usage when selling, over the two-week period for the 0.25, 0.50 and 0.75 quartiles. Meanwhile there is a sharp 'V' shape pattern centering on the day of the 52WHMAX. The lack of any noticeable pattern for TRS for the non 52WHMAX quartiles (0.25, 0.5 and 0.75) strengthens the claim that the 52WHMAX is a unique anchor point which household investors rely on to make selling decisions and is not solely a feature of past returns[6].

[Insert Figure 4 here]

3.6. Post 52 week high returns

Birru (2015) finds that the 52WH acts as a psychological barrier for investors, leading to expectational errors[7] and under-reaction to positive news at the 52WH. The implication is that households expect the 52WH price to be the maximum potential price that a given stock can reach. If households exhibit anchoring bias, the disposition effect, or expectational errors, the cost would be borne in terms of post-event returns following the 52WH (George

[6]The regressions were also completed with high and low momentum as the variable of interest. We did not observe a 'V' shape or investor behavior intensifying around the event day for either TRADEIMB or TRS, further ruling out momentum as a possible explanation or as a similar phenomenon to the 52WH.

[7]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, that is, they are more prone to errors in forecasting.

and Hwang, 2004), which reflect forgone profits on account of their selling. In addition, we test if high levels of household limit order selling at, and leading up to, the 52WH intensify post-event returns, as predicted by Stoffman (2014). Prior research (Avramov et al., 2016) has documented a positive link between liquidity and momentum returns.

We aim to quantify the household contribution to this effect using regressions on the 90- and 180-day cumulative raw returns (RT) and cumulative abnormal returns (CAR), respectively, against the 52WH and investor behavior metrics. We introduce variables that reflect the level of household limit order selling in the five-day period prior to the 52WH day. For the average 52WH, we see a steady increase in household limit order usage in the lead-up to the 52WH. As such, the counterparty to household trades at the 52WH would have been able to extract liquidity in the lead-up to the day itself. On the other hand, for new or unexpected 52WHs (such as that seen in Figure 3, panel d), there is a spike in household limit order usage at the 52WH. Here, a counterparty would have been less able to extract liquidity in the lead-up to the event.

We construct the indicator variable $\text{TRSLOW}_{i,t}$ which takes a value of one for stock-day cases in the lowest quartile of household limit order selling. In this scenario, households provide more liquidity to counterparties on the 52WH day (lower values of TRS indicate more liquidity provision by households). If household liquidity provision creates trading opportunities for institutional investors, TRSLOW should be positively related to post-52WH returns. We construct a second variable $\text{LAGTRSLOW}_{i,t}$, which takes a value of one for stock-day cases in which the average of TRS over days $t-5$ to $t-1$, is in the lowest quartile. In cases where TRSLOW takes a value of one, households have supplied a relatively high amount of liquidity (submitted a larger proportion of limit orders than normal) in the previous five days.[8] We then interact our 52WH indicator variable (52WHMAX) with household liquidity supply variables (TRSLOW and LAGTRSLOW) to determine whether

[8]Arguably, an institution may not be able to predict which stocks will exhibit high levels of household liquidity supply on the 52WH day. However, LAGTRSLOW is observable prior to day t, and is potentially available to institutional investors.

the willingness of households to supply liquidity at the 52WH intensifies post-52WH returns.

To examine the returns, we estimate the following regression:

$$\begin{aligned} \mathrm{RETURNS}_{i,[t,t+j]} = \beta_0 + \beta_1 \mathrm{52WHMAX}_{i,t} + \beta_2 \mathrm{TRSLOW}_{i,t} + \beta_3 \mathrm{LAGTRSLOW}_{i,[t-5,t-1]} \\ + \text{interactions} + \text{controls} + \epsilon_t, \end{aligned} \tag{8}$$

where $\mathrm{RETURNS}_{i,[t,t+j]}$ denotes either the raw cumulative return (RT) or the cumulative abnormal return (CAR), which is the daily raw return less the daily market return, from day t to day $t+j$. In the regressions j takes the value of either 90 or 180 days. $\mathrm{52WHMAX}_{i,t}$ is an indicator variable that has a value of one if the stock i is within 3% of the 52WH price at the open of day t, zero otherwise[9]. $\mathrm{TRSLOW}_{i,t}$ is an indicator variable that has a value of one, if TRS in stock i is in the lowest quartile on day t, zero otherwise. $\mathrm{LAGTRSLOW}_{i,[t-5,t-1]}$ is an indicator variable that has a value of one if the lag 5 day average TRS in stock i is in the lowest quartile on day t, zero otherwise. The controls include: $\mathrm{MKTCAP}_{i,t}$, which is the market capitalization of the stock in 100 millions of euros. $\mathrm{LAGRETURN}_{i,t}$, which is the lagged raw return of stock i for the prior 90 days.

[Insert Table 8 here]

The results of regressions are presented in Table 8. Consistent with the observations of George and Hwang (2004), the 52WHMAX leads to future positive returns at the 90 and 180 day horizons. From Table 8, panel a, Model I, for instance, we estimate an excess return of 2.2% at the 90 day horizon for stocks at the 52WH. We next observe the effect of TRSLOW unconditionally in Model II. When households are selling primarily with limit orders, where TRSLOW takes a value of one, returns average an excess of 0.7% over the following 90 days. Substantial household limit order selling is thus a positive predictor of future returns, on aggregate. In Model IV, we find that stocks in the top quartile of household limit order

[9] We use the 3% threshold in the regressions to increase the sample of 52WH observations. Qualitatively similar results are obtained using 1% and 0.01% thresholds for the 52 week high price.

selling in the previous five days do not exhibit unconditional lead returns.

