
MOMENTUM, ACCELERATION, AND REVERSAL

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This paper studies the impact of accelerated stock price increases on future performance. Accelerated stock price increases are a strong contributor to both poor future performance and a higher probability of reversals. It implies that accelerated growth is not sustainable and can lead to drops. The acceleration mechanism is also able to reconcile the well-documented 2–12 month momentum phenomenon and 1-month reversal.



The relative performance of stocks based on their historical returns has been studied extensively. Lehmann (1990) shows evidence of short-term “reversals” that generate abnormal returns to contrarian strategies that select stocks based on their performance in the previous month—the well-known 1-month reversal. On the other hand, Jegadeesh (1990) and Jegadeesh and Titman (1993, 2001) show robust profits to “momentum” strategies that buy stocks based on their previous 2–12 months. More recently, Heston and Sadka (2008) document an interesting

seasonality pattern (up to 20 annual lags) superimposed on the general momentum/reversal patterns. Interestingly, Novy-Marx (2012) shows that momentum can be mostly explained by 7–12 month returns prior to portfolio formation, and recent 6-month returns (lags 1–6) are irrelevant, thus, as he says, momentum is not really momentum.

What drives momentum and reversal is still not very clear. Popular explanations are under-reaction to news in an intermediate time horizon, such as 6 months, and over-reaction in a short horizon, such as 1 month. In this paper, we attempt to reconcile these two opposite findings with some new thoughts. Our hypothesis is that the momentum strategy leads to an accelerated price increase perhaps via positive feedback. However, the acceleration is not sustainable, hence the reversal. Indeed, we show evidence that accelerated price increase is a strong contributor to poor future performance.

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Little research has been performed on stock crashes at the individual stock level on a cross-sectional basis. Chen *et al.* (2001) use skewness as a measure for stock crashes and show that crashes are more likely to occur in individual stocks that (1) have experienced an increase in trading volume relative to the trend over the prior 6 months, (2) have had positive returns over the prior 36 months, and (3) are larger in terms of market capitalization.

We show that accelerated returns also increase the likelihood of individual stock drops, and thus provide explanations for poor future performance. A natural question to ask is how accelerated price increases can occur. One possibility is the well-known positive feedback process or herding, which can lead to an accelerated price increase. An example of the positive feedback process is that investors who bought stock and made money today cause more investors to buy stock tomorrow, which pushes stock price higher at an increasing rate.

At the market level, we have witnessed quite a few market crashes resulting from accelerated growth. Examples include the Internet bubble that peaked in early 2000 and the U.S. housing price increase before 2006. One characteristic associated with those crashes was the accelerated growth coupled with investors' excitement before the market crash. In these and many other similar cases, asset prices increased at an increasing rate, resulting in unsustainable growth and an eventual market crash.

1 Description of data

Our dataset consists of all the stocks on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) over the 52-year period from January 1960 through December 2011.¹ Daily returns, daily exchange-based trading volumes, and daily number of shares outstanding (not

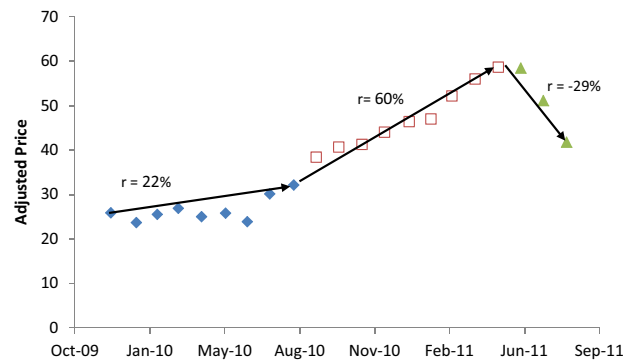


Figure 1 An illustration of accelerated price increase that results in a reversal.

adjusted for free-float) are collected from the University of Chicago Center for Research in Security Prices (CRSP). We include stocks with an initial price greater than \$2.² We exclude derivative securities like ADRs of foreign stocks.

2 Example of accelerated price increases

Accelerated price increases or acceleration simply means that the return is increasing over time, and thus the price increases at an increasing rate. We will introduce a way to measure the acceleration of returns later. Figure 1 shows a price increase that is accelerating for a NASDAQ-traded stock (ticker name INFA). The return is about 22% in the first period (diamond symbols, from December 2009 to August 2010), and accelerates to 60% in the second period (squares, from August 2010 to May 2011). The stock price plummeted about 29% from the peak (triangles, from May 2011 to August 2011) after accelerated price increase over the two periods.

