How the 52-week high and low affect option-implied volatilities and stock return moments*

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Abstract

We provide a new perspective on option and stock price behavior around 52-week highs and lows. We analyze whether option-implied volatilities change when stock prices approach or break through their 52-week high or low. We also study the effects of highs and lows on a stock's beta and return volatility. We find that implied volatilities and stock betas decrease when approaching a high or low, and that volatilities increase after breakthroughs. The effects are economically large and significant. The approach results can be explained by the anchoring theory. The breakthrough results are consistent with anchoring and the investor attention hypothesis.

JEL classification: G12, G14

Keywords: 52-week high and low, implied volatility, anchoring, investor attention, price barriers.

1. Introduction

The 52-week high and low stock prices are arguably the most readily available aspects of past stock price behavior.[1] Several researchers have empirically found that hitting the high or low affects trading behavior (Grinblatt and Keloharju, 2001), exercise of executive stock options (Heath et al., 1999), exercise of exchange-traded stock options (Poteshman and Serbin, 2003), trading volume (Huddart et al., 2008), pricing of mergers and acquisitions (Baker et al., 2009), and asset prices (Brock et al., 1992; George and Hwang, 2004; Huddart et al., 2008, and Li and Yu, 2010). These findings have been supported by a variety of theoretical explanations, including anchoring (Tversky and Kahneman, 1974), prospect theory (Kahneman and Tversky, 1979), and investor attention effects (Barber and Odean, 2008).

Despite this attention to 52-week highs and lows, a clear and complete picture about the impact on asset price behavior is lacking. In this paper we argue that a lot can be learned by studying higher moments of stock returns. Our main focus is the information embedded in stock option prices: we investigate the effect of 52-week highs and lows on implied stock-option volatilities. In addition, we study the betas and volatilities of the underlying stock returns.

We make three main contributions to the literature. First, as mentioned above, we focus on the effect of the 52-week highs and lows on option-implied volatilities, and the effect on the beta and volatility of stock returns. Option-implied volatilities provide forward-looking information on stock price behavior and are thus ideal to analyze whether 52-week extremes affect market prices. In addition, second moments of stock returns (beta, volatility) can be measured much more precisely than the first moment (abnormal return), see e.g. Merton (1980). This is important because the existing work on the first moment is inconclusive. For example, Huddart et al. (2008) find positive abnormal returns after hitting the 52-week low,

[1] For example, the Wall Street Journal, Bloomberg, and Yahoo Finance (finance.yahoo.com) report the 52-week high and low for stocks.

while Brock et al. (1992) find negative abnormal stock index returns after hitting the past 200-day low. George and Hwang (2004) find negative abnormal returns for stocks trading close to their 52-week low. Hence, even though there is considerable evidence that 52-week highs and lows affect individual trading behavior, it is unclear whether this aggregates to actual effects on the stock price.

Second, while existing work mainly focuses on behavior after hitting a high or low, we study volatility and beta effects both when the stock price approaches its 52-week high or low and after breaking through the high or low. This is an important contribution since the different explanations for the relevance of highs and lows have different implications for the stock price behavior before and after hitting the high or low. As discussed below in more detail, the investor attention hypothesis (Barber and Odean, 2008) only generates effects after breaking through the highs or lows, while the anchoring hypothesis also generates price effects when stock prices approach the 52-week extremes. Further, technical traders believe that 52-week high and low values act as resistance and support levels, respectively, and that breaking through these barriers generates trending stock price behavior (Brock et al., 1992). In this case, stock prices would be affected both when approaching the resistance and support levels and after breaking through these levels.

Third, we perform a joint study of stock and stock-option markets. By studying the effects of the 52-week high and low stock prices on return volatility and option-implied volatility, we perform a strong consistency check on our results. Furthermore, we can investigate whether the option market correctly incorporates the patterns observed in the underlying stock volatility. This builds on existing work that investigates behavioral effects in option market. For example, Han (2008) finds that investor sentiment affects the steepness of the implied volatility skew and Stein (1989), Poteshman (2001), and Goyal and Saretto (2008) find evidence supportive of overreaction of option prices to volatility shocks.

Our empirical analysis uses all stocks listed on NYSE and AMEX from July 1963 to the end of 2008 and option price data from OptionMetrics for a subset of 295 stocks from 1996 to 2008. The empirical strategy is as follows. For each stock, we model implied volatilities as a function of nearness to the 52-week high or low. Specifically, we include both "approach dummies," which equal one if the stock price is sufficiently close to the 52-week high or low (but hasn't crossed it), and "breakthrough dummies," which equal one on days following the breakthrough. We estimate this model using linear regression for all options on a given stock, and then focus on the average dummy coefficients across stocks. When regressing option-implied volatilities on the approach and breakthrough dummies we control for many known determinants of implied volatilities, such as lagged volatilities and the leverage effect.

To study the effects on the underlying stock returns, we specify an ARCH-type model where both the mean return equation and variance equation include the approach and breakthrough dummies. We estimate the mean and variance equations jointly using Maximum Likelihood. For the stock return analysis, we control for several variables that are known to affect betas and volatility, including past returns and volatility, and for size, value and momentum factors. Finally, we study whether stock trading volume depends on the approach and breakthrough dummies.

Our key findings are as follows. First, we observe a strong decrease in implied volatilities when approaching 52-week highs or lows. The implied stock volatility decreases by about 1 volatility point when approaching the 52-week high (the average implied volatility for stocks in our sample is 43 volatility points), and about 0.4 volatility point when approaching the 52-week low. We find similar effects in the underlying stock returns: approaching the 52-week high or low has a strong effect on volatility. The idiosyncratic stock return variance decreases significantly when approaching the 52-week high or low, controlling for the usual determinants of return variance. In addition, a stock's beta decreases by about 0.12 (0.05) when the stock price is within 3% from the 52-week high (low). Finally, we find that trading volume of stocks increases significantly when approaching a high or low. All these results are statistically significant and robust to changing the setting in several dimensions.

Second, we find a strong and significant increase in option-implied volatility after breaking through the 52-week high or low. Implied stock-option volatilities increase by more than 1 volatility point when stock prices break through the 52-week high or low. Consistent with this finding, the underlying stock return variance increases by about 19% on the day after breaking through the 52-week high and 43% after breaking through the 52-week low. The after-breakthrough variance effects last for a few days. The effect of breakthroughs on the stock's beta is smaller. Finally, stock trading volume increases by a large amount after breakthroughs, in line with findings of Huddart et al. (2008).

We implement a simple option pricing model with stochastic volatility to assess whether the variance effects in the underlying stock returns are quantitatively consistent with the observed effect on option-implied volatilities. Overall, we find that the effects on implied volatilities seem to be somewhat larger than the effects on the underlying return variances. In addition, we find some evidence that option traders do not anticipate the huge increase in variance after a potential breakthrough when the stock price is close to the low but has not (yet) crossed it.

Finally, we also study the first moment (abnormal returns) when approaching the 52-week high or low and after breakthroughs. In line with our discussion above, we find less stable and insignificant results. This supports our view that reliable measurement of abnormal returns is difficult and that much can be learned from studying option-implied volatilities and higher moments. The only result on the first moment that is somewhat stable is a positive abnormal return after breaking through the 52-week high.

We discuss the different theories employed to explain existing findings on the effects the 52-week high and low: anchoring, prospect theory, and investor attention. The before-breakthrough patterns are consistent with the anchoring theory of Tversky and Kahneman (1974). These before-breakthrough patterns do not confirm or falsify prospect theory or the investor attention hypothesis. The results for the after-breakthrough case are consistent with both the attention hypothesis of Barber and Odean (2008) and the anchoring hypothesis.

Our paper is also related to a literature studying price barrier effects in financial markets. Specifically, a series of articles has investigated whether stock prices are affected by psychological barriers such as round numbers. Donaldson and Kim (1993) analyze such effects for stock market indices, Mitchell and Izan (2006) for currency markets, and Aggarwal and Lucey (2007) for gold markets. Our work is related in that sense that we provide evidence that the 52-week high and low also act as "price barriers". Recent work of Li and Yu (2010) is also related as they study the effects of nearness to the 52-week high versus nearness to the all-time historical high on the Dow index price. They find that nearness to the 52-week high positively predicts stock index returns, while nearness to the all-time high negatively predicts index returns, and explain these findings using the investor attention and anchoring hypotheses.

The rest of the paper is structured as follows. In Section 2 we discuss existing theories for the relevance of the 52-week high and low. In Section 3 we describe the data and empirical methodology. Section 4 presents all empirical results. Section 5 concludes.

2. Theoretical Background and Literature

In this section we discuss the various theories that have been applied to understand the effects of the 52-week high and low on investor behavior and prices.

Anchoring: Tversky and Kahneman (1974) discuss the concept of anchoring and adjustment, which implies that individuals use irrelevant but salient anchors to form beliefs. In the context of financial markets, Baker et al. (2009) argue that the 52-week high serves as anchor for pricing of mergers and acquisitions. George and Hwang (2004) argue that investors use the 52-week high as an anchor relative to which they evaluate new information: if good news arrives when the stock price is close to the 52-week high, traders are reluctant to bid up the price above the anchor even if the good news would justify this. This implies that the 52-week high acts as a resistance level. In Section 3, we use a simulation study to show this implies that both a stock's beta and variance decrease when approaching the resistance level.

Similar effects occur for the 52-week low when bad news arrives, in which case the 52-week low acts as a support level, lowering the beta and variance of a stock when approaching the low. In addition to the beta and volatility effects, the disagreement between buyers (rational agents subject to limits of arbitrage) and sellers (agents subject to anchoring) may increase trading volume when approaching the high or low, see for example Dumas et al. (2009) and Beber et al. (2010).