Our main findings come from interacting stocks with high levels of household limit order selling with those at the 52WHMAX. In Model III, for instance, both 52WHMAX and TRSLOW contribute positively to future returns. The interaction term 52WHMAX × TRSLOW increases the 52WHMAX return by an additional 85%. Thus, the 52WH effect appears to be intensified in stocks with high levels of household limit order usage. In Model V, we see that high levels of household limit order usage in the lead-up to the 52WH, proxied by LAGTRSLOW, enhances the 52WH return strategy with a similar magnitude to TRSLOW. In Model VI, TRSLOW and LAGTRSLOW as well as interactions with 52WHMAX are used as independent variables. Both the household limit order usage variables are significant in forecasting future returns. The result suggests that household liquidity supply in the lead-up to, and on the day of, the 52WH intensify post-52WH returns. Based on the size of the estimated coefficients, a stock that is at the 52WH, and in the top quartile of both household limit order use variables would earn more than two and a half times the additional return (adding up the coefficients involving TRSLOW and LAGTRSLOW) than other stocks at the 52WHMAX.

In Table 8, panel a, Model VII - XII, we re-examine the results at the 180-day horizon. If the effect was driven purely by short-term household liquidity supply, we might expect to see a reversal of the returns between the 90- and 180-day period. However, the returns at the 90-day horizon are largely consistent with the 180-day returns. For instance, in Model VII, the 180-day excess lead return for stocks at the 52WH is 2.5%, not growing substantially above than the 90-day return. Stocks with high levels of limit order use by households exhibit even larger increases in returns between the 90 and 180-day horizons. From Model IX, for example, the coefficient of 0.031 on 52WHMAX × TRSLOW at the 180-day horizon is almost 50% larger than the corresponding coefficient at the 90-day window. Stocks with a relatively high level of household limit order usage therefore appear to be particularly profitable when purchased at the 52WHMAX. A lack of reversal over the 180-day horizon indicates that systematic household limit order use when selling is positively related to future returns. Grinblatt and Han (2005) argue that excessive household selling may artificially depress prices at the 52WH, leading to post-52WH drift. Our finding is consistent with household liquidity provision enabling institutions to open up momentum-like positions (Edelen et al., 2016) relatively cheaply.

We next test in Table 8, panel b, the effect of the 5WHMAX on CAR over the subsequent 90- and 180-day periods. Similarly to the RT regressions, we observe that the 52WHMAX is positive at the 90- and 180-day level. However, there is some mean-reversal in the 52WHMAX at the 180-day CAR. Mean reversal can be seen as the 52WHMAX coefficient in Model I (0.021) is larger than the 52WHMAX coefficient for the 180-day CAR in Model VII (0.018). Moreover, this mean reversal does not exist during periods of high household limit order selling at the 52WHMAX. In Model III and Model V, we see that TRSLOW × 52WHMAX and LAGTRSLOW × 52WHMAX lead to positive 90-day CAR of 0.014 and 0.015, respectively. Showing no signs of mean reversion out to 180 days, both TRSLOW × 52WHMAX and LAGTRSLOW × 52WHMAX lead to an additional 50% higher return relative to the 90-day return. When including both contemporaneous and lagged TRS at the 52WHMAX in Model VI and X, we see that LAGTRSLOW × 52WHMAX leads to a positive and significant future return. This supports the claim that liquidity build-up prior to the 52WHMAX is driving a substantial portion of the future CARs at the 90 and 180 day level. The findings in Table 8, panel b, support the claim that increased household limit order selling at, and prior to, the 52WH effectively double the unconditional 52WHMAX post-event returns.

Overall, the results support our expectations that households suffer, in the form of post-event returns, due to their anchoring behavior (Barber et al., 2008). Moreover, the post-52WH returns are intensified by household liquidity provision. The disposition effect, anchoring, and the placement of unsupervised limit orders (Kelley and Tetlock, 2013) by households allow counterparties to open up momentum-like positions that, in turn, generate significantly higher post-52WH returns and help to explain the continual under-performance of household investors.

4. Conclusion

This study exploits a rich data set from the NASDAQ Helsinki to examine how individual investors contribute to the 52WH effect. We investigate the behavior of household investors at and around the 52WH price; in particular, the trade direction, order submission type and the subsequent price movements.

We uncover that individual investors undertake disposition effect-style behavior, selling winners and anchoring around the 52WH price. They do so with latent limit order selling, which is intensified if the 52WH becomes more prominent, either due to newness or volatility. We highlight, through an event study, that the 52WH day is in fact the unique point of interest. We show that household limit order selling drastically increases leading up to, and on, the 52WH day, then recedes back to normal levels soon after. We also exhibit the 52WH is unique, as we do not find similar investor behavior at other quartile points of the 52WH ratio.

We further contribute to the literature by showing that the 52WH post-event momentum-like returns are intensified by household limit order sells placed at, and five days prior to, the 52WH. This behavior directly benefits institutional investors, which are the counter-parties to the observed trades. As a result of this bias, households provide liquidity for other investors to open up momentum-like positions that generate more than double the unconditional post-52WH returns seen over a subsequent 180-day period.

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 drivers of individual investor behavior and their tendency to provide liquidity, particularly around anchors and attention-grabbing events.

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Table 1

Investor behavior descriptive statistics

This table reports the descriptive statistics for the investor behavior metrics. For each daily observation the mean, standard deviation, 25th percentile (25th Pctl), median and 75th percentile (75th Pctl) are reported. TRADEIMB is the daily ratio of household net buying with institutional investors (INSTO). TRS is the ratio of household market order usage when selling to institutions. BETWEEN_TURNOVER is the ratio of household to institution volume relative to all volume. INSTO_TURNOVER is the ratio of institution to institution volume relative to total volume. HH_TURNOVER is the ratio of household to household volume relative to total volume. The sample covers January 2000 to December 2009.

