MANAGEMENT SCIENCE
Vol. 00, No. 0, Xxxxx 0000, pp. 000–000
ISSN 0025-1909 | EISSN 1526-5501 | 00 | 0000 | 0001

INFORMS
DOI 10.1287/xxxx.0000.0000

Volume and Price Patterns Around a Stock's 52-Week Highs and Lows: Theory and Evidence

Steven Huddart
Smeal College of Business, Pennsylvania State University, University Park, PA 16802-3603, huddart@psu.edu, http://www.personal.psu.edu/sjh11/

Mark Lang
Kenan-Flagler Business School, University of North Carolina at Chapel Hill, Chapel Hill, NC 27599-3490, langm@bschool.unc.edu, http://public.kenan-flagler.unc.edu/faculty/langm/index.html

Michelle H. Yetman
Graduate School of Management, University of California at Davis, Davis, CA 95616-8609, mhyetman@ucdavis.edu, http://www.gsm.ucdavis.edu/Faculty/YetmanM/

We provide large sample evidence that past price extremes influence investors' trading decisions. Volume is strikingly higher, in both economic and statistical terms, when the stock price crosses either the upper or lower limit of its past trading range. This increase in volume is more pronounced the longer the time since the stock price last achieved the price extreme, the smaller the firm, the higher the individual investor interest in the stock, and the greater the ambiguity regarding valuation. These results are robust across model specifications and controls for past returns and news arrival. Volume spikes when price crosses either the upper or lower limit of the past trading range, then gradually subsides. After either event, returns are reliably positive and, among small investors, trades classified as buyer-initiated are elevated. Overall, results are more consistent with bounded rationality—specifically, the attention hypothesis posited by Barber and Odean (2008)—than with other candidate explanations.

Key words: decision analysis, prospect theory, value function, reference point, behavioral finance, attention
History:

1. Introduction

What prompts investors to trade? One strand of literature suggests that investors focus on salient aspects of the past stock price series in making trading decisions, most notably the purchase price of a stock. Laboratory experiments show that price levels other than the purchase price affect subjects' decisions, particularly past extremes. In this paper, we provide large sample archival evidence that past price extremes are important to investors' stock trading decisions and investigate potential explanations for those effects.

A stock's trading range is defined by the highest and lowest prices it has achieved over a prior period, conventionally over the prior year. We call these limits the previous high and previous low. Event studies of volume around the dates on which a firm's stock price moves above a previous high or below a previous low reveal patterns of volume in event time that are quite similar. In the week that the stock price crosses either limit, volume spikes, is elevated for several weeks, and gradually subsides to normal levels. These spikes in volume are robust to inclusion of controls for contemporaneous and past stock returns, market-wide volume, earnings announcements, dividend record dates, stock price volatility, news announcements, and firm and date fixed effects. The previous high and low are significantly associated with volume while, other deciles of the frequency distribution of past prices over the benchmark period typically are not. The increase in volume when the stock price crosses either limit of its trading range is distinct from a more general correlation between price and volume. The magnitude of the abnormal volume when a stock breaches its prior trading range is at least as large as the volume spike associated with an earnings announcement or dividend record date, and an order of magnitude larger than the volume increase that occurs when a firm receives a mention in the news.

Furthermore, the increase in volume is more pronounced the longer the time since the previous high or low was established. This suggests that the limits of the past trading range become more salient the longer the stock remains inside the range. Additionally, the effect is stronger in periods of high investor sentiment as defined by Baker and Wurgler (2007), consistent with the notion that the increased volume reflects speculative trading by individual investors. Finally, the effect is more pronounced for firms that are small, are likely to have more individual investor interest, and have greater ambiguity regarding valuation as measured by return volatility and firm age.

To assess whether this additional volume is associated with price movements, we examine stock returns after a stock moves beyond either its previous high or previous low. The risk-adjusted returns over the following week and month are positive, particularly for smaller firms where individual investor trading is more likely to affect share price.

To provide intuition for why stock returns are positive after a stock crosses either limit of its trading range, we examine detailed trade and quote data around the events where the prices of stocks in our sample move outside of their respective trading ranges. Although it is difficult to definitively assign trade direction or trader type to specific transactions, our results suggest that much of the increase in volume is due to purchases by small investors. Barber, Odean and Zhu (2008) document that detailed trade and quote data small trades are highly correlated with retail broker trades, suggesting that the actors behind the trades at our events are most likely individuals trading on personal accounts. The fact that crossing the limits of the trading range is associated with an increase in small buyer-initiated trades complements the evidence discussed above of a stronger volume effect for firms that are small, are likely to have more individual investor interest, and have greater ambiguity regarding valuation.

To our knowledge, ours is the first paper to provide large-scale, market-wide empirical evidence that investors attend to past stock price paths in making trading decisions. We consider several candidate explanations for this evidence. The evidence, as a whole, is most consistent with bounded rationality and the associated attention hypothesis posited by Barber and Odean (2008).

Bounded rationality provides a potential explanation for why prior trading ranges matter to investor trading decisions. In particular, if investors are able to evaluate only a limited number of companies, stocks entering investors' choice sets will be those that attract their attention. Stocks that breach their trading ranges are likely to attract investor attention because the 52-week highs and lows are widely reported, and business publications such as the *Wall Street Journal* highlight stocks that have established new highs and lows. In addition, the financial press often defaults to a 52-week window for plotting a stock's price path. Moreover, a variety of studies highlight the salience of past extremes in individual decision making, suggesting that the breach of a prior trading range likely attracts attention to a stock. Research in learning and memory suggests that individuals are likely to focus on extreme observations even if they are uninformative and irrelevant (see, e.g., Frederickson and Kahneman, 1993; and Fiske and Taylor, 1991), so an investor following a stock price path is likely to notice the level of the current price relative to a trading range defined over a 52-week window.

Bounded rationality also suggests the effect is likely to be particularly pronounced for individual investors since they do not have the resources to follow as wide an array of stocks as do institutional investors. The effect should be more pronounced for purchases since individual investors face a huge array of potential stocks that they could purchase (and hence cannot follow each one closely), but are limited in their sales choices to firms currently in their portfolios. As noted in Barber and Odean (2008), individual investors tend to hold a relatively small number of stocks in their portfolios and rarely sell short.

Our results are strongly consistent with the effects of bounded rationality, and suggest that the increase in volume is likely the effect of increased investor attention when a stock exits its trading range. Taken together, the results suggest that: exiting the trading range attracts attention, the effect is more noteworthy the longer the time since the range was established, and attention gradually dissipates. Further, the stocks most affected are those traded predominantly by smaller investors (small and NASDAQ stocks) with more valuation uncertainty (younger firms with more volatile returns). Moreover, effects are strongest in periods in which individual investors are most active in the market. Importantly, the effect appears to be driven by purchases, particularly among small investors, for both new highs and new lows, suggesting similar effects irrespective of which direction a stock breaks out of the prior trading range, and is accompanied by positive returns, consistent with buying pressure.

Research such as Barber and Odean (2008) and Yates (2007) suggests that attention can have significant effects on subsets of investors. Barber and Odean (2008) document that investors are net buyers and professional investors are net sellers of stocks when attention to that stock is likely to be high, as indirectly measured by its presence in the news, high trading volume, and extreme returns. However, for these three proxies for attention, it is difficult to disentangle effects related to attention from those related to investors' reassessments of a stock's fundamentals. An advantage of our setting is that breaking out of a prior trading range should not convey news about fundamental value, but does attract investor attention. Also, Barber and Odean assume that volume and returns are indicators of attention, while our analysis demonstrates that attention precedes (and plausibly creates) subsequent volume and trade imbalances that, in turn, lead to predictable returns. Yates (2007) provides evidence that investors at a brokerage firm tend to buy shares when a stock's price breaks out of its prior trading range and documents a positive one day return.[1]

Our findings differ from and contribute to the prior literature in several ways. While prior research reveals attention effects among particular subsets of investors, our firm-level analysis suggests that attention effects are pervasive enough to have economic and statistically significant effects on overall trading volume. We document that a price breakout results in abnormal volume that is of similar magnitude to major information events such as earnings announcements. Furthermore, the effect on volume is "sticky" in that volume spikes in the week after the breach of the range and remains elevated for several weeks, gradually diminishing over time. Consistent with the attention hypothesis, we show that the pattern of trading volume over time is strongest for firms that are relatively small, trade on NASDAQ and have more valuation uncertainty, and the results are most pronounced in periods of high investor sentiment. Positive excess returns extending for at least a week, and as long as a month, follow the attention event and are strongest for small firms, where small investors are likely to initiate a larger fraction of all stock trades. These results contrast with the findings of Barber and Odean, who find no relation between attention buying and future returns and no difference in attention effects between small and large cap stocks. It may be that our setting better enables us to focus on attention effects rather than on more general announcements that likely contain information on firm fundamentals. Finally, as discussed in more detail in the next section, we are able to use our empirical setting to distinguish between bounded rationality/attention explanations and other psychological or economic effects that might be at work. Taken as a whole, our evidence is strongly consistent with a bounded rationality/attention explanation for the results and inconsistent with potential alternative explanations.