Now we turn to the implications of anchoring after a breakthrough. The anchoring theory implies that, eventually, the new information will be incorporated in stock prices, which implies that stock prices are expected to increase after breaking through the resistance level and decrease after breaking through the support level. This again leads to increased trading volume as the agents subject to anchoring update their beliefs and increase their positions in these assets. This increased trading volume may also lead to higher volatility after the breakthrough, as several studies argue that trading volume goes along with or even causes higher volatility (see for example Hiemstra and Jones (1994)). The anchoring theory does not generate a direct effect on the beta after a breakthrough.

Note that the anchoring theory is in line with how technical traders perceive the role of 52-week highs and lows. Indeed, Brock et al. (1992) describe how technical traders view the high (low) as a resistance (support) level, and that breaking through this level provides a buy (sell) signal.

Prospect theory: Prospect theory of Kahneman and Tversky (1979) proposes that investors evaluate gains and losses relative to a reference point, with "extra aversion" to losses at the reference point and an S-shaped value function. While in many financial applications the reference point is assumed to be the purchase price, both Heath et al. (1999) and Baker et al. (2009) argue that the 52-week high could also serve as reference point. In this case, investors may want to hold a stock as long as the stock price is below the reference point, since the value function is convex in this region, and only sell the stock when the stock price crosses the reference point, because the value function is concave above the reference point and due to the additional effect of loss aversion. Hence, this version of prospect theory would imply selling pressure when stock prices break through 52-week highs. As with the anchoring theory, this selling pressure could also lead to increased trading volume and volatility after a breakthrough due to disagreement between prospect-theory agents and rational agents. Prospect theory does not imply a direct effect on the beta after a breakthrough. Turning to the 52-week low, there is no existing work that proposes this as reference point. If it would serve as reference point to prospect theory agents, they would tend to buy a stock when it breaks through the 52-week low, since they become risk seeking in this domain of the value function.

It is less clear that prospect theory generates any strong effects on beta, volatility or volume when approaching the 52-week high or low, since the kink at the reference is not crossed.

Attention hypothesis: Barber and Odean (2008) describe the attention hypothesis, which states that individual investors have limited capabilities to track the entire universe of stocks and thus focus on a subset of stocks that grab their attention. They also argue this mainly matters for purchase decisions of individuals, since individuals rarely sell short and thus only sell stocks they already own. Huddart et al. (2008) apply the attention hypothesis to explain volume and price patterns when stocks break through their 52-week high or low, arguing that such breakthroughs generate attention of individual investors. The attention hypothesis implies increased volume after a breakthrough due to extra purchases of individual investors, and positive subsequent returns due to this buying pressure. Again, the increased volume after the breakthrough may go along with increased volatility. The attention hypothesis does not generate any effect on the beta after breakthroughs, nor any effects on beta, volatility or volume when approaching the 52-week high or low.[2]

[2] By using stock-level 52-week highs and lows, we focus on stock-specific attention effects. Yuan (2009) finds that market-wide attention effects also affect trading behavior of individual investors. For example, Yuan (2009) finds that investors sell more stocks when the DJIA index hits its historical high.

In Table I we summarize the predicted effects of these three theories. For prospect theory, this table refers to two versions of the theory, one where the 52-week high serves as the reference point, and an alternative version where the 52-week low serves as reference point. Formally, prospect theory only allows for one reference point, which would imply that prospect theory has implications either for 52-week highs or for 52-week lows.

3. Empirical Methodology

We first describe how we define the approach and breakthrough dummies. Next, we describe the methodology to detect price patterns related to these approach and breakthrough dummies. We demonstrate in a simulation exercise the possible effect of anchoring. Finally, we discuss the stock and option data.

3.1. DEFINITION OF APPROACH AND BREAKTHROUGH DUMMIES

For the approach dummy, we need to set a range where the price level is considered to be close to the 52-week high or low. In the baseline case, the closing price needs to be within a 3% band below the 52-week high or within 3% above the 52-week low. We perform robustness checks on this choice later. Furthermore, we rule out situations where the 52-week high or low was set very recently, since in those cases it is unlikely that the high or low represents an anchor or reference point, or grabs the attention of new investors. Specifically, we focus on cases where the 52-week high or low was set at least 30 days ago (i.e. the last breakthrough is at least 30 days ago). To summarize, our key dummy variable for approaching (a) a 52-week high (h), D_t^{ah}, is then equal to one if the following two conditions are satisfied

$$(1-\kappa)\max\{P_{t-1},...,P_{t-k}\} \quad < \quad P_t < \max\{P_{t-1},...,P_{t-k}\} \tag{1}$$

$$\arg\max\{P_{t-1},...,P_{t-k}\} \quad < \quad t-m \tag{2}$$

where P_t is the closing price of a stock on day t, k is the number of trading days in the past 52 weeks, $\kappa = 0.03$ and $m = 30$. The dummy for approaching the 52-week low, D_t^{al}, is defined similarly.

The breakthrough dummies D_t^{bh} and D_t^{bl} are equal to one on the *first* day that the closing price is higher (lower) than the 52-week high (low), again only incorporating those cases where the 52-week high or low was set more than 30 days ago.

We rule out stock split or dividend payout events because it is meaningless to compare the pre-event maximum with the post-event price.

3.2. EMPIRICAL SPECIFICATIONS

We first discuss the benchmark regression where option-implied volatilities are regressed on approach and breakthrough dummies. Next we describe specifications where the alpha and market beta of the stock return are functions of these dummies. Last, we explore the effect of these dummy variables on the stock trading volume. In all cases, our empirical strategy follows a two-step approach. In the first step we perform an estimation for each stock separately. In a second step we average the relevant coefficient estimates across stocks.

3.2.1. *Option-Implied Volatilities*

Our first set of regressions uses implied volatilities of options. We impose the constraint that only stocks with at least 10 nonzero observations for each dummy variable are included to avoid outliers. On each day, we observe per stock i closing implied volatilities of $K_{i,t}$ options on this stock with different maturities and strike prices, which we denote $IV_{i,k,t}$, for $k = 1, .., K_{i,t}$. We then run the following regression per stock,

$$IV_{i,k,t} = \gamma_{0,i} + \gamma_{1,i} D_{i,t} + \gamma'_{2,i} x_{i,t} + \nu_{i,k,t} \tag{3}$$

where $D_{i,t}$ is the dummy variable of interest (approach/breakthrough of high/low), and $\nu_{i,k,t}$ is the option-specific error term. We perform a separate regression for each dummy variable in order to maximize the number of stocks that can be included in the analysis. Note that there is no need to lag the dummy variables or controls by one day: our option-implied volatilities are based on closing option prices at day t. We can therefore directly analyze the contemporaneous relation between the option-implied volatilities and the approach dummy variables. Similarly, when performing the breakthrough regressions, we again focus on the contemporaneous relation between the implied volatility and breakthrough variables. Given that a breakthrough is defined as the closing price being higher (lower) than the 52-week high (low), the breakthrough will have happened at some point during the trading day, and we thus analyze the effect of this breakthrough on the closing option prices (or implied volatilities) at the end of that day. However, below we also study whether the effects of a breakthrough persist over time, by analyzing the relation between implied volatilities and lagged breakthrough dummy variables.

We are mainly interested in the average effect of the 52-week high and low on implied volatilities. We therefore follow a two-step procedure. First, we run regression (3) for each stock separately. In a second step, we calculate the weighted average of the estimated coefficients across stocks. The weight of each stock is based on the number of nonzero dummy observations. Because the precision of the estimates depends on the frequency of observing approaches and breakthroughs, using a weighted average improves the precision of the estimates.

The standard errors for the average coefficients across stocks are based on the variance-covariance matrix of the estimated coefficients from the option-level time-series regressions. Importantly, we thus do not assume that the estimated coefficients are independent across options. Instead, we estimate the variance-covariance matrix of the estimated regression coefficients through the cross-correlations of the error terms $\nu_{i,k,t}$ of the option IV regression in Equation (3) across stocks. We have multiple options per stock. When calculating these standard errors, we cluster all options at the stock level and thus allow for cross-correlation across stocks. The appendix gives a brief derivation for these standard errors.

3.2.2. *A Model for the Mean and Variance of Stock Returns*

For the underlying stock returns, we allow both the expected return and return variance to depend on the approach and breakthrough dummies. As discussed below in detail, we perform a joint estimation of the mean and variance equations.

We first discuss the case of approaching a 52-week high or low. For the mean equation, we specify a market model where we interact the alpha and beta with the approach dummies and control variables. Specifically, for each stock i the excess return $R_{i,t}$ satisfies

$$\begin{aligned} R_{i,t} \quad = \quad & \alpha_{0,i} + \alpha_{1,i} D^{ah}_{t-1,i} + \alpha_{2,i} D^{al}_{t-1,i} + \alpha'_{3,i} x_{i,t-1} + \\ & \left(\beta_{0,i} + \beta_{1,i} D^{ah}_{t-1,i} + \beta_{2,i} D^{al}_{t-1,i} + \beta'_{3,i} x_{i,t-1} \right) R_{m,t} + h_{i,t} z_{i,t} \end{aligned} \tag{4}$$

where $R_{m,t}$ is the excess market return, $z_{i,t}$ a standard normal idiosyncratic shock, $h_{i,t}$ the conditional variance and $x_{i,t}$ a vector with control variables. Define the total residual shock as $\varepsilon_{i,t} = h_{i,t} z_{i,t}$. Note that in Equation (4) we study whether the return on day t is affected by conditioning variables (approach dummies and controls) observed at the previous day $t-1$. Specifically, we analyze whether the alpha and beta of a stock return on day t depend on whether the stock price was close to the 52-week high or low on the previous day.