	Mean	Std. Dev.	25th Pctl	Median	75th Pctl
TRADEIMB	0.006	0.740	-0.742	0.000	0.747
TRS	0.523	0.363	0.194	0.525	0.897
BETWEEN_TURNOVER	0.543	0.364	0.185	0.588	0.907
INSTO_TURNOVER	0.142	0.293	0.000	0.000	0.030
HH_TURNOVER	0.315	0.353	0.017	0.150	0.551

Table 2

Household behavior by 52 week high price deciles

This table presents the household between group trading on a day stock basis by 52 week high (52WH) deciles (Far to Near). Panel a reports the mean daily household TRADEIMB and TRS sorted by 52WH decile over the sample period 2000-2009. Panel b reports the difference between the Near minus Far decile and the Near minus '9' decile for TRADEIMB and TRS. The sample covers January 2000 to December 2009. The p-values are presented in parentheses, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

52WH Decile	TRADEIMB	TRS
Panel a: household behavior metrics by 52WH decile		
1 (Far)	0.163	0.546
2	0.116	0.555
3	0.076	0.537
4	0.069	0.532
5	0.051	0.533
6	0.004	0.532
7	-0.022	0.527
8	-0.083	0.516
9	-0.126	0.494
10 (Near)	-0.248	0.462
Panel b: household mean difference in behavior		
Near - Far	-0.411***	0.084***
	(0.000)	(0.000)
Near - 9	-0.122***	0.032***
	(0.000)	(0.000)

Table 3

Household behavior by 52 week high ratio

This table presents the results for the investor behavior metrics by 52WH RATIO. Panel a reports the mean and observations (Obs) of the household TRADEIMB by 52WH RATIO. Panel b reports the mean difference TRADEIMB between the 52WH RATIOs. Panel c reports the mean and Obs of the household TRS by 52WH RATIOs. Panel d reports the mean difference TRS between the 52WH RATIOs. The sample covers January 2000 to December 2009. The p-values are presented in parentheses, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

52WH RATIO	Mean	Obs
Panel a: TRADEIMB by 52WH RATIO		
< 0.95	0.044	142,301
[0.95, 0.96)	-0.076	6,590
[0.96, 0.97)	-0.104	6,869
[0.97, 0.98)	-0.122	7,132
[0.98, 0.99)	-0.130	7,700
[0.99, 1.00)	-0.188	7,449
1.00	-0.311	5,969

52WH ratio	< 0.95	[0.95, 0.96)	[0.96, 0.97)	[0.97, 0.98)	[0.98, 0.99)	[0.99, 1.00)
Panel b: TRADEIMB Mean Difference by 52WH RATIO						
[0.95, 0.96)	-0.120***					
	(0.000)					
[0.96, 0.97)	-0.148***	-0.028				
	(0.000)	(0.498)				
[0.97, 0.98)	-0.166***	-0.046***	-0.018			
	(0.000)	(0.004)	(0.760)			
[0.98, 0.99)	-0.173***	-0.054***	-0.026	-0.008		
	(0.000)	(0.000)	(0.680)	(0.880)		
[0.99, 1.00)	-0.232***	-0.112***	-0.084***	-0.066***	-0.059***	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
1.00	-0.355***	-0.235***	-0.207***	-0.189***	-0.182***	-0.123***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

52WH RATIO	Mean	Obs
Panel c: TRS by 52WH RATIO		
< 0.95	0.534	142,301
[0.95, 0.96)	0.524	6,590
[0.96, 0.97)	0.525	6,869
[0.97, 0.98)	0.500	7,132
[0.98, 0.99)	0.498	7,700
[0.99, 1.00)	0.467	7,449
1.00	0.412	5,969

52WH ratio	<0.95	[0.95, 0.96)	[0.96, 0.97)	[0.97, 0.98)	[0.98, 0.99)	[0.99, 1.00)
Panel d: TRS Mean Difference by 52WH RATIO						
[0.95, 0.96)	-0.009					
	(0.471)					
[0.96, 0.97)	-0.009	0.001				
	(0.482)	(0.750)				
[0.97, 0.98)	-0.034***	-0.024***	-0.025***			
	(0.000)	(0.004)	(0.002)			
[0.98, 0.99)	-0.036***	-0.026***	-0.027***	-0.002		
	(0.000)	(0.001)	(0.000)	(0.580)		
[0.99, 1.00)	-0.066***	-0.057***	-0.058***	-0.033***	-0.031***	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
1.00	-0.122***	-0.112***	-0.113***	-0.088***	-0.086***	-0.055***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 4

Household behavior on the new 52 week high day

This table presents the results for the investor behavior metrics for the NEW52WH. Panel a reports the daily mean and observations (Obs) of the household TRADEIMB for stocks on Non 52WH days, and stocks that are at the 52WHMAX (within 1% of the 52WH) and have last reached it 1 day prior (52WHMAX), 7 days prior (NEW7), and 14 days prior (NEW14). Panel b reports the daily mean difference TRADEIMB by stock across the prior specifications. Panel c reports the daily mean and Obs of the household TRS for stocks on Non 52WH days, and stocks that are at the 52WHMAX, NEW52WH7 and NEW52WH14. Panel d reports the daily mean difference TRS by stock across the prior specifications. The sample covers January 2000 to December 2009. The p-values are presented in parentheses, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