[1] Seasholes and Wu (2007) examine stock price moves and order imbalances after a stock price run-up of 10% triggers a trading halt under the rules of the Shanghai Stock Exchange. They find evidence of a temporary stock price increase the day after the halts that is associated with a buy-side imbalance among individual investors.

Our research makes several other contributions. Our evidence suggests potentially important determinants of trading volume. As Statman, Thorley, and Vorkink (2006) discuss, determinants of trading volume are poorly understood and models of rational utility-maximizing economic agents do not fit observed patterns well, although behavioral models offer novel testable predictions about determinants of volume. Chordia, Huh and Subrahmanyam (2007) survey the substantial literature on trading volume and provide evidence that trading volume is affected by stock visibility, portfolio rebalancing needs, differences of opinion, and uncertainty about value. Our results suggest that past extreme points in a stock's price path are salient cues that affect current trading decisions.

Additionally, we build on the behavioral finance research that investigates the importance of the past stock price path to investor decision-making. Prior research, including Shefrin and Statman (1985) and Ferris, Haugen, and Makhija (1988), focuses on the salience of the purchase price. Our archival analysis is motivated by human-subjects laboratory experiments that indicate past price extremes are salient to investors. Consistent with the laboratory experiments, we find strong volume and stock price effects in the neighborhood of stock price extremes.

Finally, our results on returns complement those in George and Hwang (2004), who seek to better understand momentum investing and focus on stocks that trade in the top 30% of the prior trading range. Since our volume results suggest that the event of crossing outside the prior trading range has specific importance to investors, we instead focus on returns following that event. We document significant positive returns, on average, for a stock whose price rises above its previous high. Further, we document that similar volume and returns results hold for stocks whose prices fall below previous lows, which suggests that similar forces are at work at both edges of the prior trading range.

In the next section, we discuss alternative candidate explanations for why volume might increase when a stock crosses either limit of its past trading range. We explain why none of these alternatives fits our data as well as the attention effects hypothesis implied by bounded rationality. Section 3 describes the data and our analysis in detail. Section 4 concludes.

2. Alternative Explanations

There are several candidate explanations for increases in trading volume as a function of past stock price trading ranges other than attention effects. First, increased trading could be due to the actions of traders who are hedging or replicating the payoffs from certain financial derivatives contracts. Would these traders trade more heavily when stock prices cross the previous high or low? Standard calls or puts should not cause abrupt changes in volume since the deltas of calls and puts change smoothly as the price of the underlying stock changes and do not depend on whether the stock is near a past price extreme. However, some exotic derivatives oblige hedgers and replicators to create portfolios that change composition rapidly in the neighborhood of a price extreme. In particular, consider a lookback call (put), which is the right to buy (sell) the underlying asset at the lowest (highest) price over the life of the option, or a lookback straddle, which is a long position in both a lookback call and a lookback put. Scenario B in Figure 6 of Fung and Hsieh (2001, p. 339) plots the delta of a lookback straddle on a stock whose price first rises to a new high, then falls, and finally rises past the prior extreme. The lookback straddle's delta increases sharply before the extreme, indicating that replicators and hedgers are trading heavily with each other. At the extreme, there is a kink. After stock reaches a new high, the delta is nearly constant, indicating that replicators and hedgers are no longer trading with each other. Thus, hedging and/or replication of a lookback straddle implies heavy trade before the prior price extreme is reached and little trade afterwards.

Exotics are unlikely to be driving our empirical results for four reasons. First, we find abnormally high trading volume only *after* the price extreme is reached, which is inconsistent with the trading pattern implied by either hedging or replication of lookback options described above. Second, our evidence is stronger for smaller firms, on which exotics are less likely to be written. Third, the abnormal volume we observe is primarily composed of small trades, which are more likely to be initiated by unsophisticated individual investors than by institutions. Finally, the results are more pronounced when we exclude from our analyses observations corresponding to stocks on which option contracts were traded.[2]

[2] Specifically, Table 3 specifications (1)–(3) yield much larger z-statistics and the coefficient estimates are comparable

A second possibility is that our results reflect the effects of past stock price movements unrelated to the high or low. Research by Statman, Thorley and Vorkink (2006), Glaser and Weber (2008), and Griffin, Nardari and Stultz (2007) documents a relation between prior returns and trading volume. Research on momentum suggests predictable autocorrelation in returns series.

Several features of our results suggest that they are not driven purely by past returns. First, our volume and returns analyses explicitly include controls for past returns, and suggest substantial *incremental* effects for firms that exit the prior trading range. Further, we find similar results and, in particular, positive abnormal returns after the stock crosses either its previous high or low, suggesting returns continuations at the top of the trading range and reversals at the bottom of the trading range. Neither momentum (which predicts continuations) nor contrarianism (which predicts reversals) can explain both the patterns of returns we observe at the top and at the bottom of the trading range.

A third possibility is that trading costs deter some investors from trading, leading to an information cascade (during which the price series exhibits momentum) followed by a trigger event and an information avalanche (during which the price series reverses direction). For instance, Lee (1998) and Cao, Coval, and Hirshleifer (2002) develop models in which transactions costs deter some informed investors from trading, leading to a stage with little trading volume during which the private information of a subset of informed investors is not impounded in price. Prices in this stage are fragile, so that when the sidelined investors do trade, a rapid reassessment of fundamental value by all traders and a spike in volume accompanied by a rapid price change can follow.

There are at least two ways in which the pattern of volume and returns over time that we report is inconsistent with avalanche models. First, those models imply no connection between the specific event we study, namely a stock's price moving outside of its past trading range, and a trigger event that would prompt informed utility-maximizing traders to revise their prior beliefs and trade. Second, even if moving outside the trading range were the trigger event, Lee's model predicts

or larger. This analysis is restricted to 1998-2006 due to data availability constraints in the CBOE Equity Option Volume Archive.

subsequent price moves that are inconsistent with our findings. The most striking prediction of Lee's avalanche model is that, after the trigger event, prices that have been drifting upwards crash; we find that prices after a maximum continue to drift upwards.

The price dynamics in Cao et al. (2002) are more complicated, but figure 9 on page 642 plots price and the number of buyer-initiated and seller-initiated trades over time for several scenarios and shows that price may swing up and down repeatedly before converging to fundamental value. Again, the limits of the previous trading range play no special role in the model, and neither total informed order flow nor its buy-side and sell-side components spikes systematically as the price path moves outside the bounds established by the previous high and low prices. Further, buyers and sellers in the model are more active when the stock price changes direction, whereas our results indicate that trading volume increases after the stock price crosses the bounds of the prior trading range.

A fourth set of candidate explanations derives from the observation that investors' stock trades may be influenced by the present level of the stock price in relation to a past stock price level that they recall as the status quo and which serves as a reference point. Kahneman and Tversky (1979) propose that prospect theory explains decision making in the face of risk better than expected utility theory. Applied to stock trading, prospect theory implies that stockholders are more likely to liquidate stock positions when the stock price is above the reference point than when the stock price is below the reference point. Empirical and experimental research in behavioral finance has operationalized the reference point as the price at which an investor purchased the stock. For instance, Shefrin and Statman (1985) provide evidence of a "disposition effect," under which investors are reluctant to sell a stock when its current price is below the purchase price.

The disposition effect is at odds with our evidence on several fronts. First, we know of no reason to expect a disproportionate number of current investors to have purchased at the previous high or low and thereby establish the previous high or low stock price as their status quo reference point. Second, we observe increased volume when the stock reaches a previous low, while the disposition effect implies that there ought to be *less* trade when the stock is below the reference point. Finally, our empirical results are unaffected when we control for the volume of stock traded in the past at various price levels, which Ferris et al. (1988) use as a proxy for likely purchase prices.