3 Term structure of past 1-month return

Figure 2 shows strategies based on quintile portfolios (Q_1 – Q_5) that are sorted on a single lagged month's returns. It is similar to the term structure of momentum reported in Heston and Sadka (2008) and Novy-Marx (2012). For example, lag-1 means that the portfolios are formed on last

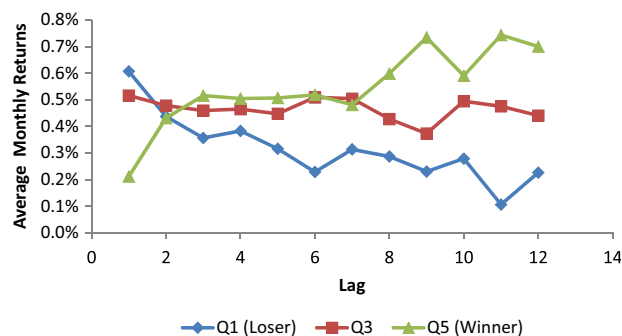


Figure 2 Forward 1-month quintile portfolios' performance across the term structure of 1–12 month lags. Q_5 (Q_1) is a portfolio of the previous winner (loser) stocks.

month's returns; lag-2 means that the portfolios are formed on the second-to-last month's returns; and so on. All portfolios are value-weighted and held for the next 1 month.³ *All portfolio returns are in excess of T-Bills in this paper.* Q_5 (Q_1) denotes the forward 1-month performance of the previous ranked winner (loser) stocks of the five portfolios.

It is interesting to observe that the forward 1-month performance of Q_3 is somewhat flat, whereas Q_5 (Q_1) has a positive (negative) slope. In addition, Q_1 and Q_5 are almost symmetric. A positive slope for Q_5 indicates winning stocks keep winning *more* from lag-2 to lag-12, hence a positive acceleration in returns. The unsustainable acceleration can explain the 1-month reversal at lag-1. In an opposite way the negative slope for Q_1 corresponds to a negative acceleration in returns (losing stocks keep losing *more*).⁴

We then calculate the long/short profit by subtracting Q_1 from Q_5 for each lagged month. Figure 3 plots the results, and the general trend is upward sloping for ($Q_5 - Q_1$, empty squares). The trend for ($Q_5 - Q_1$) can be fitted by an exponential function. Using the average of two winning or losing quintiles, $\text{avg}(Q_1, Q_2)$ or $\text{avg}(Q_4, Q_5)$, the trend is smoother (solid diamonds in Figure 3). The negative return in lag-1 is consistent with the

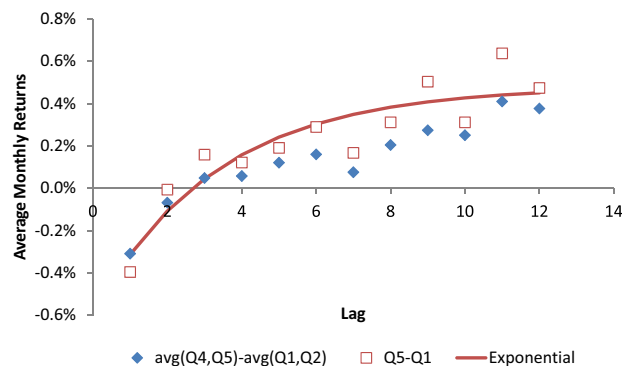


Figure 3 Forward one-month performance for the long Q_5 (winner)/short Q_1 (loser) portfolio across the term structure of 1–12 month lags.

*The exponential fit is for the term structure of ($Q_5 - Q_1$).

well-documented 1-month reversal. The positive returns in lags 3–12 are consistent with the documented momentum phenomenon. The picture is largely consistent with the results of Jegadeesh (1990), and the return-response profile studied in Heston and Sadka (2008) in their study of seasonality in the cross-section of returns, as well as the 1-month term structure of momentum by Novy-Marx (2012).

Figures 2 and 3 clearly suggest that the 1-month reversal and the 2–12 month momentum are two ends of the spectrum. The general trend in both figures indicates that positive acceleration leads to reversals or negative acceleration leads to rebound.⁵ In other words, unsustainable acceleration leading to reversal can reconcile the 1-month reversal and 2–12 month momentum. The key is that it implies that acceleration is not sustainable.

