
Highs and lows: a behavioural and technical analysis

Bruce Mizrach* and Susan Weerts

Department of Economics, Rutgers University, New Brunswick, NJ, USA

We find that turnover rises on n -day highs and lows and is an increasing function of n . We offer several explanations from the technical and behavioural finance literature for why traders might use these signals. Turnover is persistent following these events, and new lows provide abnormal returns for up to 6 trading days.

‘Technical analysis is about as useful as going to a fortuneteller, as far as I’m concerned. There is simply no evidence that these patterns mean anything...’¹ (Burton Malkiel, 2003).

I. Introduction

The behavioural finance literature tries to explain what motivates investors to trade. Barber and Odean (2008) emphasize that investors tend to focus on ‘attention grabbing’ stocks. They find abnormal volume and returns attract buyers to a stock. Seasholes and Wu (2007) observe that daily price limits influence trading activity on the Shanghai stock exchange. Experiments by Das and Raghubir (2006) show that stock price trends influence perceived risk. Heath *et al.* (1999) report that when the stock price is above a 1-year maximum, stock option exercise nearly doubles.

This article provides clear evidence that technical indicators stimulate trading. We find a sharp rise in turnover as a stock crosses an n -day high or low and that turnover is increasing in n . This finding is robust to a number of controls, including market volume, returns, and news about earnings, dividends and analyst rating changes.

Our research extends Huddart *et al.*’s (2007) study of 52-week highs and lows to six additional time

frames: 10-, 25-, 50-, 100-, 150- and 200-day. We document that trading volume increases significantly whenever price exits these trading ranges. Moreover, abnormal turnover generally increases in n . It is also persistently abnormal for at least 2 weeks.

The literature does show that this trading may result in positive returns. George and Hwang (2004) found that the 52-week high is a good proxy for Jegadeesh and Titman’s (1993) momentum factor. By calculating the trading imbalance and the percentage of the first-time stock buyers, Seasholes and Wu (2007) found that Shanghai traders could profit from volume-induced exuberance.

We find that George and Hwang’s result does not hold, either long or short, for a random selection of stocks not in the momentum portfolio. Following an n -day high, there is a strong one-day reversal, and returns are insignificantly different from zero thereafter. The returns following an n -day low cannot be explained by momentum. Traders should not, as we show, short stocks hitting new lows. There are strong, persistent reversals with significant risk-adjusted returns on long positions for up to 6 days following an n -day low.

The article is organized into the following sections. Section II describes the technical and psychological reasons behind choosing n -day high/lows. Section III explains our data selections. We model turnover in the fourth section. Persistence of both volume and

*Corresponding author. E-mail: mizrach@econ.rutgers.edu

¹Interview in *Portfolio*, The National Association of Realtors, October/November 2003, available at: <http://www.nareit.org/portfliomag/03sepoct/capital.shtml>

returns is analysed in Section V. Finally, we present our conclusions.

II. Behaviour Behind Technical Analysis

There are approximately 7000 stocks in the US equity market. It is a formidable task to analyse them one-by-one to determine which ones to trade. Even institutional brokerage firms do not cover every company. This section reviews the behavioural finance and technical analysis literature that helps motivate our choice of the n -day high or low.

Investor rules of thumb

Research in decision theory has helped to explain why investors might use rules of thumb rather than solving a complex dynamic optimization. Kahneman and Tversky (1974) found agents used recent, salient, concrete and personally relevant information, rather than fundamental values as a basis for their decision-making. Ariely *et al.* (2003) present experimental evidence that prices paid to avoid painful stimuli depend upon an arbitrary high/low anchor.

The behavioural finance literature has introduced a variety of nonoptimizing decision criteria. Studying several large databases with a variety of retail and institutional traders, Barber and Odean (2008) showed that attention is a scarce resource; investors are most likely to trade ‘attention grabbing’ stocks. Prior returns and high turnover are the factors that most strongly influence trading activity. Statman *et al.* (2006) note that overconfidence leads to persistently high trading volume in stocks with high returns.

Studies from experimental stock markets support the importance of specific price levels. Das and Raghuram (2006) find that people perceive local maxima and minima as salient points. They define the run length of a stock as the number of consecutive price changes in the same direction, positive or negative. In their experiments, investors prefer a stock with shorter run length because they perceive it to be less risky. This could potentially explain the absence of a momentum effect at new highs or lows.

Survey evidence

There is not much evidence, even in the practitioner’s literature, on what rules technical analysts actually use. Menkhoff and Schmidt (2005) report that 36%

of German fund managers surveyed allocating funds using alternative strategies including technical analysis. A survey by Mizrach and Weerts (2007) of semi-professional traders suggests that simple rules like moving averages (52%) and chart patterns (56%) are preferred.

Technical analysis

Technical analysis is the use of past price and volume information to predict stock returns. Often, technical analysts are called ‘chartists’ because they employ graphical presentations of their trading rules. Phillips and Todd (2003) find these charts served as landmarks for human perception. They specifically cite local maxima and minima as salient points. In the *New York Times*, stocks hitting their 52-week highs and lows and those with abnormally high volume are bold faced in the stock page listings.