	Mean	Obs
Panel a: TRADEIMB by days since 52WHMAX		
Non 52WH Day	0.026	182,522
52WHMAX	-0.192	18,311
NEW7	-0.393	1,210
NEW14	-0.313	841

	Non 52WH Day	52WHMAX	NEW52WH7
Panel b: Mean difference TRADEIMB by days since 52WHMAX			
52WHMAX	-0.218***		
	(0.000)		
NEW7	-0.420***	-0.202***	
	(0.000)	(0.000)	
NEW14	-0.340***	-0.122*	0.080
	(0.000)	(0.057)	(0.245)

	Mean	Obs
Panel c: TRS by days since 52WHMAX		
Non 52WH Day	0.531	182,522
52WHMAX	0.452	18,311
NEW7	0.337	1,210
NEW14	0.355	841

	Non 52WH Day	52WHMAX	NEW52WH7
Panel d: Mean difference TRS by days since 52WHMAX			
52WHMAX	-0.079***		
	(0.000)		
NEW7	-0.194***	-0.115**	
	(0.000)	(0.043)	
NEW14	-0.175***	-0.097***	0.018
	(0.000)	(0.000)	(0.589)

Table 5

The effect of volatility on household behavior on the 52 week high day

This table presents the results for the investor behavior metrics by volatility tercile on the 52WHMAX day. Panel a reports the mean and observations (Obs) of the household TRADEIMB for stocks on the 52WHMAX (within 1% of the 52WH) day sorted by 20 day lagged EuroSTOXX volatility (VIX) terciles (LOWVIX, MEDVIX and HIGHVIX). Panel b reports the mean difference TRADEIMB for the prior specifications. Panel c reports the mean and Obs of the household TRS for stocks on the 52WHMAX (within 1% of the 52WH) day sorted by 20 day lagged VIX terciles. Panel d reports the mean difference TRS for the prior specifications. The sample covers January 2000 to December 2009. The p-values are presented in parentheses, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

TRADEIMB	Mean	Obs
Panel a: TRADEIMB on 52WHMAX by VIX		
LOWVIX 52WHMAX	-0.187	10,810
MEDVIX 52WHMAX	-0.215	4,663
HIGHVIX 52WHMAX	-0.185	3,128

	LOWVIX 52WHMAX	MEDVIX 52WHMAX
Panel b: Mean difference TRADEIMB on 52WHMAX by VIX		
MEDVIX 52WHMAX	-0.028*	
	(0.065)	
HIGHVIX 52WHMAX	0.002	0.029
	(0.358)	(0.188)

TRS	Mean	Obs
Panel c: TRS on 52WHMAX by VIX		
LOWVIX 52WHMAX	0.485	10,810
MEDVIX 52WHMAX	0.418	4,663
HIGHVIX 52WHMAX	0.373	3,128

	LOWVIX 52WHMAX	MEDVIX 52WHMAX
Panel d: Mean difference TRS on 52WHMAX by VIX		
MEDVIX 52WHMAX	-0.068***	
	(0.000)	
HIGHVIX 52WHMAX	-0.112***	-0.044***
	(0.000)	(0.000)

Table 6

Regression of household trade imbalance on the 52 week high day

This table presents results from the daily regression of TRADEIMB and AB_TRADEIMB on the 52WH. The regressions include fixed effects for the firm and day level. TRADEIMB is the daily ratio of household net buying with institutional investors, abnormal TRADEIMB is the daily TRADEIMB less the average 90-day lagged stock level TRADEIMB. The independent variables in the regression are as follows: 52WHMAX is an indicator variable with a value of one, if the stock price opens within 1% of the 52WH price, zero otherwise. NEW52WH is an indicator variable with a value of one, if the stock price opens within 1% of the 52WH price and has not been at the 52WH in the 7 calendar days prior, zero otherwise. JTMOMHIGH is an indicator variable that has a value of one, if the lagged 90-day stock return is in the highest tercile on the day, zero otherwise. HIGHVIX is an indicator variable that has a value of one, if the lagged 20-day average EuroVIX index value is in the highest tercile, over the sample, zero otherwise. HIGHVIX × 52WHMAX is an indicator variable that has a value of one, if the lagged 20-day average EuroVIX index value is in the highest tercile over the full sample period, and the stock is at the 52WH, zero otherwise. The regressions include the following controls: MKTCAP, which is the market capitalization of the stock in 100 millions of euros. VIX is the average value for the EuroVIX index for the prior 20 days. PRICE is the closing price of stock. RISK is the lagged 20-day average standard deviation of returns in the stock. The sample covers January 2000 to December 2009. White (1980) standard errors are used to compute the p-values, reported in parentheses beneath the coefficients, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

	Dep Var: TRADEIMB			Dep Var: AB_TRADEIMB		
	I	II	III	IV	V	VI
Intercept	-0.085***	-0.101***	0.028***	-0.014***	-0.023***	0.003
	(0.000)	(0.000)	(0.004)	(0.006)	(0.000)	(0.237)
52WHMAX	-0.212***		-0.195***	-0.131***		-0.123***
	(0.000)		(0.000)	(0.000)		(0.000)
NEW52WH		-0.286***			-0.180***	
		(0.000)			(0.000)	
HIGHVIX			0.144***			0.026***
			(0.000)			(0.000)
HIGHVIX × 52WHMAX			-0.157***			-0.053*
			(0.004)			(0.073)
JTMOMHIGH	-0.132***	-0.142***	-0.132***	-0.035***	-0.041***	-0.035***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKTCAP	0.000	0.000	0.000	0.000***	0.000***	0.000***
	(0.638)	(0.598)	(0.539)	(0.000)	(0.000)	(0.000)
VIX	0.006***	0.007***		0.001***	0.001***	
	(0.000)	(0.000)		(0.000)	(0.000)	
PRICE	-0.001*	-0.001*	-0.001*	0.000	0.000	0.000
	(0.059)	(0.062)	(0.079)	(0.344)	(0.347)	(0.349)
RISK	-0.002	-0.001	-0.001	0.001	0.001	0.001
	(0.609)	(0.680)	(0.840)	(0.833)	(0.775)	(0.774)
Obs	199,954	199,954	199,954	199,954	199,954	199,954
R-squared	0.023	0.020	0.023	0.003	0.001	0.003
Firm FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Table 7