The conditional variance is modelled using a GARCH-style approach. At first sight, one might consider using a GARCH(1,1) model for daily returns and add exogenous variables (approach/breakthrough dummies) to this equation. Such an approach may not be ideal for our purpose. This is because, in many cases, the stock price was already close to the 52-week high on the previous day, which implies that both the lagged conditional variance $h_{i,t-1}$ and lagged shock $\varepsilon^2_{i,t-1}$ are already lower than usual. As a result, a standard GARCH(1,1) approach may not be the best way to identify the effect of closeness to the high or low on the variance.

To avoid this issue, we lag the ARCH terms by 10 trading days, and do not include the

GARCH term (h_{t-1}).[3] To have some flexibility to capture the persistence in volatility, we include 5 ARCH terms,

$$\begin{aligned} h_{i,t} &= \delta_0 + \delta_1 \varepsilon^2_{i,t-10} + \delta_2 \varepsilon^2_{i,t-10-1} + \delta_3 \varepsilon^2_{i,t-10-2} + \delta_4 \varepsilon^2_{i,t-10-3} + \delta_5 \varepsilon^2_{i,t-10-4} \\ &\quad + \delta_6 D^{ah}_{i,t-1} + \delta_7 D^{al}_{i,t-1} + \delta'_8 x_{i,t-1} \end{aligned} \tag{5}$$

The mean and variance Equations (4)-(5) are then jointly estimated using Maximum Likelihood.[4] This estimation is performed for each stock separately. As with the option analysis, we then average all coefficients across stocks to obtain insight in the average effect of the approach and breakthrough dummies.[5] Also note that we do not focus on the total variance of the stock return since this variance will be affected by a change in the market beta. By looking at the idiosyncratic conditional variance $h_{i,t}$ we take out any effect of the beta.

For the case of breaking through the 52-week high or low, we perform a similar analysis, but now focusing on the return and conditional variance on the day *after* the breakthrough. We estimate the breakthrough model separately since we have a smaller sample of stocks with a sufficient number of breakthroughs (a stock is included in our sample if it has at least 10 breakthrough events). Finally, in some cases we allow for multiple factors (size, value and momentum) in the mean Equation (4).

[3] One could lag the GARCH-term h_t by several periods, say 5 days, but if one rewrites this into an ARCH model, it implies that only squared returns at day $t-5$, $t-10$, $t-15$, ..., matter for the conditional variance.

[4] We thank the anonymous referee for suggesting a GARCH approach and the joint estimation of the mean and variance equations.

[5] In contrast to the option analysis, we do not correct the standard errors for cross-sectional correlation across the error terms $\varepsilon_{i,t}$, since this is numerically infeasible with ML estimation. We have checked the impact of this simplification using OLS-based estimates for regressions (4) and (5) and find that it hardly affects the standard errors.

3.2.3. *Trading Volume*

We test whether the stock trading volume changes when approaching the 52-week high or low or after breaking through the 52-week high or low. Let $V_{i,t}$ be the dollar trading volume of stock i on day t. This trading volume may be nonstationary. We consider two approaches to deal with this nonstationarity.[6] First, we use as left-hand-side variable the change in log trading volume over a 10-day period: $\ln(1 + V_{i,t}) - \ln(1 + V_{i,t-10})$. We use a 10-day period to avoid similar problems as with the GARCH(1,1) approach above: using daily changes in trading volume is not ideal as the stock may already have been close to the high or low on the previous day. Second, we use as left-hand-side variable the log daily trading volume $\ln(1 + V_{i,t})$ divided by the log of the average daily volume over the past month. We then regress these trading volume measures on the approach and breakthrough dummies and several control variables. As before, we perform this estimation per stock, and then average coefficients across stocks. Standard errors are corrected for cross-sectional correlation of the regression errors (see Appendix for details).

3.3. SIMULATION STUDY

To illustrate the potential effects of approaching a 52-week high and low on the beta and variance of a stock, we perform a simple simulation exercise. We focus on the approach case and the presence of anchoring effects, because the effect on betas and variances for this case has not been studied before. Note that by studying the implications for the stock variance we also assess, indirectly, how implied volatilities are affected by anchoring.

We mimic our empirical setup by simulating 15 years of daily returns for $2,700$ stocks in 1000 simulations. We distinguish between the fundamental and actual price of a stock. The fundamental price of each stock follows a one-factor market model with 1% alpha, unit beta, 8% expected market excess return, 15% market volatility and 30% idiosyncratic volatility per annum. The fundamental price dynamics are not affected by closeness to the

[6] We thank the anonymous referee for suggesting these methods.

52-week high or low. However, with some positive probability the actual price remains at the level of the previous day if the fundamental price breaks through the 52-week high, which thus is a resistance level. In this way we mimic the anchoring mechanism of George and Hwang (2004), where good news is not directly incorporated in the stock price when the stock price is close to the 52-week high.

Specifically, on a given day the actual price has 25% probability to remain at the same level when the fundamental price breaks through the 52-week high on that day. With 75% probability the actual price does not remain at last day's level, but converges to the fundamental price. For this convergence we consider two alternative assumptions. In the first set of simulations, we assume direct and full convergence to the fundamental price in one day. As an alternative, we assume slow convergence over a 10-day period in a second set of simulations.[7] In addition, we also allow the actual price to remain at the same level for more than one period, but the probability decays over time: conditional on the actual price remaining at the same level and the fundamental price still being above the resistance level, the probability of the actual price remaining at the same level for the next period is decaying with the inverse of the number of divergence days.

We then estimate the mean and variance Equations (4) and (5) on these simulated data, to obtain the effect of approaching the 52-week high on the alpha, beta, and idiosyncratic return variance. In contrast to the empirical analysis, where we use Maximum Likelihood to jointly estimate the mean and variance equations, in our simulation analysis we estimate the mean and variance equations separately using linear regression.[8] Also, given that the

[7] In the slow-convergence case, the actual price has the following process

$$P^a_{t+1} = P^a_t + (P^f_t - P^a_t) * (\frac{c + (10 - c) * u}{10})$$

where c is the number of days after the breakthrough, P^a_t is the actual price at time t, P^f_t is the fundamental price at time t, and u is a random variable with uniform distribution.

[8] We use linear regressions because we would have to perform 2700 times 1000 = 2.7 million numerical MLE optimizations, which is computational infeasible.

model has a constant variance for the underlying returns, the variance equation for the simulation is simply

$$\ln(\widehat{\varepsilon}_{i,t}^2) = \theta_{0,i} + \theta_{1,i} D_{t-1,i}^{ah} + \theta_{2,i} D_{t-1,i}^{al} + \eta_{i,t} \tag{6}$$

where $\widehat{\varepsilon}_{i,t}^2$ is the residual from the mean equation and we use the log transformation to make interpretation easier.

We report the average coefficient across individual stocks using either the number of nonzero dummy observations or the inverse of the coefficient standard errors as weights.

The results for simulations 1 and 2 are in Table II. In both simulation settings the beta and idiosyncratic variance decrease by a considerable and significant amount, due to the resistance effect of the 52-week high on the actual stock price. The effect on the abnormal return (alpha) is less clear and depends on how quickly the actual price converges to true price. In case of direct convergence (simulation 1), the effect is positive because the price level is corrected on the day when the actual stock price breaks through the high. In case of slow convergence (simulation 2), the alpha dummy is negative because on the breakthrough day, which is the final day that the lagged approach dummy equals one, the stock price does not converge fully to the actual price.

Table II also reports the "simulation standard errors", calculated as the standard deviation of the coefficient estimates across the 1000 simulations, divided by $\sqrt{1000}$. This is the standard error of the average of the coefficient estimates (across the 1000 simulations), and helps to see whether 1000 simulations is sufficient to precisely assess the effect of the approach dummies. Table II clearly shows that these standard errors are always extremely small, implying that the reported simulation averages are very accurate.

In sum, this simulation exercise shows that anchoring to the 52-week high may temporarily decrease the beta and variance of stock return when the stock price approaches this 52-week high. In addition, the results show that using the second moments is informative since the effect on the first moment (alpha) is ambiguous.

3.4. DATA DESCRIPTION

We use all stocks listed on NYSE and AMEX from July 1, 1963 to December 31, 2008 from the Center for Research in Security Prices (CRSP) dataset. The option data come from OptionMetrics for the period January 1, 1996 to September 30, 2008. For the option analysis, we focus on stocks that (i) are liquid (nonzero trading volume on all days in the sample) and (ii) have option prices available on all days in the sample. Since we focus on short-term effects on prices, we only include options with maturities between 8 and 64 calendar days. In total, this gives $6,448,486$ call option prices from 295 stocks.[9]

4. Empirical Results

In this section we discuss the empirical evidence on the effect of approaching and breaking through the 52-week high and low on stock and option price dynamics.

4.1. OPTION-IMPLIED VOLATILITY RESULTS

The regression specification for implied volatilities is given by Equation (3). The dependent variable is the implied volatility (IV) of options, measured in percentage points (often called "volatility points"). In addition to dummies for approaching or breaking through a 52-week high or low, we include several control variables as independent variables. We include a dummy for when the option maturity is less than 21 days and a dummy for when the option is close to at-the-money, defined as a strike to spot price ratio between 0.95 and 1.05, since we know that implied volatilities of individual stock options exhibit a smile pattern across strikes. We also include the contemporaneous return, the lagged realized volatility, and the lagged return (split into positive and negative lagged return to allow for an asymmetric relation). The contemporaneous return is included to control for the usual leverage effect in

[9] We focus on call options. Stock options are American, so that put-call parity does not hold exactly. However, given that we focus on short maturities the implied volatilities of put and call options are extremely close.

option markets: positive stock returns typically coincide with decreasing IVs. This control is particularly important for breakthrough days, as these days by construction exhibit large (positive or negative) stock returns. Finally, we include the contemporaneous level of the VIX index and the lagged IV of the stock to control for general variation in market volatility and for persistence in the IV. For the approach regressions, we use the lagged IV of 22 days ago in order to avoid that the lagged IV picks up part of the effect of being close to the high or low. For the breakthrough regressions, we lag the IV by one day, so that breakthrough dummy coefficients capture the change in IV due to the breakthrough event.

