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BETA MOMENTUM STRATEGY AFTER EXTREME MARKET MOVEMENTS

Abstract

The authors adopt an event study method and empirically investigate the performance of a beta momentum strategy (long in past winners of small beta and short in past losers of large beta) after extreme market movements in 20 countries. The researchers find that the beta momentum strategy yields material abnormal returns after controlling for return factors of size (SMB), book-to-market (HML) and momentum (UMD). The results are consistent for both extreme market UP days or DOWN days and regardless of whether the extreme market movements are identified by three percent or two percent cut-off points. In addition, the results based on the beta momentum strategy are more consistent than those of conventional momentum and betting against beta (BAB) strategies over different test windows from (0, +1) days to (0, +90). Finally, the abnormal returns based on momentum, BAB, and our beta momentum strategies are statistically insignificant for the Asian and Australian subsamples, whereas the results are significant for the European and North American samples.

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INTRODUCTION

Although whether beta is priced to the degree predicted by the standard capital asset pricing model (CAPM) and whether beta is dead or alive are hot debated and unsettled issues in recent years (Fama & French, 1992, 1995; Chan & Lakonishok, 1993; Berk et al., 1999; Roll & Ross, 1994; Campbell & Vuolteenaho, 2004), undoubtedly, beta is still an important factor in portfolio formation and trading strategies. For example, Karceski (2002) shows that actively managed funds tend toward large beta stocks, because high-beta stocks outperform low-beta stocks after market run-ups. Frazzini and Pedersen (2014) further find that a betting against beta (BAB) strategy, which is long in low beta assets and short in high beta assets, yields superior risk-adjusted returns not only in equity markets, but also in other asset classes.

In this paper, we propose a new strategy – beta momentum strategy, which is buying small-beta stocks of past winners (SB-W) and selling large-beta stocks of past losers (LB-L) around extreme market movements. This strategy is in essence a combination of the common subsets of a momentum strategy (buying past winners and selling past losers) and the BAB strategy. We conjecture that our beta momentum strategy reduces the potential contaminating effects among the BAB and momentum strategies and yields more consistent results for two reasons.

First, the momentum strategy is based on the belief that investors underreact to information so that the past winners (losers) will continue to outperform (underperform) in the future. Many studies such as

Jegadeesh and Titman (1993, 2001), Chan et al. (1996), and Barberis et al. (1998) show that buying past winners recoups higher returns, and selling past winners reduces additional delayed losses. However, whether and/or when investors underreact or overreact is an open empirical question, because many studies also show that contrarian strategies yield material returns too, but contrarian strategies are based on the belief that investors overreact to information and push down (up) the prices of past losers (winners) away from their intrinsic value so that long in past losers and short in past winners are profitable (DeBondt, 1985, 1987; Chan, 1988; Jagadeesh & Titman, 1995; Antoniou, Galariotis, & Spyrou, 2006, Filbeck, Li, & Zhao, 2013).

We suggest that extreme market movements provide a better setting for testing the momentum strategy. According to Griffin and Tversky (1992), individuals tend to underreact to sporadic and intermittent events, but overreact to prolonged news and events. This is related to the conservatism, which suggests that individuals are reluctant and slow to change their prior beliefs in the face of new information or shocks; conversely, the representativeness suggests that individuals overreact to a series of events[1]. Given the sporadic nature of extreme market movement events, if momentum strategy is profitable, it is expected to yield more consistent results from extreme market events, since the premise of momentum strategy is investor under-reaction or slow adjustment to information.

Second, among the winners and losers in the context of momentum strategy, they are likely to have different characteristics. Thus, some winners have relatively larger betas (LB-W) than other winners (SB-W). Similarly, some losers are large beta losers (LB-L), while others are small beta losers (SB-L). However, according to Frazzini and Pedersen (2014), constrained investors bid up large-beta assets (including stocks) so that large-beta assets generate low future alphas, and small-beta assets generate high future alphas, which is the premise of the BAB strategy, buying small-beta assets and selling large-beta assets. In other words, the momentum strategy focuses only on past performance and ignores asset's beta. In contrast, the BAB strategy proposed by Frazzini and Pedersen (2014) focuses only on asset's beta and ignores the asset past performance. Thus, a simple BAB strategy consists of long positions in small-beta stocks that likely include both small-beta winners and small-beta losers and short positions in large-beta stocks that could be large-beta winners and large-beta losers.

Specifically, a momentum strategy can be described as buying (SB-W, LB-W) and selling (SB-L, LB-L), whereas the BAB strategy is illustrated as buying (SB-W, SB-L) and selling (LB-W, LB-L). Our beta momentum is described as buying (SB-W) and selling (LB-L), which eliminates the possible conflicting components of buying (LB-W) in momentum strategy vs buying (SB-L) in BAB, and the conflicting components of selling (SB-L) in momentum strategy vs selling (LB-W) in BAB strategy.

This study sheds light on the literature in several ways. First, although many studies focus on the BAB, and momentum versus contrarian strategies, it is unclear whether extreme market movements affect the profitability of these strategies and whether the impact would be different under different market conditions such as extreme UP and DOWN days. Because the profitability of these strategies is affected by investor under/overreaction, under/overconfidence, and the conservatism/representativeness biases, it is essential to understand the influence of extreme market movements when analyzing these strategies, since investors' trading behavior is affected by market conditions (Filbeck, Li, & Zhao, 2013). Second, some anecdotal evidence indicates that investing during market DOWN days works. For example, a Bloomberg Businessweek article by Lu Wang (2014) shows that buying during stock setbacks has been an effective strategy in 2014. Russoliloo (2013) published a blog on Dowjones Newswires, showing that investors continue to use the recent dips as buying opportunities.