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

This table presents results from the daily regressions of TRS and AB_TRS on the 52WH. The regressions include fixed effects for the firm and day level. TRS is the ratio of household market order usage when selling to institutions, AB_TRS is the daily TRS less the average 90-day lagged stock level TRS. The independent variables in the regression are as follows: 52WHMAX is an indicator variable with a value of one, if the stock price opens within 1% of the 52WH price, zero otherwise. NEW52WH7 is an indicator variable with a value of one, if the stock price opens within 1% of the 52WH price and has not been at the 52WH in the 7 calendar days prior, zero otherwise. JTMOMHIGH is an indicator variable that has a value of one, if the lagged 90-day stock return is in the highest tercile across the day, zero otherwise. HIGHVIX is an indicator variable that has a value of one, if the lagged 20-day average EuroVix index value is in the highest tercile, over the sample, zero otherwise. HIGHVIX × 52WHMAX is an indicator variable that has a value of one, if the lagged 20-day average EuroVIX index value is in the highest tercile over the full sample period, and the stock is at the 52WH, zero otherwise. The regressions include the following controls: MKTCAP, which is the market capitalization of the stock in 100 millions of euros. VIX is the average value for the EuroVIX index for the prior 20 days. PRICE is the closing price of stock. RISK is the lagged 20-day average standard deviation of returns in the stock. The sample covers January 2000 to December 2009. White (1980) standard errors are used to compute the p-values, reported in parentheses beneath the coefficients, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

	Dep Var: TRS			Dep Var: AB_TRS		
	I	II	III	IV	V	VI
Intercept	0.575***	0.566***	0.543***	0.016***	0.010***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
52WHMAX	-0.110***		-0.097***	-0.082***		-0.073***
	(0.000)		(0.000)	(0.000)		(0.000)
NEW52WH		-0.175***			-0.157***	
		(0.000)			(0.000)	
HIGHVIX			-0.036***			-0.012***
			(0.000)			(0.000)
HIGHVIX × 52WHMAX			-0.055**			-0.051***
			(0.022)			(0.000)
JTMOMHIGH	-0.010***	-0.015***	-0.009***	0.008***	0.004**	0.008***
	(0.003)	(0.000)	(0.003)	(0.000)	(0.048)	(0.000)
MKTCAP	-0.000**	-0.000*	-0.000**	0.000***	0.000***	0.000**
	(0.040)	(0.050)	(0.050)	(0.008)	(0.000)	(0.015)
VIX	-0.002***	-0.001***		-0.000***	-0.000***	
	(0.000)	(0.000)		(0.000)	(0.000)	
PRICE	0.000	0.000	0.000	-0.000*	-0.000*	-0.000**
	(0.455)	(0.450)	(0.447)	(0.051)	(0.063)	(0.041)
RISK	-0.002	-0.002	-0.002	-0.002***	-0.002***	-0.002***
	(0.362)	(0.411)	(0.300)	(0.000)	(0.000)	(0.000)
Obs	166,835	166,835	166,835	166,835	166,835	166,835
R-squared	0.007	0.003	0.007	0.003	0.001	0.003
Firm FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES

Table 8

The effect of household behavior on returns following the 52 week high

This table presents results from the OLS regressions of 52WH and investor behavior on lead 90- and 180-day raw returns (RT) and cumulative abnormal returns (CAR), respectively . The 52WHMAX is an indicator variable with a value of one, if the stock price opens within 3% of the 52WH price, zero otherwise. The TRSLOW is in indicator variable that has a value of one, if the TRS is in in the lowest quartile, zero otherwise. LAGTRSLOW is in indicator variable that has a value of one, if the lag 5-day average TRS is in in the lowest quartile, zero otherwise. The controls include: MKTCAP, which is the market capitalization of the stock in 100 millions of euros. LAGRETURN, which is the lagged raw return for the prior 90-days. The sample covers January 2000 to December 2009. The p-values, are clustered at the firm and day level and are reported in parentheses below the coefficients, ***, **, *, indicate significance at the 1%, 5% and the 10% levels, respectively.

