# Liquidity and Price Impact at the 52 Week High

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**Abstract**

A stock's 52 week high price represents an extremely salient anchor in an investor's trading decision. Using trade and quote data, we document that stocks near the 52 week high price exhibit significantly higher levels of liquidity than stocks far from the 52 week high. This increase in liquidity is concentrated on the supply side, with depth on the ask side essentially doubling relative to a normal day. Price impact declines by as much as two-thirds on the 52 week high day. We argue that the abnormal increase in liquidity is driven by disposition and anchoring effects. These findings help explain the role of the 52 week high as a barrier to information discovery and a potential driver of long run momentum.

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## 1. Introduction

The fifty-two week high (52WH) price of a stock represents a salient anchor for investment trading decisions. Prior research (e.g. George and Hwang (2004)) documents that stocks close to the 52WH tend to continue upwards. Investors who hold the stock, and evaluate trading performance based on a reference price, prefer to sell, rather than purchase new shares (Grinblatt and Keloharju, 2001) near historical highs. This slows the incorporation of recent good news, may lead to the upwards price drift (Grinblatt and Han, 2005).

In this paper, we examine how the 52WH affects stock-level liquidity, and consider the impact of this price anchor on informational efficiency. Prior studies have documented the preference of individuals to use limit orders, and that the buildup of liquidity from limit orders can lead to market distortions (e.g. Linnainmaa (2010), Kelley and Tetlock (2013)). Arguably, distortions are more likely to occur as the 52WH represents a salient price and visible anchor of interest to (particularly uninformed) investors. We argue that the 52WH creates a barrier for information integration (Birru, 2015), driven by non-informational selling through household limit orders. As liquidity clusters around the 52WH, a decrease in informational efficiency arises, resulting in an informational barrier.

We use intra-day trade and quote (TAQ) data from Finland NASDAQ OMXH over the period 2000-2014 to obtain bid-ask spread and depth liquidity measures (depth slope and bid-ask asymmetry, which capture sidedness in order flow) from Goyenko et al. (2009). Stocks at the 52WH exhibit higher levels of liquidity up to five levels of depth in the order book. 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. For example, the quoted spread averages 106 basis points across our sample of stocks, but only 60 basis points on days when the stock opens within 3% of the 52WH. The 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 towards the ask side, 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. The price impact of trades (Hasbrouck, 1991) is dampened as an excess of liquidity is available at the 52WH. A reduction in 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).

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 households destabilize markets. Moreover, we lend support to the view that institutional investors trade on the same side as momentum traders (e.g. Edelen et al. (2016), Baltzer et al. (2019)).

This paper proceeds as follows. Section 2 discusses the prior research. Section 3 outlines the hypothesis development, Section 4 introduces the data and the method used to measure liquidity and informational efficiency. Section 5 outlines the empirical design and reports the key findings and discusses their significance in relation to the literature. Lastly, section 6 concludes.

## 2. Literature review

This study 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.

### *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.

$$52WeekHighRatio_{i,t} = \frac{Price_{i,t}}{High_{i,t}} \tag{1}$$

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, 2008) 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. 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, Grinblatt and Han (2005) 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 [2].

The importance of the 52WH is not just limited to the level of accumulated capital

[2]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

gains, as the 52WH day can act as a key attention grabbing event. Barber and Odean (2008) 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. (2020) 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 their selling towards this upper bound price.

Prior research into the 52WH offers considerable insight into the 52WH effect generally[3], 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] For a more comprehensive discussion of the 52WH in other areas of finance see Della Vedova et al. (2020)

### 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 (2008), there could be increased liquidity at the 52WH in the short term as investors place latent unsupervised limit orders at the anchor price (Linnainmaa, 2010; Kelley and Tetlock, 2013). 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.

### 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 (Chiao and Wang, 2009; Box and Griffith, 2016; 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 [4], 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.

### *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

[4] 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.

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 (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. 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.

Della Vedova et al. (2020) 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 effi-

ciency as the investors entering the market are doing so for primarily non-informational reasons, thus dampening the effect of trading on price movements.

## 4. Data and Metrics

The data set used includes all stocks for which comprehensive tick data was available for the Helsinki NASDAQ OMHX, a total of 78 stocks over the time period from 1 January 2000 to 31 December 2014. This data, obtained from the Thomson Reuters Tick History (TRTH) database, includes all the millisecond stamped TAQ data, along with depth at the five best bid and ask prices. TAQ data was augmented with stock price data from the Wharton Research Data Services (WRDS) Compustat data set.