Highs and lows are also inputs into a number of other technical indicators² including the stochastic oscillator. Let $H_{i,t,n} = \max(p_{i,t}, p_{i,t-1}, \dots, p_{i,t-n+1})$ be the highest price p_i achieved by a stock i during an n -day period, and let $L_{i,t,n} = \min(p_{i,t}, p_{i,t-1}, \dots, p_{i,t-n+1})$ be the corresponding minimum. The stochastic %K developed by Lane (1984),

$$\%K = \frac{p_{i,t} - L_{i,t,n}}{H_{i,t,n} - L_{i,t,n}}$$

and Williams (1973) %R,

$$\%R = \frac{nH_{i,t,n} - p_{i,t}}{n(H_{i,t,n} - L_{i,t,n})}$$

both rely on n -day highs and lows.

Psychological, behavioural, survey and experimental evidence appears to support our choice of simple, widely reported, and graphically-oriented rules like the n -day high and low. Our empirical analysis proceeds in two steps. We first verify that people trade using these rules by looking at turnover. We then see if returns justify their choices.

III. Data Selection

Random sample

Since the breaching of n -day highs or lows is a daily event,³ we concentrated on the daily frequency, instead of weekly as in Huddart *et al.* (2007). One-thousand symbols from the New York Stock

² I rely on www.stockcharts.com for these definitions, but these are widely utilized indicators in the practitioner literature.

³ Huddart *et al.* (2007) use ‘the the highest (lowest) daily closing stock price in the 52-week benchmark period ending 20 trading days... before the last day of the observation week’. We did not follow this construction.

Exchange (NYSE) and National Association of Securities Dealers Automated Quotations (NASDAQ) were randomly selected from all the stocks that traded on the two exchanges between 1 January 1993 and 31 October 2003. The final sample included 849 stocks. Among them, 151 were discarded due to changes in symbols and not enough data (less than 1 year trading history during the 10-year period). We had a total of 1 160 951 observations, but since we lose 1 year of data constructing the 52-week highs, the final sample contains 939 092 cross-section time-series observations.

488 of the listings are from NASDAQ and 361 from the NYSE. They have a \$1.8 billion market capitalization on average. Their mean length of survival in the sample is 1106 days or 4.39 years. Daily trading volume ranges from 0 to 814 million shares.

Frequency of highs and lows

As shown in Table 1, 840 of 849 stocks achieved 10-day highs at least once over the 10-year span.

The percentage of stocks that had at least one breakout decreased at 25-, 50-, 100- and 150-day horizons. It troughs at 71.50% for the 150-day and then picked up both at 200-day and 52-week highs, 83.86%.

The percentage for stocks with n -day lows showed the same pattern as n -day highs. On 8.03% of the overall 939 092 stock trading days, there are breaches of 10-day lows. The percentage went as low as 0.59% for breaching 150-day lows. Again, n -day lows held the same patterns as n -day highs.

Turnover

Lo and Wang (2000) proposed to use the turnover as a canonical measure of trading activity among numerous alternatives, such as total numbers of shares traded $VOL_{i,t}$ or dollar volume, $\$p_{i,t} \times VOL_{i,t}$. Turnover, $\tau_{i,t}$, scales the daily trading volume by the number of shares outstanding $SO_{i,t}$,

$$\tau_{i,t} = \frac{VOL_{i,t}}{SO_{i,t}} \quad (1)$$

The advantage of turnover, they argue, is that it not effected by stock splits and dividends.

Table 2 provides a statistical description of daily turnover. The average for our sample was 0.636%, similar to the market's daily turnover of 0.638%.

⁴The trading volumes on NYSE and NASDAQ market are calculated differently due to their different market microstructures. A trade is counted only once when the NYSE specialist matches a buyer and a seller. A trade is generally double-counted on NASDAQ during our sample. If a buyer sells a trade to a market maker, and he then resells the trade to a seller, NASDAQ will record this as two trades.

Table 1. Frequency of n -day highs and low

	Variable	# of stocks	Obs.
<i>Highs</i>			
10-day	D_{10}^H	840	75 367
25-day	D_{25}^H	811	34 211
50-day	D_{50}^H	769	22 942
100-day	D_{100}^H	688	9 710
150-day	D_{150}^H	607	5 554
200-day	D_{200}^H	641	6 014
52-week	D_{52w}^H	711	40 126
<i>Lows</i>			
10-day	D_{10}^L	842	83 439
25-day	D_{25}^L	822	29 681
50-day	D_{50}^L	801	26 059
100-day	D_{100}^L	734	10 475
150-day	D_{150}^L	607	5 612
200-day	D_{200}^L	521	3 563
52-week	D_{52w}^L	650	28 112

Notes: The table reports the total number of stocks experiencing the event of an n -day high or low. We record the event for the largest n . Observations are the number of time-series cross-section observations for which the dummy variable takes the value 1 rather than 0.

Daily turnovers are positively skewed. The mean daily turnovers of 10-day, 25-day, 50-day, 100-day, 150-day, 200-day and 52-week highs are 0.57, 0.68, 0.82, 0.93, 0.91, 1.16 and 1.36%. Except for the 10-day interval, the means of our n -day highs are above the sample means of daily turnover. For $n \geq 25$, the turnover is in the 75th percentile, and the 52-week high is above the 90th percentile. Moreover, these turnovers show a monotonic increase with n except for $n = 150$.

The means of daily turnovers on n -day lows are relatively smaller than n -day highs. They are above the sample means except for the 10-day and 25-day lows. The means on the event days of n -day lows are also increasing in n except a drop from 200-day low to 52-week low.