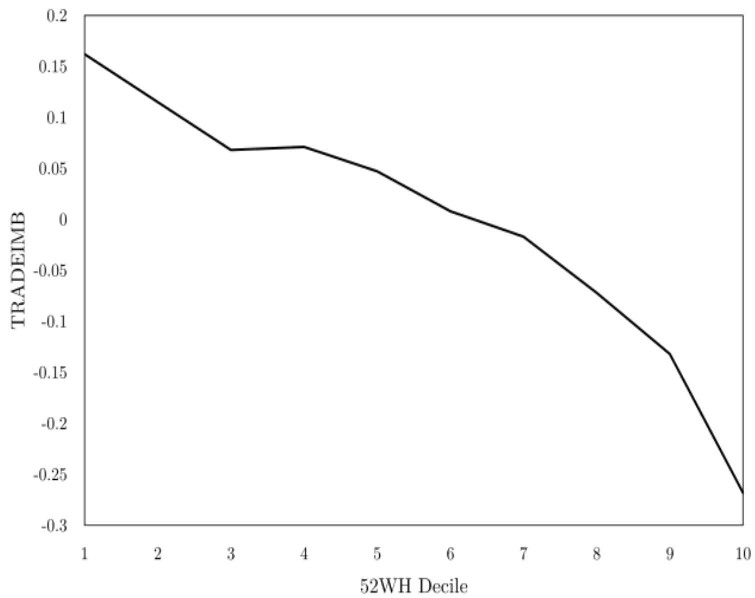
Panel a: Raw return regressions

	Dep Var: RT90						Dep Var: RT180					
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Intercept	0.040***	0.034***	0.030***	0.043***	0.040***	0.030***	0.084***	0.066***	0.061***	0.085***	0.084***	0.061***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
52WHMAX	0.022***		0.025***		0.021***	0.024***	0.025***		0.032***		0.022***	0.031***
	(0.000)		(0.000)		(0.000)	(0.000)	(0.004)		(0.000)		(0.010)	(0.000)
TRSLOW		0.007***	0.005**			0.006**		0.019***	0.016***			0.016***
		(0.006)	(0.037)			(0.016)		(0.000)	(0.000)			(0.000)
TRSLOW × 52WH			0.021***			0.013**			0.031***			0.020**
			(0.000)			(0.017)			(0.001)			(0.020)
LAGTRSLOW				0.002		-0.001				0.009**		0.004
				(0.418)		(0.800)				(0.037)		(0.328)
LAGTRSLOW × 52WHMAX					0.021***	0.021***					0.038***	0.029***
					(0.002)	(0.003)					(0.000)	(0.003)
MKTCAP	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.008)	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.029)	(0.023)	(0.024)	(0.028)	(0.029)	(0.024)
LAGRETURN	0.052***	0.058***	0.046***	0.062***	0.052***	0.046***	0.052*	0.057**	0.041	0.063**	0.052*	0.041
	(0.005)	(0.001)	(0.009)	(0.001)	(0.005)	(0.009)	(0.076)	(0.025)	(0.119)	(0.026)	(0.076)	(0.119)
Obs	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073
R-squared	0.010	0.009	0.011	0.008	0.010	0.012	0.009	0.010	0.011	0.008	0.009	0.012
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

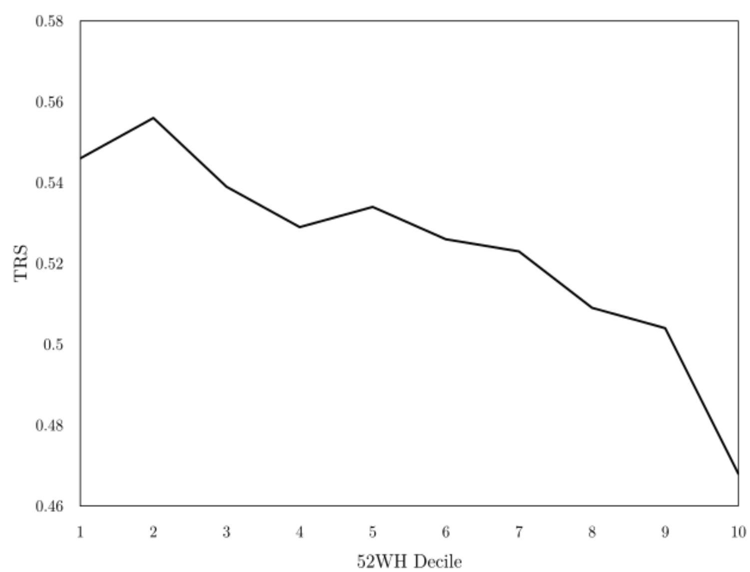
Table 8: Continued

Panel b: Cumulative abnormal return regressions

	Dep Var: CAR90						Dep Var: CAR180					
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Intercept	0.029***	0.028***	0.024***	0.031***	0.029***	0.024***	0.056***	0.047***	0.044***	0.056***	0.056***	0.043***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
52WHMAX	0.021***		0.022***		0.020***	0.021***	0.018**		0.019**		0.016**	0.018**
	(0.000)		(0.000)		(0.000)	(0.000)	(0.020)		(0.013)		(0.037)	(0.019)
TRSLOW		0.005***	0.004*			0.004**		0.013***	0.011***			0.011***
		(0.008)	(0.052)			(0.032)		(0.000)	(0.002)			(0.001)
TRSLOW × 52WHMAX			0.014**			0.007			0.020**			0.010
			(0.016)			(0.121)			(0.022)			(0.177)
LAGTRSLOW				0.003		0.001				0.010**		0.006
				(0.138)		(0.519)				(0.016)		(0.110)
LAGTRSLOW × 52WHMAX					0.015**	0.017***					0.026***	0.025***
					(0.030)	(0.005)					(0.005)	(0.002)
MKTCAP	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	0.000	0.000	0.000	0.000	0.000	0.000
	(0.047)	(0.046)	(0.046)	(0.048)	(0.047)	(0.046)	(0.305)	(0.340)	(0.337)	(0.309)	(0.305)	(0.338)
LAGRETURN	-0.007	-0.01	-0.021	0.002	-0.007	-0.021	-0.028	-0.041*	-0.051**	-0.021	-0.028	-0.052**
	(0.682)	(0.506)	(0.159)	(0.876)	(0.681)	(0.159)	(0.263)	(0.051)	(0.018)	(0.396)	(0.262)	(0.018)
Obs	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073	232,073
R-squared	0.003	0.002	0.005	0.001	0.003	0.005	0.002	0.003	0.004	0.002	0.002	0.005
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Day FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES



(a) TRADEIMB



(b) TRS

Fig. 1. Household behavior by 52 week high decile rank.
The figure plots the household investor behavior when trading with institutions, sorted into deciles, based on the stock's 52WH ratio from 1 (furthest from 52WH price) to 10 (nearest to the 52WH price). Panel a plots the average value of TRADEIMB within each decile, and Panel b plots the results of TRS within each decile.