4 Accelerated stock price increases lead to poor returns

In this section, we test our hypothesis that accelerated stock price increase is a strong contributor to poor future performance. The rationale is that accelerated growth is not sustainable. We form portfolios by sorting stocks into quintiles based

on their accelerated returns over the last 1 year. We measure the performance for the five portfolios at the end of the 13th month on a rolling basis and rebalance the portfolios monthly.

We need to determine how to measure the acceleration of returns. One way to do it is to put different weights on the last 12-month returns, with positive weights on more recent returns and negative weights on more remote returns. In this way, the most recent strong returns will contribute more to the acceleration measure, and thus it highlights the acceleration of returns.

Figure 4 shows two weighting schemes for measuring the acceleration of returns. One is a step-function, and another is an exponential function. The step-function simply puts weight of +1 to the most recent 6 months (lag-1 through lag-6) and weight of -1 to the second recent 6 months (lag-7 through lag-12). The exponential weighting is

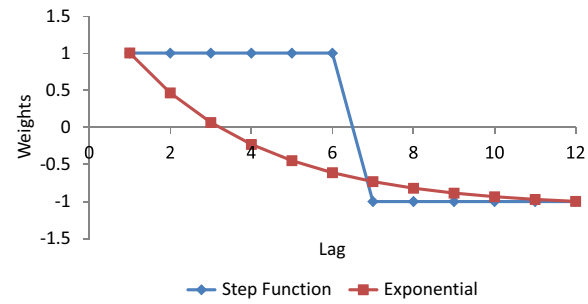


Figure 4 Two weighting schemes for measuring acceleration of returns.

motivated by the results shown in Figure 3, where the long/short portfolio shows accelerated returns which can be fit by an exponential function. The exponential function in Figure 4 is the flipped one in Figure 3 with a different scale. The exponential weighting highlights the impact of most recent acceleration of returns. The results for the acceleration using the exponential weighting are shown in the bottom panel of Table 1. We will show more

Table 1 The forward 1-month performance for 1-month reversal, 2–12 month momentum, and acceleration (exponential weighting) from January 1963 to December 2011.*

1-month reversal	Q_1 (1-month loser) (%)	Q_2 (%)	Q_3 (%)	Q_4 (%)	Q_5 (1-month winner) (%)	Q_1-Q_5 (%)
Ari. mean	7.53	8.21	6.37	5.38	2.57	4.96
Geo. mean	5.15	6.74	5.17	4.22	1.16	4.00
Std. dev.	21.07	16.50	15.07	14.85	16.51	4.56
Momentum (2–12)	Q_1 (Low momentum) (%)	Q_2 (%)	Q_3 (%)	Q_4 (%)	Q_5 (High momentum) (%)	$Q_5 - Q_1$ (%)
Ari. mean	1.01	4.76	4.63	7.11	11.27	10.26
Geo. mean	-1.37	3.34	3.44	5.79	9.23	10.60
Std. dev.	21.87	16.53	15.10	15.77	19.22	-2.65
Acceleration	Q_1 (Least accelerated) (%)	Q_2 (%)	Q_3 (%)	Q_4 (%)	Q_5 (Most accelerated) (%)	Q_1-Q_5 (%)
Ari. mean	12.25	8.21	6.01	3.41	-1.49	13.74
Geo. mean	10.14	6.85	4.85	2.20	-3.12	13.26
Std. dev.	19.50	15.88	14.78	15.30	18.08	1.41

*All numbers are annualized. Each column is in excess of T-Bills except the last column (Q_1-Q_5).

testing results with the step-function weighting scheme later.

The top panel of Table 1 shows the 1-month reversal effect. The 1-month loser outperforms the 1-month winner by 4.96% in arithmetic mean, and 4% in geometric mean. The mid panel shows the 2–12 month momentum effect. The 2–12 month winner outperforms the loser by 10.26% in arithmetic mean, and 10.60% in geometric mean.

In the bottom panel of Table 1, comparing “Least Accelerated Q_1 ” to “Most Accelerated Q_5 ,” the annualized arithmetic return is 13.74% higher, and the annualized geometric mean is 13.26% higher. The return spread between Q_1 and Q_5 is the largest for the acceleration panel in Table 1. It is almost the sum of return spreads of 1-month reversal and 2–12 month momentum. Note that the most accelerated quintile portfolio (Q_5) has a negative 3.12% of geometric mean over the whole 49-year sample period when stock prices were rising.