### *4.1. 52 Week high measures*

We construct two variables to measure the distance of a stock from its 52WH. The, the 52 Week High Ratio is used to measure a stock's distance from the 52WH anchor. The second, 52 Week High Max is a simple indicator variable used to determine whether a stock is at the 52WH.

#### *4.1.1. 52 week high ratio*

A stock's 52WH ratio is defined, following George and Hwang (2004), as follows:

$$\text{52 Week High Ratio}_{i,d} = \frac{Price_{i,d}}{High_{i,d}} \tag{2}$$

where $High_{i,d}$ is the highest daily closing price for stock $i$ over the past year $(d - 252, d)$, where $d$ indexes days, while $Price_{i,d}$ is the current stock price. The ratio represents the nearness, in percentage terms, of the stock's current price to its 52WH price. A value closer to 1 indicates that a stock is closer to its 52WH.

#### *4.1.2. 52 week high max*

We employ a simple measure of whether a stock is at the 52WH by constructing an indicator variable that takes a value of 1 if the stock commences trading on day $d$ within 3% of it's 52WH, and 0 otherwise.

$$\text{52 Week High Max}_{i,d} = \mathbf{1}_{\text{52 Week High Ratio}_{i,d} \geq 0.97}, \tag{3}$$

where **1** denotes the indicator function.

### *4.2. Liquidity measures: bid-ask spreads*

Several liquidity and price discovery measures, as discussed by Goyenko et al. (2009) and Foucault et al. (2013), are adopted. An advantage of the intra-day data set it that it is possible to use higher speed measures aggregated to the daily level alongside other direct daily measures.

Our liquidity metrics first focus on different measure of the prevailing bid-ask spread as a proxy for liquidity. We utilize quoted spreads, effective spreads, and realized spreads as representative spread-based liquidity measures, as defined in Huang and Stoll (1996).

#### *4.2.1. Quoted Spreads*

The quoted spread (Q-spread) reports the round-trip cost of a given market order that executed against the current bid and ask price. The Q-spread is time-weighted and aggregated at the daily level, as per McInish and Wood (1992), and calculated as follows.

$$\text{Q-Spread}_{i,t} = \frac{(Ask_{i,t} - Bid_{i,t})}{m_{i,t}}, \tag{4}$$

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 $t$.

*4.2.2. Effective Spreads*

The effective spread (E-spread) reflects the round cost trip of a liquidity demanding trade (market order). Our metric for E-spread is the euro volume-weighted average of the effective spreads for each completed trade within the day.

$$\text{E-Spread}_{i,t} = \frac{2q_{i,t}(P_{i,t} - m_{i,t})}{m_{i,t}}, \tag{5}$$

where $q_{i,t}$ is a trade direction indicator, $+1$ for buyer initiated trades and $-1$ for seller initiated trades. The execution price of the trade is $P_{i,t}$.

*4.2.3. Realized Spreads*

The realized spread (R-spread) is similar to the effective spread insofar as it reflects the round trade cost of a liquidity demanding trade. However, is calculated relative to the midpoint five minutes subsequent to the trade, from which it is assumed price impact has been revealed.

$$\text{R-Spread}_{i,t} = (P_{i,t} - m_{i,t+5min})q_{i,t}, \tag{6}$$

where $m_{i,t+5min}$ is the mid-quote price of the stock $i$ at time $t + 5$ minutes. We aggregate the realized spread using euro weighted volume throughout the trading day.

*4.3. Liquidity measures: limit order book depth*

The above spread measures provide insight into the liquidity at the prevailing bid and ask. Depth metrics may provide additional information regarding liquidity beyond the first level of quotes. A steeply sloping order book indicates a lack of depth beyond the best bid or ask quote, a sign of Illiquidity. If the 52WH encourages the use of limit order sales, we should thus expect to find a flatter ask slope than bid slope for these stocks.

*4.3.1. Ask Slope*

The Ask Slope is used to gauge the supply of stock available. With a greater level of liquidity available to investors willing to execute purchase market orders, the ask slope will be flatter. We use the available depth at the five best ask prices in the computation of the slope.

$$\text{Ask Slope}_{i,t} = \frac{\sum_{x=1}^{5} AskDepth_{i,t,x}}{Ask5_{i,t} - m_{i,t}} \tag{7}$$

where $AskDepth_{i,t,x}$ is the sum of the quantity of available at ask depth level $x$ in stock $i$ at time $t$ and $Ask5_{i,t}$ is the ask price at the 5th level above the best ask price.