Table III presents the estimates of regression (3). In addition to the weighted-average regression coefficient across stocks, we present the median regression coefficient in square brackets and the standard error of the average in parentheses.

Table III shows that implied volatilities decrease substantially when the stock price approaches the 52-week high or low. The average change in the IV across stocks equals -0.90 (approaching high) and -0.40 (approaching low) volatility points. These effects are highly significant with t-statistics of 12.9 and 3.8, respectively. We report the median coefficient across stocks to check whether the results are driven by outliers, and find that this is not the case. The median effect is -0.92 for approaching the high and -0.23 for the low. This decrease in volatility when approaching the 52-week high or low is in line with the results of the simulation model based on the anchoring hypothesis.

We then focus on the change in IV on breakthrough days. We see that implied volatilities increase strongly on these days, by 1.12 volatility points when breaking through the high, and by 1.16 volatility points for breaking through a low. Even though we have less observations for breakthroughs, these results are significant with t-statistics of 5.6 (high) and 3.9 (low).

We also see that many of the control variables are significant with the expected sign. For example, we see a negative coefficient for the contemporaneous return ("leverage effect"), and positive coefficients for the VIX and lagged IV.

In Table IV we test for the longevity of the increase in implied volatility following a breakthrough of a 52-week high or low, by looking at the effect of the breakthrough dummy on IVs on the days following the breakthrough. We do this by rerunning the regressions of Table III, but adding dummies for two to five days after breaking through a 52-week high or low. We see that the effect is only present on the first two days following the breakthrough. In other words, the increase in implied volatilities is temporary and reverses in a few days.

In Table V we perform several robustness checks on the IV results in Table III. First, we use a different definition for when a price is considered to be close to a 52-week high or low. In the benchmark analysis, we set the approach dummy equal to one when the stock price is less than 3% below the high or above the low. Using either 2% or 4% to define this range leads to very similar results. Second, we use different methodologies for determining the weights for the reported weighted-average regression coefficients across stocks. We obtain similar results when using either weights based on the number of nonzero dummy observations or weights based on the standard error of the regression coefficient. Finally, winsorizing the cross-section of stock-level coefficients at the 2.5% and 97.5% percentiles gives very similar results.

4.2. RESULTS FOR MEAN RETURN EQUATION

We now turn to the impact of the 52-week high and low on the underlying stock returns. As mentioned above, we perform a joint estimation of the mean and variance equations. In this subsection, we discuss the results for the mean equation.

Approaching the 52-week high or low: In Table VI we present the baseline-case result for the market model in case of approaching a 52-week high or low. We first present the results corresponding to the CAPM augmented with 52-week high and low dummies in the alpha and beta, see Equation (4). To preserve space we do not report the average unconditional alpha and beta ($(1/N)\Sigma_i \alpha_{0,i}$ and $(1/N)\Sigma_i \beta_{0,i}$ in Equation (4)).

Table VI shows that the alpha is not significantly affected when approaching the 52-

week high or low. In contrast the CAPM beta decreases by 0.12 and 0.05 when approaching the 52-week high or low, respectively. This is significant at the 1% significance level and economically meaningful given that the average stock has a market beta of around 1.0. We also present results when also including, as independent variables, the return on the Fama and French (1992) small-minus-big market cap (size) and high-minus-low book-value-to-price ratio (value) factor, as well as the Carhart (1997) winner-minus-loser (momentum) factor. Again, to preserve space we do not report coefficients on these additional regressors. The alpha effect remains economically and statistically insignificant. The beta effect is again significantly negative when controlling for value, size and momentum factors, similar to the CAPM result, and has a comparable average and median coefficient.

In Table VII we again show results for approaching a 52-week high or low, Equation (4), but now including the past week, month, or year individual stock return as control variables in both the alpha and beta. The specification is motivated by a large body of academic literature documenting price momentum and reversal patterns.[10] As in Table VI, the effect of approaching a 52-week high or low on the alpha is insignificant. The effect on beta is very similar to the benchmark results: a significant and economically meaningful decrease when approaching a 52-week high or low.

Breaking through the 52-week high or low: Next we focus on what happens after a breakthrough of a 52-week high or low price. We first note that we have less statistical power for detecting breakthrough patterns, giving rise to higher standard errors relative to the approach case. This is a direct consequence of the fact that the number of occasions the breakthrough dummies take the value one is $62,459$, about 10 times less than the $590,313$ occasions the approach dummies take the value one. The large discrepancy arises from the fact that a stock price can be classified as approaching a 52-week high or low price for several days, but by construction cannot be classified as breaking through a 52-week high or low for two days in a row, since we require that the 52-week high or low was obtained at

[10] Early references on momentum include Jegadeesh and Titman (1993) and Asness (1994).

least 30 days ago (Equation (2)).

In Table VI we present the baseline-case result for the market model in case of breaking through a 52-week high or low price. Notice that the dummies are lagged, so if a 52-week high or low was broken between the close of day t and $t+1$, we analyze the effect on the excess return between the close of day $t+1$ and $t+2$.

For the market beta we find that it decreases after breaking through the 52-week high and increases after breaking through the 52-week low. Only the increase in beta after breaking through a low is robust to controlling for value, size and momentum factors (Table VI) and to including the past week, month, and year return (Table VII). However, when restricting the breakthrough dummy to cases where the stock price was within 3% of the 52-week high or low the day before, the beta dummy for a 52-week low becomes mostly insignificant (Table VII). We include this control variable to distinguish cases where the breakthrough happened "suddenly" and cases where the price was already close to the 52-week extreme.

For the CAPM specification in Equation (4), Table VI shows that the daily alpha is 0.144% and 0.164% higher after a breakthrough of the 52-week high and low, respectively, both significant at the 1% significance level. We estimate that round-trip transaction cost for US stocks vary between 0.10% and 1.00%, mainly depending on size and liquidity. Therefore, it is not clear that one can profitably trade on this pattern. The results for the alpha remain mostly statistically significant when controlling for the value, size, and momentum factors (Table VI), and when controlling for momentum and reversal (Table VII). The coefficient estimates for the alpha effects do vary somewhat across these specifications however. Also, when restricting the breakthrough dummy to cases the stock price was within 3% of the 52-week high or low the day before, the alpha dummy for the 52-week low is not significant. Focusing on the cases where the stock price was within 3% of the high or low excludes some of the large breakthroughs (of more than 3%). These results thus suggest that the positive alpha after breaking through the 52-week low mainly captures a price reversal after a large negative shock.

In Table VIII we check the robustness of changes in the CAPM alpha and beta around 52-week high and low prices to (i) using a different definition for when a price is considered to be close to a 52-week high or low, (ii) different methodologies for determining the weights for the reported weighted-average regression coefficients across stocks, and (iii) winsorizing the stock-level regression coefficients used for the reported weighted-average regression coefficients. We see that the beta effects are reasonably stable. Only when using a small range to define closeness to the high or low (2%) are the beta estimates insignificant (though still negative). The finding of a positive alpha after a breakthrough is also reasonably robust to these choices, although the alphas are not always statistically significant.

4.3. RETURN VARIANCE RESULTS

Next we turn to the results for the idiosyncratic return variance when approaching and breaking through a 52-week high or low price, following Equation (5). As mentioned earlier, this equation is estimated jointly with the mean equation using ML. We control for an asymmetric effect of lagged returns by including $\max(R, 0)$ and $\min(R, 0)$, with R the stock return over the previous month, as control variables. The results are presented in Table IX. In line with the option-implied volatility results, we find that the conditional variance decreases when approaching a 52-week high or low and increases after breaking through a 52-week high or low. In each case the result is significant at the 1% level. Economically, the effects are also large. To see this, note that in Table IX the coefficients give the change in the conditional return variance due to the 52-week high and low dummies, where returns are measured as percentage daily returns. Across all stocks, the unconditional variance of daily returns equals 4.6 (squared %). Then, approaching the 52-week high lowers the conditional variance by -0.22. Relative to the unconditional variance level of 4.6, this effect equals -0.22 divided by 4.6, hence about 4.8%. After a breakthrough the variance increases very substantially. For the 52-week high, the increase equals 0.86, or 0.86/4.6 or 19% in relative terms. For the 52-week low, the conditional variance increases by 1.99, hence 1.99/4.6 or 43% in relative terms.

To test for the longevity of the increase in idiosyncratic variance after breaking through a 52-week high or low, we rerun the regressions of Table IX, but adding dummies for two to five days after breaking through a 52-week high or low. Table X shows that the effect tapers off rather quickly: for the 52-week high the dummy coefficient is in fact negative for the third day and beyond, while for the 52-week low the coefficient is still positive for the second day and beyond, but well below the coefficient for day one.

In addition to these volatility results, we perform an additional analysis to validate these results in a simple way. We calculate the probability density of daily stock returns, both unconditionally and conditional upon approaching the 52-week high or low. We pool all stocks and then take the ratio of the conditional density and the conditional density (for 0.5% return intervals).[11] Note that this analysis is simple in the sense that it focuses on the total return, and thus does not separate alpha, beta and volatility effects. Figure 1 presents the ratio of the densities. The figure very clearly shows that when a stock approaches a high or low, it has much lower return volatility than usual. We perform a similar analysis for the density of returns on days following breakthroughs. Even though we have less observations in this case, Figure 2 shows a higher variance of returns on days following a breakthrough. The strongest effect is for breaking through a 52-week low, in line with the results from the ML estimation. For breaking through a 52-week high there seems to be some asymmetry: large positive returns are more likely than large negative returns. This is in line with the evidence for a positive alpha after breaking through a 52-week high.