In the acceleration panel of Table 1, by construction, the Q_1 portfolio most likely has experienced a large price correction in the past 1 year. Hence Q_1 may have earned a downside or tail risk premium (see Xiong *et al.*, 2014) perhaps because of panic selling. This downside risk premium can partly explain the outperformance of Q_1 .

In contrast, the Q_5 portfolio, by construction, has experienced the most impressive accelerated price increase over the last 1 year. The forward month underperformance is mostly due to its unsustainable growth. Later, we show that accelerated price increases lead to a higher probability of big drops, which is consistent with the underperformance of Q_5 .

5 Robustness test

While a single sorting on acceleration in Table 3 provides useful information, the performance

will be coupled with other factors, such as stock volatility, 1-month reversal, momentum, liquidity,⁶ market cap and book-to-market ratio. Hence we are more interested in performance evaluation by controlling any one of these factors. In other words, we perform double sorting by first sorting on one of these factors and second on acceleration. The acceleration is measured by the exponential weighting scheme.

For example, to control for the effect of momentum, we sorted stocks into starting quintiles based on the trailing 2–12 month momentum. Then, within each momentum-based quintile, we sorted the stocks into the second quintiles based on acceleration. Thus, we have 25 portfolios.

All of the 25 portfolios are hold for 1 month—the 13th month. At the end of the 13th month, we re-form the 25 portfolios using the same double sorting algorithm on a monthly rolling basis. Hence the 25 portfolios are monthly rebalanced from January 1963 through December 2011. The excess returns (over T-Bill) for each one of the 25 portfolios are averaged with capital weights. The performance results for the 25 portfolios controlling for momentum are shown in Table 2. Table 3 shows the corresponding results controlling for the 1-month reversal effect.

Both Tables 2 and 3 show that the most accelerated quintiles significantly underperform the least accelerated quintiles in each controlled quintile, and the average annual underperformance is 10.54% and 10.68% when the momentum and 1-month reversal effects are controlled, respectively.

Next, we repeated the same analysis by controlling for other factors, such as stock volatility, liquidity, market cap, and book-to-market ratio. The outperformance for Q_1 and underperformance for Q_5 after controlling for each of these factors are all similar to Tables 2 and 3. They are

Table 2 Acceleration sorts (exponential weighting) controlling for the 2–12 month momentum.

	1 Low momentum (%)	2 (%)	3 (%)	4 (%)	5 High momentum (%)	Average (%)
1 Low acceleration	7.53	11.83	10.27	12.20	15.83	11.53
2	7.75	9.07	7.23	10.31	14.31	9.73
3	1.58	4.70	6.14	9.70	11.98	6.82
4	-3.77	1.75	3.20	4.42	9.54	3.03
5 High acceleration	-9.50	-0.27	1.04	5.73	7.99	1.00
Low-high	17.03	12.11	9.23	6.47	7.85	10.54

Table 3 Acceleration sorts (exponential weighting) controlling for the 1-month reversal.

	1 Low 1-month (%)	2 (%)	3 (%)	4 (%)	5 High 1-month (%)	Average (%)
1 Low acceleration	13.52	11.74	10.81	11.16	8.49	11.14
2	11.51	10.37	7.09	6.66	3.88	7.90
3	10.04	9.84	6.81	2.86	2.71	6.45
4	5.15	7.17	5.65	3.72	-0.54	4.23
5 High acceleration	2.25	3.28	2.21	-0.15	-5.26	0.47
Low-high	11.27	8.46	8.60	11.31	13.75	10.68

not reported for brevity. The results indicate that the underperformance of most accelerated stocks is robust after controlling for other factors.

6 More testing on acceleration

We construct a few different acceleration schemes based on the step-function in this section. We first break the last 12-month period into two 6-month periods, and denote $(r_{1-6} - r_{7-12})$ as the increased return over the last year. The average monthly return r_{1-6} is over the most recent 6 months (lags-1-6). The average monthly return r_{7-12} is over the second recent 6 months (lags-7-12). If $(r_{1-6} - r_{7-12}) > 0$, then returns are accelerating over the last year. In this weighting scheme, we compare the difference in 6-month returns by multiplying by +1 and -1 to the most recent 6-month returns and the second recent 6-month returns, respectively.