Using stocks in 20 countries that are included in the MSCI index between 2004 and 2013, we find that our beta momentum strategy yields significant abnormal returns after controlling for return factors

1 Li and Yu (2012) provide more detailed discussions related to this topic.

such as size (SMB), book-to-market (HML), and momentum (UMD). The cumulative abnormal returns (CARs) of the beta momentum strategy range from 0.26% over the test window (0, +1) days to 10.21% over the window (0, +90) days. More importantly, the abnormal return of the beta momentum strategy is more consistent than other two strategies. For example, the CAR of momentum strategy is 2.00% and significant at the 0.01 level over the test window (0, +15) after extreme market DOWN days, but it is 0.25% and insignificant (at the 0.1 level) after extreme market UP days. The CAR of the BAB strategy is –1.32% and 0.83% over the test window (0, +15) after extreme DOWN and UP days, respectively, both numbers are significant at the 0.01 level, but have opposite signs. In contrast, the beta momentum yields a consistent CAR of 1.41% and 1.65% over the test window (0, +15) after extreme DOWN and UP days, respectively, and both numbers are significant at the either 0.05 or 0.01 levels.

The remainder of this paper is organized as follows. The literature review is presented in section 1, then, followed by our sample and methodology in section 2. We discuss our event study results in section 3 and make concluding remarks in last section.

1. LITERATURE REVIEW AND HYPOTHESES

1.1. Momentum strategies and related explanations

Jegadeesh and Titman (1993, 2001) document that investors who use momentum strategies by purchasing stocks based on superior past six-month returns and holding them for the following six months obtain significant positive returns. They argue that the results are due to delayed price reactions to firm specific information rather than to lead-lag effects of common factors. Chan, Jagadeesh, and Lakonishok (1996) confirm that the market responds slowly to new information, while Conrad and Kaul (1993) argue that momentum profits arise because of cross-sectional differences in expected returns rather than because of time-series return patterns. Barberis, Shleifer, and Vishny (1998) confirm an underreaction of stock prices to news such as earnings announcements, but an overreaction of stock prices to a series of good or bad news. They also argue that time-varying expected returns may serve as a possible explanation for momentum payoffs. Siganos and Chelly-Steely (2006) investigate profitability of momentum strategies following bull and bear markets. They discover that investors can gain stronger momentum profits by adopting the continuation strategy after observing poor lagged market returns. In addition, the longer the duration used to describe the bear state, the stronger the realized momentum-based returns.

Many other studies investigate the profitability of momentum strategy based on firm characteristics. Hong, Lim, and Stein (2000) find that the profitability of momentum strategies declines sharply with firm size, that momentum strategies work better among stocks with low analyst coverage, and that the effect of analyst coverage is greater for stocks that are past losers rather than past winners. Sagi and Seasholes (2007) find that momentum strategies carried out in high revenue volatility firms, low cost firms, and high market-to-book firms produce greater returns than the Jegadeesh and Titman (1993) strategy.

Other studies investigate momentum strategies in international markets. Rouwenhorst (1998) finds that portfolios of past medium-term winners outperform a portfolio of medium-term losers by more than one percent per month after correcting for risk using firms from 12 European countries. Chan, Hameed, and Tong (2000) examine the profitability of momentum strategies on international stock market indices and find statistically significant evidence of momentum profits. Chui, Titman, and Wei (2010) examine how cultural differences influence the returns of momentum strategies. They find that momentum profits are also positively related to analyst forecast dispersion, transaction costs, and the familiarity of the market to foreigners, and negatively related to firm size and volatility. They argue that the Jegadeesh and Titman (1993) momentum effect provides a major challenge to the efficient market hypothesis and momentum strategies generated with global data yield even higher Sharpe ratios, which further challenges traditional finance theories.

1.2. Literature on contrarian strategy

The contrarian strategies assume that investors overreact to firm specific or market wide information shocks, which implies that a quick profit can be made by buying recent losers and selling recent winners. Among many other studies, Chan (1988) finds that the small contrarian returns remain even after controlling for changes in risk of winners and losers and other factors. DeBondt and Thaler (1985) find loser portfolios outperform the market by about 19.6% within a 36-month periods after portfolio formation, whereas winner portfolios underperform the market by about 5%. They also show that the overreaction is asymmetric, and the overreaction of loser portfolios is larger than that of winner portfolios (also see DeBondt & Thaler, 1987). Jones (1993) provides additional explanations on contrarian profits observed in the previous studies. However, Conrad and Kaul (1993) argue that previous studies typically overestimated the returns to the long-term contrarian strategies due to the methodology used to cumulate multi-period returns. They indicate that after dropping the upward bias, there is no relation between true returns of loser or winner firms and overreaction. Using international samples, Baytas and Cakici (1999) indicate that there is no overreaction in US markets, but statistically significant returns to long-term contrarian strategies are obtainable in other countries. Jegadeesh and Titman (1995) document significant contrarian profit and suggest that the majority proportion is due to market overreaction and a very small proportion is associated with the lead-lag effect[2].

Many studies, such as Statman et al. (2006), Daniel et al. (1998) and Gervais and Odean (2001), attribute the mixed results on the profit of contrarian strategy to investor behavior. Specifically, Gervais and Odean (2001) and Statman et al. (2006) argue that the success of contrarian strategies is attributed to the overconfidence of both traders and shareholders. Lo and MacKinlay (1990) find that the returns on large stocks systematically lead those of smaller stocks and suggest that investor overreaction is not the only source of contrarian profits. Antoniou et al. (2006) find that the short-term contrarian strategies generate material profits based on a UK sample and that the profits are more pronounced for stocks with extreme market capitalization.