*4.3.2. Bid Slope*

The counterpart on the demand side to the Ask Slope variable, the variable Bid Slope is used to examine the liquidity available to investors wishing to execute a sell market order.

$$\text{Bid Slope}_{i,t} = -\frac{\sum_{x=1}^{5} BidDepth_{i,t,x}}{Bid5_{i,t} - m_{i,t}} \tag{8}$$

where $BidDepth_{i,t,x}$ is the sum of the quantity of available bids from the 1st to the 5th level by stock and $Bid5_{i,t}$ is the prevailing ask price at the 5th level. The negative coefficient is used to ensure positivity.

*4.3.3. Scaled Depth Difference*

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. We construct a variable Scaled Depth Difference (SDD) to examine the relative level of asymmetry in the order book at a particular point in time.

$$\text{SDD}_{i,t,x} = \frac{QuoteAsk_{i,t,x} - QuoteBid_{i,t,x}}{QuoteAsk_{i,t,x} + QuoteBid_{i,t,x}} \tag{9}$$

where $QuoteAsk_{i,t,x}$ and $QuoteBid_{i,t,x}$ is the respective ask and bid quotes at depth level $x$ in stock $i$ at time $t$. It represents a scaled level of asymmetry at the prevailing quote to level $x$, with the denominator ensuring a value between $-1$ and 1. A value of Scaled Depth Difference greater than zero indicates asymmetry in the direction of the ask side of the book.

### *4.4. 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. We employ two measures: five-minute simple price impact (simple price impact henceforth) and a more robust permanent price impact.

#### *4.4.1. Simple Price Impact*

The simple price impact measures the subsequent mid-quote price change five minutes following a trade, and is calculated as follows (Foucault et al., 2013).

$$\text{Simple Price Impact}_{i,t} = \frac{2q_{i,t}(m_{i,t+5min} - m_{i,t})}{m_{i,t}} \tag{10}$$

A key consideration of the 52WH is the entrant of new investors trading for non-informational reasons. If trades at the 52WH are less informed, we would expect to see lower levels of Simple Price Impact for stocks at the 52WH.

#### *4.4.2. Permanent 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).

We thus implement a vector auto-regression (VAR) model (Hasbrouck, 1991) that uses a system of equations modeling signed order flow and log returns. We employ the reduced form VAR to infer the dynamics of the structural model.

$$x_t = u^x + \sum_{i=1}^{60} a_i^r r_{t-i} + \sum_{i=1}^{60} a_i^x x_{t-i} + e_t^x \tag{11}$$

$$r_t = u^r + \sum_{i=1}^{60} a_i^r r_{t-i} + \sum_{i=1}^{60} a_i^x x_{t-i} + e_t^r \tag{12}$$

where $t$ indexes 1-second intervals, and $x_t$ is signed-dollar-volume of trades in the 1-second interval, $t$. The term $r_t$ is the log-mid-quote change in the $t$-th interval, while $e_x^t$ 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 $r_t$ 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.

## 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.

### 5.1. *Descriptive statistics*

Table 1 reports the descriptive statistics for the stocks, equally weighted, in the sample. The data is winsorized at the 5th and 95th percentile to prevent data errors and extreme values skewing the results.

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 Ask Slope is similar to the mean Bid Slope (251 vs 236), suggesting that liquidity does not cluster (typically) on one side of the order book. The mean simple price impact of a trade is 28bps while permanent price impact has a mean of 17bps. Both of the price impact measures are skewed due to the equal weighting of the data; the median permanent price impact of 1.86bps (far lower than the mean) reflects the fact that the majority of trade occurs in liquid stocks.

[Insert Table 1 here]

Table 2 reports the correlations between all liquidity and price impact measures. 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. There are negative correlations between Bid and Ask Slopes of the order book and each of the spread metrics.

[Insert Table 2 here]

*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 Panel a, we document a 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. In turn, liquidity provision through marketable limit orders is less profitable.

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 levels. Our measure for Ask Slope from 7 increases (more limit order sell quantity) as it approaches the 52WH. Thus, there is a greater level of liquidity beyond the best ask quotes as stocks approach the 52WH, indicative of increased limit order usage. The inverse is observed for the Bid Slope (i.e. there is a smaller quantity of limit order buys in the order book). Simply put, stocks near the 52WH have much more liquidity available to buyers - as sellers increase their willingness to provide liquidity to the market. In effect, the 52WH induces an 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 of Della Vedova et al. (2020) 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.