Next, we construct $(r_{2-6} - r_{7-12})$, and all the way to $(r_6 - r_{7-12})$. Specifically, we fix the second 6-month returns (r_{7-12}), but gradually remove the most recent months in the first 6-month period, 1 month at a time. For example, r_{2-6} is the average monthly return over the 5 months with lags-2-6, i.e. the most recent month is excluded. By excluding the most recent 1 month, we are effectively controlling the 1-month reversal effect. These settings allow us to see an incremental damage to future performance by acceleration of recent month returns.

Figure 5 shows that the impact of acceleration on future performance exists for all the most recent 6 months, and the drag becomes more significant for the most recent 1 month. The performance drag is significant at the 5% level for all scenarios except when the most recent 5 months are removed (the right endpoint in Figure 5).

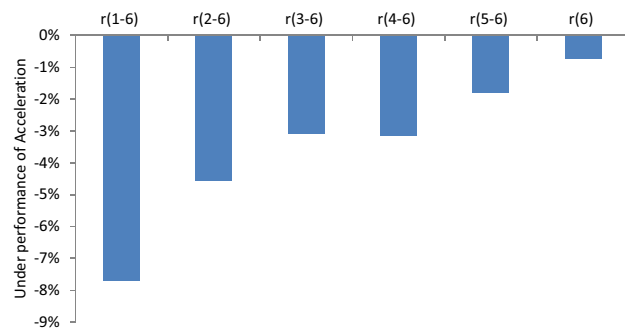


Figure 5 Incremental damage to performance by acceleration of more recent months' returns.*

*The acceleration is measured by the step-function weighting scheme. The average monthly return for the second six-month $r(7-12)$ is subtracted from all bars. For example, the first bar, $r(1-6)$, means $r_{1-6} - r_{7-12}$. The underperformances of acceleration are annualized.

In short, both Table 1 and Figure 5 show that accelerated returns have poor future performance, and it indicates that acceleration is not sustainable.

7 Accelerated returns increase the likelihood of reversals

We test our hypothesis that accelerated stock price increases lead to a higher probability of big reversals using regressions in this section. The step-function weighting scheme is used to measure the acceleration of returns.⁷ We employ three stock risk metrics for big reversals or crashes: skewness (SKEW), excess conditional value-at-risk (ECVaR), and maximum drawdown (MDD). SKEW is a measure of the asymmetry of the data around the sample mean. It is the third standardized moment. Negative skewness indicates the propensity to have large negative returns with greater probability. SKEW is measured on log daily market-adjusted returns similar to Chen *et al.* (2001). We follow them to interpret conditional skewness as a measure of reversal or big drop expectations.⁸

The second crash measure, ECVaR, measures specifically the left tail risk, and it is based on conditional value-at-risk (CVaR). It was introduced in the study by Xiong *et al.* (2014) to measure the tail risk of an equity fund. A different name for CVaR is the expected tail loss. ECVaR is defined as a stock's CVaR in excess of the implied CVaR with a normal distribution with the same mean and standard deviation in a given period. In other words, the stock's ECVaR is a normalized version of CVaR by controlling the volatility of the stock.⁹

The third measure, maximum drawdown (MDD), is defined as the cumulative loss from the peak to the trough over a given time period. Hence it quantifies the worst case scenario of an investor buying at a high and selling at a low. MDD is a popular downside risk measure. For example, Zhou and Zhu (2010) studied the 2008 financial crisis using drawdown probability. By definition, MDD will have negative value unless the price never declines in a given period, in which case MDD has a maximum value of zero. In our context, $MDD = -50\%$ is read as MDD has a value of -50% or the drawdown is 50%.

Table 4 shows the average contemporaneous correlation among the three crash variables that we studied in this paper: MDD, SKEW, and ECVaR.

Table 4 The average contemporaneous correlation among the four risk measures: standard deviation, maximum drawdown, skewness, and ECVaR from January 1960 to December 2011.*

	SD	MDD	SKEW	ECVaR
SD	1	-0.58	0.07	0.06
MDD		1	0.27	0.33
SKEW			1	0.75
ECVaR				1

*All variables are measured in a 6-month period using daily returns.

We add the standard risk measure, standard deviation (SD), for comparison purposes. All the four variables are computed over a 6-month period using daily returns. The correlation matrix of the four variables is measured from June 1960 to December 2011 for each stock, and then averaged over the cross-sectional NYSE/AMEX stock universe.