[11] This analysis is inspired by the work of Donaldson and Kim (1993) who study how probability densities depend on psychological barriers.

4.4. VOLUME RESULTS

In Table XI we present results for testing the dependence of trading volume on approaching and breaking through the 52-week high and low. We include the contemporaneous daily stock return, the lagged realized volatility, the lagged stock return (split into positive and negative lagged return to allow for an asymmetric relation), and lagged volume as control variables. As mentioned above, we deal with potential nonstationarity of volume by either looking at changes in (log) volume ("Spec 1"), or by looking at log daily volume relative to the log average volume over the previous month ("Spec 2").

Volume is significantly higher both when approaching and breaking through a 52-week high and low. The effect is much larger for after breaking through a 52-week high or low. The coefficients are most easily interpreted for "Spec 1", where the dependent variable in the change in log volume. In this case, the coefficient can be interpreted as the relative change in volume in log terms, and we find an increase in volume of 7% for approaching the high and an increase of 10% for approaching the low. The volume effects after a breakthrough are much larger, with an increase of 55% after breaking through a high and 58% after breaking through a low. Again we test for the longevity of the effect, this time in the increase of volume, in Table X, by rerunning the regressions of Table XI, but adding dummies for two to five days after breaking through a 52-week high or low. The increase in volume is most pronounced on the day immediately following the breakthrough and slowly tapers off on the subsequent days.

4.5. CONSISTENCY BETWEEN STOCK AND OPTION RESULTS

The results above reveal strong effects on the stock return variance and option-implied volatilities both before and after breakthroughs. To analyze whether the stock and option results are quantitatively consistent with each other, we implement a simple option pricing model with stochastic volatility. We calibrate this model to capture the variance effects observed in the underlying stock returns, and then assess whether the option price effects generated by this model are similar to the observed option price effects.

In our stochastic volatility model, the stock price follows a continuous-time process

$$dS_t = \mu S_t + \sigma_t S_t dW_t \tag{7}$$

where S_t is the stock price, μ the expected return, σ_t the volatility at time t and dW_t a Brownian motion. There are three regimes for the variance of the stock return σ_t^2: the normal level, the approach level, and the breakthrough level. These variance levels are obtained from the estimates for the beta and idiosyncratic variance in Tables VI and IX. Specifically, we use that $Var_{t-1}(R_{it}) = \beta_{t-1}^2 Var(R_{m,t}) + Var_{t-1}(\varepsilon_{i,t})$, where β_{t-1} and $Var_{t-1}(\varepsilon_{i,t})$ depend on whether the approach or breakthrough dummies equal one at $t-1$. We also incorporate that after a breakthrough the variance is affected for several days. Each day, the variance regime can switch as a result of movements in the stock price, and we use the historically observed switching frequencies to estimate the switching probabilities. For simplicity we neglect that volatility is also stochastic on "normal" days (as captured empirically by our ARCH model). Hence, in this option pricing model volatility only changes when the stock price gets close to a high or low or when it breaks through a high or low.

To keep the model tractable, we assume independence between stock returns and variance changes. Denoting the Black-Scholes price as a function of variance by $BS(\sigma^2)$, Hull and White (1987) show that in case of return-variance independence the option price is given by a risk-neutral expectation of the Black-Scholes price over the average realized variance

$$E_0^Q \left[BS\left(\frac{1}{T} \int_0^T \sigma_t^2 dt\right) \right] \tag{8}$$

where T is the maturity date.[12] To implement this equation for our purposes, we simulate

[12] Note that the option price is obtained by a risk-neutral expectation over the variance levels. When calibrating the model to underlying stock return variances, we thus assume a zero volatility risk premium. For the short-term high-frequency variance effects that we focus on, this seems a reasonable assumption.

daily variance levels according to the regime-switching model, and then calculate model-based call option prices for the typical option in our sample, an ATM call option with 30 calendar days to maturity. We do this for three initial variance levels (normal, approach, and breakthrough). We invert these model-based option prices to implied volatilities so that we can compare how option-implied volatilities (IVs) change conditional upon being in one of three variance states.

We first discuss the case of approaching a high or low. When approaching a high, the option pricing model generates a decrease in the IV equal to -0.13 volatility points, which is negative but much smaller than the observed effect (-0.90 volatility points, Table III). When approaching a low, the model-implied effect is 0.10 volatility points, while the observed effect equals -0.40. The model generates a positive effect because the underlying stock variance only decreases marginally when approaching a low, while after a breakthrough the stock variance increases dramatically (Table IX). The option pricing model incorporates the possibility of a breakthrough when the stock price approaches the 52-week low, while it seems that the option market only incorporates the current effect of lower stock variance when the stock price is close to the 52-week low.

For the breakthrough case, the option pricing model generates an increase in IV of 0.01 and 0.84 volatility point for a high and low, respectively, while the actual effects equal 1.12 and 1.16 volatility point in Table III. For the breakthrough of a high, the effect is essentially zero since we incorporate the five-day effects on return variance after a breakthrough, where we see that the increase in return variance on the first day after a breakthrough is followed by decreasing variances.

Obviously, we do not expect a perfect fit for this analysis given the simplicity of the option pricing model. Also, the effects on underlying return variances are potentially more dependent on modelling and specification choices, whereas the effects on IVs can be measured very directly. Still, it seems that the effects on option IVs are somewhat larger than the effects on the underlying return variances.

4.6. ADDITIONAL ROBUSTNESS CHECKS

We now briefly discuss several additional robustness checks on the empirical results presented above. The tables related to these results are available upon request.

We first check whether our results are affected by earnings announcements. As is well known, earnings announcements can create large abnormal returns and hence cause breakthroughs in some cases. In addition, there is evidence of underreaction to such announcements. We therefore remove all days where there is an earnings announcement and the approach or breakthrough dummy equals one from the sample, and redo all analyses above. We find that this does not impact our results. The coefficients on the dummy variables are essentially unchanged when we remove days with earnings announcements, for all measures we focus on (alpha, beta, volatility, volume and implied volatility).

We also analyze whether the approach and breakthrough effects are concentrated within small stocks with high arbitrage costs. We do this in two ways. First, we redo the entire analysis for the subset of 295 stocks for which we have option data available. These stocks are typically more liquid and larger than the average stock in our entire cross-section. We find results that are quantitatively very similar to the benchmark results in all cases (IV, alpha, beta, volatility, volume). Second, we analyze the cross section of approach and breakthrough effects across stocks (recall that we estimate these effects per stock), by regressing the estimated dummy coefficients on the market capitalization (size) and stock price level. These variables have been associated with high arbitrage costs, see for example Baker and Wurgler (2006). We take the time-series average of size and stock price level for this cross-sectional regression. The results show that there is no evidence that the approach and breakthrough effects are only present in hard-to-arbitrage stocks: in most cases the coefficients on size and price level are insignificant and small.

Finally, we estimate the mean and variance equations for stock returns using standard least squares methods instead of Maximum Likelihood. We do this in two steps. In the first step, we estimate the mean Equation (4) by linear regression, and in a second step, we take the squared first-step residuals and regress these on the approach and breakthrough dummy coefficients. We find similar results for the effects on alpha, beta, and return variance.

4.7. EMPIRICAL RESULTS VERSUS THEORETICAL EXPLANATIONS

Approaching a high or low: As discussed above, we find a strong decrease in option-implied volatilities, idiosyncratic volatilities and betas when the stock price approaches a 52-week high or low. As shown by the simulation in Section 3.3, these results are consistent with the anchoring effect. When approaching the 52-week high or low the anchor reduces the willingness to bid up or down prices in a direction that would result in a breakthrough and thus decreases the co-movement with the market, as measured by the CAPM beta, and idiosyncratic volatility. We also find an increase in volume when approaching a high or low, which could be the result of disagreement between behavioral agents (subject to the anchoring bias) and rational agents (subject to limits to arbitrage). As discussed in Section 2, prospect theory and the attention hypothesis have no clear predictions for approaching a 52-week high or low and thus are not suited to explain the observed patterns, nor are they falsified by these patterns.

Breaking through a high or low: Our results show that after a breakthrough both idiosyncratic return volatilities and option-implied volatilities increase significantly. We also observe a strong increase in stock trading volume. The increase in variance and volume after breaking through a 52-week high is consistent with all three hypotheses considered. In all three theories (anchoring, prospect theory, and attention hypothesis), a breakthrough generates trading signals for the behavioral agents, which leads to increased trading volume and, in turn, may lead to increased volatility.

In addition to the volume and volatility effects, we find some evidence for positive abnormal returns after breaking through a high, in line with Huddart et al. (2008). This result is consistent with both the anchoring theory and attention hypothesis, which both predict that stock prices increase after breaking through a high, while prospect theory predicts a negative alpha in this case. For breaking through the 52-week low we find a significantly positive alpha in some cases, but insignificant alphas in other cases. Hence, we cannot draw strong conclusions on the validity of the different theories in this case. In general, empirical results are more stable and precise for the second moments, in line with the motivation of our paper.

Taking everything together, we find that the anchoring theory is consistent with our findings for before and after breakthroughs, while the investor attention hypothesis is also consistent with the after-breakthrough results.