[Insert Table 3 here]

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 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 18.062 bps 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.

*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.

[Insert Table 4 here]

We start by examining the liquidity metrics at the 52WH day in comparison to an average day. In Table 4 we see significant decreases in all spread metrics, indicative of strong increases in liquidity at the best prices. Q-spread falls by half ($-47$ bps), 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, there is a significant decline in informational efficiency at the 52WH day. Simple price impact declines by 9.39 bps, while there is also a 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.

$$\begin{aligned} LiquidityMetrics_{i,t} = \beta_0 + \beta_1 52WHMax_{i,t} + \beta_2 52WHRatio_{i,t} + \beta_3 Price_{i,t} + \\ \beta_4 MarketCap_{i,t} + \beta_5 LagReturn_{i,t} + \beta_6 IdiosyncraticRisk_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{13}$$

Where the $LiquidityMetrics_{i,t}$ are the daily Q-spread, E-spread and R-spread within stock $i$. The independent variables of interest are $52WHMax_{i,t}$, 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 $52WHratio_{i,t}$, the ratio between the stocks current price and its 52WH price. We expect to find negative coefficients on each of the 52 week high variables if there is a reduction in spreads at that point.

We control for other liquidity-related factors in (13). $Price_{i,t}$ is the contemporaneous price of the given stock $i$ at time $t$; $MarketCap_{i,t}$ is the current price multiplied by shares outstanding in tens of millions of Euros; $LagReturn_{i,t}$ the sum of the daily returns 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.

[Insert Table 5 here]

Table 5 reports the results for spread-based liquidity measures against the 52WH variables. Supporting hypothesis 1, we see large and significant negative coefficients for the $52WHRatio_{i,t}$ and $52WHMax_{i,t}$ across all spread measures. A key insight is the strong role of the 52WH ratio that drives much of the liquidity. By including Lag Return, 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. As expected, the control variables are significant and in the direction forecast by prior research (Goyenko et al., 2009) and economic intuition.

The relatively small co-efficient of Lag Return is also informative as past returns could act as an attentional driver (Barber and Odean, 2008), or encourage sales by investors with prospect theory preferences (Grinblatt and Keloharju, 2001). Despite this prediction, the lagged return 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.

$$\begin{aligned} DepthMetrics_{i,t} = \beta_0 + \beta_1 52WHMax_{i,t} + \beta_2 52WeekHighRatio_{i,t} + \beta_3 Price_{i,t} + \\ \beta_4 MarketCap_{i,t} + \beta_5 LagReturn_{i,t} + \beta_6 IdiosyncraticRisk_{i,t} + \epsilon_{i,t} \end{aligned} \tag{14}$$

Where the $DepthMetrics_{i,t}$ are: Ask Slope, Bid Slop, SDD at the 1st level, and SDD at the 5th level, for stock $i$ at time $t$. The independent variables and controls are as defined in (13).

[Insert Table 6 here]

In Table 6 we document a significant buildup of liquidity on the ask side with positive and significant coefficients at the 52WH max. In other words, there is a higher supply of liquidity on the ask side of the book on 52WH days. The increased liquidity we observe from Table 5 is a result of the sell side rather than the buy side. This is further supported by observing the SDD at the 5th level, where depth available at the 5th best asking price is higher than the depth available at the 5th best bid price. 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 next assess the result of the 52WH on informational efficiency and price impact.

$$\begin{aligned} PriceImpactMetrics_{i,t} = \beta_0 + \beta_1 52WHMax_{i,t} + \beta_2 52WHRatio_{i,t} + \\ \beta_3 Price_{i,t} + \beta_4 MarketCap_{i,t} + \beta_5 LagReturni,t + \beta_6 \\ IdiosyncraticRisk_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{15}$$

Where the $PriceImpactMetrics_{i,t}$ are the daily Simple Price Impact and Permanent Price Impact, as defined in equations (10) and (12). The independent variables and controls are as employed in regression 13.

[Insert Table 7 here]

Table 7 reports the results for the regressions in equation (7). The key finding is that the 52 week high ratio and 52 week high max variables are both negatively related to Simple Price Impact. However, for Permanent price impact, only the 52 week high 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. Trade made at the 52WH exhibit lower price impact and thus are less informative than trades at other times.

*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 to, and 5 days following the 52WH day (denoted by $t$ in this subsection).

