Forecasting Market Bubbles and Crashes

Extreme stock downturns are preceded by a sustained period of accelerating growth rates.
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This article originally appeared in the August/September 2013 issue of MorningstarAdvisor magazine. To subscribe, please call 1-800-384-4000.

This article is an abbreviated version of a research paper undergoing peer review for journal publication.

Market crashes have profound consequences on societal wealth and portfolio management. Notorious examples include the Dutch tulip mania in 1637, the South Sea bubble in England in 1720, the Great Depression in 1929, and the Internet bubble that peaked in early 2000. One characteristic associated with those crashes was tremendous growth coupled with investors' euphoria before the market crash. In these and many other similar cases, asset prices rose at an increasing rate, resulting in unsustainable growth and an eventual market crash.

Bubbles and crashes are often associated with each other. An asset bubble is often defined as an asset's price that exceeds its fundamental value for an extended period of time. This definition is subject to criticism because it is difficult to identify a bubble before it pops and even more difficult to predict when a bubble will burst.

Standard neoclassical theory and the efficient market hypothesis imply the absence of bubbles, because the large number of well-informed arbitrageurs guarantees that any mispricing caused by investors' behavior will be corrected. Blanchard and Watson (1983), however, argue that bubbles are consistent with rationality, and runaway asset prices and market crashes are consistent with rational bubbles. Abreu and Brunnermeier (2003) demonstrate that bubbles can exist for a substantial period as rational arbitrageurs understand that the market will eventually crash but will ride the bubble for a time to generate high returns.

There is little research, however, on stock crashes at the individual stock level. Chen, Hong, and Stein (2001) use skewness as a measure for stock crashes and show that three robust findings about conditional skewness emerged from their analysis of individual stocks. They found that, in the cross-section, negative skewness is greater in stocks that have experienced an increase in trading volume relative to the trend over the prior six months, have had positive returns over the prior 36 months, and are larger in terms of market capitalization. Their second finding shows the impact of past returns or growth rates on stock crashes. In the context of a bubble model, high past returns over the prior 36 months imply that the bubble has been building up for a long time, so there is a large correction or burst when prices fall back to fundamentals.

In this article, we extend Chen, Hong, and Stein and focus on a more powerful growth path of returns over the past two or three years: accelerated rate of price growth. We show that accelerated price growth is a strong contributor to stock crashes. This is meaningful because investors can better forecast crashes based on past accelerated growth rates.

A natural question to ask is how accelerated price growth can occur. One possibility is the well-known positive feedback process. For example, investors invest (or withdraw) money today, which causes more investors to invest (withdraw) money tomorrow. The positive feedback process is closely related to herd behavior. A number of studies have considered herd behavior as a possible explanation for the excessive volatility observed in financial markets. Shiller (2005) provides massive evidence to support his argument that irrational exuberance played a significant role in producing the ups and downs of the stock and real estate markets. He listed 12 precipitating factors that gave rise to the booms in the stock and housing markets. These factors are amplified through feedback loops and naturally occurring Ponzi schemes, aided by the news media, and can ultimately lead to market crashes.

The Law of Exponential Growth

The law of exponential growth for an asset price can be written as:

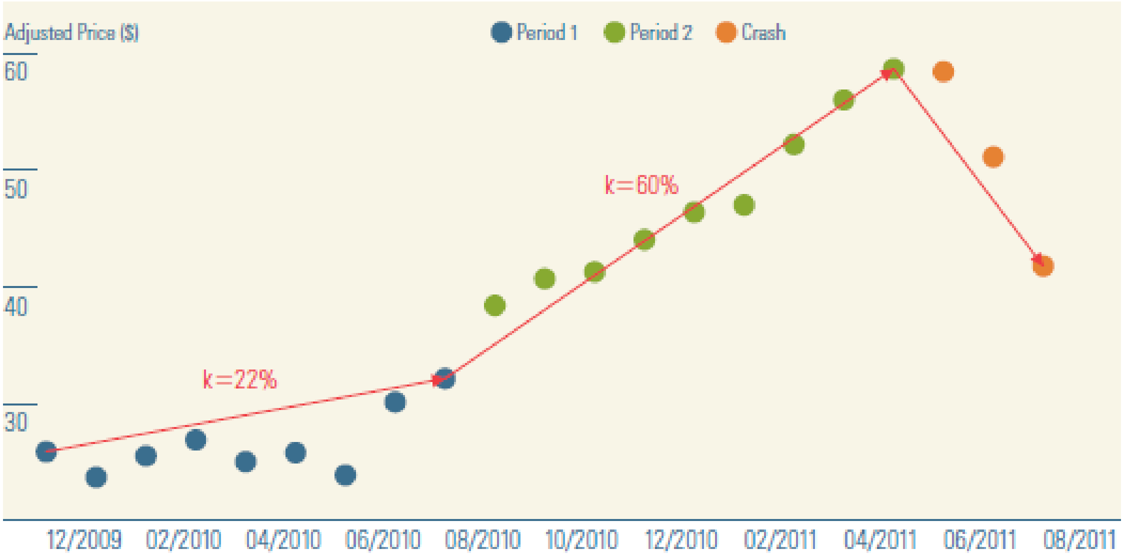
$$p_t=p_0e^{k\cdot t}$$

Where p_t is the stock price at time t. k is the exponential growth rate, also called the logarithmic return, or continuously compounded return. k is usually greater than the risk-free rate for stocks, and it may be viewed as emerging from a series of unusual positive shocks that gradually make investors more and more optimistic about future growth. Abreu and Brunnermeier (2003) assume that bubbles grow at a constant exponential rate in their model. In this article, we are more interested in the impact of accelerated price growth. Its definition is that the growth rate k is increasing over time, and thus the price increases at an increasing rate.

It is easy to see that the impact of accelerated growth on a bubble is much more powerful than that of constant exponential growth. For accelerated growth, a bubble grows at an increasing rate, and it should have a higher probability of bursting than a bubble experiencing a constant exponential growth rate.

Exhibit 1 shows a growth rate that is accelerating for Informatica Corp. INFA, a Nasdaq-traded stock. The growth rate is about 22% in the first period (from December 2009 to August 2010) and accelerates to 60% in the second period (from August 2010 to May 2011). The stock price plummeted about 30% from the peak (from May 2011 to August 2011) after faster-than-exponential growth over the two periods.

Exhibit 1 Rise and Fall of Informatica Corp.: A Stock's Accelerated Price Growth and Crash



Stock Crash Measures

The data set in our study consists of all the stocks that meet our criteria on the New York Stock Exchange and the American Stock Exchange from January 1960 through December 2011. Daily returns, daily exchange-based trading volumes, daily number of shares outstanding, and monthly book-to-market ratios are collected from Morningstar's equity database.

We employ three stock-crash metrics: skewness, excess conditional value at risk (ECVaR), and maximum drawdown. Skewness is a measure of the asymmetry of the data around the sample mean. Negative skewness indicates that there is a greater probability to have large negative returns. In other words, skewness is a measure of crash expectations. ECVaR specifically measures the left tail risk, and it is based on conditional value-at-risk, or the expected tail loss. A stock's ECVaR is a normalized version of conditional value-at-risk by controlling for the volatility of the stock. Maximum drawdown is the cumulative loss from the peak to the trough over a given time period. It quantifies the worst-case scenario of an investor buying high and selling low. Maximum drawdown is a popular downside risk measure. By definition, it will have a negative value unless the price never declines, in which case it has a maximum value of zero.

Exhibit 2 shows the average correlation among the five variables that we studied in this paper: growth rate (k), standard deviation, maximum drawdown, skewness, and ECVaR. All five variables are computed over a six-month period using daily returns. The correlation matrix of the five variables is measured for each stock, and then averaged over our stock universe from June 1960 to December 2011.

The growth rate and maximum drawdown are correlated at a positive coefficient of 72% because a negative growth rate usually accompanies a more negative maximum drawdown in a given period. The correlation between skewness and ECVaR is 78%, indicating that they capture much of the same tail information of the return distribution even though they are constructed in very different ways. Both skewness and ECVaR have a relatively low correlation with maximum drawdown, so it is informative to include maximum drawdown as an alternative crash measure. The correlation between the value of maximum drawdown and standard deviation is negative 60% mainly because of asymmetric volatility (volatility is higher when drawdown is more severe).