5. Conclusion

In this paper we propose a new way of studying price irregularities when stock prices are close to or breaking through a 52-week high or low price. Instead of focusing on noisy measurements of abnormal returns, we focus on stock-option implied volatilities and second moments of stock returns (beta, idiosyncratic volatility). In addition, while existing work mainly focuses on price behavior after breaking through the 52-week high or low, we study both the stock price behavior when current prices are close to the 52-week high or low, and the behavior after a breakthrough. This provides new insights into the validity of theories that have been put forward to explain the effect of a 52-week high and low. In particular, we find strong evidence that beta, idiosyncratic volatility and option-implied volatility decrease when stock price are close to their 52-week high or low. This is in line with the anchoring hypothesis of Tversky and Kahneman (1974). After breaking through the 52-week high or low, we find a strong increase in stock return volatility and implied volatility, consistent with both anchoring and the investor attention hypothesis of Barber and Odean (2008).

An interesting question is whether it is possible to develop a trading strategy that exploits the predictive patterns documented in this paper. The evidence shows that option implied volatilities respond more strongly to approaching and breaking through the 52-week high or low than the underlying return volatility does. This would imply that options are cheap when approaching a 52-week high or low, and expensive just after a breakthrough of the 52-week high or low. Economically, these effects are large, between 0.40 and 1.16 volatility points in absolute terms. A trader could potentially exploit this by buying options when the stock price approaches the 52-week high or low, and selling these options after a breakthrough, while delta-hedging with the underlying stock. Of course, transaction costs in option markets are substantial (Mayhew (2002)), hence such a trading strategy may only be profitable for the subset of liquid options.

Finally, even though we focus in this paper on the 52-week high and low, our approach of analyzing implied volatilities and second moments of returns around specific events can be applied whenever a researcher is investigating short-term price irregularities.

Appendix

In this appendix we show how to derive the standard error for the weighted average of dummy coefficients across stocks. To illustrate, we only give an example of two stocks. The variance of $\overline{\overline{\beta}}$ can be written as follows

$$\begin{aligned} Var(\overline{\overline{\beta}}) &= Var(\omega_1\hat{\beta}_1 + \omega_2\hat{\beta}_2) \quad (9) \\ &= \{\omega_1^2 Var(\hat{\beta}_1) + \omega_2^2 Var(\hat{\beta}_2) + 2\omega_1\omega_2 Cov(\hat{\beta}_1, \hat{\beta}_2)\} \\ &= \{\omega_1^2 (X_1'X_1)^{-1} X_1'\hat{\varepsilon}_1\hat{\varepsilon}_1' X_1 (X_1'X_1)^{-1} \\ &\quad + \omega_2^2 (X_2'X_2)^{-1} X_2'\hat{\varepsilon}_2\hat{\varepsilon}_2' X_2 (X_2'X_2)^{-1} \\ &\quad + 2\omega_1\omega_2 (X_1'X_1)^{-1} X_1'\hat{\varepsilon}_1\hat{\varepsilon}_2' X_2 (X_2'X_2)^{-1}\} \end{aligned}$$

where ω_1 and ω_2 are the weights (adding up to one). If we assume that the error term for each stock is *i.i.d.* and the cross-sectional correlation is only contemporaneous, we have

$$\begin{aligned} Var(\overline{\overline{\beta}}) &= \{\omega_1^2 (X_1'X_1)^{-1}\hat{\sigma}_1^2 + \omega_2^2 (X_2'X_2)^{-1}\hat{\sigma}_2^2 \quad (10) \\ &\quad + 2\omega_1\omega_2\hat{\sigma}_{12} (X_1'X_1)^{-1} X_1' X_2 (X_2'X_2)^{-1}\} \end{aligned}$$

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Table I: Theoretical Predictions of Anchoring, Prospect Theory and Attention Hypothesis

Panel A shows the sign of the predicted effects on the implied volatility, CAPM alpha, CAPM beta, idiosyncratic volatility, and volume, for the case where the stock price approaches a 52-week high, and for the case where the stock price breaks through a 52-week high. Predictions are given for three theories: anchoring, prospect theory and the attention hypothesis. Panel B shows the sign of the predicted effects on the alpha for the case where the stock price approaches a 52-week low and for the case where the stock price breaks through a 52-week low. The predictions for beta, idiosyncratic volatility, implied volatility and volume are the same as for 52-week high.

Panel A: Approaching / breaking through a 52-week high				
		Anchoring	Prospect Theory	Attention
Implied Volatility	Approaching	−	0	0
	Breakthrough	+	+	+
Alpha	Approaching	+/0/−	0	0
	Breakthrough	+	−	+
Beta	Approaching	−	0	0
	Breakthrough	0	0	0
Idiosyncratic Volatility	Approaching	−	0	0
	Breakthrough	+	+	+
Volume	Approaching	+	0	0
	Breakthrough	+	+	+

Panel B: Approaching / breaking through a 52-week low				
		Anchoring	Prospect Theory	Attention
Alpha	Approaching	+/0/−	0	0
	Breakthrough	−	+	+

Table II: Simulation Study: Anchoring Effect of Approaching a 52-week High

This table shows results of the simulation study described in Subsection 3.3, to analyze how anchoring to the 52-week high affects alpha, beta and volatility when approaching the high. We simulate 15 years daily returns for $2,700$ stocks in 1000 simulations. The fundamental price of each stock follows a one-factor market model with 1% alpha, unit beta, 8% excess return, 15% market volatility and 30% idiosyncratic volatility per annum. The observed price has 25% probability to remain at last days' level when the true price has broken through the historical high. Conditional on the observed price remaining at the same level and the fundamental price still being above the historical high, the probability of the observed price remaining at the same level is decaying each subsequent day. In the alternative case of a breakthrough, the observed price converges to the fundamental price immediately in Simulation 1. The observed price converges to the fundamental price slowly within 10 following days in Simulation 2. For each simulation we run the market model regression in Equation 4. Firms with less than 10 positive observations for approaching 52-week high dummy are excluded. The first two rows report approach dummy coefficients for the alpha and beta. The last row reports the dummy coefficient of idiosyncratic variance (Equation 5). We report the average coefficient from individual stocks using the square root of number of nonzero approach dummies (NW) or the standard error as weight (SW). We also report the average standard error across 1,000 simulations for each coefficient as the "Average standard error" and the standard deviation of the coefficient estimates across the 1,000 replications and divide by square root of 1,000 as the "Simulation standard error".

	Simulation 1		Simulation 2	
	NW	SW	NW	SW
Alpha 52-week High (%)	0.0133	0.0187	−0.0315	−0.0264
Avg. standard error	(0.0056)	(0.0056)	(0.0052)	(0.0051)
Simulation standard error	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Beta 52-week High	−0.0927	−0.0938	−0.1201	−0.1177
Avg. standard error	(0.0141)	(0.0139)	(0.0058)	(0.0057)
Simulation standard error	(0.0033)	(0.0002)	(0.0002)	(0.0002)
Idio. Volatility 52-week High	−0.0861	−0.0822	−0.1674	−0.1637
Avg. standard error	(0.0064)	(0.0064)	(0.0064)	(0.0063)
Simulation standard error	(0.0002)	(0.0002)	(0.0002)	(0.0002)

Table III: Stock-option Implied Volatility Results

This table shows the results of regression Equation 3, analyzing the effect of approaching and breaking through the 52-week high or low on the implied volatility of stock call options, in column 1 to 4 respectively. The medians of the 52-week dummy estimations are shown below between square brackets and the standard errors are in parentheses and are corrected for the correlations between stocks (see Appendix). The short maturity dummy is equal to one if the maturity is less than 21 days. The at-the-money dummy is equal to one if the strike/spot ratio is within 0.95 and 1.05. The lagged standard deviation is calculated using daily returns from $t-44$ to $t-23$. The lagged return is the return from $t-22$ to $t-1$. The lagged implied volatility for approaching and breaking through the 52-week extremes is the implied volatility level on day $t-22$ and $t-1$, respectively. Contemporaneous return is the stock return on day t. The estimates are weighted averages from regressions ran by individual stocks. The weight is the number of nonzero approach or breakthrough dummies. Significance levels are 1% for ***, 5% for ** and 10% for * respectively.

	Approaching		After Breakthrough	
	High	Low	High	Low
52-Week Dummies	$^{***}-0.901$	$^{***}-0.402$	$^{***}1.117$	$^{***}1.164$
	[−0.916]	[−0.230]	[0.632]	[0.726]
	(0.070)	(0.105)	(0.201)	(0.397)
Short Maturity	$^{***}5.534$	$^{***}5.573$	$^{***}5.336$	$^{***}4.781$
	(0.149)	(0.151)	(0.134)	(0.137)
At-The-Money	$^{***}-9.528$	$^{***}-9.667$	$^{***}-8.705$	$^{***}-8.391$
	(0.050)	(0.051)	(0.052)	(0.052)
Contemporaneous Return	$^{***}-0.388$	$^{***}-0.389$	$^{***}-0.563$	$^{***}-0.490$
	(0.027)	(0.027)	(0.026)	(0.028)
Lagged Std	$^{***}0.136$	$^{***}0.138$	$^{***}0.066$	$^{***}0.054$
	(0.005)	(0.005)	(0.004)	(0.005)
Positive Lagged Return	$^{***}0.102$	$^{***}0.102$	$^{***}0.071$	$^{***}0.060$
	(0.006)	(0.006)	(0.004)	(0.005)
Negative Lagged Return	$^{***}-0.490$	$^{***}-0.485$	$^{***}-0.107$	$^{***}-0.080$
	(0.003)	(0.003)	(0.002)	(0.002)
Contemporaneous VIX	$^{***}0.384$	$^{***}0.380$	$^{***}0.119$	$^{***}0.103$
	(0.012)	(0.012)	(0.008)	(0.008)
Lagged Implied Volatility	$^{***}0.413$	$^{***}0.411$	$^{***}0.751$	$^{***}0.808$
	(0.004)	(0.004)	(0.003)	(0.004)
Number of Stocks	281	260	175	75

Table IV: Effect for the Five Days Following a Breakthrough

This table shows the five-day effects on call option implied volatility after breaking through the 52-week high or low. The control variables are the same as in Tables III, but not reported for brevity. The standard errors are below between parentheses and are corrected for the correlations between stocks (see Appendix). Significance levels are 1% for ***, 5% for ** and 10% for * respectively.