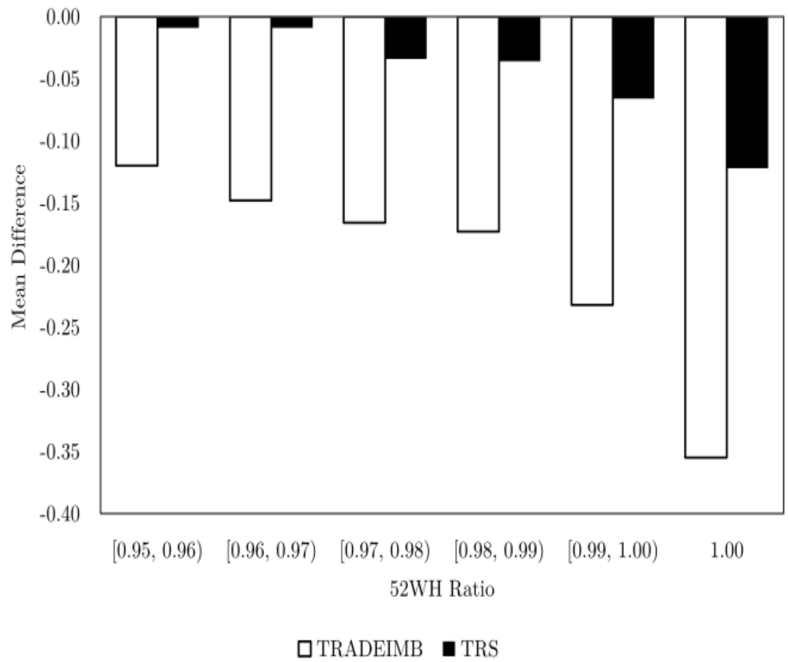
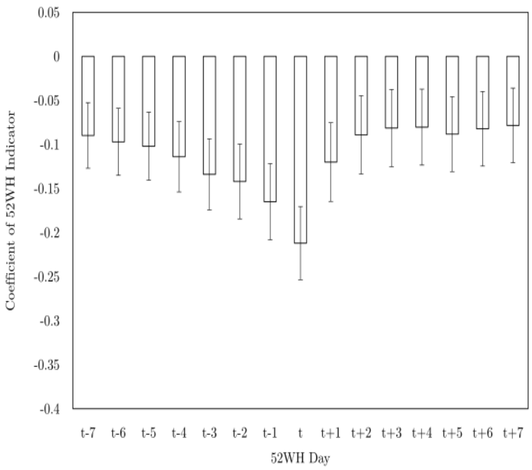
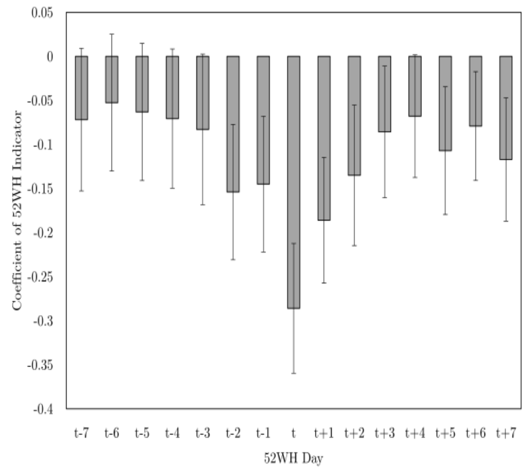


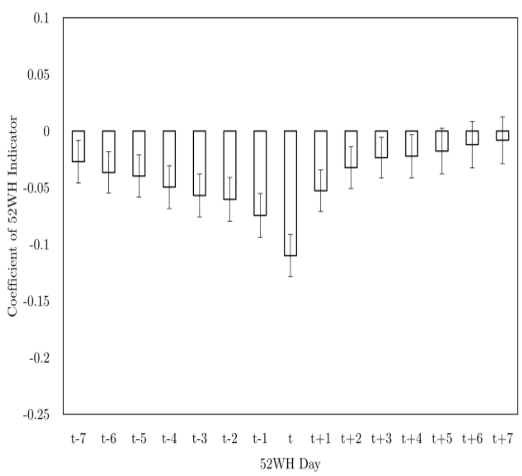
Fig. 2. Mean difference in household behavior by 52 week high ratio
The figure plots the difference in TRADEIMB and TRS for stocks in percentage bands approaching the 52WH relative to the bounded mean (when the 52WHRATIO is less than 0.95). The white columns plot the differences in TRADEIMB for the 52WH percentage bands relative to the bounded mean. The black columns plot the difference in TRS by 52WH percentage bands relative to the bounded mean.



