Momentum, Acceleration, and Reversal

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Abstract

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 one-month reversal.

Momentum, Acceleration, and 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 one-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 to 12 months. More recently, Heston and Sadka (2008) documented 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 to 12 month returns prior to portfolio formation, and recent six-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 six months, and over-reaction in a short horizon, such as one 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.

Little research has been performed on stock crashes at the individual stock level on a cross-sectional basis. In a seminal work, Chen, Hong, and Stein (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 six 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.

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 adjusted for free-float) are collected from the University of Chicago Center for Research Data Services (CRSP). We include stocks with a price greater than $2.[2] We exclude derivative securities like ADRs of foreign stocks.

## Example of Accelerated Price Increases

Accelerated price increases simply means that the return is increasing over time, and thus the price increases at an increasing rate. 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

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[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.

(triangles, from May 2011 to August 2011) after accelerated price

increase over the two periods.

Figure 1. An Illustration of Accelerated Price Increase that
Results in a Reversal
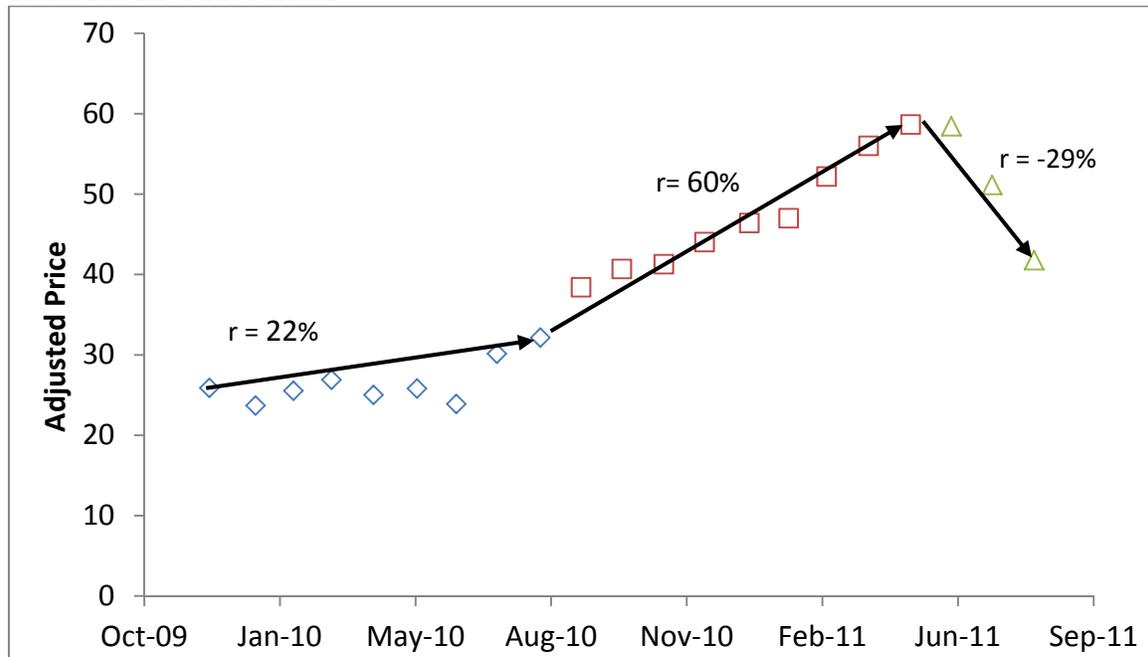
Term Structure of Past One-Month Return

    Figure 2 shows strategies based on quintile portfolios (Q1 to Q5)

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 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 one month.[3] *All portfolio returns*

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[3] We also tested equal-weighted portfolios, and the results are similar. We choose the holding period at one
month to keep the number of scenarios manageable.

are in excess of T-Bills in this paper. Q5 (Q1) denotes the forward one-month performance of the previous ranked winner (loser) stocks of the five portfolios.