The raw turnovers have a time trend. We render them stationary by regressing them on market turnover $\tau_{M,t}$ as in Ferris *et al.* (1988),

$$\tau_{i,t} = \rho_{0,i,t} + \rho_{1,i,t} \tau_{M,t} + \varepsilon_{i,t,\tau} \quad (2)$$

We take market turnover⁴ to be either the NYSE or NASDAQ measure depending upon where the shares

Table 2. Daily turnover in percent

Sample	Obs.	Mean	SD	Skew	Median	75th%	90th%
Full sample	938 499	0.6364	2.46	33.17	0.1913	0.5204	1.2875
<i>Highs</i>							
10-day	75 367	0.5684	1.82	14.83	0.1740	0.4817	1.2108
25-day	34 211	0.6823	3.16	64.94	0.2117	0.5645	1.4019
50-day	22 942	0.8202	3.39	38.22	0.2485	0.6679	1.6216
100-day	9 710	0.9250	3.50	18.93	0.2597	0.7526	1.9274
150-day	5 554	0.9142	2.98	14.15	0.2889	0.7539	1.9423
200-day	6 014	1.1604	3.60	10.67	0.3252	0.9126	2.3739
52-week	40 126	1.3579	4.72	20.24	0.3671	1.0970	2.9117
<i>Lows</i>							
10-day	83 439	0.5134	1.87	18.01	0.1591	0.4235	1.0140
25-day	39 681	0.5895	2.47	31.58	0.1712	0.4701	1.1626
50-day	26 059	0.6585	2.32	15.03	0.1795	0.5046	1.3091
100-day	10 475	0.7370	3.84	55.76	0.1926	0.5672	1.5009
150-day	5 612	0.7988	3.46	20.96	0.2067	0.6174	1.5874
200-day	3 563	0.8795	3.97	22.71	0.1987	0.6216	1.6326
52-week	28 112	0.7346	3.22	44.80	0.2190	0.6029	1.4658

Notes: The table reports the daily turnover on days in which the stock achieves an n -day high or low. We use the largest n that applies. We study 849 stocks with 939 499 time-series cross-section observations.

are listed. $\varepsilon_{i,t,\tau}$ is the excess (or abnormal) turnover. Excess turnover on the event days showed almost identical traits as raw turnover.

Returns

We want to control for the effect of returns on turnover. Again, following Lo and Wang, we adjusted our raw returns using the Fama–French (1993) factors and momentum,

$$AR_{i,t} = \alpha_i + \beta_{1,i}R_{M,t} + \beta_{2,i}SMB_t + \beta_{3,i}HML_t + \beta_{4,i}Mom_t + \varepsilon_{i,t,r} \quad (3)$$

$AR_{i,t}$ is the abnormal daily return of stock i . It is the daily stock return including dividends $R_{i,t}$ minus the risk-free rate Rf_t , which we measure as the 1-month Treasury bill rate. $R_{M,t}$ is the market return. It is the value weighted return on all NYSE, NASDAQ and American Stock Exchange stocks minus the risk-free rate. The factor SMB_t adjusts for market capitalization. It places one-third weights on the difference between three small portfolios and three big portfolios consisting of value, neutral and growth stocks. HML_t is the factor adjusting for value versus growth. It is the average difference of two value and two growth portfolios. These data were all obtained from Ken French's website.⁵

The momentum factor, Mom_t , is the daily return difference between an equal weighted portfolio of the high and low return stocks, using the methodology of

Carhart (1997) and Barber *et al.* (2006). The portfolio was constructed to include the stocks with the highest and lowest 30% of returns in the preceding trading month. $\varepsilon_{i,t,r}$ are excess returns after adjusting for the factors.

IV. Model for Excess Turnover

We complete the specification of our model for excess turnover by incorporating the additional covariates in Lo and Wang. They include market capitalization, p_tSO_t , volatility, which is measured as the 40-day moving SD, and the stock price level, for which we use the high ask price for the day, $ASKHI_{i,t-1}$. We form a time-series cross section. Individual stock fixed effects are handled by taking first differences.

The model then includes seven dummy variables for the n -day highs, $D_{i,t,n}^H$, and lows, $D_{i,t,n}^L$,

$$\begin{aligned} \Delta\varepsilon_{i,t,\tau} = & \gamma_1\Delta\varepsilon_{i,t,r} + \gamma_2\Delta\varepsilon_{i,t-1,r} + \gamma_3\Delta\varepsilon_{i,t-1,\tau} \\ & + \gamma_4\Delta(p_{i,t-1}SO_{t-1}) + \gamma_5\Delta\sigma_{i,t-1}^2 \\ & + \gamma_6\Delta ASKHI_{i,t-1} \sum_n \theta_n^H D_{i,t,n}^H \\ & + \sum_n \theta_n^L D_{i,t,n}^L + \varepsilon_{i,t,TO} \end{aligned} \quad (4)$$

Since 52-week highs are also 200-day highs, etc., we turn on only the indicator with the longest length.