We first plot the mean values of the spread metrics, weighted by price, at time $t$, around the 52WH day. There is clear 'V'-shaped pattern, centering on the high day and reverting upwards immediately after the 52WH day. There is a downward trend prior to the 52WH day for quoted and (to a lesser extent) realized spreads, suggesting some anticipation of the breach. The sharp reversal in spreads following the 52WH day supports the hypothesis that the 52WH induces latent liquidity. Immediately afterwards

We next plot the depth measures in Figure 2 and see very similar effect for the Ask Slope and the Scaled Depth Difference at the 5th level. The ask slope increases prior to, and drops off sharply following the 52WH day, indicating that much of the increase in depth is at ask quotes beyond the best. In contrast, the bid slope increases sharply following the 52WH day, highlighting a shift in willingness to buy (likely driven by profit-taking motives). The results on the SDD metrics indicate that there is little asymmetry between the bid and ask sides of the book in terms of depth at the best quotes, but a pronounced asymmetry in depth (towards the ask) at the 5th level of the order book. Traders thus appear to submit limit orders outside the marketable range, near to or above the 52WH. This is consistent with a preference by individuals to submit limit orders, favoring price over immediacy (e.g. Linnainmaa (2010); Kelley and Tetlock (2013)).

Last, in Figure 3, we plot our two measures of price impact around the day of the 52WH. We observe 'V' shape around the 52WH day, similar to that observed with the liquidity (spread) metrics. The 'V' shape is more pronounced for the Permanent price impact measure, with a consistent downward trend prior to the 52WH day. We argue that the 52WH day provides a strong barrier to information integration, as a general rule greater liquidity results in greater informational efficiency.

## 6. Conclusion

This study uses intra-day Finnish OMXH TAQ and depth data to explore the liquidity dynamics at the 52WH and its effect on the price impact of trades. We observe the changes in different measures of the bid ask spread, as well as the shape and symmetry of the limit order book, and the effect of trades on price as stocks approach their 52WH price.

This study finds a monotonic increase in the liquidity of stocks as they approach, of which they peaks at, the 52WH day. We observe that the spread measures: Q-Spread, E-Spread and R-spread essentially halve relative to average stocks when they are at the 52WH. This increase in liquidity is supported by observing the shape of the limit order book (up to 5 levels) which is increasingly built up towards the ask side. This unexpected increase in investor liquidity provision supports that investors succumb to the disposition effect (selling winners) and anchoring at the 52WH price (Jegadeesh and Titman, 1993; Kahneman and Tversky, 1979).

As the increase in liquidity is for non-informational reasons (Barrot et al., 2016), we find that it sharply decreases the informational efficiency of stocks at the 52WH. By observing the impact of trades on price, we see that the price change that occurs by a given trade drop by as much as half. Overall, this supports our hypothesis that the 52WH acts as a driver of uninformed selling and as a result leads to a dampening of the price discovery process.

These findings are supported by observing the liquidity and price discovery metrics 5 days pre and 5 days prior to the 52WH. We see an inverted 'V' and 'V' shaped pattern on the 52WH day which is indicative of peak liquidity and floor price impact respectively, thus further highlighting the importance of the 52WH day as an anchor for uninformed traders and as a driver of expectational errors Birru (2015). 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 demonstrates, contrary to the expectations of extant microstructure literature, that an increase in liquidity can result in a significant deterioration in informational efficiency. 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. This research opens up room for future research into the liquidity and informational efficiency dynamics of many more asset pricing anomalies including momentum. In addition, further exploration into the role of the stock liquidity and the timing of information disclosures.

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## 7. Tables and Figures

**Table 1:** Descriptive statistics

This table reports means, standard deviations, and quartiles (25th percentile, median, and 75th percentile) of variables calculated at the stock-day level. Market cap is the price multiplied by 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. Q-Spread is quoted spread the round trip cost of a given market order that executes against the current best bid and ask prices. E-Spread (Effective spread) is the execution cost of a round trip of a liquidity demanding trade. The R-Spread (realized spread) is the change in price against the mid-quote five minutes following the trade relative to the mid-quote at time $t$. Ask Slope 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 Pctl. | Median | 75th Pctl. |
|---|---|---|---|---|---|
| *Stock characteristics:* | | | | | |
| Market cap ($\times$10m Euros) | 25.165 | 114.935 | 1.505 | 5.283 | 14.628 |
| Volume/day (m) | 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:* | | | | | |
| Q-Spread | 98.525 | 102.099 | 22.715 | 59.500 | 134.348 |
| E-Spread | 81.465 | 79.946 | 22.577 | 51.281 | 110.374 |
| R-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 (1st Level) | 0.046 | 0.244 | -0.105 | 0.033 | 0.189 |
| SDD (5th Level) | 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 2:** Correlations between liquidity and price impact measures