Related to the notion that the purchase price affects investor behavior, research on learning and memory suggests that individuals reference points may adapt over time.[3] For instance, long after a stock was purchased, an investor may consider the purchase price less salient. If the previous extreme replaces the purchase price as the reference point, then investors will be more likely to sell when the price is above the previous extreme. However, our results suggest that trades around extremes are mainly initiated by buyers, whereas prospect theory predicts that trade would be initiated by sellers. Further, the selling activity predicted by prospect theory when the previous high is the reference point suggests that subsequent returns ought to be negative, while we find that they are positive.[4]

3. Data and Analysis

The unit of observation for our primary analyses is a firm-week. Our tests examine the association between volume and the location of the weekly closing stock price in the frequency distribution of prices from a rolling benchmark period. We call the range of prices in the benchmark period the trading range and focus on firm-weeks for which the closing stock price is outside the trading range. Following Heath et al. (1999), we define the previous high (low) as the highest (lowest) daily closing stock price in the 48-week benchmark period ending 20 trading days before the last day of the observation week. Our choice of a 52-week period is based on its prominence in the business press and evidence in Heath et al. (1999) that it performs well relative to other benchmark periods

[3] Research on the peak-end hypothesis finds that individuals' remembered utility is based on extreme and ending values (Kahneman, Wakker, and Sarin, 1997). Gneezy (1998) finds evidence that both purchase and previous high stock prices appear to precipitate trading in the laboratory and that the previous high price may be more salient than the purchase price. Das and Raghubir (2006) study graphical information processing and find that individuals focus on extreme points of prior stock price series. Heath, Huddart, and Lang (1999), Core and Guay (2001) and Poteshman and Serbin (2003) provide evidence that prior 52-week highs influence employees' and investors' decisions to exercise stock options.

[4] Alternatively, investors may focus on price levels because they believe that past price ranges suggest likely future stock price directions. For example, investors may believe that stocks trading below (above) the prior trading range are more likely to be priced below (above) intrinsic value and so be more likely to buy (sell). However, that would imply selling pressure and negative returns after a firm exceeds a prior maximum, whereas we observe buying pressure and positive returns.

in explaining option exercise. Excluding prices in the 20 days preceding the observation week is ad hoc, but reflects an assumption that reference points adjust gradually with the passage of time. This choice also increases the frequency of observations at the extremes; otherwise, cases of stocks trading at extremes would be relatively rare because the reference point would reset immediately.[5]

3.1. Sample

We base our analysis on a random sample of 2,000 firms drawn from the Center for Research in Security Prices (CRSP) universe of common stocks listed on the NYSE, Amex, or NASDAQ exchanges at some point in the period from November 1, 1982, to December 31, 2006, with at least one year of available price data, which is required to compute the 52-week extremes. We begin our analysis on November 1, 1982, because that is the first date for which NASDAQ volume is available on CRSP.[6] We limit the sample to 2,000 firms to keep the resulting dataset tractable. Because we use weekly observations for 2,000 firms over a period of 24 years, there are nearly 800,000 firm-week observations in total. We include ordinary common shares listed on any of the three major U.S. exchanges so that findings apply to U.S. equities generally. Our primary sample excludes companies incorporated outside the United States, closed-end funds, and REITs, but we do conduct robustness tests using these firms.

3.2. First-stage regression

Our tests examine the association between volume and the location of the weekly closing stock price in the frequency distribution of prices from a rolling benchmark period. Our primary analysis is performed in two stages, similar to Ferris et al. (1988). In the first-stage regression, we define abnormal trading volume, ABNVOL, for a given firm-week to be the residual from firm-by-firm regressions of average daily firm volume as a percentage of firm shares outstanding for the week on average daily market volume as a percentage of market shares outstanding for the week. We use

[5] Our results are not sensitive to shortening the time from the end of the benchmark period until the observation week from four weeks to one week. When the benchmark period ends closer to the observation week, the number of observations for which the stock price in the observation week is outside of the trading range decreases, but the regression coefficient estimates measuring the increased volume in such weeks remain positive and strongly significant.

[6] As a robustness test, we collect a random sample of 500 firms beginning in 1963 and replicate our analysis. Inferences are the same.

the NASDAQ (NYSE) market volume for firms trading on the NASDAQ (NYSE or Amex). The dependent variable in our second-stage regressions is ABNVOL. In these regressions, we examine the relation between a stock's market-adjusted volume and aspects of the stock's past price series across all sample firms and years. We use average daily volume over a week since daily volume is likely to be highly correlated and monthly volume may be too aggregated to detect specific effects.

3.3. Descriptive statistics

Table 1 provides descriptive statistics on the regression variables. To mitigate the effects of extreme values, we winsorize our variables at the 1% and 99% levels. Conclusions are not sensitive to winsorization. The mean value of VOL, is 0.40%, which implies annual volume of about 100% of shares outstanding. By construction, the mean of ABNVOL is nearly 0; the small difference from 0 is due to winsorization. The key explanatory variables for the second-stage regression are the indicator variables MAX and MIN, which distinguish firm-weeks when the stock price is outside its trading range. MAX (MIN) is 1 when the closing price for the observation firm-week is at or above the prior high (at or below the prior low), and 0 otherwise. The mean value of MAX in Table 1 shows that in 13.4% of the observations, the firm-week closing stock price is above the previous high; the mean value of MIN shows that in 9.1% of the observations, it is below the previous low. Weekly stock returns excluding dividends, RET0, average 0.20%, implying annual returns of about 10%. Other variables are described as they are introduced into the analysis.

3.4. Second-stage regression analysis

Table 2 reports the basic regression of abnormal volume on the indicator variables, MAX and MIN with t-statistics clustered by firm.[7] We include contemporaneous and prior returns as control variables in the regression because prior research indicates that volume is associated with contemporaneous and past returns (Statman et al., 2006, Griffin et al., 2007, and Glaser and Weber, 2008.) Statman et al. (2006) suggest that the relation between volume and returns may be asymmetric,

[7] To account for cross-correlation, we utilize multiple estimation methods including panel data regression techniques such as clustering by firm, clustering by date, including fixed firm and date effects, and using an autoregressive model. Examining the results across the multiple estimation methods shows that our results are robust and that our concern is primarily with a firm effect. After clustering by firm, adding date fixed effects has virtually no effect on the standard errors.

Table 1 Descriptive statistics on regression variables.

Variable	Number of observations	Mean	Standard Deviation	25^{th} Percentile	Median	75^{th} Percentile
VOL	793,738	0.4044	0.6223	0.0759	0.1900	0.4475
ABNVOL	793,738	-0.0362	0.4603	-0.1872	-0.0581	0.0346
MAX	793,738	0.1338	0.3405	0.0000	0.0000	0.0000
MIN	793,738	0.0911	0.2878	0.0000	0.0000	0.0000
RET0	793,738	0.0020	0.0693	-0.0278	0.0000	0.0267
DIV	793,738	0.0383	0.1918	0.0000	0.0000	0.0000
EARNANN	793,738	0.0549	0.2277	0.0000	0.0000	0.0000
SDVOL	793,684	0.4673	0.3115	0.2456	0.3882	0.5988
STORIES	265,068	1.3396	4.1123	0.0000	0.0000	0.0000
WORD_ADJ	265,068	50.7535	146.7163	0.0000	0.0000	0.0000
LHIGH	106,238	12.4928	11.5389	4.4286	6.5714	15.5714
LLOW	72,313	14.6545	12.3853	5.0000	8.4286	22.1429
SENT	761,351	0.1347	0.7039	-0.3476	-0.0055	0.4892

The unit of observation is a firm-week. For a randomly selected sample of 2,000 firms, all firm-weeks in the period November 1, 1982, to December 31, 2006, with available data are included. VOL is the average daily number of firm shares traded as a percentage of firm shares outstanding in the observation week. ABNVOL is the residual from firm-by-firm OLS regressions of VOL on market volume, where market volume is measured as the average daily number of shares traded on the exchange where the stock is listed (Nasdaq or NYSE/Amex), expressed as a percentage of the number of shares outstanding for issues listed on that exchange in the observation week. MAX (MIN) is an indicator variable that takes the value 1 if the closing stock price for the observation week is above (below) the highest (lowest) price attained in the 48-week period ending 20 trading days before the last day of the observation week. RET0 is the raw stock return, excluding dividends, over the observation week. DIV and EARNANN are indicator variables taking the value 1 if a dividend record date (from CRSP) or an earnings announcement (from COMPUSTAT), respectively, occurs during the observation week. SDVOL is the annualized standard deviation of stock returns computed from the 26 weekly observations prior to the observation week. STORIES is the number of news stories reported in Dow Jones News Service mentioning the firm during the week. WORD_ADJ is the number of words in the stories mentioning the firm in the week; where a story mentions multiple firms, the number of words in the story is divided by the number of firms to assign the words across the firms. LHIGH (LLOW) is the time in weeks since the prior high (low) was reached, given the current price is above (below) the prior high (low). SENT is the monthly sentiment index based on Baker and Wurgler (2007), which removes business-cycle variation from each of the sentiment proxies prior to the principal components analysis used to construct the sentiment index. All variables are winsorized at the 1% and 99% levels.

with negative returns reducing volume more than positive returns increase it, while Barber and Odean (2008) show that retail investors are more likely to trade when returns are large in absolute value. We include contemporaneous and lagged returns for each of the preceding four weeks, and weeks -26 to -5, inclusive, as controls in the regression, and split returns by sign. For brevity, the coefficient estimates on the returns variables are not reported.[8]

[8] In the regressions, returns variables are constructed as follows: For $i \in \{1,2,3,4\}$, RETi is the stock return in week $-i$ relative to the event. RET5 is the return over weeks -26 to -5, inclusive. In the regressions, the returns are split by sign so the returns regressors are PRET$i = \max(\text{RETi}, 0)$ and NRET$i = \min(\text{RETi}, 0)$ for $i \in \{1, \dots, 5\}$. Belsey, Kuh, and Welsch (1980) indicate that a condition index of 10 suggests the potential for weak dependencies to affect the regression estimates. All of our condition indices are below 10. Our largest variance inflation factor is 2.9 (on SDVOL)

Table 2 Regression of ABNVOL on characteristics of the past price series and control variables.