⁵ http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 3. Model for abnormal turnover

Regressor	Coeff.	t-ratio	Coeff.	t-ratio
$\Delta \text{Abn. ret}_t$	0.0235	11.96	0.0235	11.96
$\Delta \text{Abn. ret}_{t-1}$	0.0184	12.91	0.0184	12.92
$\Delta \text{Abn. vol}_{t-1}$	-0.3167	-16.51	-0.3172	-16.52
$\Delta \text{Market cap}_{t-1}$	-0.4908	-2.76	-0.4901	-2.75
$\Delta \text{Volatility}_{t-1}$	-17.5359	-4.34	-17.8969	-4.41
$\Delta \text{High price}_{t-1}$	0.0224	2.43	0.0225	2.43
10-day high	0.1332	21.13	0.1322	20.97
25-day high	0.1871	21.70	0.1842	21.41
50-day high	0.2367	21.26	0.2339	21.05
100-day high	0.2760	15.35	0.2732	15.25
150-day high	0.3060	9.90	0.3035	9.83
200-day high	0.2600	11.18	0.2579	11.12
52-week high	0.3808	30.30	0.3779	30.14
10-day low	0.1928	34.29	0.1936	34.47
25-day low	0.2496	27.94	0.2499	28.00
50-day low	0.3011	27.65	0.3002	27.64
100-day low	0.3301	14.27	0.3267	14.18
150-day low	0.3500	9.05	0.3472	9.00
200-day low	0.3097	10.13	0.3079	10.12
52-week low	0.2376	23.38	0.2382	23.52
Dividends			0.0174	1.29
Earnings			0.5395	24.97
Analyst recs			0.3321	11.31
\overline{R}^2	0.111		0.112	

Notes: The table reports estimates of the model for abnormal turnover (4). The coefficients for market capitalization are $\times 10^4$. HAC t -ratios are in the columns next to the coefficient estimates.

If our technical indicators are impacting trading volume, we should find θ_n^H and $\theta_n^L > 0$.

Coefficient estimates from (4) with heteroscedastic and autocorrelation consistent (HAC) t -ratios are in Table 3.

The coefficients on the Lo and Wang controls are all significant. The positive sign on excess returns means that the high return would bring extra trading activity. The significance of lagged excess returns and turnover motivates our persistence results in the next section.

The coefficients on the indicator variables of n -day highs are all positive and highly significant, and, except for a slight kink at 200-day, are increasing with n . We depict this graphically in Fig. 1.

The 52-week high has the largest impact. The 0.3808% rise in turnover represents an increase of more than two-thirds over the average trading day.

The coefficients of n -day lows also increase with n , except for a slight drop at the 200-day. This is depicted graphically in Fig. 2. The largest marginal effect is for the 150-day low at 0.35%. This marginal effect is similar in magnitude to the n -day highs despite the fact that there is lower turnover overall when returns are negative.

The results contrast Huddart *et al.* (2007) who found that trading volume did not spike when prices crossed percentiles of the past price distributions other than the 52-week. Our results show that it is not the past price distribution, which affects trading activities, but rather the time frame that matters.

Can the effect of n -day highs or lows on trading volume simply reflect information flow? We control for major news events with dummy variables for dividends $D_{i,t}^D$, earnings $D_{i,t}^E$ and analyst recommendations, $D_{i,t}^A$. There are 8981 dividend issues and 14640 analysts' upgrade/downgrade over 10 years for our sample of 849 stocks.

We expanded our basic regression to control for these three events,

$$\begin{aligned} \Delta \varepsilon_{i,t,\tau} = & \gamma_1 \Delta \varepsilon_{i,t,r} + \gamma_2 \Delta \varepsilon_{i,t-1,r} + \gamma_3 \Delta \varepsilon_{i,t-1,\tau} \\ & + \gamma_4 \Delta(p_{i,t-1} SO_{t-1}) + \gamma_5 \Delta \sigma_{i,t-1}^2 \\ & + \gamma_6 \Delta \text{ASKHI}_{i,t-1} + \sum_n \theta_n^H D_{i,t,n}^H + \sum_n \theta_n^L D_{i,t,n}^L \\ & + \psi_1 D_{i,t}^D + \psi_2 D_{i,t}^E + \psi_3 D_{i,t}^A + \varepsilon_{i,t,TO} \end{aligned} \quad (5)$$

Table 3 shows the coefficient estimates before and after the news dummies. The extra control variables have little or no impact on estimates or statistical significance of the n -day highs and lows. Given that

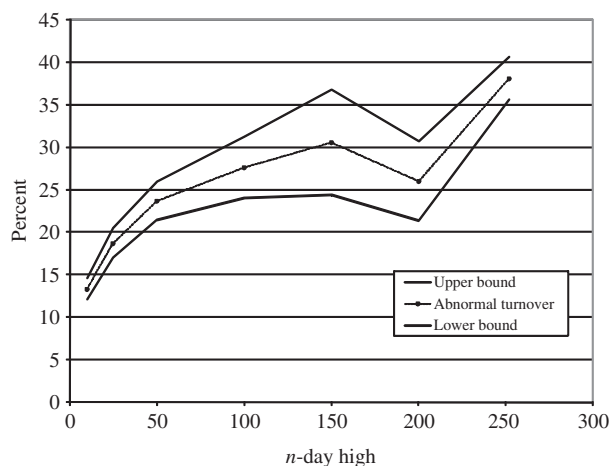


Fig. 1. Effect of n -day high on abnormal turnover percentage

Notes: The figure reports percentage effects on abnormal turnover of an n -day high event based on estimates from (4). The dark bands are 95% confidence intervals.