This table reports correlations between liquidity and price impact metrics. Q-Spread (quoted spread) is the round trip cost of a given market order that executes against the current best bid and ask prices. E-Spread (effective spread) is the execution cost of a round trip of a liquidity demanding trade. R-Spread (realized spread) is the change in price against the mid-quote five minutes following the trade relative to the mid-quote at time t. Ask Slope 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, reported for the 1st and 5th levels. Simple price impact measures the subsequent mid-quote price change five minutes following a trade. The Perm. 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.

| | Q-Spread | E-Spread | R-Spread | Ask Slope | Bid Slope | SDD (1st Level) | SDD (5th Level) | Simple price impact | Perm. price impact |
|---|---|---|---|---|---|---|---|---|---|
| Q-Spread | 1 | | | | | | | | |
| E-Spread | 0.871*** | 1 | | | | | | | |
| | (0.001) | | | | | | | | |
| R-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) | | | | | |
| SDD (1st Level) | 0.074*** | 0.077*** | 0.064*** | −0.056*** | −0.088*** | 1 | | | |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | | | | |
| SDD (5th Level) | 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) | | |
| Perm. 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) | |

**Table 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 stock price on day $d$ and its 52 week high price (the highest price the stock has traded for over the prior year). Q-Spread (quoted spread) is the round trip cost in basis points of a given market order that executes against the current best bid and ask prices. E-Spread (effective spread) is the execution cost in basis points of a round trip, liquidity demanding trade. R-Spread (realized spread) is the basis point 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.

| | Q-Spread | E-Spread | R-Spread | Simple price impact | Perm. 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 (1st Level) | SDD (5th Level) |
|---|---|---|---|---|
| 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) |

**Table 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 opens within 3% of the 52 Week High. Q-Spread (quoted spread) is the round trip cost in basis points of a given market order that executes against the current best bid and ask prices. E-Spread (effective spread) is the execution cost in basis points of a round trip, liquidity demanding trade. R-Spread (realized spread) is the basis point 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 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

| | Q-Spread | E-Spread | R-Spread | Simple price impact | Perm. 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 | SDD (1st Level) | SDD (5th Level) |
|---|---|---|---|---|
| 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) |

**Table 5:** Effects of 52 week high on liquidity

This table reports OLS regression estimates using a stock-day panel. Q-Spread (quoted spread) is the round trip cost in basis points of a given market order that executes against the current best bid and ask prices. E-Spread (effective spread) is the execution cost in basis points of a round trip, liquidity demanding trade. R-Spread (realized spread) is the basis point 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 multiplied by the number of shares outstanding in tens of millions of Euros. Lag return is the sum of stock $i$'s daily returns for the prior 3 months. Idiosyncratic risk is the standard deviation of the daily returns for the prior 3 months by stock. Standard errors are clustered at stock level, 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

| | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Q-Spread | | E-Spread | | R-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) | (0.09) | (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 | 224,269 | 201,001 | 22,1384 | 198,832 | 221,337 | 198,794 |
| Adj R-sq | 0.148 | 0.162 | 0.142 | 0.162 | 0.086 | 0.091 |

**Table 6:** Effects of 52 week high on depth

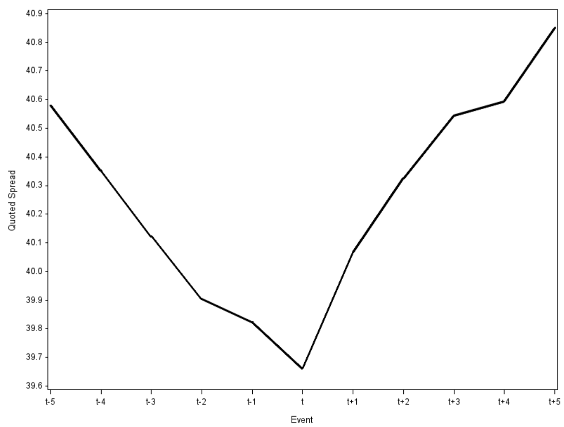
This table reports OLS regression estimates using a stock-day panel. Ask (bid) Slope is the gradient of the order book up to five levels. SDD represents a scaled level of asymmetry at the prevailing quote, 1 and 5 respectively. The variable 52 week high max is an indicator variable taking a value of 1 on days 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 current price multiplied by the number of shares outstanding in tens of millions of Euros. Lag return is the sum of stock $i$'s daily returns for the prior 3 months. 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

| | Dependent Variable: | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Ask Slope | | Bid Slope | | SDD (1st Level) | | SDD (5th Level) | |
| 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 | 138,873 | 124,908 | 138,872 | 124,908 | 138,870 | 124,908 | 138,875 | 124,909 |
| Adj R-sq | 0.210 | 0.296 | 0.203 | 0.303 | 0.004 | 0.005 | 0.008 | 0.018 |