Specification	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t	Coeff.	t
MAX	0.0996	19.9	0.0892	18.1	0.1002	12.2	0.0789	7.7	0.065	5.94	0.083	10.02
PCT90							-0.0153	-1.5				
PCT80							-0.0281	-2.8				
PCT70							-0.0264	-2.6				
PCT60							-0.0178	-1.7				
PCT50							-0.0203	-2.0				
PCT40							-0.0217	-2.1				
PCT30							-0.0271	-2.5				
PCT20							-0.0197	-1.9				
PCT10							-0.0212	-2.0				
PCT0							0.0014	0.1				
MIN	0.1190	25.7	0.1054	23.9	0.1293	18.9	0.1176	11.5	0.1081	11.26	0.1192	14.96
LLHIGH									0.0028	6.16		
LLOW									0.0014	3.38		
MAX×SENT											0.0575	4.19
MIN×SENT											0.0253	2.19
SENT											-0.0215	-3.76
DIV			0.0599	13.7	0.0865	12.8	0.0862	12.7	0.0865	12.75	0.0872	12.78
EARNANN			0.1076	20.9	0.0934	12.3	0.0933	12.3	0.0934	12.3	0.0934	12.32
SDVOL			-0.1513	-15.6	-0.1536	-9.4	-0.1505	-9.2	-0.1574	-9.63	-0.1516	-9.29
STORIES					0.0059	8.5	0.0060	8.5	0.006	8.5	0.0059	8.52
WORD_ADJ					0.0002	9.1	0.0002	9.1	0.0002	9.1	0.0002	9.21
Pseudo-R^2	0.0735		0.0811		0.1094		0.1137		0.1100		0.1099	
N	793,738		793,684		265,068		265,068		265,068		265,068	

Variables are defined in Table 1 with the following additions. The regression includes returns variables, split by the sign of the return for weeks −1, −2, −3, −4, and weeks −5 to −26 relative to the observation week. For brevity, the coefficient estimates for these return variables are not reported. PCTi is an indicator variable that takes the value 1 if the closing stock price for the observation week is above the percentile PCTi, but at or below the next percentile, where percentiles are calculated relative to the distribution of prices over the year-long period ending 20 trading days before the last day of the observation week. The exception is PCT90, which takes on the value 1 when the price is above the 90th percentile and below the maximum. The coefficient estimate for each PCTi variable is the difference from the mean of the PCTi estimates in the specification. Intercepts are not reported.

From specification (1) of Table 2, the principal variables of interest, MAX and MIN, have positive and highly significant coefficient estimates of 0.0996 and 0.1190, respectively. A change in abnormal

and variance inflation factors on the MIN and MAX variables are 1.4 and 1.3, also suggesting that multicollinearity is not a major problem.

volume of that magnitude is enough to move volume from the median to about the 75th percentile, indicating a substantial increase when the stock price moves outside its normal trading range. The table reports the deviance-based pseudo-R^2, which is defined as the relative reduction in deviance due to the covariates in the model. Despite the fact that the overall magnitude of the effect based on the coefficient estimate is substantial and the t-statistic is large due to the large number of observations, the explanatory power of the regression is relatively low. In part, this reflects the fact that we control for market volume in the first-stage regressions, which biases against finding the predicted results since it eliminates the effect of cases in which market volume is generally high because a disproportionate share of stocks are trading outside of prior trading ranges. However, analysis of ABNVOL focuses attention on firm-specific effects. Further, the regression does not capture firm-specific news that may affect firm-specific volume, except insofar as this news is reflected in the returns variables. We return to this issue later.

One potential concern with specification (1) of Table 2 is that the preceding results might be driven by the effect of earnings announcements or dividend record dates. In particular, volume is likely to be higher around earnings announcements because of the arrival of new information and around dividend record dates because of tax-based dividend capture strategies. We define DIV and EARNANN as indicator variables taking the value 1 if a dividend record date or an earnings announcement, respectively, occurs during the observation week. Also, the volatility of returns may affect volume for at least two reasons. First, increased return volatility may reflect increased uncertainty in the market, which may lead to additional trading. Second, prospect theory suggests that higher volatility may affect decisions to sell. We define stock volatility, SDVOL, as the annualized standard deviation of stock returns computed from the 26 weekly observations prior to the observation week. Specification (2) in Table 2 reports results controlling for earnings announcements, dividend record dates, and return volatility. As expected, volume is on average higher around dividend record and earnings announcement dates. The standard deviation of past returns is negatively correlated with volume, suggesting that return volatility drives out volume.

Most importantly, the indicator variables for prior extremes remain highly significant and only drop very slightly with inclusion of the additional variables.

It might be that the significant coefficients on MAX and MIN capture the arrival of news other than earnings. Barber and Odean (2008) present evidence that individual investors are net purchasers of stocks on days when stocks are in the news. To address this possibility, we include measures of news from Barber and Odean (2008) for the subset of our sample for which their data are available. We include two variables—the number of stories published in the week on the Dow Jones News Retrieval service that mention a firm (STORIES) and the number of words in those articles deflated by the number of companies discussed (WORD_ADJ). Because the database of news variables covers only 1994–2000, we lose more than half of our observations for this subsample. Specification 3 of Table 2 indicates that, as expected, volume is significantly higher for firms with news in the event week. However, the previous high and low variables remain significant and, in fact, increase in magnitude for this subsample and set of controls. The coefficient estimates on MAX and MIN indicate the effect on abnormal volume associated with moving outside the trading range is as great as the effect associated with an earnings announcement or dividend record date, and an order of magnitude greater than the effect associated with a mention of the company name in the business press. This confirms that breaking outside of a prior trading range has an economic and statistically significant effect on trading, of comparable or greater magnitude than most announcements.[9]

Alternatively, it could be that volume is nonlinear in returns, and price tends to exit the prior trading range through a particularly large positive or negative return. Thus, the indicator variables MAX and MIN might be significantly associated with extreme volume because they are correlated with extreme returns. In our primary analysis, we winsorize returns and volume at the 1% and 99% levels, which should mitigate this issue. We also replicate the analysis including both return and

[9] To rule out the possibility that we have misspecified the relation between news and volume with our measures, we replicate the analysis excluding all weeks in which there was a news story about a firm. While the sample size drops, results are very similar. Further, it might be the case that volume increases in anticipation of news or persists after the release of news. To address this possibility, we replicate the analysis excluding news weeks, as well as the preceding week and following week. Results are again very similar.

the square of the return as explanatory variables with similar results (not tabulated). In addition, various rules for eliminating observations with extreme returns do not affect inference: regression analysis of subsamples that exclude observations with contemporaneous returns in excess of 10% and 5% in absolute value yield very similar results (not tabulated).

3.5. Comparison with other percentiles of the past price distribution

Another potential concern is that other percentiles of the price distribution might have explanatory power. For example, investors might focus on a measure of central tendency like the median, or volume may spike across other percentiles of the prior trading range. While it seems unlikely that most investors would know percentiles of the prior distribution such as the median since they are generally not reported, investors may have a general sense for central tendency over the prior year.