Impact of Fast Growth on Performance

Our cross-sectional regression results provide strong evidence that faster-than-exponential growth rates can lead to stock crashes. Here, we investigate the impact of accelerated growth on portfolio performance. We form portfolios by sorting stocks into quintiles based on their changing growth rates over the past two six-month periods (($k_t - k_{t-1}$). Our thesis suggests that the portfolio of stocks that have experienced higher increased growth rates will suffer a higher probability of a crash.

While a single sorting on ($k_t - k_{t-1}$) will provide useful information, the performance will be coupled with other factors, such as stock volatility. We are more interested in performance evaluation by controlling the volatility. In other words, we perform double sorting, with first sorting on volatility and then on ($k_t - k_{t-1}$).

Using 12 months of returns, we compute the increased growth rate or change in growth rate from the first six-month period to the second six-month period ($k_t - k_{t-1}$). To control for the effect of volatility, we sort stocks into starting quintiles based on the trailing, rolling 36-month volatility. Then, within each volatility-based quintile, we sort the stocks into five equally weighted composites (Q1, Q2, etc.) based on ($k_t - k_{t-1}$). Thus, we have 25 composites (five Q1 composites, five Q2 composites, etc).

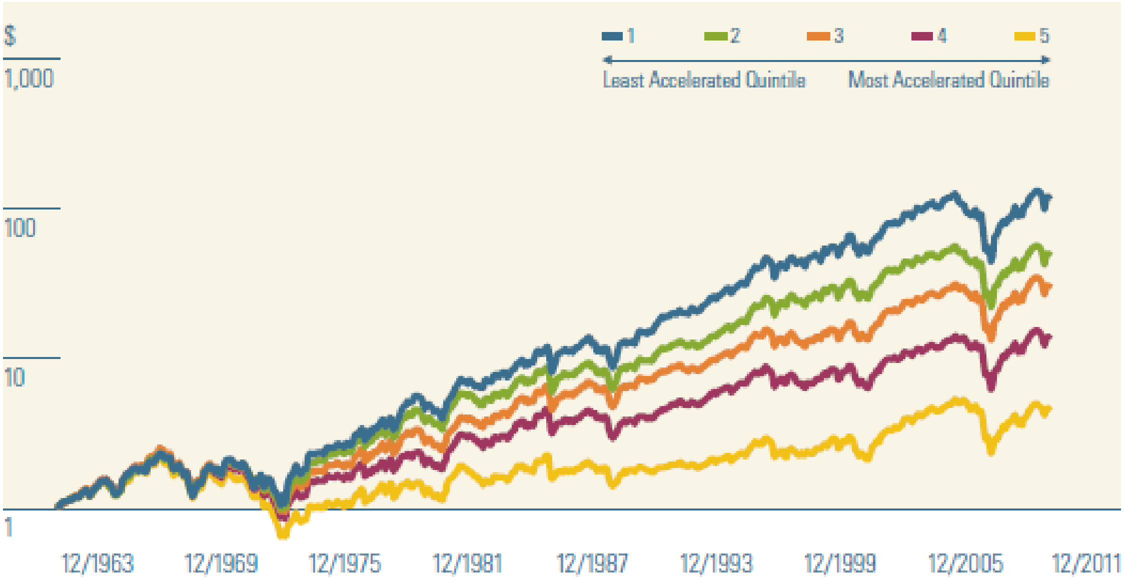
The past 12 months of growth rate changes ($k_t - k_{t-1}$) were used to form the 25 composites, and all of the composites were held for one month—the 13th month. At the end of the 13th month, we re-form the 25 composites using the same double-sorting algorithm on a monthly rolling basis. The 25 composites are rebalanced monthly from January 1964 to December 2011. The excess returns (over the T-bill) for each one of the 25 composites are averaged with equal weights. Finally, the five Q1 composites are averaged to derive the Q1 portfolio with equal weights, and the same procedure is repeated for the five Q2 through Q5 composites.