It is interesting to observe that the forward one-month performance of Q3 is somewhat flat, while Q5 (Q1) has a positive (negative) slope. In addition, Q1 and Q5 are almost symmetric. A positive slope for Q5 indicates winning stocks keep winning *more* from lag-2 to lag-12, hence a positive acceleration in returns. The unsustainable acceleration can explain the one-month reversal at lag-1. In an opposite way the negative slope for Q1 corresponds to a negative acceleration in returns[4].

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[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.

Figure 2. Forward One-Month Quintile Portfolios' Performance across the Term Structure of 1-12 Month Lags. Q5 (Q1) is a portfolio of the previous Winner (Loser) stocks.
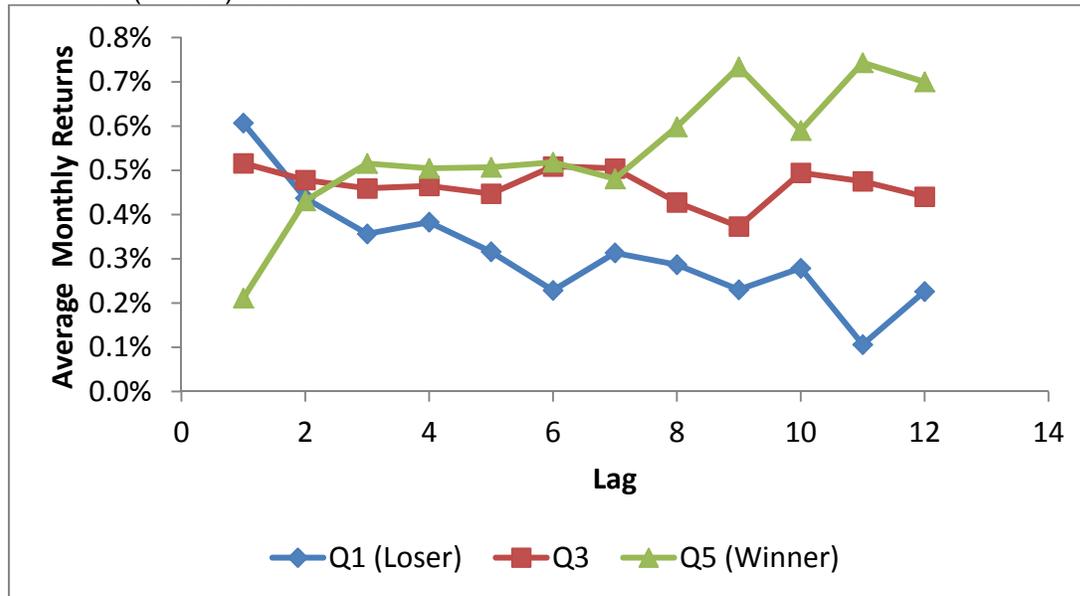
We then calculate the long/short profit by subtracting Q1 from Q5 for each lagged month. Figure 3 plots the results, and the general trend is upward sloping for (Q5-Q1, empty squares). Using the average of two winning or losing quintiles, avg(Q1,Q2) or avg(Q4,Q5), the trend is smoother (solid diamonds in Figure 3). The negative return in lag-1 is consistent with the well-documented one-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 one-month term structure of momentum by Novy-Marx (2012).