Specification (4) of Table 2 presents coefficient estimates from a regression that includes a set of indicator variables, PCT0 through PCT90, that partition the prior price distribution by decile. For example, PCT0 takes on a value of one if price is above the previous low and at or below the 10th percentile of the past price distribution, and is zero otherwise; PCT10 takes on a value of one if price is above the 10th percentile of the past price distribution and at or below the 20th percentile of the past price distribution and is zero otherwise; and so on. The exception is PCT90, which takes on a value of one if the price is above the 90th percentile but below the previous high, since MAX takes on a value of one for a firm trading at or above the previous high. For expositional convenience, observations are adjusted by the mean volume across all percentiles, so coefficient estimates can be interpreted as the weighted-average volume in a given price percentile relative to the average across all percentiles. Results show clear spikes at the high and low. More to the point, there is no clear evidence of spikes within the trading range.[10]

[10] One potential concern is that volume might tend to be higher the more unusual is the price level regardless of whether the price is outside the prior trading range. To address that possibility, we construct a variable measuring the distance of the observation week price from the median price over the benchmark period, defined as the absolute value of the difference between 0.50 and the location of the current price in the distribution of past prices, expressed as a percentile of the past price distribution. Results (not tabulated) are robust to inclusion of this variable. In addition, results are robust to inclusion of a control for share price, suggesting that the results do not reflect a general relation between volume and share price.

3.6. Effect of time elapsed since the extreme was attained

Breaches of prior trading ranges are more likely to be noteworthy the longer the time elapsed since the previous breach because investors are more likely to notice events that are unusual relative to recent experience. For example, a new high for a stock repeatedly setting highs as it trends upwards is less likely to be salient than a stock that sets a new high after a long period of trading within the prior range. To examine this relationship, we include variables in the regression specification that measure the time in weeks since the previous high (low) was reached, given the price in the observation firm-week is above (below) the prior high (low), which we label LHIGH (LLOW). For firm-weeks where price is below (above) the prior high (low), LHIGH (LLOW) is set to zero.

Table 1 reports descriptive statistics on LHIGH and LLOW. The LHIGH (LLOW) descriptive statistics are computed over the 106,238 (72,313) firm-weeks where the closing weekly stock price is above the upper (below the lower) limit of the trading range. The means of LHIGH and LLOW are 12.49 and 14.65 weeks, respectively, with interquartile ranges of more than 11 weeks, suggesting that there is substantial variation in the times since the prior extremes were attained. The coefficient estimates on LHIGH and LLOW, reported in specification (5) of Table 2, are positive and statistically significant, suggesting that breaking outside the prior trading range is more noteworthy the longer the time since the range was set.

3.7. Differences across time

We investigate whether time-series variation in investor sentiment affects the relationship between trading volume and a firm trading at its high or low. Baker and Wurgler (2007) define sentiment as the propensity to speculate and argue that sentiment drives the relative demand for speculative investments. We hypothesize that the volume effects of trading outside of a trading range will be increasing in investor sentiment.

We include SENT, which is Baker and Wurgler's (2007) monthly sentiment index and is available through 2005, as a control variable, and interact it with MIN and MAX. Table 1 reports descriptive statistics on SENT. The mean of 0.1347 and the standard deviation of 0.7039 provide evidence of the substantial variation in SENT. Specification (6) of Table 2 shows that regression results are robust to inclusion of SENT as a control. More importantly, consistent with the notion that the effect is correlated with individual investor trading, specification (6) of Table 2 shows that the volume effect of trading at or above (below) a previous high (low) is increasing in investor sentiment.

3.8. Differences across firm characteristics

Finally, we examine whether the strength of the relation differs across firm characteristics. To the extent that the increase in volume reflects increased trading by individual investors, it should be particularly pronounced for firms that are relatively small, are likely to have more individual investor interest, and have greater ambiguity regarding valuation. We partition our results across exchanges because NASDAQ and Amex firms are on average smaller than NYSE firms, have a significantly smaller percentage of institutional holdings, and are less likely to have traded options (Chan, Leung, and Wang, 2004). Additionally, we partition our results across size by assigning stocks to groups based on their previous month's market value of equity relative to the distribution of the NYSE market value of equity, where the lower (upper) 30% are defined as small (large). Furthermore, we partition our analysis across volatility by assigning firms equally across three groups based on their average level of volatility, SDVOL.[11] If volatility serves as a proxy for greater ambiguity about valuation or if less sophisticated traders are attracted to higher volatility stocks, then we should find our results to be stronger for high volatility stocks. Finally, we partition our analysis across firm age by defining young firms as those that were first listed within the past 5 years. The IPO long-run underperformance anomaly suggests that the prices of newly-issued firms' shares are not efficient for up to five years following issuance, consistent with new issues being difficult to value (see Ritter and Welch 2002).

Table 3 reports the statistics for our primary variables of interest across the separate regressions for each partition of the fully-controlled model. The spike in volume subsequent to moving outside the trading range is strongly significant for all subsamples. However, results are significantly

[11] One concern is that volatility of a stock may change over our time period. Results are robust to categorizing the firms using firm-week volatility.

Table 3 Regression of ABNVOL on MAX, MIN, and controls across firm attributes.

	MAX					MIN						
	Coef.	Z score	a vs. b	b vs. c	c vs. a	Coef.	Z score	a vs. b	b vs. c	c vs. a	N	R^2
By Exchange:												
a) NYSE	0.0458	6.2	***			0.0672	8.0				92,171	0.0919
b) Amex	0.1224	6.4		*		0.0822	9.2		***		29,752	0.1641
c) Nasdaq	0.1628	11.8			***	0.1463	13.7			***	143,145	0.1269
By Size:												
a) Large	0.0268	2.0	**			0.0838	4.0				28,124	0.1263
b) Medium	0.0770	5.6		***		0.1161	7.3		**		54,882	0.1407
c) Small	0.1593	13.9			***	0.1435	19.1			***	182,062	0.1130
By Volatility:												
a) Low	0.0385	5.6	***			0.0614	9.7	***			107,845	0.0630
b) Medium	0.1740	12.9		***		0.1042	9.0		**		94,617	0.1345
c) High	0.3334	10.5			***	0.1377	9.6			***	62,606	0.1598
By Age:												
a) Young	0.1310	8.4	**			0.1399	11.7	*			99,098	0.1001
b) Mature	0.0874	9.9				0.1201	15.3				165,970	0.1248

For each category, group (a) is compared with group (b), (b) is compared with (c), and (c) is compared with (a). Firm-weeks are assigned to size groups based on their previous month's market value of equity relative to the distribution of the NYSE market value of equity, where the lower (upper) 30% are defined as small (large). Firms are assigned equally across volatility groups based on their average level of SDVOL. Young firms are those that were first listed within the previous 5 years. The symbols *, **, and *** denote that the coefficient estimates for the groups are significantly different at the 0.10, 0.05, and 0.01 levels, respectively, using a two-tailed test.

stronger for both the NASDAQ and Amex firms relative to the NYSE firms. In fact, the coefficient on MAX (MIN) for NASDAQ firms is over triple (double) the corresponding coefficients for NYSE firms. Consistent with this, the returns relation for longer lags (not tabulated) is also stronger for the NASDAQ than for the NYSE firms, consistent with the notion that the effect is most pronounced for smaller firms more likely to be traded by individual investors.[12] In addition, the magnitude of the coefficients on both the MAX and MIN variables are monotonically increasing across size and volatility partitions. The coefficient on MAX (MIN) for small firms is nearly six (two) times that for large firms. Similarly, the coefficient on MAX (MIN) for high volatility firms is over eight (two) times that for low volatility firms. Finally, the results are stronger for firms in their

[12] One potential concern is that NASDAQ computes volume differently than NYSE, especially since 1992 (Atkins and Dyl 1997). To address that concern, we recompute volume in a number of ways, including rescaling it on an annual basis by the ratio of NASDAQ/NYSE volume for our sample and computing it as a percentage of annual volume rather than shares outstanding. Results are robust, with NASDAQ firms showing consistently greater sensitivity to extremes than NYSE/Amex firms.

first five years of trading as compared with more mature firms. Overall, these results suggest that the effect is more pronounced for firms that are relatively small, are likely to have more individual investor interest, and have greater ambiguity regarding valuation.

3.9. Event study

The preceding analysis pools time series and cross-section. An alternative approach to investigate the effect of extreme prices is to directly compare volume around weeks on which a firm's stock price breaks through a previous high or low. We identify a subset of observations in which a firm breaks through a previous extreme and examine volume for 10 weeks before and after crossing the threshold. To avoid overlapping event windows, we require event-weeks for a given firm to be at least 21 weeks apart.