1.3. Literature on betting against the beta strategy

Beta strategies attract increasing attention in the literature recently. For example, Campbell and Vuolteenaho (2004) break the beta of a stock into two components, one reflecting news about the market's future cash flows and one reflecting news about the market's discount rates. They suggest that the higher average returns of value stocks and small stocks are due to the higher cash-flow betas of these stocks. Cohen et al. (2009) indicate that price levels of individual stocks can be largely explained by their fundamental betas. Frazzini and Pedersen (2014) show that longing leveraged low-beta assets and shorting high-beta assets generate superior return and the effectiveness of this strategy is not limited to US stock selection or to stock selection alone, but also holds in 19 other global stock markets, and in bond and credit markets. In addition, Asness, Frazzini, and Pedersen (2014a) find that betting against beta strategy without industry bets has also delivered positive returns. Asness, Frazzini, and Pedersen (2014b) define high quality securities as stocks that are safe, profitable, growing, and well managed and find that high-quality stocks have high risk-adjusted returns. In their measures of quality, low beta is considered as an important factor of the quality aspect: "safety". Ang et al. (2009) use 23 developed markets and provide international evidence. Their results show that stocks with recent past high idiosyncratic volatility have low future average returns around the world.

2. SAMPLE AND METHODOLOGY

The initial sample includes all available stocks from the Global Compustat daily security file for 20 markets belonging to the MSCI developed countries between January 2004 and December 2013. We assign each stock to its corresponding

2 See Filbeck, Li, and Zhao (2013) for more related additional discussions on contrarian strategy literature.

Table 1. Summary statistics for different countries

Country	Number of stocks	MVE (USD billion), Mean	Number of extreme market movements (3%)	Number of extreme market movements (2%)
Australia	1,831	0.78	31	38
Austria	106	1.10	29	34
Belgium	157	1.98	28	34
Canada	2,009	1.04	22	36
Denmark	197	6.91	23	40
Finland	140	2.56	31	36
France	878	1.53	27	28
Germany	975	4.15	23	33
Hongkong	1,667	1.74	22	36
Italy	311	4.49	23	29
Japan	3,726	1.81	25	41
Netherland	168	1.79	24	28
New Zealand	144	2.23	21	47
Norway	274	1.20	35	36
Singapore	732	7.88	18	21
Spain	234	1.92	31	29
Sweden	517	2.43	28	34
Switzerland	287	0.90	19	37
United Kingdom	2,234	1.53	21	31
United States	6,356	11.56	9	29

Note: This table reports the summary statistics of stocks in 20 countries. We report the number of firms and the average firm size measured by the market value of equity (MVE) in U.S. dollars in each country in June 2013. We identify extreme market movement event days if the absolute value of a country's market index daily return is greater than 3 and 2 percent, respectively, during our whole sample period from 2004 to 2013.

market based on the location of the primary exchange. We choose this sample period, as it spans the recent financial crisis in in many countries. It is very important for investors to understand whether they could take advantage of extreme market events to earn abnormal returns by using the beta momentum strategy, since individuals tend to underreact to sporadic events and overreact to prolonged information and events.

We identify extreme market movement event days (t = 0) using each market's daily market index return. Market UP (DOWN) days are defined as the days when the respective market index is increased (decreased) by more than 3 percent, compared with the market close price of the previous day. It is common that extreme market movements are followed by market corrections. For example, on October 13, 2008, the S&P 500 had a positive return of 11.58 percent, and it was followed by a reversal of –9.03% return on October 15, 2008, and another return of –6.10 percent on October 22, 2008, and a return of 10.80 percent on October 28, 2008. Thus, to eliminate the possible compounding reversal effect, we include only the event days that are not preceded by other extreme market movements during a (–15, –1) day window.

Table 1 reports the number of firms and the average firm size measured by the market value of equity (MVE) in U.S. dollars in June 2013, and the total number of extreme market movement events identified by using both 3 and 2 percent as cut-off points during our whole sample period from 2004 to 2013. There are 490 event days in total when 3 percent cut-off point is used, and the average number of extreme market events is 23 per country during our sample period, ranging from 35 for Norway to 9 for the U.S. When 2 percent is used as a cut-off point, there are 677 extreme market events, with an average of 33.9 events per country. Our main results are based on 3 percent cut-off point, and we use 2 percent just for robustness test.

To calculate the beta for each stock, we regress a stock's daily excess return, which is the difference of the stock's raw return and the US Treasury Bill rate, on the daily return of its corresponding MSCI local market index. To make beta estimate more reliable, we include only actively traded stocks by filtering out stocks that have less than 100 observations of daily returns over the last 6 months and stocks that have more than 40 observations of zero daily return over past 6 months. We calculate alpha (abnormal return) of each stock with respect to the international market return corresponding to the MSCI local market index and factor returns based on size (SMB), book-to-market (HML), and momentum (UMD) from Asness and Frazzini (2013)[3].

Formation of winner and loser samples

For each event date t, we rank all stocks in our sample according to their average returns from day t–180 through t–1 into deciles. Following the existing literature (e.g., Filbeck, Li, & Zhao, 2013), we classify the top 10 percent of securities with the highest returns as "winners", while the bottom 10 percent securities with the lowest returns as "losers". Both the loser and winner subsamples include only actively traded stocks, since filtering out inactively traded stocks helps reduce return noise due to inactive trading. We use these subsamples to calculate abnormal returns of momentum strategy and compare them with the results of beta momentum strategy.

Formation of large and small beta samples

For each event date t, we calculate the beta for each stock using market model and the daily returns from day t–180 to t–1. Specifically, we regress a stock's daily excess return, which is the difference between the stock's raw return and the U.S. Treasury Bill rate, on the daily market return measured by the corresponding MSCI local market index. Then, we rank all stocks into deciles based on the estimated beta. The top 10 percent of securities with the largest beta are classified as "large-beta" subsample, while the bottom 10 percent securities are classified as "small-beta" subsample. We use these subsamples to compute abnormal returns of BAB and compare them with our beta momentum strategy.