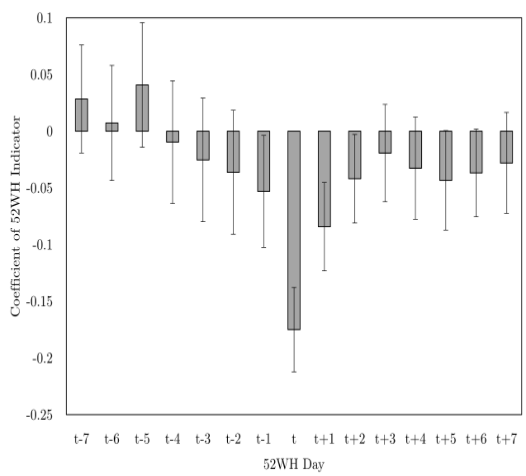
(a) TRADEIMB 52WHMAX



(b) TRADEIMB NEW7

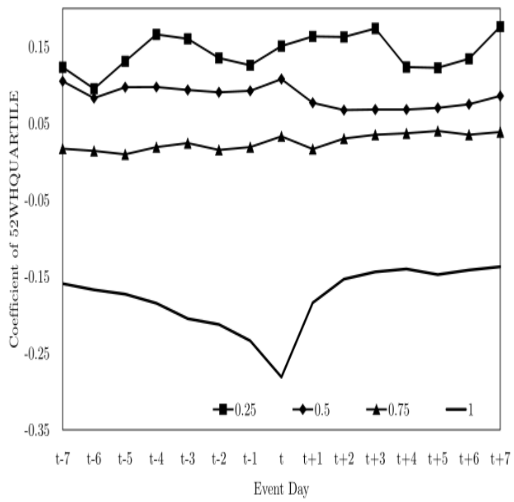


(c) TRS 52WHMAX

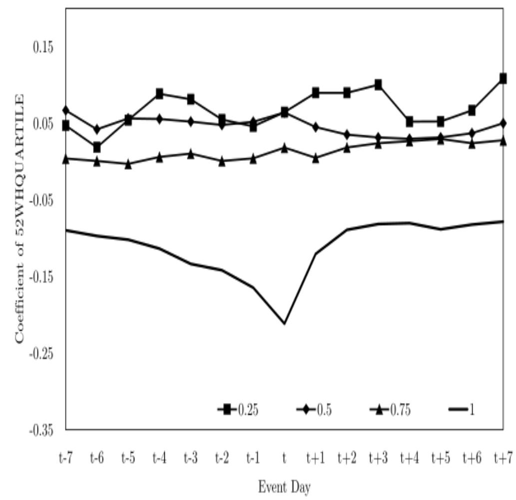


(d) TRS NEW7

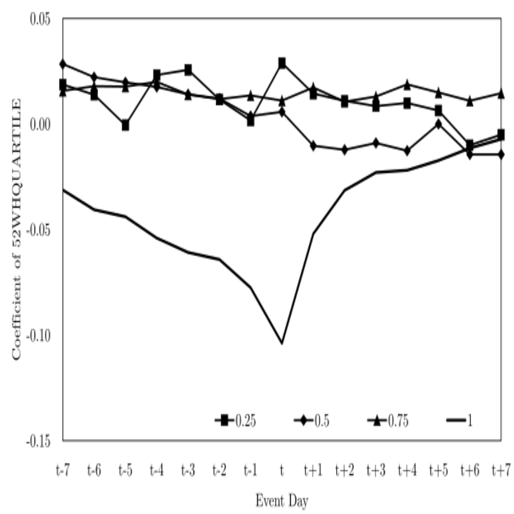
Fig. 3. Household behavior around the 52 week high and new 52 week high.
The figures plot coefficients of regressions of investor behavior (TRADEIMB and TRS) for stocks around the 52WHMAX and the NEW7 from $t-7$ to $t+7$ days, centering at the 52 week high day (t). For each column we undertake regressions as per equation 6, in which we cycle through lagged and forward TRADEIMB or TRS as a dependent variable from $t-7$ to $t+7$. We plot the coefficients of the variable 52WHMAX for panels a and c, and NEW52WH7 in panels b and d. Ninety-five percent confidence intervals are overlaid on each column based on White (1980) standard error clustering with firm and time fixed effects.



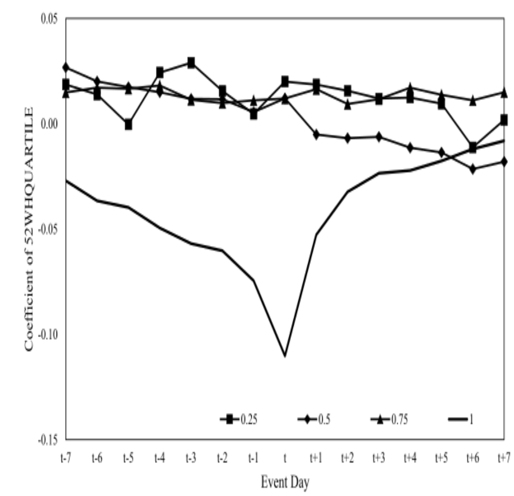
(a) TRADEIMB



(b) TRADEIMB Controls



(c) TRS



(d) TRS Controls

Fig. 4. Household behavior around the 52 week high quartiles

The figures plot coefficients of regressions of investor behavior (TRADEIMB and TRS) for stocks around the 52WHQUARTILE points (0.25, 0.50, 0.75 and 1) from $t-7$ to $t+7$ days, centering at the 52WHQUARTILE event day (t). For each day we undertake regressions as per equation 7, in which we cycle through lagged and forward TRADEIMB or TRS as a dependent variable from $t-7$ to $t+7$. We plot the coefficients of the respective 52WHQUARTILE for TRADEIMB in panels a, and b (with controls), and for TRS in panels c, and d (with controls). The 0.25 quartile is represented by a line with square markers, the 0.5 quartile by diamond markers, the 0.75 by triangle markers and lastly the 1 quartile (the 52WHMAX) is represented by a line without markers.