Figure 3. Forward One-Month Performance
for the Long Q5 (Winner)/Short Q1 (Loser) Portfolio
across the Term Structure of 1-12 Month Lags.
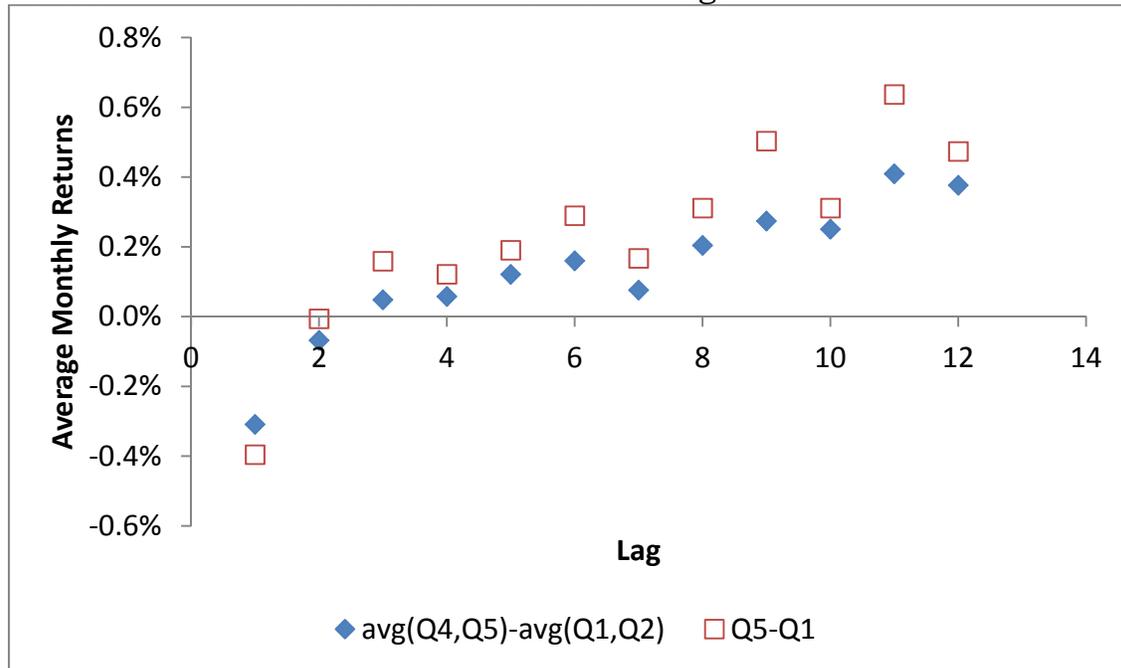
Figures 2 and 3 clearly suggest that the one-month reversal and the 2-12 month momentum are two ends of the spectrum. The general trend in both figures indicates that positive acceleration leads to reversals or negative acceleration leads to rebound.[5] In other words, unsustainable acceleration leading to reversal can reconcile the one-month reversal and 2-12 month momentum. The key is that it implies that acceleration is not sustainable.

Accelerated Stock Price Increases Lead to Poor Returns

We test our hypothesis that accelerated stock price increase is a strong contributor to poor future performance in this section. The

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[5] Breaking the entire sample period into two sub-periods yields similar trends for both periods.

rationale is that accelerated growth is not sustainable. We form portfolios by sorting stocks into quintiles based on their accelerated returns over the last one year. There are a number of ways to construct the accelerated pattern. 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.

For example, we can simply use Figure 3 as our weighting scheme but with a negative sign so that the lag-1 month has a positive weight and lag-12 month has a negative weight. The results are shown in the bottom panel of Table 1. We test a different weighting scheme in the next section.

Table 1. The Forward One-Month Performance for One-Month Reversal, 2-12 Month Momentum, and Acceleration from January 1963 to December 2011*

One-Month Reversal	Q1 (One-Month Loser)	Q2	Q3	Q4	Q5 (One-Month Winner)		Q1-Q5
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)	Q1 (Low Momentum)	Q2	Q3	Q4	Q5 (High Momentum)		Q5-Q1
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	Q1 (Least Accelerated)	Q2	Q3	Q4	Q5(Most Accelerated)		Q1-Q5
Ari. Mean	13.03%	7.84%	6.21%	2.70%	-1.26%		14.29%
Geo. Mean	10.82%	6.45%	5.05%	1.45%	-3.00%		13.82%
Std. Dev.	19.89%	16.11%	14.79%	15.62%	18.71%		1.18%

*All numbers are annualized and in excess of T-Bills.

The top panel of Table 1 shows the one-month reversal effect. The one-month loser outperforms the one-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 Q1" to "Most Accelerated Q5," the annualized arithmetic return is 14.29% higher, and the annualized geometric mean is 13.82% higher. The return spread between Q1 and Q5 is the largest for the acceleration panel in Table 1. Note that the most accelerated quintile portfolio (Q5) has a

negative 3% 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 Q1 portfolio most likely has experienced a large price correction in the past one year. Hence Q1 may have earned a downside or tail risk premium (See Xiong, Idzorek and Ibbotson, 2014) perhaps because of panic selling. This downside risk premium can partly explain the outperformance of Q1.