Formation of large-beta loser and small-beta winner subsamples

For each event date t, we further rank the stocks in the large-beta and small-beta subsamples based on the past six month average returns. The stocks ranked at the bottom 30 percent in the large-beta sample are classified as "large-beta losers", while those ranked at the top 30 percent in the small-beta sample are classified as "small-beta winners". We define the beta momentum strategy as buying small-beta winners and selling large-beta losers stocks.

The descriptive statistics are reported in Table 2 for each sample defined above. For each event date t in each country, we calculate the numbers of stocks for each subsample, the average daily returns in the previous six-month from t–180 to t–1, and the average beta. The descriptive statistics are computed for each sample across 20 countries during the whole sample period. For example, the average number of stocks in the loser sample is 64, the average daily return from t–180 to t–1 for this sample is –0.34 percent, and the average beta is 0.56. The winner subsample has an average daily return of 0.61 percent in the previous six months, and the average beta is 0.60. The average beta of the large-beta subsample is 1.29 in the previous six months, whereas the average beta of the small-beta subsample is only –0.06. The large-beta loser subsample has slightly lower returns (–0.41 percent) than the whole loser subsample (–0.34 percent). The small-beta winner subsample has slightly higher returns (0.74 percent) than the whole winner sample (0.61 percent).

3. EMPIRICAL RESULTS ON THE PROFITABILITY OF BETA MOMENTUM STRATEGY

3.1. Cumulative abnormal returns (CARs)

We test investor reaction to each extreme market event using cumulative abnormal returns (CARs) from $t = 0$ (the day of extreme market movement

3 We download the data from http://www.econ.yale.edu/~af227/data_library.htm

Table 2. Descriptive statistics for different subsamples

Variable	Mean	Standard deviation	Percentile				
			Min	25	50	75	Max
Loser subsample							
Sample size	64	102	4	13	22	71	638
Avg. daily returns (%)	–0.34	0.20	–1.15	–0.47	–0.31	–0.20	0.11
Beta	0.56	0.26	–0.07	0.37	0.51	0.70	1.72
Winner subsample							
Sample size	64	102	4	13	22	72	638
Avg. daily returns (%)	0.61	0.54	0.01	0.33	0.48	0.74	5.42
Beta	0.60	0.29	–0.50	0.42	0.57	0.75	2.71
Small-beta subsample							
Sample size	64	102	4	13	22	72	638
Avg. daily returns (%)	0.13	0.37	–0.43	–0.02	0.06	0.18	5.06
Beta	–0.06	0.19	–0.93	–0.13	–0.04	0.05	0.35
Large-Beta subsample							
Sample size	64	102	4	12	22	72	638
Avg. daily returns (%)	0.14	0.35	–0.57	–0.06	0.12	0.28	4.20
Beta	1.29	0.32	0.65	1.09	1.25	1.42	3.94
Small-beta winners							
Sample size	26	36	4	6	13	30	211
Avg. daily returns (%)	0.74	1.03	0.01	0.34	0.51	0.85	14.54
Beta	–0.02	0.37	–2.04	–0.04	0.09	0.16	0.63
Large-beta losers							
Sample size	27	41	4	6	12	26	235
Avg. daily returns (%)	–0.41	0.21	–1.10	–0.55	–0.37	–0.25	0.16
Beta	1.10	0.27	0.66	0.90	1.06	1.23	2.03

Note: This table reports the descriptive statistics for different subsamples. For each event day t, we rank all stocks based on their average daily return during the previous six months from day t–180 through t–1 into deciles. The top (bottom) 10 percent of securities with the highest (lowest) returns are classified as "winners" ("losers") subsample. Similarly, for each event day, we rank all stocks based on their beta estimated during the previous six month into deciles. The top (bottom) 10 percent of securities with the largest betas are classified as large (small) beta subsample. We further rank the stocks in the large-beta and small-beta subsamples based on the past six months average returns. The stocks ranked at the bottom 30 percent in the large beta sample are classified as "large beta losers", while those ranked at the top 30 percent in the small beta sample are classified as "small beta winners". For each event day t in each country, we compute the numbers of stocks (sample size) in each subsample, the average daily returns in the previous six-month from t–180 to t–1, and the average betas. Then, we calculate the descriptive statistics for each subsample across 20 countries during the whole sample period.

until up $t = 90$ (the 90th trading day) ($t = 90$) after the event day. Following Asness and Frazzini (2013) and Frazzini and Pedersen (2014), we calculate daily abnormal return (alpha) with respect to the international market (the MSCI local market index) and factor returns based on size (SMB), book-to-market (HML), and momentum (UMD).[4]

Table 3 reports the CAR for different subsamples. Over the event window (0, +1), the loser subsample yields a CAR of –0.61 percent (panel A), which is significant at the 0.01 level, while the CAR for the winner subsample is –0.09 percent and statistically insignificant. These results indicate that after extreme market movements, a momentum strategy yields a CAR of 0.52 percent [–0.61 – (–0.09)] during the event window (0, +1), and it is significant at the 0.01 level. As we expand the event window, the CAR of the momentum strategy increases monotonically. The CARs are 0.76, 1.35, 2.97, and 8.40 percent during the event windows (0, +5), (0, +15), (0, +30), and (0, +90), respectively, which are all statistically significant at the 0.01 level.