	52-week high	52-week low
First Day	$^{***}1.124$	$^{***}1.189$
	(0.201)	(0.398)
Second Day	$^{***}0.962$	0.338
	(0.194)	(0.331)
Third Day	$^{*}-0.315$	-0.156
	(0.162)	(0.261)
Fourth Day	-0.173	-0.162
	(0.181)	(0.248)
Fifth Day	0.199	0.154
	(0.182)	(0.313)
Controls	YES	YES

Table V: Implied Volatility: Robustness Check

This table shows robustness results on the results reported in Table III, analyzing the effect of approaching and breaking through a 52-week high or low on call option implied volatility. The definition of closeness to the 52-week extremes used for the approach dummy, kappa, varies: in specification 1 we set kappa equal to 2% while in specification 2 we set kappa equal to 4%. The breakthrough dummies are identical under the two specifications. The estimates are a weighted average from regressions ran by individual stocks. We show results where the weight is the number of nonzero approach or breakthrough dummies (NW) or the inverse of standard errors for the dummies from the stock-level regressions (SW). Column 5 to column 8 show the results when coefficients across stocks are winsorized at 2.5% and 97.5% level. The standard errors are below between parentheses and are corrected for the correlations between stocks (see Appendix). Significance levels are 1% for ***, 5% for ** and 10% for * respectively.

	Original				Winsorized			
	NW	NW	SW	SW	NW	NW	SW	SW
	Spec 1	Spec 2	Spec 1	Spec 2	Spec 1	Spec 2	Spec 1	Spec 2
Approach								
High	*** − 0.933	*** − 0.961	*** − 0.895	*** − 0.969	*** − 0.943	*** − 0.953	*** − 0.907	*** − 0.959
	(0.091)	(0.060)	(0.096)	(0.064)	(0.091)	(0.060)	(0.096)	(0.064)
Low	*** − 0.557	*** − 0.443	*** − 0.467	*** − 0.379	*** − 0.576	*** − 0.477	*** − 0.487	*** − 0.403
	(0.133)	(0.091)	(0.130)	(0.100)	(0.133)	(0.091)	(0.130)	(0.100)
Breakthrough								
High	***1.117		***1.099		***1.018		***1.016	
	(0.201)		(0.182)		(0.201)		(0.182)	
Low	***1.164		***1.127		**1.017		***1.024	
	(0.397)		(0.314)		(0.397)		(0.314)	

Table VI: Alpha and Beta: Baseline Case

This table shows the results of the Maximum Likelihood estimation of Equation 4, analyzing whether the alpha and beta are affected when approaching or breaking through the 52-week historical high or low. Columns 1 and 2 show the results when the stock price is approaching the 52-week high and low. Columns 3 and 4 show the results when stock price breaks through the high and low. The estimates are weighted averages of the coefficients for the individual stock-level time-series estimations, where the weight is the square root of number of nonzero approach and breakthrough dummies. Column 1 and 3 show the results using the CAPM alpha and beta. Columns 2 and 4 show the results when adding the size, value, and momentum factors as explanatory variables. We only report the dummy coefficients of interest. The medians of the estimations are shown below between square brackets and the standard errors are in parentheses. Significance levels are 1% for ***, 5% for ** and 10% for * respectively.

	Approaching		After Breakthrough	
	CAPM	Four Factors	CAPM	Four Factors
Alpha (% daily)				
52-week High	-0.009	0.013	$^{***}0.129$	$^{***}0.132$
	[0.002]	[0.000]	[0.067]	[0.072]
	(0.027)	(0.022)	(0.046)	(0.050)
52-week Low	0.044	0.024	$^{***}0.202$	$^{***}0.214$
	[0.002]	[0.007]	[0.205]	[0.206]
	(0.031)	(0.028)	(0.056)	(0.053)
Beta				
52-week High	$^{***}-0.117$	$^{***}-0.097$	$^{*}-0.068$	-0.050
	[-0.084]	[-0.072]	[-0.101]	[-0.084]
	(0.018)	(0.017)	(0.036)	(0.036)
52-week Low	$^{***}-0.054$	$^{***}-0.057$	$^{***}0.158$	$^{***}0.118$
	[-0.034]	[-0.036]	[0.159]	[0.123]
	(0.019)	(0.018)	(0.037)	(0.037)
Number of Stocks	1789	1789	589	589

Table VII: Alpha and Beta: Controlling for Momentum and Reversal Effects

This table is similar to Table VI, but now adds both $\max(R,0)$ and $\min(R,0)$ as control variables in the alpha and beta specification, where R is the past individual stock return measured over either last week, month, or year. The table also reports the result when restricting the breakthrough dummy to cases where the stock price was within 3% of the 52-week high or low the day before, in the lower part of the each panel. The table reports the (weighted) average of the stock-level coefficient estimates. The medians of the coefficient estimates across stocks are shown below between square brackets and the standard errors are in parentheses. Significance levels are 1% for ***, 5% for ** and 10% for * respectively.

	Approaching			After Breakthrough		
	Week	Month	Year	Week	Month	Year
Alpha (%)						
52-week High	0.008	−0.010	0.009	***0.243	***0.153	***0.152
	[0.008]	[0.010]	[0.005]	[0.099]	[0.099]	[0.073]
	(0.024)	(0.025)	(0.021)	(0.044)	(0.042)	(0.042)
52-week Low	0.010	0.012	0.023	***0.146	0.073	***0.147
	[−0.018]	[−0.009]	[−0.011]	[0.156]	[0.151]	[0.163]
	(0.029)	(0.029)	(0.030)	(0.056)	(0.057)	(0.052)
52-week High (<3%)				−0.028	**0.113	0.062
				[0.047]	[0.076]	[0.064]
				(0.058)	(0.051)	(0.062)
52-week Low (>-3%)				0.063	0.010	0.038
				[0.045]	[0.062]	[0.077]
				(0.074)	(0.067)	(0.078)
Beta						
52-week High	*** − 0.091	*** − 0.088	*** − 0.067	−0.043	−0.033	−0.037
	[−0.062]	[−0.053]	[−0.057]	[−0.071]	[−0.038]	[−0.044]
	(0.017)	(0.017)	(0.016)	(0.036)	(0.034)	(0.035)
52-week Low	*** − 0.053	*** − 0.083	−0.063	**0.081	**0.074	***0.140
	[−0.032]	[−0.028]	[−0.010]	[0.080]	[0.092]	[0.155]
	(0.018)	(0.018)	(0.018)	(0.037)	(0.036)	(0.036)
52-week High (<3%)				* − 0.077	−0.015	*** − 0.116
				[−0.083]	[−0.052]	[−0.110]
				(0.045)	(0.042)	(0.044)
52-week Low (>-3%)				−0.031	−0.038	0.058
				[−0.031]	[−0.055]	[0.052]
				(0.049)	(0.046)	(0.051)

Table VIII: Alpha and Beta: Robustness Check

This table shows robustness checks on the results of Maximum Likelihood estimation of Equation 4 reported in Table VI , analyzing whether the alpha and beta are affected when approaching or breaking through the 52-week historical high or low. The definition of closeness to the 52-week extremes used for the approach dummy, kappa, varies: in Spec 1 we set kappa equal to 2% while in Spec 2 we set kappa equal to 4%. The estimates are a weighted average from regressions ran by individual stocks. We show results where the weight is the number of nonzero approach or breakthrough dummies (NW) or the inverse of standard errors for the dummies from the stock-level regressions (SW). The "Winsor." show the results when coefficients across stocks are winsorized at 2.5% and 97.5% level. Significance levels are 1% for ***, 5% for ** and 10% for * respectively.

	Approaching				After Breakthrough	
	Original Spec 1	Original Spec 2	Winsor. Spec 1	Winsor. Spec 2	Original	Winsor.
Alpha (%)						
Historical High, NW	$^{*}-0.043$	-0.015	$^{**}-0.028$	-0.013	$^{***}0.129$	$^{***}0.136$
	(0.026)	(0.025)	(0.014)	(0.016)	(0.046)	(0.033)
Historical Low, NW	0.041	$^{**}0.068$	0.036	$^{***}0.063$	$^{***}0.202$	$^{***}197$
	(0.031)	(0.029)	(0.023)	(0.021)	(0.056)	(0.049)
Historical High, SW	-0.006	-0.005	-0.006	-0.005	0.061	0.061
	(0.032)	(0.030)	(0.017)	(0.020)	(0.053)	(0.038)
Historical Low, SW	0.007	0.008	0.007	0.009	$^{**}0.154$	$^{***}0.156$
	(0.041)	(0.037)	(0.030)	(0.027)	(0.065)	(0.058)
Beta						
Historical High, NW	$^{***}-0.071$	$^{***}-0.176$	$^{***}-0.069$	$^{***}-0.182$	$^{*}-0.068$	$^{*}-0.068$
	(0.019)	(0.017)	(0.018)	(0.017)	(0.036)	(0.036)
Historical Low, NW	-0.023	$^{***}-0.108$	-0.020	$^{***}-0.111$	$^{***}0.158$	$^{***}0.158$
	(0.020)	(0.018)	(0.020)	(0.018)	(0.037)	(0.037)
Historical High, SW	$^{***}-0.088$	$^{***}-0.120$	$^{***}-0.088$	$^{***}-0.121$	-0.061	-0.061
	(0.024)	(0.021)	(0.023)	(0.020)	(0.044)	(0.044)
Historical Low, SW	-0.019	$^{**}-0.052$	-0.019	$^{**}-0.053$	$^{***}0.128$	$^{***}0.128$
	(0.026)	(0.022)	(0.026)	(0.022)	(0.048)	(0.048)
Number of Stocks	1384	2006	1384	2006	589	589

Table IX: Idiosyncratic Variance

This table shows results of Maximum Likelihood estimation of Equation 5, analyzing the effect of approaching and breaking through the 52-week high or low on the idiosyncratic return variance. The first two columns show the results when the price is approaching the 52-week high and low. The last two columns show the results after the breakthrough. Column 1 and 3 show the results using the CAPM as the mean equation. Columns 2 and 4 show the results when adding the size, value, and momentum factors as explanatory variables. The estimates are a weighted average of the coefficients from the stock-level ML estimations. The weight is the number of nonzero approach or breakthrough dummies. The medians of the coefficients are also shown below between square brackets. The standard errors are between parentheses. Significance levels are 1% for ***, 5% for ** and 10% for * respectively.