In contrast, the Q5 portfolio, by construction, has experienced the most impressive accelerated price increase over the last one 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 Q5.

More Testing on Acceleration

We construct a few different acceleration schemes in this section. We first break the last 12-month period into two six-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 six months (lags 1-6). The average monthly return r_{7-12} is over the second recent six 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 six-month returns

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

Figure 4 shows that the impact of acceleration on future performance exists for all the most recent six months, and the drag becomes more significant for the most recent one month. The performance drag is significant at the 5% level for all scenarios except when the most recent five months are removed (the right endpoint in Figure 4).

Figure 4. Incremental Damage to Performance by Acceleration of More Recent Months' Returns*
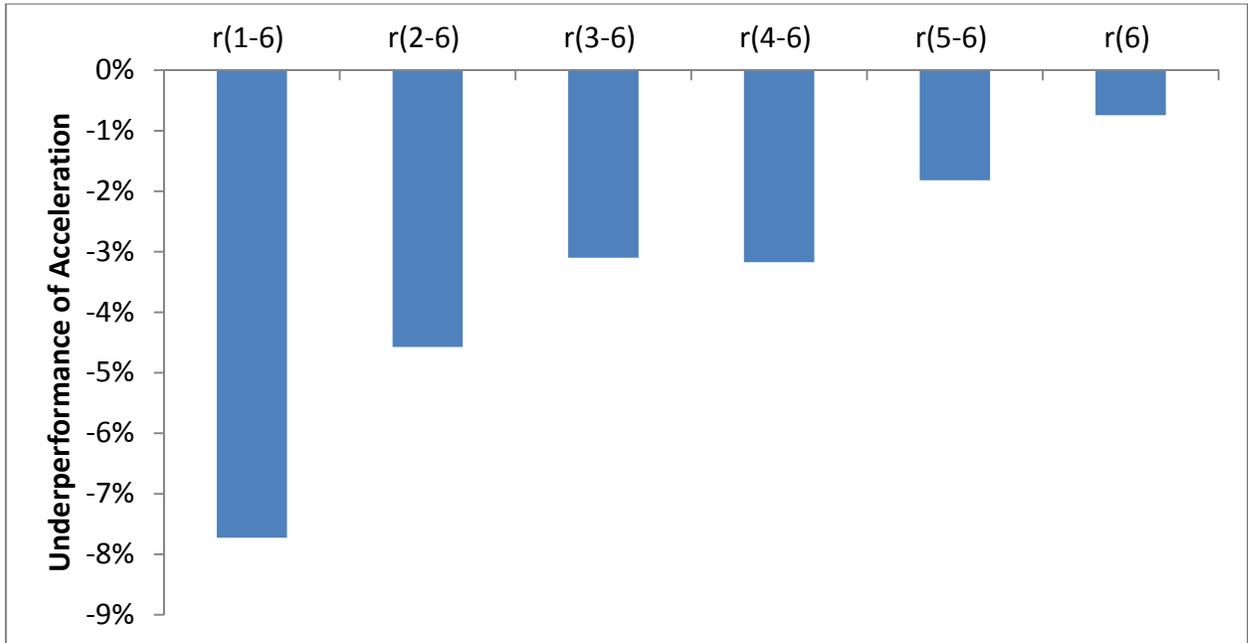
*The average monthly return for the second six-month r(7-12) is subtratced from all bars. For example,the first bar, r(1-6), means $r_{1-6} - r_{7-12}$. The underperfromances of acceleration are annualized.

In short, both Table 1 and Figure 4 show that accelerated returns have poor future performance, and it indicates that acceleration is not sustainable.