To ensure that results are not driven by other factors, we estimate a regression with the controls in Table 2, specification (2) (excluding the MAX and MIN variables), but supplemented with indicator variables for each week relative to the week when the extreme is reached. As a result, the coefficient estimates measure volume in a particular week after controlling for the effects of returns, price volatility, earnings announcements and dividend record dates. Regression coefficients for the event-time indicator variables are plotted in Fig. 1.[13] For the high, volume increases slightly in the weeks leading up to crossing the previous high, and then spikes sharply in the week the previous high is crossed. The volume remains elevated, but gradually declines over the following weeks. The pattern for lows is similar, although not as pronounced. These results confirm the conclusions from the earlier pooled analysis and provide further assurance that the preceding results are driven by the stock price paths of individual firms rather than differences across firms.[14]

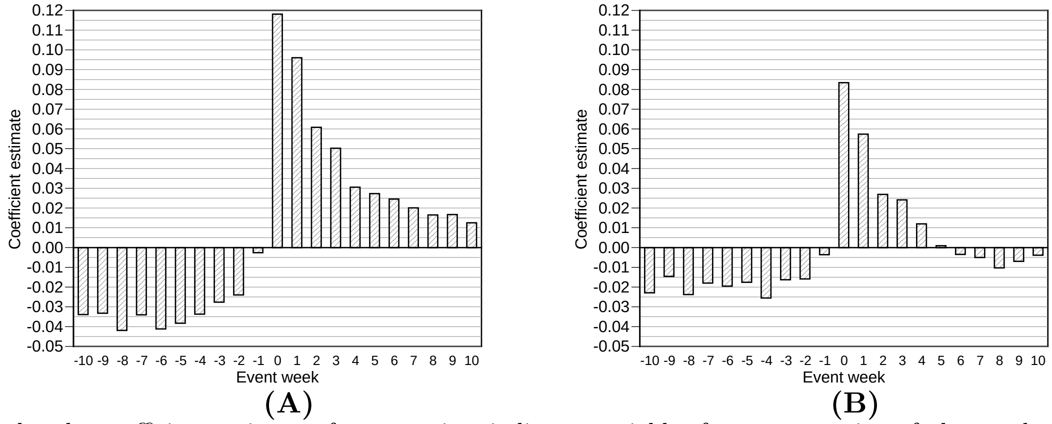
3.10. Other analyses

To investigate whether our results are sensitive to our variable definitions, we conduct a variety of untabulated specification checks. In all cases results are robust. To ensure that our results

[13] Coefficients on the control variables are very similar to those in Table 2.

[14] To further ensure that cross correlation is not driving our results, we test the robustness of the event study to using a portfolio approach. We construct 3 portfolios of stocks at time t: those firms that have a MAX event, a MIN event, and neither a MAX or MIN event. For each of the three portfolios we compute weekly averages (both value-weighted and equal-weighted) of ABNVOL. Then, allowing each week to be an observation, we compute the averages across all the weeks. Results are very similar to those presented in Figure 1.

Figure 1 **Coefficient estimates from regressions of abnormal volume on indicator variables for event time.**



Note. Bars plot the coefficient estimates for event-time indicator variables from a regression of abnormal volume, ABNVOL, on indicator variables for each week relative to the week when the extreme is reached and the same control variables as in specification (2) of Table 2 (but excluding the MAX and MIN variables). In panel A (panel B), the event is the week that the stock moves above (below) the trading range. Each regression is based on 777,501 observations. The coefficient estimates are significantly different from zero at the 0.05 level or better using a two-tailed test for all weeks except week −1 in Panel A and weeks −1 and weeks = +5 to +10 in Panel B.

are insensitive to the control for market volume, we replicate our analysis using raw volume. In addition, we re-estimate the regression using raw volume as a dependent variable and including market volume as a control in a one-stage regression (effectively constraining the market volume relation to be the same across all stocks). We also ensure results are robust to expressing volume as a percent of past average volume over the year rather than shares outstanding. To ensure that the right-skewness of volume does not affect the results, we replicate the analysis using the natural logarithm of abnormal volume in place of abnormal volume. To ensure that nonlinearity or extreme observations do not drive the results, we replicate the analysis using ranks of variables.

Another potential concern is that our analysis is detecting inter-firm rather than intra-firm differences. The event study analysis suggests that this is not the case because results are robust in a comparison of a given firm over time. However, to ensure that our results reflect differences within firms over time rather than across firms, we replicate the analysis using firm fixed effects. In addition, it could be that our analysis reflects periods in which volume is elevated and firms are trading at high prices for reasons not captured by our control variables. That seems unlikely here because our sample is randomly selected and we explicitly adjust out the market volume effects. However, to ensure that cross correlation of that type does not drive our empirical results, we replicate our analysis using date fixed effects.

Furthermore, because of concerns about nonindependence of observations in our panel data, we utilize multiple estimation methods to ensure our results are robust, including panel data regression techniques such as clustering by firm, clustering by date and including fixed firm and date effects, and using an auto regressive model.[15] In addition, we replicate all of our analysis using the Fama–MacBeth approach, where we estimate each regression model by week and evaluate the significance of the weekly coefficients across the time series. All variables of interest remain significant at conventional levels and all inferences remain the same.

Finally, we replicate our analyses on all firms incorporated outside the United States, closed-end funds, REITs and ADRs. Although the magnitude of the coefficient on MAX and MIN differ from our primary sample (i.e., with the exception of ADRs, the coefficients are smaller), the inferences with respect to significance levels remain the same.

4. Returns analysis

The preceding analyses suggest that stocks crossing outside a prior trading range experience abnormal volume. Because the elevated volume suggests increased investor interest, a related question is whether breaking out of a prior trading range is associated with predictable future returns. In particular, the attention hypothesis predicts that attention will have a greater effect on buying than selling, leading to a potential order imbalance and a consequent positive return. To investigate that question, we use daily data on all CRSP securities to identify the date on which the security breaks out of the prior trading range and track the security for the ensuing month to assess whether breaking out of the trading range appears to predict future returns.

To compute returns, we follow the calendar-time portfolio approach, where we place a firm-day into the MAX (MIN) portfolio if the stock is trading at the 52-week high (low) and has not been at the high or low in the last month. The comparison portfolio includes firm-days not trading at

[15] The autoregressive model includes 52 weekly lags and a backstep procedure, which eliminates insignificant lag terms to arrive at an appropriate lag structure. Results are similar using a Newey and West (1987) autocorrelation consistent variance estimator.

a high or low. Next, for each portfolio we calculate the daily equal- and value-weighted buy-and-hold portfolio returns beginning the day after a firm is assigned to the MAX, MIN, or comparison portfolio. We compound the equally-weighted returns to reduce bias due to the bid/ask bounce identified by Barber and Lyon (1997). Also, for each portfolio, we adjust the weekly returns for risk factors by regressing the portfolio returns on the Fama and French (1993) and Carhart (1997) risk factors: the overall market return, the performance of small stocks relative to large stocks, the performance of value stocks relative to growth stocks, and momentum. Finally, we compare the MAX and MIN portfolios to the comparison portfolio.[16]

Because the potential effect of increased attention on returns should be most pronounced for smaller firms, where (i) liquidity is lower, (ii) other information is less available, and (iii) small investors likely predominate, we partition our sample by firm size as follows. We assign stocks to size portfolios based on their previous month's market value of equity relative to the distribution of market value of equity across all three exchanges in that month. For parsimony, we report results for the two smallest quartiles and combine observations above the median.

Table 4 reports results from the returns analysis after adjusting for risk using the four-factor model. Results are similar for raw returns, as well as for returns using the three-factor model. In the week following the event of crossing a previous low, returns are consistently positive across all size portfolios. Returns are larger for equally-weighted than value-weighted returns, reflecting the fact that the effect is most pronounced for small stocks. For the smallest firms, results are particularly striking for the one week ahead return net of the comparison portfolio of 5.13% (i.e., $1.0268\% \times 5$ days). Consistent with the prediction that the effect is likely to be strongest for small firms, the magnitude of returns is smaller for the 2nd quartile and smallest, but still significantly positive, for the largest 50% of firms. Results are consistent, although not as pronounced, for the one month returns, with significant positive returns for the first two quartiles but not for the largest firms.

Results are consistent, but of smaller magnitude, for firms exceeding a previous high. Again, weekly returns are significantly positive for both weighting approaches for the two smallest quartiles

[16] Results are robust to the inclusion of delisting returns.

Table 4 Average Daily Portfolio Buy and Hold Returns, in percent.