	Approaching		After Breakthrough	
	CAPM	Four Factors	CAPM	Four Factors
52-week High	***−0.221	***−0.159	***0.857	***0.892
	[−0.267]	[−0.208]	[0.348]	[0.407]
	(0.029)	(0.030)	(0.089)	(0.088)
52-week Low	***−0.249	***−0.195	***1.992	***1.996
	[−0.299]	[−0.258]	[1.745]	[1.808]
	(0.034)	(0.036)	(0.109)	(0.105)
Number of stocks	1789	1789	589	589

Table X: Effect for the Five Days Following a Breakthrough

This table shows the five-day effects on idiosyncratic return variance and volume after breaking through the 52-week high and low. The estimation of the idiosyncratic return variance equation is the same way as in Table IX. The estimation of the volume equation is the same way as in Table XI. The control variables are not reported for brevity. Significance levels are 1% for ***, 5% for ** and 10% for * respectively.

	Idio. Var	Volume Spec 1	Volume Spec 2
52-week High			
First Day	$^{***}0.848$	$^{***}0.564$	$^{***}0.049$
	(0.089)	(0.011)	(0.001)
Second Day	0.022	$^{***}0.420$	$^{***}0.031$
	(0.085)	(0.011)	(0.001)
Third Day	$^{***}-0.278$	$^{***}0.331$	$^{***}0.020$
	(0.081)	(0.011)	(0.001)
Fourth Day	$^{***}-0.235$	$^{***}0.286$	$^{***}0.015$
	(0.080)	(0.011)	(0.001)
Fifth Day	$^{***}-0.315$	$^{***}0.256$	$^{***}0.011$
	(0.080)	(0.011)	(0.001)
52-week Low			
First Day	$^{***}2.093$	$^{***}0.588$	$^{***}0.052$
	(0.108)	(0.014)	(0.001)
Second Day	$^{***}0.979$	$^{***}0.429$	$^{***}0.032$
	(0.109)	(0.014)	(0.001)
Third Day	$^{***}0.741$	$^{***}0.379$	$^{***}0.025$
	(0.107)	(0.014)	(0.001)
Fourth Day	$^{***}0.688$	$^{***}0.335$	$^{***}0.018$
	(0.111)	(0.014)	(0.001)
Fifth Day	$^{***}0.424$	$^{***}0.302$	$^{***}0.014$
	(0.104)	(0.014)	(0.001)
Controls	YES	YES	YES

Table XI: Trading Volume

This table shows results of regressing stock trading volume on approaching and breakthrough dummies. The first two columns show the results when the price is approaching the 52-week high and low. The last two columns show the results after the breakthrough. Spec 1 uses the change in log volume on day t relative to log volume on day $t-10$ as dependent variable. Spec 2 uses the daily log volume divided by log of average daily volume over the past month as dependent variable. The lagged standard deviation is calculated using daily returns from $t-44$ to $t-23$. The lagged return is the return from $t-22$ to $t-1$. The lagged volume is the average volume from $t-22$ to $t-1$. The estimates are a weighted average of the coefficients from stock-level regressions. The weight is the number of nonzero approach or breakthrough dummies. The medians of the coefficients are also shown below between square brackets. Standard errors are between parentheses. Standard errors are corrected for the correlations between stocks. Significance levels are 1% for ***, 5% for ** and 10% for * respectively.

	Approaching		After Breakthrough	
	Volume Spec 1	Volume Spec 2	Volume Spec 1	Volume Spec 2
52-week High	$^{***}0.076$	$^{***}0.007$	$^{***}0.548$	$^{***}0.048$
	[0.069]	[0.006]	[0.534]	[0.045]
	(0.003)	(0.000)	(0.010)	(0.001)
52-week Low	$^{***}0.102$	$^{***}0.008$	$^{***}0.576$	$^{***}0.051$
	[0.104]	[0.008]	[0.564]	[0.050]
	(0.005)	(0.000)	(0.013)	(0.001)
Contemporaneous Return	$^{***}-0.442$	$^{***}-0.033$	$^{***}0.572$	$^{***}0.069$
	(0.128)	(0.011)	(0.073)	(0.005)
Lagged Return Std.Dev.	$^{***}-0.901$	$^{***}-0.105$	$^{***}-0.953$	$^{***}-0.115$
	(0.349)	(0.030)	(0.234)	(0.016)
Positive Lagged Return	$^{***}0.260$	$^{***}0.016$	$^{***}-0.127$	$^{***}-0.006$
	(0.056)	(0.005)	(0.025)	(0.002)
Negative Lagged Return	$^{***}-1.241$	$^{***}-0.105$	$^{***}-0.500$	$^{***}-0.036$
	(0.056)	(0.005)	(0.033)	(0.002)
Lagged Volume	$^{***}-0.136$	$^{***}-0.007$	$^{***}-0.045$	$^{***}0.002$
	(0.005)	(0.000)	(0.003)	(0.000)
Number of stocks	1644	1644	470	470

Figure 1. The figure presents the ratio of the stock return density conditional on approaching the 52-week high or low and the unconditional stock return density. These densities are estimated by pooling all data for stocks with at least 10 approach days, and using return intervals of 0.5%.

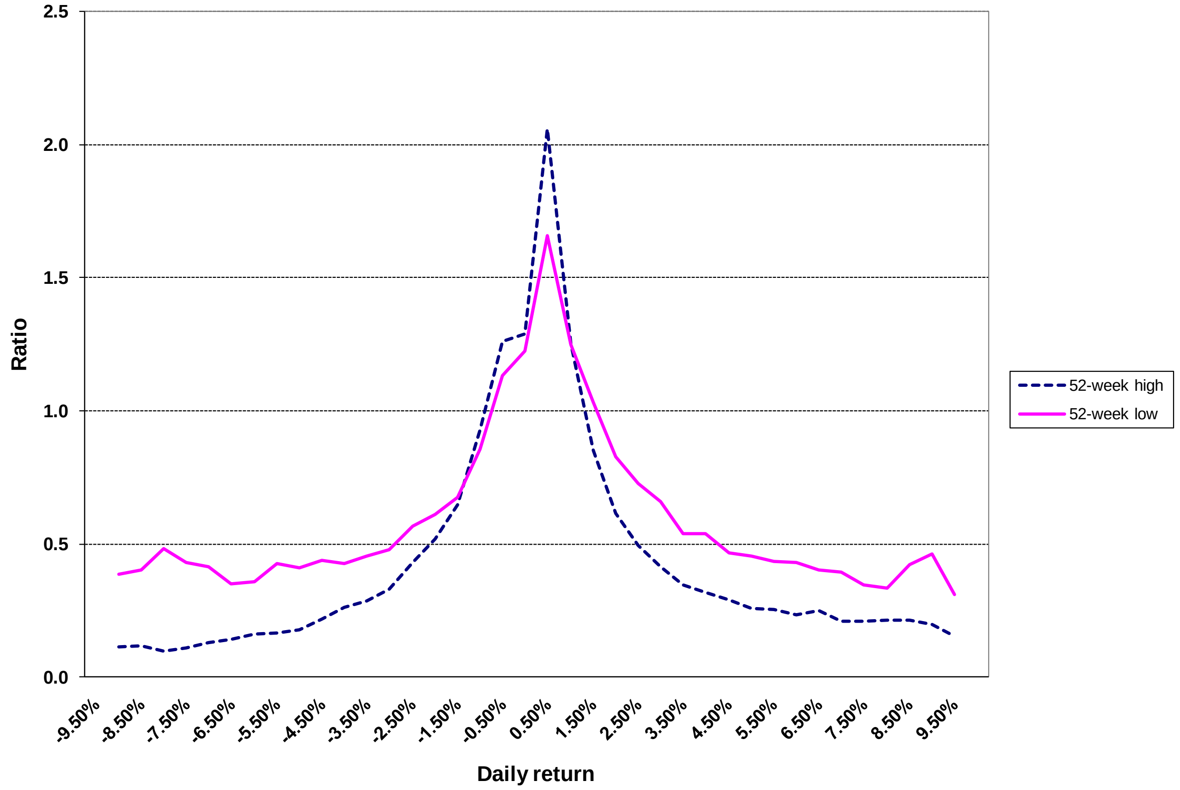

Figure 2. The figure presents the ratio of the stock return density conditional on breaking through the 52-week high or low and the unconditional stock return density. These densities are estimated by pooling all data for stocks with at least 10 breakthrough days, and using return intervals of 0.5%.