The correlation between SKEW and ECVaR is 75%, indicating that they capture much of the same tail information of the return distribution, even though they are constructed in very different ways. Both SKEW and ECVaR have a relatively low correlation with MDD, so it is informative to include MDD as an alternative crash measure. The correlation between the value of MDD and SD is high and negative 58%, indicating that volatility is higher when drawdown is more severe. Note that by definition, MDD is negative and SD is positive, therefore their high correlation to each other is negative.

Next we study the impact of accelerated price increase on big reversals or crashes with cross-sectional regressions for individual stocks. Dependent variables are the three crash measures over the next six months ($t+6$) for each stock i : $SKEW_{t+6}$, $ECVaR_{t+6}$, or MDD_{t+6} .¹⁰

Independent variables are $LAGGED_t$, ACC_t , SD_t , $LOGSIZE_t$, $DTURNOVER_t$, and $PAST12RET_t$. $LAGGED_t$ is the value of lagged dependent variable at the end of month (t).

ACC_t denotes accelerated price increase at the end of month (t), and it is defined as the average monthly return of the most recent 6 months minus the average monthly return of the second recent 6 months, i.e. $(r_{1-6} - r_{7-12})$, or the left bar in Figure 4. This is a more simplified form of acceleration pattern. As mentioned before, $(r_{1-6} - r_{7-12} > 0)$ indicates an accelerated price

increase, hence it examines the impact of accelerated price increase on stock crashes.

SD_t is the standard deviation of a stock's 12-month trailing daily returns; $LOGSIZE_t$ is the log of the stock's market capitalization at the end of month (t); and $DTURNOVER_t$ is the detrended average monthly share turnover over the last 6 months (turnover is defined as shares traded divided by shares outstanding over period t). We include the $DTURNOVER$ because it has been found to have predictive power of individual stock crashes by Chen *et al.* (2001). Finally, $PAST12RET_t$ is the average monthly return over the last 12 months and it captures the stock momentum and stock reversals.

Now we examine the influence of accelerated returns on individual stock crashes through a series of intertemporal cross-sectional regressions similar to the second step of the Fama-MacBeth (1973) approach.¹¹ The regression can be interpreted as an effort to forecast the probability of a stock crash over the next 6 months ($t + 6$) based on information available at the end of month (t).

In each non-overlapping 6-month period, starting from January 1963 to December 2011, we run a cross-sectional regression of stock crash measures in period ($t + 6$) on independent variables at the end of month (t). This gives us 96 non-overlapping semi-annual estimates of the slope coefficients along with the associated standard errors for each of the explanatory variables. We then aggregate these slope coefficient estimates across time. t -Statistics are in parentheses and adjusted for heteroskedasticity.

In Table 5, we test our main thesis to see if acceleration in returns contributes to both poor future performance and a higher likelihood of stock reversal. The regression results for RET confirm that acceleration contributes to poor future

Table 5 Accelerated price increases (ACC_t) forecast future returns (RET), and future SKEW, ECVaR, and MDD from January 1963 to December 2011.*

	Intercept	LAGGED _t	ACC _t	SD _t	LOGSIZE _t	DTURNOVER _t	PAST12RET _t
RET _{t+1} **	0.022 (11.96)	N/A N/A	-0.032 (-5.34)	-0.322 (-4.54)	-0.001 (-5.19)	-0.010 (-1.23)	0.074 (3.82)
SKEW _{t+6}	0.42 (8.26)	0.05 (10.59)	-0.44 (-5.69)	4.46 (4.33)	-0.05 (-9.92)	-0.26 (-2.09)	-2.23 (-16.94)
ECVaR _{t+6}	-0.002 (-5.41)	0.083 (16.73)	-0.006 (-8.59)	0.127 (11.98)	-0.00009 (-2.01)	-0.001 (-0.92)	-0.032 (-21.83)
MDD _{t+6}	-0.08 (-15.96)	0.25 (23.40)	-0.15 (-10.97)	-4.48 (-35.45)	0.002 (3.21)	0.05 (3.11)	-0.148 (-3.94)

*Acceleration is measured by the step-function weighting scheme. Coefficients are averaged over time using the Fama–MacBeth approach. Lagged variable is the lagged corresponding variable in the first column at the end of Month t . t -Statistics are in parentheses.