The CARs of the small- and large-beta subsamples are –0.3 percent (significant at the 0.01 level)

4 We download the data from http://www.econ.yale.edu/~af227/data_library.htm

Table 3. Cumulative abnormal returns (CARs) after extreme market movements

Subsamples	Loser subsample (1)	Winner subsample (2)	Small-beta subsample (3)	Large-beta subsample (4)	Small-beta winners (5)	Large-beta losers (6)	Momentum strategy (2) – (1)	Betting against beta strategy (3) – (4)	Beta momentum strategy (5) – (6)
Panel A. Cumulative abnormal returns (%) of event window (0, 1)									
CARs	–0.61	–0.09	–0.30	–0.01	–0.13	–0.39	0.52	–0.29	0.26
t-stat	(–9.65***)	(–1.54)	(–5.79***)	(–0.09)	(–1.20)	(–3.22***)	(7.03***)	(–3.38***)	(1.89*)
Panel B. Cumulative abnormal returns (%) of event window (0, 5)									
CARs	–0.77	–0.01	–0.35	0.09	0.20	–0.43	0.76	–0.44	0.64
t-stat	(–7.29***)	(–0.10)	(–3.79***)	(0.87)	(1.22)	(–2.09**)	(5.99***)	(–3.15***)	(2.44**)
Panel C. Cumulative abnormal returns (%) of event window (0, 15)									
CARs	–1.15	0.20	–0.52	–0.01	0.60	–0.89	1.35	–0.51	1.49
t-stat	(–6.42***)	(1.35)	(–3.84***)	(–0.08)	(2.15**)	(–2.77***)	(6.46***)	(–2.24**)	(3.43***)
Panel D. Cumulative abnormal returns (%) of event window (0, 30)									
CARs	–2.56	0.42	–0.83	–0.44	1.21	–2.49	2.97	–0.39	3.70
t-stat	(–9.63***)	(1.77*)	(–3.81***)	(–1.68*)	(2.77***)	(–5.32***)	(9.48***)	(–1.14)	(5.77***)
Panel E. Cumulative abnormal returns (%) of event window (0, 90)									
CARs	–7.51	0.89	–1.71	–1.93	2.67	–7.54	8.40	0.22	10.21
t-stat	(–14.61***)	(1.78*)	(–4.10***)	(–3.85***)	(2.95***)	(–8.19***)	(13.27***)	(0.33)	(7.39***)

Notes: This table reports the cumulative abnormal returns (CARs) of different subsamples and three trading strategies after extreme market movements. We identify extreme market movement event days ($t = 0$) if the absolute value of a country's market index daily return is greater than 3 percent. The CAR from the event day ($t = 0$) up to 90 trading days ($t = 90$) measures investor reaction to extreme market movements. Following Asness and Frazzini (2013) and Frazzini and Pedersen (2014), we calculate daily abnormal return (alpha) with respect to the international market (the MSCI local market index) and factor returns based on size (SMB), book-to-market (HML), and momentum (UMD). The CAR is the sum of daily abnormal return. Winners, losers, small-beta, large-beta, large-beta loser and small-beta winner subsamples are defined the same as in Table 2. ***indicates significance at the 0.01 level; **indicates significance at the 0.05 level; *indicates significance at the 0.1 level.

and –0.01 percent (insignificant) during the event window (0, +1), respectively. These results indicate that the BAB strategy (i.e., buying small-beta stocks and selling large-beta stocks) yields a CAR of –0.29 percent [–0.30 – (–0.01)], which is significant at the 0.01 level. When the event window expands to (0, +5) and (0, +15), the CARs of the BAB strategy are –0.44 and –0.51 percent, both are significant at the 0.01 level. However, over the event windows (0, +30) and (0, +90), the CARs of BAB strategy are –0.39 and 0.22 percent, which are insignificant at the 0.1 level.

The beta momentum strategy (buying small-beta winners and selling large-beta losers) yields significant profits over all event windows, and the CAR increases both in magnitude and significance level as the event window widens. For example, the CAR is 0.26 percent and significant at the 0.1 level over the event window (0, +1), and it increases to 3.70 and 10.21 percent over the event windows (0, +30) and (0, +90), respectively, both are significant at the 0.01 level. Note also that the beta momentum strategies outperform both the momentum strategy and BAB strategy in all longer terms. For example, over the event window (0, +15), the CAR of beta momentum strategy is 1.49 percent, compared with 1.35 percent and -0.51 percent for the momentum and BAB strategies, respectively. Over the event window (0, +90), the CAR of the beta momentum strategy (10.21) is about 1.80 percent higher than that of the momentum strategy (8.40), and it is about 9.99 percent higher than the BAB strategy (0.22).

A. Profitability and market conditions

To test whether investors react different under different market conditions, we further divide the extreme market event days into UP days (i.e., positive event days) and DOWN days (negative event days). Panel A of Table 4 reports the CARs after DOWN and UP days over the event window (0, +15)[5]. After DOWN days, the loser sample yields a CAR of –1.71 percent, which is

5 Results for other event windows are qualitatively similar so we omit reporting the results for brevity.

Table 4. Cumulative abnormal returns (CARs) based on DOWN vs UP days and for different geographic areas

Subsamples	Loser subsample (1)	Winner subsample (2)	Small-beta subsample (3)	Large-beta subsample (4)	Small-beta winners (5)	Large-beta losers (6)	Momentum strategy (2) – (1)	Betting against beta strategy (3) – (4)	Beta momentum strategy (5) – (6)
Panel A. Cumulative abnormal returns (%) of event window (0, 15) – UP vs DOWN days									
DOWN days (*N* = 305)									
CARs	–1.71	0.30	–1.09	0.23	0.21	–1.21	2.00	–1.32	1.41
t-stat	(–8.78***)	(1.59)	(–6.57***)	(1.12)	(0.65)	(–3.25***)	(8.34***)	(–4.97***)	(2.77***)
UP days (*N* = 185)									
CARs	–0.22	0.03	0.41	–0.42	1.27	–0.38	0.25	0.83	1.65
t-stat	(–0.65)	(0.14)	(1.91*)	(–1.33)	(2.40**)	(–0.64)	(0.68)	(2.13**)	(2.06**)
Panel B. Cumulative abnormal returns (%) of event window (0, 15) – geographic areas									
Asia (*N* = 47)									
CARs	0.02	–0.37	–0.66	0.22	–0.27	0.69	–0.39	–0.88	–0.96
t-stat	(0.04)	(–0.82)	(–1.48)	(0.38)	(–0.39)	(0.83)	(–0.71)	(–1.02)	(–0.93)
Australia (*N* = 52)									
CARs	–0.61	–0.42	–1.08	–0.61	–0.27	–0.02	0.20	–0.48	–0.25
t-stat	(–1.03)	(–0.71)	(–2.36**)	(–0.77)	(–0.38)	(–0.02)	–0.29	(–0.53)	(–0.46)
Europe (*N* = 360)									
CARs	–1.33	0.32	–0.46	0.06	0.82	–1.13	1.66	–0.52	1.95
t-stat	(–6.29***)	(1.93*)	(–2.91***)	(0.32)	(2.32**)	(–2.97***)	(6.72***)	(–2.13**)	(3.76***)
North America (*N* = 31)									
CARs	–1.60	0.65	–0.06	–0.23	0.97	–1.89	2.25	0.17	2.86
t-stat	(–4.25***)	(1.58)	(–0.15)	(–0.40)	(1.45)	(–3.43***)	(4.17***)	(0.19)	(3.15***)