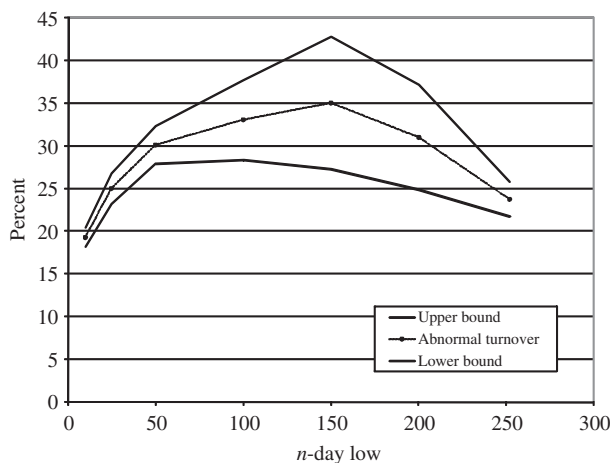


Fig. 2. Effect of n -day low on abnormal turnover percentage

Notes: The figure reports percentage effects on abnormal turnover of an n -day low event based on estimates from (4). The dark bands are 95% confidence intervals.

the earnings and recommendations news events are highly significant, we confirm that these are separate phenomena.

V. Persistence of Turnover and Returns

We must consider the possibility that traders rationally enter stocks when they hit n -day highs and lows. If trading activity is predictable following these technical signals, it might make sense for traders to either trade long or sell short. We should expect to

see some continuation in turnover and returns if these were the case. This section considers both hypotheses.

Turnover persistence

We earlier documented in Table 2 that turnover surges when an n -day high or low is achieved. We now look at the 10-day interval following these events,

$$(\varepsilon_{i,t,\tau}, \varepsilon_{i,t+1,\tau}, \dots, \varepsilon_{i,t+10,\tau}) \quad (6)$$

SEs are the sample SDs for event and nonevent days.

In Fig. 3, we look at turnover persistence for the seven different n -day highs. Abnormal turnover sharply rises on the event day highs except for the 10-day. For the other six, turnover rises from 7% for the 25-day high to 69% for the 52-week high. Turnover drifts down after the event. It is significantly negative for the 10–100-day highs after the second day for the full 2 weeks. While abnormal turnover also falls for the 200-day and 52-week highs, the initial surge is so large, turnover is abnormally positive for 6 days for the 200-day and all 10 days for the 52-week. Abnormal turnover is still 16% higher 2 weeks after the 52-week high.

For the n -day lows in Fig. 4, surges in turnover are less pronounced, consistent with the usual result that bull markets have higher volume. The 50-day to 52-week lows have positive abnormal event turnover, ranging from 6% for the 50-day to 26% for the 150-day.

Abnormal turnover then falls after the event day, with the exception of the 10-day low. The 10-day, 50-day, 150-day and 52-week lows show significantly negative abnormal turnover for the full weeks.

We now turn our attention to returns.

Return persistence

Raw returns $R_{i,t}$ typically remain positive after the n -day highs. This may explain why traders make use of the signals. We find that the returns, which are fairly small to begin with, have a negative risk-adjusted return, $AR_{i,t}$. We again analyse the 10-day period following the event:

$$(AR_{i,t}, AR_{i,t+1}, \dots, AR_{i,t+10}) \quad (7)$$

and compute confidence intervals from the sample of event and nonevent days in Fig. 5.

Abnormal returns on the event day highs range from 2.73% for the 52-week high to 3.38% for