**The holding period is 1 month for RET, and 6 months for SKEW, ECVaR, and MDD.

performance, and the coefficient is significant at the 1% level. The coefficient, -0.032 , is interpreted as the future 1-month return and is reduced by 3.2 bps when the average monthly return over the most recent 6 months exceeds the average monthly return of the second recent 6 months by 1%. The significant coefficients for SD, LOGSIZE, and PAST12RET confirm the well-known low-volatility anomaly, small-cap premium, and momentum effect, respectively. The negative coefficient on DTURNOVER is not significant.

The regression results for the SKEW, ECVaR, and MDD variables in Table 5 show that both accelerated price increase and past 12-month return contribute to stock reversals for all of the three crash measures, and the coefficients are all significant at the 1% level.¹² For MDD, the coefficient of acceleration, -0.15 , is interpreted as the future 6-month maximum drawdown and is increased by 15 bps when the acceleration over the last 1 year is 1%. Therefore, accelerated price increase will increase the probability of a stock crash via a more negative SKEW, a more negative ECVaR, and a more severe MDD for the stock.

Lagged crash measures (i.e. past SKEW, ECVaR, or MDD in period t) have a significant positive coefficient for all three crash measures, indicating past crash-prone stocks tend to be crash-prone in the future. Other independent variables such as SD, LOGSIZE, and DTURNOVER have mixed coefficients for the three crash measures. The coefficient on LOGSIZE and DTURNOVER are negative for SKEW, suggesting that negative skewness is more likely in large-cap stocks and turnover-surged stocks over the past 6 months. These findings are largely consistent with Chen *et al.* (2001). However, DTURNOVER has a positive coefficient on MDD, suggesting that surged turnover fails to forecast a more severe drawdown. In contrast, acceleration in returns has a significant negative coefficient on all of the three crash variables with very robust t -statistics. Hence, accelerated returns appear to have a higher predictive ability in forecasting crashes than DTURNOVER, in particular when MDD is the crash measure.¹³

Overall, these cross-sectional regressions provide strong evidence that an accelerated price increase

Table 6 Accelerated market returns forecast aggregate market reversals from January 1953 to December 2012.*

	Intercept	LAGGED _t	ACC _t	SD _t	PAST12RET _t
SKEW _{t+6}	-0.02 (-0.21)	0.11 (2.15)	-2.99 (-2.65)	0.20 (0.02)	-12.32 (-3.57)
ECVaR _{t+6}	0.000 (-0.05)	0.235 (3.65)	-0.011 (-1.60)	-0.052 (-0.94)	-0.07 (-3.82)
MDD _{t+6}	-0.07 (-5.52)	0.04 (0.30)	0.29 (1.53)	-2.77 (-1.55)	0.63 (1.06)

*Acceleration is measured by the step-function weighting scheme.

will increase the probability of stock crashes, and thus poor future performance.

8 Forecasting aggregate market reversals

It is interesting to investigate the impact of an accelerated price increase on the aggregate market from an economic viewpoint. Our proxy for the aggregate market is the S&P 500 Index. The daily return data of the S&P 500 Index covers the 63-year period from January 1950 to December 2012.

We use the same independent variables as last section and perform similar regressions to Table 5, except that we exclude DTURNOVER and LOG-SIZE variables. DTURNOVER is not significant in forecasting conditional skewness for the aggregate market as shown in Chen *et al.* (2001). In order to add statistical power, we now use monthly overlapping observations. The *t*-statistics are adjusted for serial correlation and heteroskedasticity using Newey and West (1987). The regression results are shown in Table 6.

Table 6 shows that the acceleration has significant impact on the negative skewness of S&P 500 at the 1% level. The acceleration has significant impact on the negative ECVaR around the 10% level. As expected, the momentum has significant impact on both negative skewness and negative ECVaR at the 1% level. It is interesting

that the coefficient of acceleration for the market is much higher than the coefficient of acceleration for individual stocks, but the *t*-statistics is much lower.

For MDD, none of the independent variables are significant. The coefficient of acceleration is positive, which is inconsistent with the corresponding negative sign as shown in Table 5. It appears that the *t*-statistics are, on average, less significant in Table 6 for the aggregate market than that in Table 5 for cross-sectional individual stocks.¹⁴ This is not surprising since we have only one set of time-series data for the aggregate market, which limits statistical power, whereas we have cross-sectional data for the many individual stocks.