Notes: Panel A reports the cumulative abnormal returns (CARs) after extreme market UP and DOWN days, and panel B reports the results for different geographic areas. We identify extreme market movement event days ($t = 0$) if the absolute value of a country's market index daily return is greater than 3 percent. The CAR from the event day ($t = 0$) up to 15 trading days ($t = 15$) measures investor reaction to extreme market movements. Following Asness and Frazzini (2013) and Frazzini and Pedersen (2014), we calculate daily abnormal return (alpha) with respect to the international market (the MSCI local market index) and factor returns based on size (SMB), book-to-market (HML), and momentum (UMD). The CAR is the summation of daily abnormal return. ***indicates significance at the 0.01 level; **indicates significance at the 0.05 level; *indicates significance at

significant at the 0.01 level, while the CAR of the winner sample is 0.30 and statistically insignificant at the 0.1 level. These results indicate that a momentum strategy is profitable, since the CAR is 2.00 percent and significant at the 0.01 level. The CARs for the small-beta and large-beta samples are –1.09 percent (significant at the 0.01 level) and 0.23 percent (insignificant at the 0.1) over the test window (0, +15), respectively, which result in a CAR of –1.32 percent for the BAB strategy, and it is significant at the 0.01 level. The CARs for the small-beta winner and large-beta loser subsamples are 0.21 percent (insignificant at the 0.1 level) and –1.21 percent (significant at the 0.01 level), which result in a CAR of 1.41 percent (significant at the 0.01 level) for the beta momentum strategy. These results are qualitatively similar to the pooled results reported in Table 2.

After extreme market UP days, the CAR generated from the momentum strategy is 0.25 percent during the event window (0, +15) and insignificant. The CAR of BAB strategy is 0.83 percent and significant at the 0.05 level. Similarly, the beta momentum strategy yields a CAR of 1.65 percent, which is significant at the 0.05 level. Overall, the beta momentum strategy yields a statistically significant positive CAR in both market UP days and DOWN days, whereas the results of momentum and BAB strategies are inconsistent for extreme UP and DOWN days.

Panel B of Table 4 shows the cumulative abnormal returns of different subsamples and the three strategies for different geographic areas over the event window (0, +15). For the Asian subsample, the CARs of momentum, BAB and the beta momentum strategies are –0.39, –0.88, and

Table 5. Descriptive statistics for matched samples

Variable	Mean	Standard Deviation	Percentile Min	25	50	75	Max
Loser subsample							
MVE (USD billion)	4.58	14.87	0.05	0.36	0.92	2.37	155.35
Matched MVE (USD billion)	4.32	13.57	0.02	0.42	0.94	2.33	149.30
Winner subsample							
MVE (USD billion)	8.94	32.55	0.03	0.54	1.59	4.37	443.80
Matched MVE (USD billion)	8.62	26.14	0.03	0.65	1.67	4.66	290.41
Small-beta subsample							
MVE (USD billion)	2.75	8.05	0.01	0.19	0.43	1.47	80.55
Matched MVE (USD billion)	2.64	8.04	0.01	0.20	0.46	1.28	119.87
Large-beta subsample							
MVE (USD billion)	24.10	62.65	0.14	2.97	6.67	16.70	522.96
Matched MVE (USD billion)	22.12	59.41	0.20	2.83	5.47	16.94	484.96
Small-beta winners							
MVE (USD billion)	4.72	17.78	0.00	0.16	0.49	1.38	204.70
Matched MVE (USD billion)	4.49	15.39	0.00	0.18	0.48	1.36	116.27
Large-beta losers							
MVE (USD billion)	11.24	49.27	0.03	0.46	1.15	3.61	680.47
Matched MVE (USD billion)	8.59	28.72	0.03	0.45	1.23	4.21	284.18

Note: This table reports the descriptive statistics for the matched samples. For each country and each event day, we match each of our sample stock (e.g., winners or losers) with a stock of the closest size proxied by market value of equity (MVE) in the same country, and the matched stocks are used as the benchmarks of the sample stocks.

–0.96 percent, respectively, and all these numbers are insignificant at the 0.1 level. The results for the Australian subsample are also statistically insignificant. For the European and North American subsamples, the results based on momentum and beta momentum strategies are significant and consistent with the whole sample. Specifically, the momentum strategy and beta momentum strategy yield a CAR of 1.66 percent and 1.95 percent for the European sample, and 2.25 percent and 2.86 percent for the North American sample, respectively. All these are significant at the 0.01 level. The CAR of the BAB strategy is –0.52 percent and significant at the 0.05 level for the European sample, whereas it is 0.17 percent and insignificant for the North American sample.

This evidence suggests that investors in different countries react to extreme market movements differently and results obtained in one market or country may not be applied to other markets. The insignificant results of Asian and Australian subsamples are largely consistent with the previous studies. For example, Chui et al. (2000) find weaker evidence in the momentum profit in Asian Markets, and Hameed and Kusnadi (2002) find no evidence of momentum profits in six Pacific Basin markets.