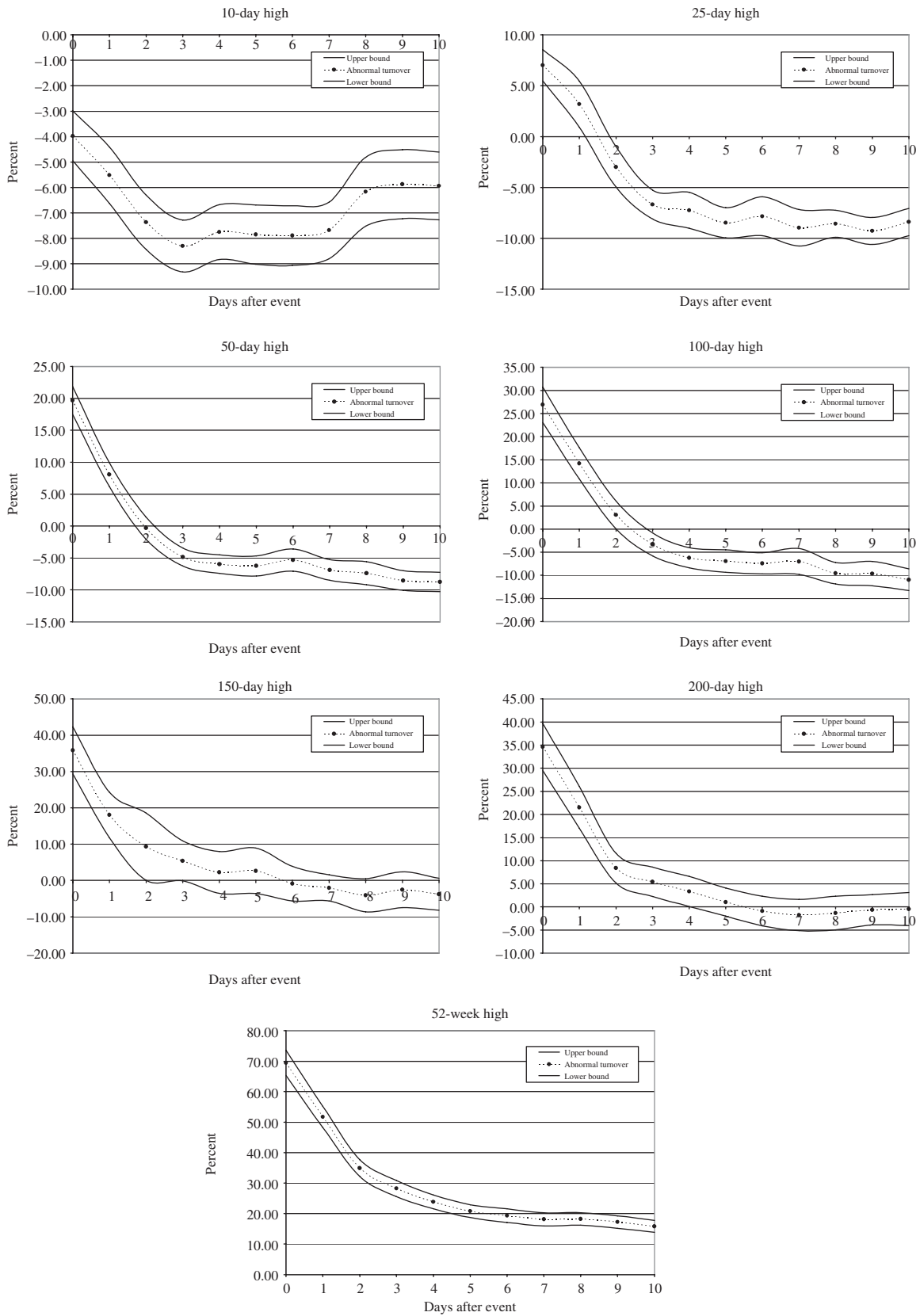


Fig. 3. Turnover persistence after n -day highs

Notes: The figures graphs persistence in abnormal turnover (6) for 10 days after an n -day high. 95% confidence intervals are in the dark bands.