	1 week				1 month			
	Gross		Net		Gross		Net	
	Return	*t*-stat	Return	*t*-stat	Return	*t*-stat	Return	*t*-stat
MIN 0 − 25th size percentile								
Abn. Return 4 factor, EW	1.0372	32.7	1.0268	31.9	0.2625	19.4	0.2549	17.5
Abn. Return 4 factor, VW	0.7345	28.7	0.7497	28.7	0.1521	12.7	0.1642	12.6
MIN 25th − 50th size percentile								
Abn. Return 4 factor, EW	0.2647	12.5	0.2852	13.2	0.0375	4.0	0.0543	5.3
Abn. Return 4 factor, VW	0.2391	11.2	0.2600	12.0	0.0309	3.3	0.0484	4.8
MIN 50 − 100th size percentile								
Abn. Return 4 factor, EW	0.0689	5.1	0.0755	5.5	0.0002	0.0	0.0075	1.1
Abn. Return 4 factor, VW	0.0741	4.5	0.0751	4.5	0.0163	1.7	0.0180	1.9
MAX 0 − 25th size percentile								
Abn. Return 4 factor, EW	0.1359	4.7	0.1255	4.3	0.0979	7.9	0.0903	6.7
Abn. Return 4 factor, VW	0.0941	3.3	0.1093	3.8	0.0823	6.5	0.0944	6.9
MAX 25th − 50th size percentile								
Abn. Return 4 factor, EW	0.1070	5.6	0.1275	6.5	0.0722	9.0	0.0891	9.9
Abn. Return 4 factor, VW	0.1041	5.6	0.1250	6.6	0.0729	9.2	0.0904	10.3
MAX 50 − 100th size percentile								
Abn. Return 4 factor, EW	0.0293	3.7	0.0359	4.4	0.0262	6.0	0.0335	7.0
Abn. Return 4 factor, VW	-0.0040	-0.4	-0.0030	-0.3	0.0080	1.4	0.0097	1.6

Average daily portfolio buy-and-hold returns (in %) are measured for the subsequent week and month beginning the day after a firm is assigned to the MAX, MIN, or comparison portfolio. Firms are assigned to a size group based on their previous month's market value of equity relative to the distribution of market value of equity across all three exchanges. Net returns are adjusted for the comparison portfolio returns. Equal-weighted (EW) and value-weighted (VW) portfolio returns are calculated daily and the portfolio is rebalanced at the end each day. EW returns are compounded to reduce bid ask bias. The four-factor adjusted return is the intercept from a regression of the daily portfolio return on Fama and French (1993) factors and the Carhart (1997) momentum factor.

of firms. On average, the smallest firms crossing their previous high earn a four-factor risk-adjusted one week ahead return net of the comparison portfolio of 0.63%, which is significantly greater than 0 at conventional levels. As predicted, the effect tends to be strongest for the smaller firms. Results for the largest firms are significant for equally weighted returns, but not for the value weighted returns, reflecting the fact that the effect is weaker for large firms. Returns over the following month tend to remain significantly positive.[17]

[17] One potential concern with the returns results is that Gervais, Kaniel and Mingelgrin (2001) document a positive relation between high volume and future returns. To address that issue, we replicate our returns analysis by first adjusting firm returns for the effects of firm-specific volume over the preceding weeks. Results are very similar to

While our analysis cannot isolate the factors that drive the future stock returns, they do suggest that moving outside a prior trading range is associated not only with predictable volume patterns, but also with predictably positive returns. This result is important because it suggests, consistent with the predictions of the attention hypothesis, that buying predominates following breaches of prior trading ranges for both maxima and minima, particularly for small firms.

5. Trade and Quote Analysis

The analysis to this point documents that stocks crossing outside a prior trading range experience abnormal volume and that the elevated volume suggests increased investor attention, which is associated with predictable future returns. To better understand the mechanism driving these findings, we attempt to infer trader identity and trade direction using Trade and Quote (TAQ) data, which provide trade-by-trade information. Recall that the attention hypothesis predicts that increased trading will be more prevalent for small traders who have access to relatively little other information and do not have the resources to conduct detailed analysis of all stocks, and trading will be more prevalent on the buy side than on the sell side because the population of potential stocks available for purchase is much broader than for sales.

Using our random sample of 2,000 stocks, we identify event-days in which a firm breaks through a previous extreme after trading within its trading range for at least one month and examine abnormal trade and order imbalance for the subsequent week and month. To avoid overlapping event windows and to keep the TAQ dataset tractable, we require event-days for a given firm to be at least 126 trading days apart.

Table 5 summarizes the mean and median standardized trade value and order imbalance for the week and the month after the stock price falls below its previous low (Panel A) or rises above its previous high (Panel B). Trade value is computed each day for each stock by summing the dollar value of all shares traded on that day, and is standardized by subtracting the mean of the daily trade values and dividing by the standard deviation of the daily trade values over event days −25

those reported in Table 4. Also, our results are similar when we use firm returns adjusted for the effects of size and lagged return (similar to the method of George and Hwang, 2004).

to −14, inclusive. Standardized trade values are winsorized at the 5% and 95% levels. In the weekly analysis, daily trade values for a given event are averaged over days +1 to +5 to give a mean value for the week. The mean and median of these averaged values across all events are reported in the table. Consistent with the analysis of volume earlier in the paper, the mean and median trade values are significantly positive at the 0.0001 level, although test statistics are not tabulated.

To gain insight into whether the change in aggregate trade value after an event differs across individual and institutional investors, the analysis tracks small trades, defined as trades with a value less than or equal to $10,000, and, separately, large trades, defined as trades with a value greater than or equal to $50,000. This approach relies on the notion that larger investors are likely to trade in larger blocks. It likely measures trader identity with noise because it is an indirect measure and, for example, large traders may split up blocks to execute trades, while small investors may be more likely to liquidate an entire position in one trade. Lee and Radhakrishna (2000) present evidence that the trade size proxy is effective in separating the trading activities of individual and institutional investors and that the likelihood of misclassification is reduced by using a "buffer zone" of medium-sized trades ($10,000 to $50,000 in our analysis).

Table 5 reports means and medians for each group, along with p-values from a t-test for a difference in means between the small and large trades and a non-parametric signed rank test. The weekly analysis is then repeated for the month following the event by averaging the daily trade value for a given event over days +1 to +21 to give a mean value for the month.

Next, the table reports order imbalances. Order imbalance on a given event day for a given event is the number of buy orders less the number of sell orders divided by the sum of the buy and sell orders (i.e., $(b-s)/(b+s)$), where the direction of trade is determined based on whether the trade takes place at the bid or the ask price using the Lee–Ready algorithm. As with the approach for inferring trader identity, the algorithm for determining trade direction is indirect and may measure trade direction with error (Lee and Ready, 1991, and Ellis, Michaely, and O'Hara, 2000).

The construction of the standardized and winsorized weekly and monthly means and medians and the calculation and presentation of the results parallel the analysis for trade value. The attention

Table 5 Abnormal trade and order imbalance after a stock moves outside its past trading range.

		Stock price moves below its previous low				Stock price moves above its previous high			
		Average daily abnormal trade		Average daily standardized order imbalance		Average daily abnormal trade		Average daily standardized order imbalance	
		Week	Month	Week	Month	Week	Month	Week	Month
All trades	Mean	2.5828	1.8393	0.0461	0.0011	0.7428	0.4524	0.1280	0.1221
	Median	1.5872	1.2490	0.0303	-0.0043	0.5236	0.3419	0.1085	0.0936
Small trades	Mean	2.1536	1.4606	0.0335	-0.0053	1.0459	0.7299	0.1415	0.1269
	Median	1.4466	1.0057	0.0336	-0.0097	0.8127	0.6295	0.1306	0.1052
Large trades	Mean	1.2244	0.9356	0.0120	-0.0144	0.4885	0.1201	-0.0360	-0.0301
	Median	0.7450	0.6344	0.0277	-0.0162	0.1236	0.0367	-0.0622	-0.0216
p-value from a t-test for difference in means between large and small trades		< 0.0001	< 0.0001	< 0.0001	0.5821	< 0.0001	< 0.0001	< 0.0001	< 0.0001
p-value from a signed rank test between large and small trades		< 0.0001	< 0.0001	0.4288	0.9933	< 0.0001	< 0.0001	< 0.0001	< 0.0001

Trade value is computed each day for each stock by summing the dollar value of all shares traded on that day. Trade value on a given day is standardized by subtracting the mean of the daily trade values and dividing by the standard deviation of the daily trade values over event days -25 to -14, inclusive. Standardized trade values are then winsorized at the 5% and 95% levels. Order imbalance on a given event day for a given event is the number of buy orders less the number of sell orders divided by the sum of the buy and sell orders, i.e., $(b-s)/(b+s)$, where b and s denote the number of buyer- and seller-initiated transactions, respectively. The direction of trade is inferred using the Lee–Raedy algorithm. Order imbalances are standardized and winsorized in the same manner as trade values. In the weekly analyses, the standardized and winsorized daily trade values and order imbalances for a given event are averaged over days +1 to +5 to give a mean value for the week. The weekly analyses are repeated for the month following the event by averaging the standardized and winsorized daily trade values and order imbalances for a given event over days +1 to +21 to give a mean value for the month.

hypothesis predicts that the increase in trading volume will be more pronounced for buy orders than for sell orders, particularly among smaller investors.