B. Buy and hold abnormal returns (BHARs)

To provide more evidence on the profitability of the three trading strategies associated with extreme market movements, we construct a matched sample on the basis of market capitalization. We use the return of matched sample as an alternative benchmark for testing the performance of the three strategies. Barber and Lyon (1997) argue that matching sample companies to control for sizes will correct the possible sources of misspecification and yield well-specified test statistics.

We calculate the market capitalization of all stocks from for Global Compustat daily security file associated with each event day in each of our sample country. Our potential universe of matching companies consists of all remaining stocks in that country. Then, for each stock in our sample, we select the stock from the matching universe with the closest market value of equity (MVE). We re-

Table 6. Buy and hold abnormal returns (BHARs) after extreme market movements

Returns	∏ (1 + Rit)	∏ (1 + *E*(Rit))	BHAR	*T*-test
Panel A. For holding period (0, 15)				
Loser sample	0.981	0.994	–0.011	–3.52***
Winner sample	0.994	0.991	0.004	1.66*
Small-beta sample	0.995	0.990	0.005	1.97**
Large-beta sample	0.986	0.996	–0.010	–3.76***
Winner small-beta sample	1.006	0.991	0.017	2.68***
Loser large-beta sample	0.977	0.991	–0.014	–2.61***
Panel B. For holding period (0, 30)				
Loser sample	0.970	0.992	–0.020	–5.61***
Winner sample	0.998	0.988	0.012	3.86***
Small-beta sample	0.991	0.989	0.002	0.74
Large-beta sample	0.985	0.995	–0.009	–2.38**
Winner small-beta sample	1.007	0.986	0.023	4.24***
Loser large-beta sample	0.968	0.989	–0.022	–3.08***
Panel C. For holding period (0, 90)				
Loser sample	0.942	0.995	–0.053	–8.64***
Winner sample	1.008	0.993	0.017	3.64***
Small-beta sample	0.994	0.987	0.007	1.35
Large-beta sample	0.982	1.004	–0.022	–3.96***
Winner small-beta sample	1.014	0.978	0.035	4.32***
Loser large-beta sample	0.941	0.992	–0.056	–4.79***

Note: This table reports the buy and hold abnormal returns (BHARs) for different holding periods after extreme market movements. First, we calculate the daily raw returns of sample stocks (Rit) and the matched stocks [*E*(Rit)]. Then, we calculate the BHAR of the sample stocks as ∏ (1+Rit) – ∏ (1 + *E*(Rit)) over different holding periods. We use t-tests to test whether the BHARs are significantly different from zero or not. ***indicates significance at the 0.01 level; **indicates significance at the 0.05 level; *indicates significance at the 0.1 level.

peat the same procedure for each event day, each country and each sample to create the matched sample. The characteristics of our subsamples and the matched sample are presented in Table 5. The table shows that our test samples and matched samples are very similar in market capitalizations. For example, the MVE for the loser subsample is USD 4.58 billion compared with USD 4.32 billion for the matched sample. The MVE for the winner subsample is USD 8.94 billion compared with USD 8.62 for the matched sample.

We calculate the buy and hold abnormal return as follows. First, we calculate the daily raw returns of sample stocks (R_{it}) and the matched stocks [$E(R_{it})$]. Then, the BHAR of the sample stocks is calculated as $\prod (1 + R_{it}) - \prod (1 + E(R_{it}))$ over different test windows. Panel A of Table 6 reports the results of BHARs over the event window (0, +15). The BHAR for each subsample is significant at the 0.1 or higher levels. For example, the BHAR for the loser and winner samples is –0.011 (significant at the 0.01 level) and 0.004 (significant at the 0.1 level), respectively. These indicate that the momentum strategy yields a 1.5 percent return. Similarly, the profit of the BAB strategy is also about 1.5 percent [0.005 – (–0.010)]. More importantly, the BHAR of beta momentum is about 3.10 percent [0.017 – (–0.014)], which is larger than the BHARs of both the momentum and BAB strategies, and it is also larger than the CAR (1.49 percent) during the same event window reported in Table 6.

When the event window expands to (0, +30) and (0, +90), the BHARs of the small-beta subsample become statistically insignificant at the 0.1 level, and the BHARs for all other subsamples remain significant and with larger absolute values compared with those over the event window (0, +15). The returns of the momentum strategy is about 3.20 percent [0.012 – (-0.02)] and 7.0 percent [0.017 – (–0.053)] over the event windows (0, +30) and (0, +90), respectively. The returns of the BAB strategy are about 2.9 percent [0.002 – (–0.009)] and 2.7 percent [0.007 – (–0.022)] over the event windows (0, +30) and (0, +90), respectively. The BHARs of the beta momentum strategy are 4.5 percent [0.023 – (–0.022)] and 9.1 percent [0.035 – (–0.056)] over

Table 7. Cumulative abnormal returns (CARs) after extreme market movements using 2 percent cut-off point