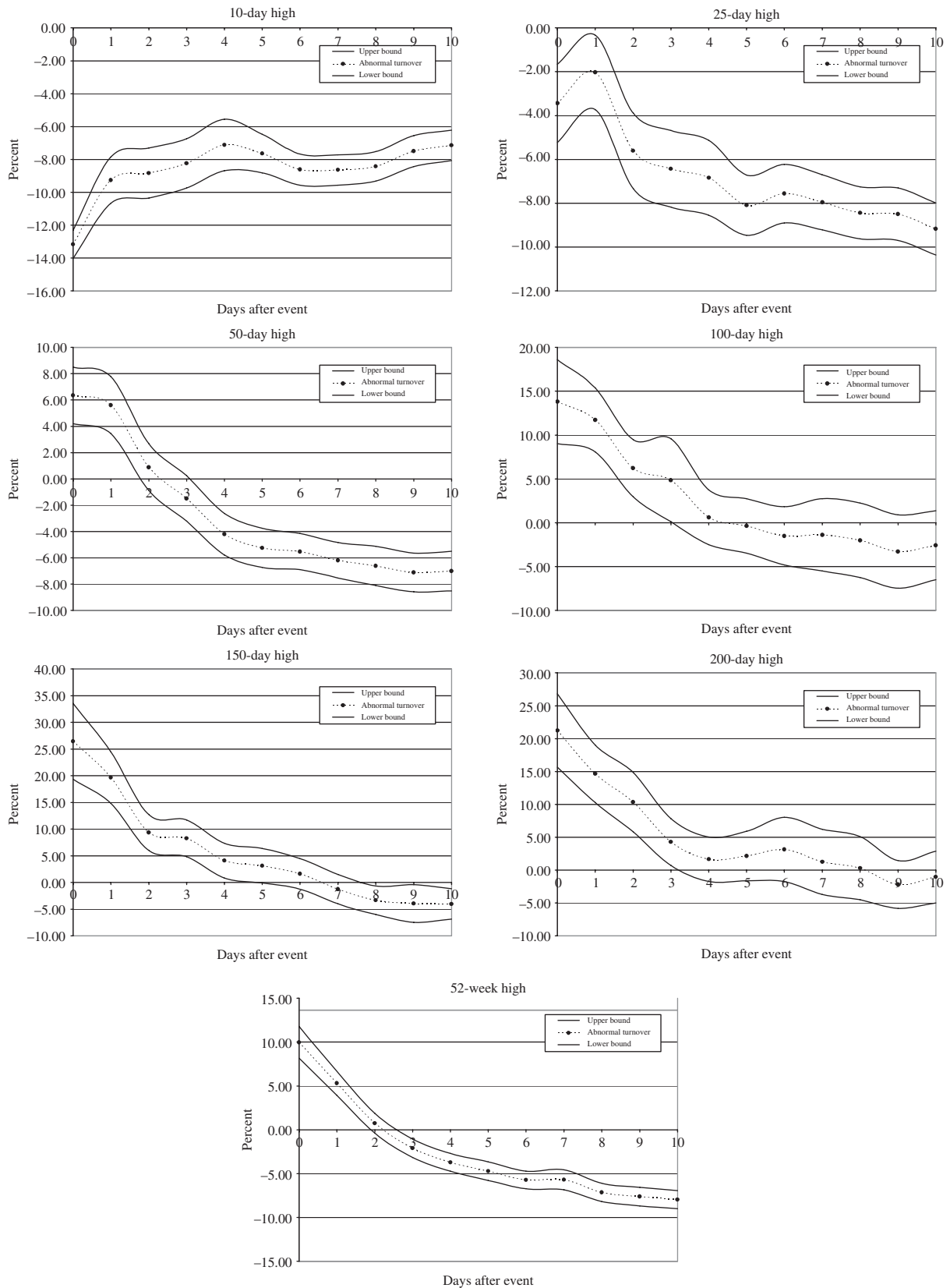


Fig. 4. Turnover persistence after n -day lows

Notes: The figure graphs persistence in abnormal turnover (6) for 10 days after an n -day low. 95% confidence intervals are in the dark bands.

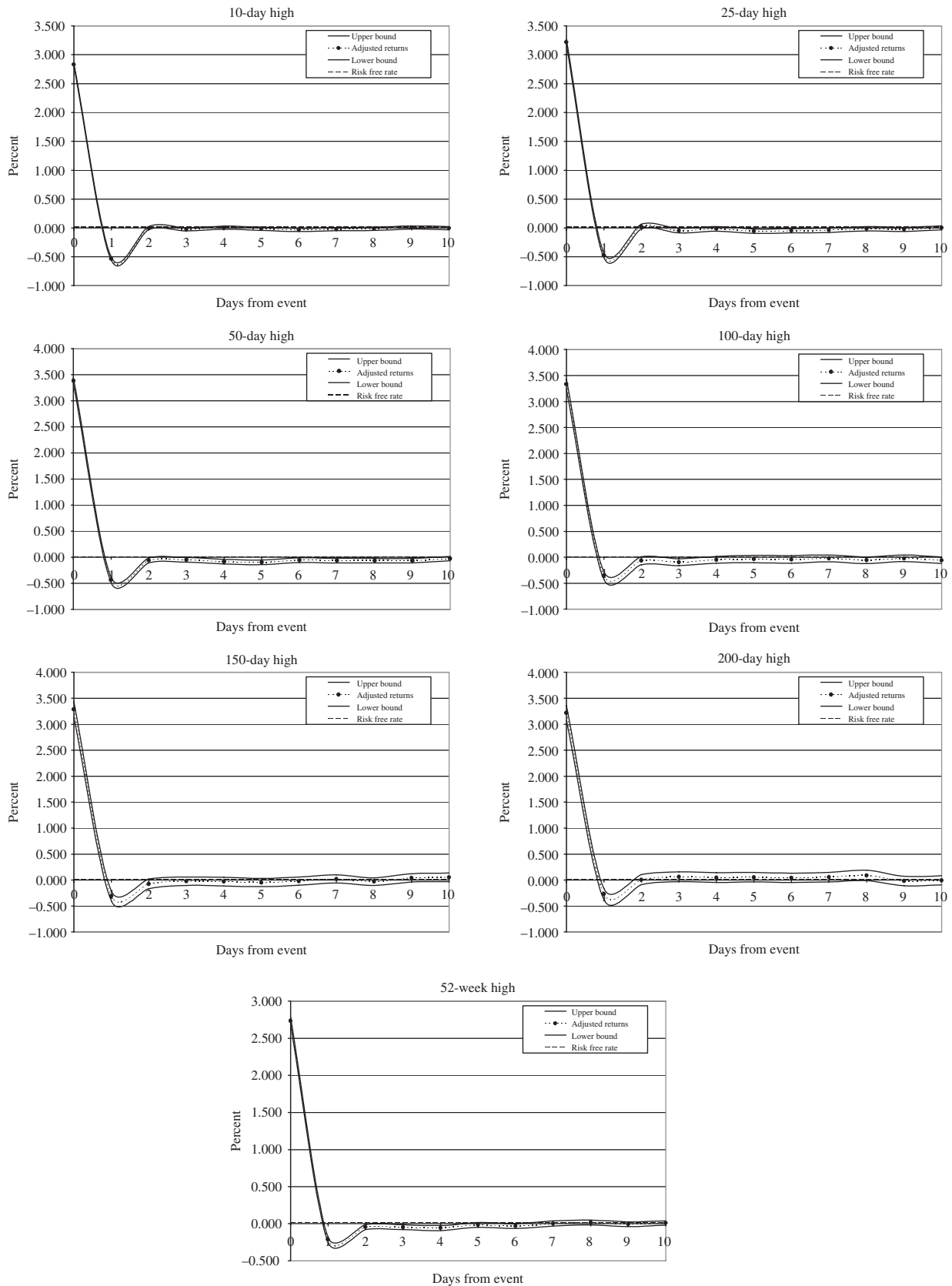


Fig. 5. Risk adjusted returns after n -day highs

Notes: The figure graphs persistence in abnormal returns (7) for 10 days after an n -day high. 95% confidence intervals are in the dark bands.