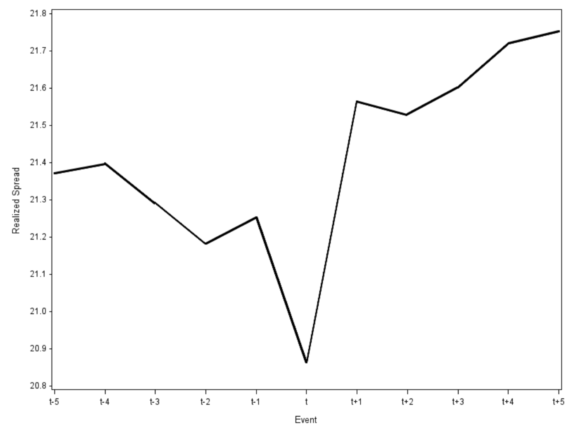
**Table 7:** Effects of 52 week high on price impact

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 variable 52 week high max is an indicator variable taking a value of 1 on days 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 current price multiplied by the number of shares outstanding in tens of millions of Euros. Lag return is the sum of stock $i$'s daily returns for the prior 3 months. 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

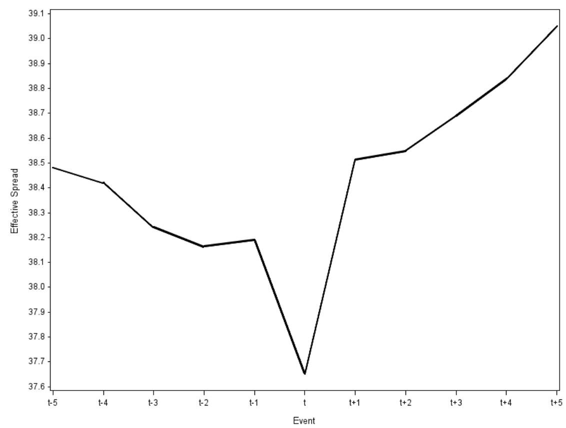
| | Dependent Variable: | | | |
|---|---|---|---|---|
| | Simple price impact | | Perm. price impact | |
| Intercept | 36.40*** | 53.87*** | 25.33*** | 24.13*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 52 week high max | −6.477*** | −1.791** | −5.761*** | −3.767*** |
| | (0.000) | (0.012) | (0.000) | (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 | 221,337 | 198,794 | 199,785 | 187,977 |
| Adj R-sq | 0.051 | 0.069 | 0.069 | 0.074 |