Comparing the least-accelerated quintile (Q1) to the most-accelerated (Q5), we find that the annual geometric return was 7.21 percentage points higher (10.4% versus 3.19%), the standard deviation was 3.43% higher (20.54% versus 17.11%), and the Sharpe ratio was more than twice as high (0.62 versus 0.28). By construction, the Q1 portfolio most likely experienced a negative growth rate or a large price correction in the past six-month period (t). Q1 may carry a downside risk premium, which tends to be realized in the next period (t+1). This can partly explain the outperformance of Q1, and it is also consistent with a contrarian strategy. On the other hand, the higher volatility for the Q1 portfolio is consistent with asymmetric volatility; stocks tend to be more volatile in negative-return periods.

Exhibit 2 Average Correlation Between Crash Metrics

	Growth	Standard Rate	Maximum Deviation	Skewness Drawdown	ECVaR
Growth Rate	1.00	–0.13	0.72	0.33	0.42
Standard Deviation		1.00	–0.60	0.11	0.01
Maximum Drawdown			1.00	0.22	0.34
Skewness				1.00	0.78
ECVaR					1.00

Exhibit 3 Performance of Five Accelerated-Growth Quintiles of Stocks



In contrast, the Q5 portfolio, by construction, experienced impressive faster-than-exponential growth over the last year. It is not surprising to observe its underperformance in the subsequent period because (k_t−k_{t-1}) has predictive power in identifying stock crashes.

Exhibit 3 shows the growth of value for the five quintiles. Q1 and Q5 have ending values of $115.5 and $4.5, respectively, over the 48-year period. The most accelerated quintile (Q5) significantly underperformed the least accelerated quintile (Q1) by a factor of 25.

As an important element in performance evaluation, we are interested in measuring the alphas of the five portfolios on a risk-adjusted basis. The alphas of the portfolios are measured against the Carhart (1997) four-factor model, the three Fama-French factors (Fama and French, 1993), plus momentum (Jegadeesh and Titman, 1993)1. The annualized alpha for the Q1 portfolio is quite large and statistically significant at 5.19%. In sharp contrast, the alpha for the Q5 portfolio is a significantly negative 3.28%.

The skewness, ECVaR, and maximum drawdown are measured on the monthly return series over the entire period from January 1964 to December 2011 for the five portfolios. Skewness for Q1 and Q5 are 0.17 and negative 0.81, respectively. ECVaR for Q1 and Q5 are negative 1.25% and negative 2.22%, respectively. Maximum drawdown for Q1 and Q5 are negative 64.83% and negative 71.15%, respectively. All of these results are expected from previous cross-sectional regression results. They confirm that ($k_t - k_{t-1}$) has predictive power in identifying future stock crashes. For both skewness and ECVaR, the values decrease monotonically across the five portfolios. For maximum drawdown, the value is nearly monotonic except for Q1. One of the reasons for this is that the maximum drawdown measure is not adjusted for volatility. Because Q1 has the highest volatility among the five composites, it tends to have a more negative value of maximum drawdown, all else the same.

Forecasting Market Crashes

Stocks that experienced the highest accelerated growth rates over the past year underperformed other stocks significantly. The annual geometric return for the highest accelerated growth quintile was reduced by 7 percentage points, and the Sharpe ratio was cut in half compared to the lowest growth quintile.

Using these findings, investors have the ability to better forecast market crashes based on past accelerated growth rates.

1 The three Fama-French factors and momentum factor are used and downloaded from the Kenneth R. French Data Library.

References

Abreu, D. and M. Brunnermeier, 2003, "Bubbles and Crashes," Econometrica.

Blanchard, O.J. and Watson, M.W., 1982, "Bubbles, Rational Expectations, and Financial Markets." Crises in Economic and Financial Structure, Wachtel, P. (Ed.), Lexington Books, pp. 295–315.

Carhart, M.M., 1997, "On Persistence in Mutual Fund Performance." Journal of Finance 52, 57–82.

Chen, J., Hong, H., and Stein, J. C., 2001, "Forecasting Crashes: Trading Volume, Past Returns and Conditional Skewness in Stock Returns," Journal of Financial Economics 61, 345–381.

Fama, Eugene F. and French, Kenneth R., 1993, "Common Risk Factors in the Returns on Stocks and Bonds," Journal of Financial Economics 33 (1): 3–56

Jegadeesh, N. and S. Titman, 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," Journal of Finance, 48, 65–91.

Shiller R.J. 2005. Irrational Exuberance (Second Edition), Princeton University Press.