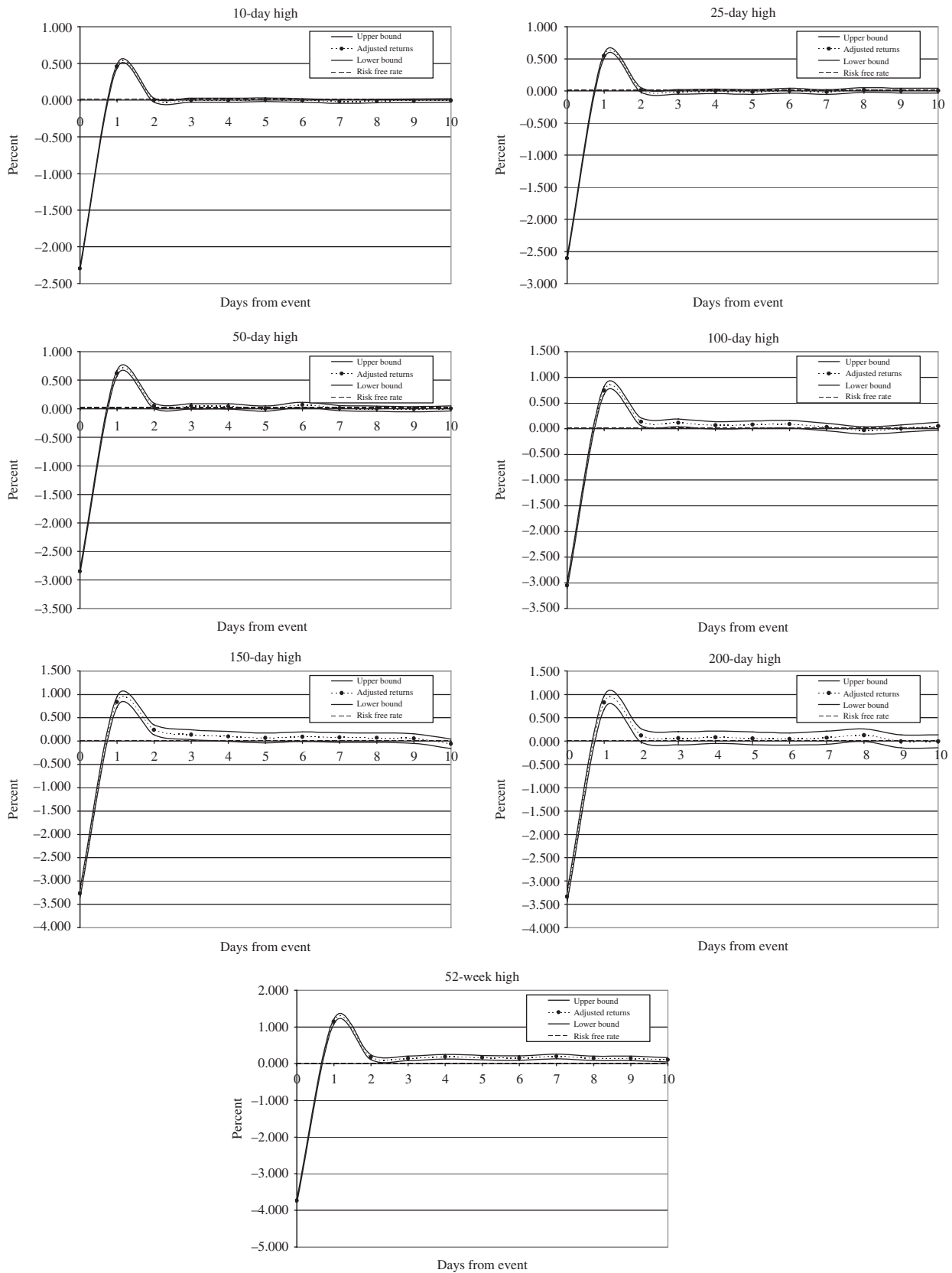


Fig. 6. Risk adjusted returns after n -day lows

Notes: The figure graphs persistence in abnormal returns (7) for 10 days after an n -day low. 95% confidence intervals are in the dark bands.

the 50-day high. The momentum factor, as George and Hwang (2004) have noted, explains more of the raw return at the 52-week interval.

There is a significant, negative, one-day abnormal return after an n -day high is achieved. This reversal is not particularly large and only slightly exceeds -0.5% . Abnormal returns are insignificantly different from zero after the second day.

On event day lows, abnormal returns, in Fig. 6, range from -2.29% for the 10-day to -3.74% for the 52-week. We find that momentum does not continue after n -day lows. Returns reverse, and because the momentum factor looks at these as short opportunities, the risk reward tradeoff is excellent. Abnormal returns for going long after an n -day low range from 0.46% for the 10-day to 1.15% for the 52-week. These risk-adjusted returns remain significantly positive for 2–10 days for $n > 25$.

VI. Conclusion

When confronting a large amount of information, agents tend to limit their attention to a smaller set of headline facts. In equity analysis, n -day highs and lows appear to be salient for traders and investors.

We established a positive relationship between abnormal turnover and the event of breaching both n -day highs and lows. Turnover is a positive and increasing function of the time frame n , even after controlling for news about earnings, dividends and analyst recommendations.

Turnover persists after the event day for at least 2 weeks, positively for the highs and negatively for the lows. Abnormal returns suggest ignoring the trend when n -day highs are achieved and being contrarian on the n -day lows.

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