(a) Quoted Spread



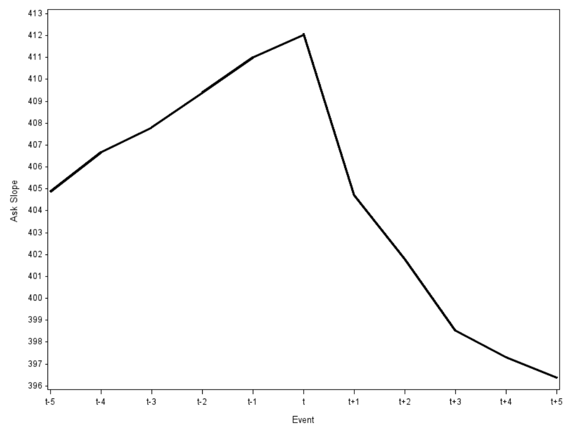

(b) Realized Spread



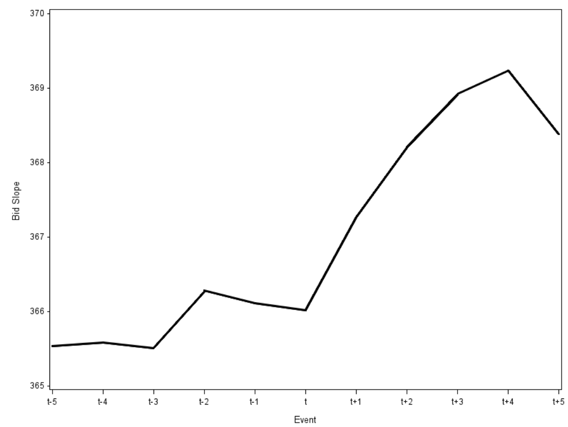

(c) Effective Spread

**Figure 1:** Spread metrics around the 52 week high day

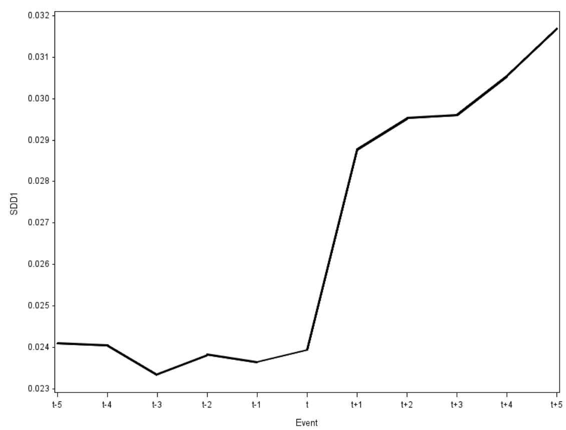
This figure plots the quoted spread (Panel a) realized spread (Panel b) and effective spread (Panel c) 5 days prior $(t-5)$ to and 5 days following $(t+5)$ the 52 week high day $(t)$. The 52 Week High day is the day in which the stock is within 3% or has surpassed the previous 52 week high price. The 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.



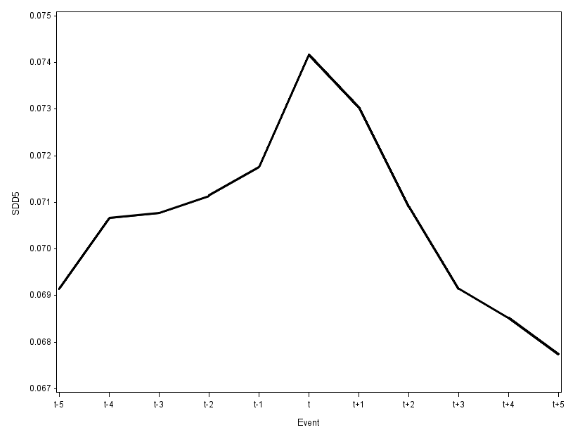

(a) Ask slope




(b) Bid slope



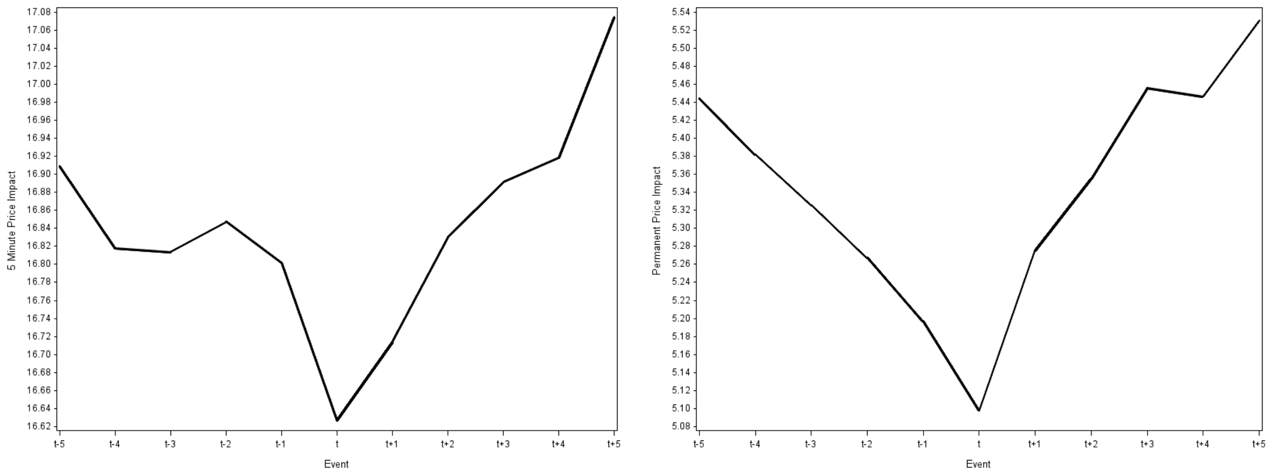

(c) Scaled depth difference 1




(d) Scaled depth difference 5

**Figure 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) 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) Simple price impact

(b) Permanent price impact

**Figure 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.