Accelerated Returns Increase the Likelihood of Reversals

We test our hypothesis that accelerated stock price increases lead to a higher probability of big reversals in this section. 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, Hong and Stein (2001). We follow them to interpret conditional skewness as a measure of reversal or big drop expectations.[6]

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 Xiong, Idzorek, and Ibbotson (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 for the volatility of the stock.[7]

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[6] Note that Chen, Hong and Stein (2001) put a minus sign in front of skewness, so our SKEW is the negative value of their NCSKEW.

[7] The ECVaR is measured on a six-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.

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 2 shows the average contemporaneous correlation among the three crash variables that we studied in this paper: MDD, SKEW, and ECVaR. We add the standard risk measure, standard deviation (SD), for comparison purposes. All the four variables are computed over a six-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.

Table 2. The Average Contemporaneous Correlation among the four risk
measures: Standard Deviation, Maximum Drawdown, Skewness, and
ECVaR from January 1960 to Dec. 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 six-month period using daily returns.

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}. [8]

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 six

months minus the average monthly return of the second recent six

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)

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[8] Both SKEW and ECVaR measure tail risk and they require enough data points. Hence, we choose a six-month period for testing crash probability.

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 stock's market capitalization at the end of month (t); and $DTURNOVER_t$ is the detrended average monthly share turnover over the last six 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, Hong and Stein (2001). $PAST12RET_t$ denotes the average monthly return over the last 12 months, and it captures the stock momentum and stock reversals documented in Chen, Hong and Stein (2001).

Now we examine the influence of accelerated returns on the cross-section of stock crashes through the standard Fama-MacBeth (1973) regressions. The regression can be interpreted as an effort to forecast the probability of a stock crash over the next six months (t+6) based on information available at the end of month (t).

In each non-overlapping six-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 3, 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 performance, and the coefficient is significant at the 1% level. The coefficient, -0.032, is interpreted as the future one-month return and is reduced by 3.2 bps when the average monthly return over the most recent six months exceeds the average monthly return of the second recent six 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.

Table 3. Accelerated Price Increases Forecast Poor Performance and Stock Reversals from January 1963 to December 2011*

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

*Lagged variable is the lagged corresponding variable in the first column at the end of Month t.
**The holding period is one month for RET, and six months for SKEW, ECVaR, and MDD.

The regression results for the SKEW, ECVaR, and MDD variables in Table 3 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.[9] For MDD, the coefficient of acceleration, -0.15, is interpreted as the future six-month maximum drawdown and is increased by 15 bps when the acceleration over the last one 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.

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[9] 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.

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 six months. These findings are largely consistent with Chen, Hong, and Stein (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-stats. Hence, accelerated returns appear to have a higher predictive ability in forecasting crashes than DTURNOVER, in particular, when MDD is the crash measure.

Overall, these cross-sectional regressions provide strong evidence that an accelerated price increase will increase the probability of stock crashes, and thus poor future performance.

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 3, except that we exclude DTURNOVER and LOGSIZE variables. DTURNOVER is not significant in forecasting conditional skewness for the aggregate market as shown in Chen, Hong, and Stein (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 4.

Table 4. 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	0.11	-2.99	0.20	-12.32
	(-0.21)	(2.15)	(-2.65)	(0.02)	(-3.57)
ECVaR$_{t+6}$	0.000	0.235	-0.011	-0.052	-0.07
	(-0.05)	(3.65)	(-1.60)	(-0.94)	(-3.82)
MDD$_{t+6}$	-0.07	0.04	0.29	-2.77	0.63
	(-5.52)	(0.30)	(1.53)	(-1.55)	(1.06)

Table 4 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-stat is much lower.

For MDD, none of the independent variables is significant. The coefficient of acceleration is positive, which is inconsistent with the corresponding negative sign shown in Table 3. It appears that the t-stats are, on average, less significant in Table 4 for the aggregate market than that in Table 3 for cross-sectional individual stocks. 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.

Conclusions

We attempt to reconcile these two opposite phenomena: one-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 one year underperformed other stocks significantly. The annualized return for a portfolio of the most accelerated quintile underperformed the least accelerated quintile by more than 14%.

With cross-sectional regressions, we demonstrate that an accelerated price increase over the last one 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.

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