Overall, we found evidence to support our thesis that accelerated price increase raises the probability of reversals in the aggregate market, even though the significance is on average lower than that at the individual stock level.

9 Conclusions

We attempt to reconcile these two opposite phenomena: 1-month reversal and 2–12 month momentum. Our main thesis is that momentum generates acceleration perhaps via positive feedback, and accelerated price increase is not

sustainable, hence the reversal. Indeed, we show that accelerated price increase is a strong contributor to not only poor future performance but also a higher probability of big reversals.

Stocks that experienced the highest accelerated returns over the last 1 year underperformed other stocks significantly. The annualized return for a portfolio of the most accelerated quintile underperformed the least accelerated quintile by 13.74%. The underperformance is robust after controlling for other factors.

With cross-sectional regressions, we demonstrate that an accelerated price increase over the last 1 year is a strong contributing factor to individual stock drops. Similar regression results are obtained for the aggregate stock market, even though the significance is lower than for individual stocks.

Overall, the findings provide economically valuable information allowing an investor to better forecast individual or aggregate market reversals based on the past accelerated returns.

Acknowledgments

The authors thank David Brown, Lisa Goldberg, Thomas Idzorek, Daniel Y. Kim, Peter Bull, Michael Ng, Warren Miller, Alexa Auerbach, and the anonymous referees for their helpful comments.

Notes

- ¹ The same analyses are performed for NASDAQ-traded stocks from January 1983 to December 2011 for a robustness check. They are not reported for brevity. All of the conclusions remain largely unchanged for NASDAQ stocks.
- ² We also studied a truncated sample by removing the micro-cap stocks in the NYSE/AMEX universe—specifically, those with a market capitalization below the 20th percentile of the NYSE/AMEX universe.

We repeated all analyses, and found that none of results were materially changed.

- ³ We also tested equal-weighted portfolios, and the results are similar. We choose the holding period at 1 month to keep the number of scenarios manageable.
- ⁴ Note that the sample period was a rising market. Thus, all returns were positive on average over the sample period. We have to compare all the returns relative to each other.
- ⁵ Breaking the entire sample period into two sub-periods yields similar trends for both periods.
- ⁶ Amihud and Mendelson (1986) use the quoted bid–ask spread as a measure of liquidity and tested the relationship between stock returns and liquidity during the period of 1961–1980. They found evidence consistent with the notion of a liquidity premium. Datar *et al.* (1998) use the turnover rate (number of shares traded as a fraction of the number of shares outstanding) as a proxy for liquidity and find that stock returns are strongly negatively related to their turnover rates, confirming the notion that less liquid stocks provide higher average returns.
- ⁷ The exponential weighting scheme yields more significant results for the impact of acceleration. However, it is easier to interpret the regression results by using the step-function weighting scheme.
- ⁸ Note that Chen *et al.* (2001) put a minus sign in front of skewness, so our SKEW is the negative value of their NCSKEW.
- ⁹ The ECVaR is measured on a 6-month period and the left tail has about seven data points when the confidence level is 95% ($0.05 * 125 = 7$). One might have concerns about estimation errors for ECVaR due to the small number of data points. We repeated the analysis using the confidence level of 90% for ECVaR and found no impact on the acceleration coefficient.
- ¹⁰ Both SKEW and ECVaR measure tail risk and they require enough data points. Hence, we choose a 6-month period for testing crash probability.
- ¹¹ The Fama–MacBeth (1973) approach is typically used to test time stability of the coefficients. We also ran one regression by pooling all the cross-sectional data over time, and the results are similar.
- ¹² We also added the book-to-market ratio to the regression shown in Table 3. The coefficient for the book-to-market ratio is significantly positive at the 5% level for all three crash measures, indicating that more glamorous stocks tend to be more prone to crash. The addition of book-to-market ratio has no impact on the acceleration coefficient.

- ¹³ We also ran regressions for the first difference of the three dependent variables (e.g. $SKEW_{t+6} - SKEW_t$) against the same independent variables except the lagged variable (e.g. $SKEW_t$), and the significance for the acceleration coefficient remained unchanged.
- ¹⁴ We ran the regression for the lead market return (RET_{t+1} , not reported) as we did in the first row of Table 5, and found that none of the coefficients are significant.

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Keywords: Momentum; acceleration; reversal; forecasting skewness