Subsamples	Loser subsample (1)	Winner subsample (2)	Small-beta subsample (3)	Large-beta subsample (4)	Small-beta winners (5)	Large-beta losers (6)	Momentum strategy (2) – (1)	Betting against beta strategy (3) – (4)	Beta momentum strategy (5) – (6)
Panel A. Cumulative abnormal returns (%) of event window (0, 15)									
CARs	–1.53	0.43	–0.19	–0.47	0.73	–1.87	1.97	0.29	2.60
t-stat	(–11.10***)	(3.25***)	(–1.61)	(–3.59***)	(2.98***)	(–7.78***)	(11.88***)	(1.57)	(7.58***)
Panel B. Cumulative abnormal returns (%) of event window (0, 15) – UP days vs DOWN days									
Down days (*N* = 397)									
CARs	–1.96	0.28	–0.91	–0.14	0.04	–1.65	2.24	–0.77	1.69
t-stat	(–10.88***)	(1.60)	(–6.12***)	(–0.82)	(0.13)	(–5.52***)	(10.23***)	(–3.20***)	(4.10***)
Up days (*N* = 280)									
CARs	–0.93	0.66	0.84	–0.94	1.73	–2.18	1.58	1.78	3.91
t-stat	(–4.40***)	(3.13***)	(4.89***)	(–4.75***)	(4.14***)	(–5.49***)	(6.28***)	(6.96***)	(6.65***)
Panel C. Cumulative abnormal returns (%) of event window (0, 15) – geographic areas									
Asia (*N* = 77)									
CARs	–1.80	–0.85	–0.72	–0.75	–1.03	–2.05	0.95	0.02	1.02
t-stat	(–4.94***)	(–2.21**)	(–2.36**)	(–1.76*)	(–1.99*)	(–3.42***)	(2.43**)	(0.04)	(1.38)
Australia (*N* = 85)									
CARs	–0.36	0.50	–0.22	–1.18	–0.32	–1.23	0.86	0.97	0.91
t-stat	(–0.86)	(1.25)	(–0.55)	(–2.83***)	(–0.50)	(–1.68*)	(1.68*)	(1.67*)	(1.18)
Europe (*N* = 450)									
CARs	–1.74	0.65	–0.08	–0.36	1.32	–2.10	2.39	0.28	3.42
t-stat	(–9.88***)	(3.85***)	(–0.54)	(–2.25**)	(3.98***)	(–6.71***)	(11.25***)	(1.25)	(7.35***)
North America (*N* = 65)									
CARs	–1.34	0.41	–0.27	–0.02	0.21	–0.85	1.74	–0.25	1.05
t-stat	(–4.71***)	(1.47)	(–1.14)	(–0.07)	(0.53)	(–1.89*)	(5.26***)	(–0.51)	(1.74*)

Note: This table reports cumulative abnormal returns (CARs) after extreme market movements using 2 percent as a cut-off point. We identify extreme market movement event days ($t = 0$) if the absolute value of a country's market index daily return is greater than 2 percent. The CAR from the event day ($t = 0$) up to 15 trading days ($t = 15$) measures investor reaction to extreme market movements. Following Asness and Frazzini (2013) and Frazzini and Pedersen (2014), we compute daily abnormal return (alpha) with respect to the international market (the MSCI local market index) and factor returns based on size (SMB), book-to-market factor (HML), and momentum (UMD). The CAR is the summation of daily abnormal return over the event window (0, +15). *** indicates significance at the 0.01 level; ** indicates significance at the 0.05 level; * indicates significance at the 0.1 level.

the event windows (0, +30) and (0, +90). Overall, the results based on BHARs are consistent with those of CARs, indicating that the three strategies are profitable, especially the momentum and the beta momentum strategies.

C. Robustness tests

It is possible that our results are sensitive to how extreme market conditions are defined. Thus, we use 2 percent as a cut-off point to define extreme market events. As we reported in Table 1, there are 677 event days identified by this method for the 20 countries during our sample period from 2004 to 2013. We report the CARs for the different subsamples in Table 7. For brevity, we only report the results over the event window (0, +15). The results are largely consistent with the results we just reported, indicating that our results are not sensitive to different cutoff point selection criteria. For example, when all event days are pooled together (panel A), the CAR of the momentum strategy is 1.97 percent and significant at the 0.01 level, compared with 1.35 percent when 3 percent cut-off point is used in Table 3. The CAR of the BAB strategy is 0.29 percent and insignificant at the 0.1 level, which is different from the negative and significant CAR (–0.55 percent) reported in Table 3. For the beta momentum strategy, the CAR is 2.60 percent and significant at the 0.01 level, compared with the CAR of 1.49 percent in Table 3 when 3 percent cut-off is used.

Panel B of Table 7 reports the CARs after extreme market DOWN and UP days. After DOWN days, the CARs for the momentum, BAB, and beta momentum strategies are 2.24, –0.77, and 1.69 percent, respectively, over the event window (0, +15), and all these numbers are significant at the 0.01 level. After UP days, the CARs for these three strategies are 1.58, 1.78 and 3.91 percent, respectively. These results are consistent with those reported in panel A of Table 4, but with larger magnitude.

Panel C of Table 7 reports the results for different geographic areas. The CARs of momentum strategy for the Asian and Australian subsamples are 0.95 (significant at the 0.05 level) and 0.86 percent (significant at the 0.1 level), respectively, whereas the CARs of the momentum strategies for these two subsamples are insignificant when 3 percent cutoff point is used in Table 4, panel B. The CAR of the BAB strategy is 0.97 percent and significant at the 0.1 level for the Australian subsample, whereas the corresponding number in Table 4 is insignificant. The CARs for the beta momentum strategies remain insignificant for these two subsamples. The CARs of the momentum and beta momentum strategies are positive and significant at the 0.1 or higher levels for both the European and North American subsamples, which are largely consistent with those reported in Table 4 when the 3 percent cut-off point is used, whereas the CARs of BAB for the European and North American subsamples are insignificant.

CONCLUSION

There have been numerous studies on momentum and betting against beta strategies, however, there is limited evidence on how these strategies perform during the extreme market movements. Given the frequent occurrences of extreme market movement, it is important to investigate whether it is profitable for investors to adopt beta and/or momentum strategies after extreme market movements. Using different cut-off points (3% and 2%) to identity extreme market conditions from 2004 to 2013, we find that the beta momentum strategy is more profitable strategy after extreme market movements. These results are robust after considering multiple systematic factors and using different benchmarks for expected returns. The result suggests that investors underreact to extreme market movements, and acute investors are able to earn abnormal returns by using beta momentum strategies.

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