Results from the TAQ analysis for stocks crossing prior minima suggest several conclusions. First, abnormal trading activity is elevated for the week and month after a stock falls below its previous low, consistent with the preceding results. Importantly, the effect is significantly stronger for small traders than large traders, consistent with the predictions of the attention hypothesis.

In terms of imbalance, results are also generally consistent with predictions. The overall trade imbalance tends to be weighted toward buy-initiated orders, consistent with the previous results that average returns are positive after firms break through a previous low. More importantly, the positive order imbalance tends to be more positive for the small traders, consistent with the predictions of the attention hypothesis. In fact, for stocks that fall below the previous low, the order imbalance among large trades is insignificantly negative. Similar results hold for stocks that exceed the previous high. Again, there is an increase in trading volume for all investors, but particularly for small investors, in the week after a stock moves above its prior trading range. Again, there is evidence of order imbalance in favor of buy orders in the week following a high, with small investors showing a greater tendency to increase buying (although the difference is significant only for the mean). As was the case for the returns, results are mixed for the month following a high, suggesting that the effect is primarily limited to the first week after the event.

Overall, conclusions from the TAQ analysis are consistent with the results from the preceding analyses and with the attention hypothesis, confirming that trading volume tends to be elevated and buy-initiated orders predominate after stocks break out of prior trading ranges. This analysis, which allows us to better isolate the identity of traders, suggests that the predominant effects are on small traders, consistent with the predictions of the attention hypothesis.

6. Conclusions

Our results suggest that extreme prices in a stock's past price path affect investors' trading decisions in equity markets. Across a broad sample of stocks representative of U.S. equities, volume fluctuates depending on the location of the current price in the distribution of prices over the prior year: volume is higher when the stock price is above the 52-week high or below the 52-week low, suggesting that the prior extremes are salient in decision-making. While our results do not imply that all investors use these cues, the 52-week highs and lows appear to be salient enough to some investors that this phenomenon can be observed in aggregate volume data. Further, the magnitudes of the effects are statistically significant and are economically as large as or larger than the effects of prominent information events, including earnings announcements and tax-based trading strategies, such as dividend capture. These results are striking because they are associated with an event that does not convey information about firm fundamentals.

The results we observe are very consistent with the predictions of the attention hypothesis in Barber and Odean (2008). In particular, trading volume tends to be more pronounced the longer the time since the last extreme price was set and tends to be greater for firms that are relatively small, are more likely to have significant individual investor interest and have greater ambiguity about valuation. Further, stocks breaking outside prior trading ranges appear to earn positive excess returns following the event, consistent with the Barber and Odean (2008) finding that attention affects buying more than selling. Analysis of detailed trading data confirms an increase in abnormal volume and buy orders and suggests that the effect is concentrated among smaller traders, consistent with predictions.

Subject to the caveat that it is difficult to assign causality given the measurement challenges inherent in this type of analysis, our results suggest that prior extremes are important determinants of trading volume, especially among small investors. The stock price path appears to drive investor attention to certain stocks with consequent predictable effects on stock returns. Our results contribute to the academic research on determinants of trading volume and the salience of extreme observations. Further, they suggest a rationale for technical analysis that uses past trading ranges in predicting market activity.

References

Atkins, A., E. Dyl. 1997. Market structure and reported trading volume: NASDAQ versus the NYSE. *J. Financial Research* **20**(3) 291–304.

Baker M., J. Wurgler. 2007. Investor sentiment in the stock market. *J. Economic Perspectives* **21**(2) 129–151.

Barber, B., T. Odean. 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, forthcoming.

Barber, B., T. Odean, N. Zhu. 2008. Do noise traders move markets? *Review of Financial Studies*, forthcoming.

Barber, B. M., J. D. Lyon. 1997. Detecting long-run abnormal stock returns: the empirical power and specification of test statistics. *J. Financial Economics* **43**(3) 341–372.

Belsey, D. A., E. Kuh, R. E. Welsch. 1980. *Regression Diagnostics.* New York: John Wiley & Sons.

Cao, H. H., J. D. Coval, D. Hirshleifer. 2002. Sidelined investors, trading-generated news, and security returns. *Review of Financial Stududies* **15**(2) 615–648.

Carhart, M. M. 1997. On persistence in mutual fund performance. *J. Finance* **52**(1) 57–82.

Chan, S.H., W. Leung, K. Wang. 2004. The impact of institutional investors on the Monday seasonal. *J. Business* **77**(4) 967–986.

Chordia, T., S.-W. Huh, A. Subrahmanyam. 2007. The cross-section of expected trading activity. *Review of Financial Studies* **30**(2) 709–740.

Core, J., W. Guay. 2001. Stock option plans for non-executive employees. *J. Financial Economics* **61**(2) 253–287.

Das, S., P. Raghubir. 2006. The long and short of it: Why are stocks with shorter runs preferred? Working paper, Santa Clara University, Santa Clara, CA.

Ellis, K., R. Michaely, M. O'Hara. 2000. The accuracy of trade classification rules: evidence from Nasdaq. *J. Financial and Quantitative Analysis* **35** (4) 529–551.

Fama, E., K. French. 1993. Common risk factors in the returns on stocks and bonds. *J. Financial Economics* **33**(1) 3–56.

Ferris, S., R. Haugen, A. Makhija. 1988. Predicting contemporary volume with historic volume at differential price levels: evidence supporting the disposition effect. *J. Finance* **43**(3) 677–697.

Fiske, S. P., S. E. Taylor. 1991. *Social Cognition*, 2nd ed. McGraw-Hill, New York, NY.

Fredrickson, B., D. Kahneman. 1993. Duration neglect in retrospective evaluations of affective episodes. *J. Personality and Social Psychology* **65**(1) 45–55.

Fung, W., D. Hsieh. 2001. The risk in hedge fund strategies: theory and evidence from trend followers. *Review of Financial Studies* **14**(2) 313–341.

George, T. J., C.-Y. Hwang. 2004. The 52-week high and momentum investing. *J. Finance* **59**(5) 2145–2176.

Gervais, S., R. Kaniel, D. H. Mingelgrin. 2001. The high-volume return premium. *J. Finance* **56**(3) 877–919.

Glaser, M., M. Weber. 2008. Which past returns affect trading volume? *J. Financial Markets*, forthcoming.

Griffin, J., F. Nardari, R. Stultz. 2007. Do investors trade more when stocks have performed well? *Review of Financial Studies* **30**(2) 905–951.

Gneezy, U. 1998. Updating the reference level: experimental evidence. Working paper, University of Haifa, Israel.

Heath, C., S. Huddart, M. Lang. 1999. Psychological factors and stock option exercise. *Q. J. Economics* **114**(2) 601–627.

Kahneman, D., A. Tversky. 1979. Prospect theory: an analysis of decision and risk. *Econometrica* **47** (2) 263–291.

Kahneman, D., P.P. Wakker, R. Sarin. 1997. Back to Bentham? *Q. J. Economics* **112** (2) 375–405.

Lee, C. M. C., B. Radhakrishna. 2000. Inferring investor behavior: evidence from TORQ data. *J. Financial Markets* **3**(2) 83–111.

Lee, C. M. C., M. Ready. 1991. Inferring trade direction from intraday data. *J. Finance* **46** (2) 733–746.

Lee, I. H. 1998. Market crashes and informational avalanches. *Econometrica* **65**(4) 741–759.

Newey, W. K., K. D. West. 1987. A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica* **55**(3) 703–708.

Poteshman, A., V. Serbin. 2003. Clearly irrational financial market behavior: evidence from the early exercise of exchange traded stock options. *J. Finance* **58**(1) 37–70.

Ritter, J.R. and I. Welch. 2002. A review of IPO activity, pricing, and allocations. *J. Finance* **57**(4) 1795–1828.

Seasholes M., G. Wu. 2007. Predictable behavior, profits, and attention. *J. Empirical Finance*, forthcoming.

Shefrin, H., M. Statman. 1985. The disposition to sell winners early and ride losers too long: theory and evidence. *J. Finance* **40**(3) 777–790.

Statman, M., S. Thorley, K. Vorkink. 2006. Investor overconfidence and trading volume. *Review of Financial Studies* **19**(4) 1531–1565.

Yates, M. 2007. How does attention affect stock returns? Working paper, University of Texas at Austin, TX.