Navigating Stock Price Crashes

B Korcan Ak

Steve Rossi, CFA

Richard Sloan

Scott Tracy, CFA

June 2015

Abstract

This paper analyzes procedures for forecasting and avoiding stock price crashes. First, we identify the underlying events that cause stock prices to crash. Second, we synthesize previous academic research on the prediction of stock price crashes and construct a parsimonious model for forecasting stock price crashes. Third, we examine how positioning a portfolio to reduce exposure to stocks with high crash risk improves investment performance. Our research should help investors to construct equity portfolios with fewer stock price crashes, higher returns and lower volatility.

B Korcan Ak is a PhD Candidate at the University of California, Berkeley. Steve Rossi, CFA, is an analyst with RS Investments. Richard Sloan is a professor of accounting at the University of California, Berkeley. Scott Tracy, CFA, is a portfolio manager with RS Investments. We are grateful to RS investments for research support and to Pete Comerford and Jason Ribando and Matt Scanlon for helpful support, comments and suggestions. Thanks also to Ryan Davis for research assistance.

Stock price crashes are dreaded events for active investors. A single stock price crash can erase an otherwise strong quarter of investment performance. Moreover, an active investor with a large position in a stock that suffers a well-publicized crash can suffer a loss of reputational capital. Unfortunately, however, stock prices are quite prone to such crashes. It has long been established that the distribution of stock returns is leptokurtic, meaning that extreme outcomes are more common than for a normal distribution (see Fama, 1965). To put some numbers on this phenomenon, over 10% of stocks have at least one daily return lower than -20% during a typical year.

Despite the significance of stock price crashes, there is little practical guidance to aid investors in avoiding crashes. In this paper, we identify (i) the causes of stock price crashes; (ii) information that can help investors to anticipate and avoid stock price crashes and (iii) the gains to investment performance that result from positioning an investment portfolio to avoid stock price crashes.

We begin by defining and measuring stock prices crashes from the perspective of an investment practitioner. Existing academic research defines stock price crashes relative to the *ex post* distribution of stock returns. But since the events causing stock price crashes often change other characteristics of the distribution of stock returns, this approach misclassifies some crashes. Instead, we recommend that crashes be defined with respect to the *ex ante* distribution of stock returns. In other words, we define a stock price crash as a large and abrupt negative stock return relative to the distribution of returns leading up to the crash.

We next examine the events that cause stock prices to crash. While previous research has identified earnings announcements as one common cause of stock price crashes (see Skinner and Sloan, 2001), there is no systematic evidence. Our analysis confirms that earnings announcements are the most common cause of stock price crashes, accounting for around 70% of all crashes. Other common events precipitating stock price crashes include earnings preannouncements and the outcome of clinical trials (for healthcare stocks).

We then turn to the central topic of forecasting stock price crashes. Previous research has identified a number of characteristics that forecast stock price crashes, including abnormally high share turnover, low book-to-market ratio, high short interest, low accounting quality and high growth expectations. We distill this research to identify a parsimonious set of crash predictors.

Finally, we design a practical strategy for avoiding stock price crashes. The strategy not only reduces the incidence of future stock price crashes, but also generates higher future stock returns with lower risk.

Research Design

Our research design proceeds in two stages. In the first stage, we discuss the definition and measurement of stock price crashes. In the second stage, we describe the variables used to forecast crashes.

Defining and Measuring Stock Price Crashes. A stock price crash is an unusually large and abrupt drop in the price of a stock. Existing academic literature in this area uses two different measures of crashes. Beginning with Chen, Hong and Stein (2001), one line of literature measures realized stock price crashes in terms of the negative skewness in the distribution of daily stock returns, computed using the sample analog of the negative coefficient of skewness (*NCSKEW*):

$$NCSKEW_{i,t} = - \frac{n(n-1)^{\frac{3}{2}} \sum R_{i,t}^{3}}{(n-1)(n-2)(\sum R_{i,t}^{2})^{\frac{3}{2}}}$$

where $R_{i,t}$ denotes the sequence of demeaned daily stock returns to stock i during period t and n is the number of daily stock returns in the period. This measure indicates whether the left tail of the distribution of stock returns is either longer or fatter than the right tail of the distribution. Note that a negative sign is placed in front of the expressions, meaning that a larger positive value implies a larger stock price crash. The logic underlying the use of this measure is that a stock price crash will result in an extreme left-tail outcome. This measure, however, is subject to two limitations. First, a crash is defined as a large negative return (i.e., a long left tail), while negative skewness can also be caused by several less extreme negative returns (i.e., a fat left tail). Second, this measure eliminates stocks that are prone to both crashes <u>and</u> jumps (i.e., large and abrupt increases in stock returns).

The second approach to measuring stock price crashes, attributable to Hutton, Marcus and Tehranian (2009), defines a crash as a return falling more than 3.09 standard deviations below the mean (with 3.09 chosen to represent an expected frequency of 0.1% in the normal distribution). This measure addresses the two limitations described above. A limitation of this measure, however, is that it is binary in nature and does not utilize information concerning the relative magnitude of the crash. A final limitation of both of the above measures is that they can misclassify crashes that are accompanied by an increase in the standard deviation of stock returns. This is because each of these two measures identifies crashes relative to the distribution of returns in the same period. Unless the crash happens to occur on the last day of the measurement period, this means that the post-crash return distribution is used to identify crashes.

In order to address the limitations of the measures described above, we measure crashes using a modified version of the second measure that takes the negative ratio of the minimum daily return over the period to the sample standard deviation of returns for the previous period:

$$CRASH_{i,t} = \frac{-Min(R_{it})}{\sqrt{\sum R_{i,t-1}^2/(n-1)}}$$

where $R_{i,t}$ denotes the sequence of demeaned daily stock returns to stock i during period t and n is the number of daily stock returns in the period. We also use two additional crash measures to corroborate our results. First, we use *NCSKEW*, as defined above. Second, we use the negative of the minimum daily return for the period (MINRET). This second measure is chosen for simplicity and ease of interpretation. Note that each of the measures is constructed so that a larger positive value indicates a bigger stock price crash. Following Chen, Hong and Stein (2001), we measure stock price crashes over 6 month periods using daily market adjusted stock returns (see section 3 for details).

Forecasting Stock Price Crashes. Stock price crashes are typically caused by the arrival of unexpectedly bad news. Prior research has identified a number of variables that are robust predictors of stock price crashes. First, Chen, Hong and Stein (2001) find that abnormally high stock price volume predicts crashes. The intuition underlying this prediction is that some investors are aware of the pending bad news, resulting in elevated trading between these investors and other uninformed investors. Second, Chen et al. (2001) find that 'glamour' stocks with high past stock returns and low book-to-market ratios are more likely to experience stock price crashes. Third, Chen at al. (2001) find that stocks with higher analyst coverage are more likely to experience stock price crashes. They hypothesize that this results arises because analysts facilitate the timely disclosure of bad news. Fourth, Hutton et al. (2009) predict and find that accounting opacity, measured by the volatility of accounting accruals, is related to stock price crashes. The theory underlying this prediction is that managers use accruals to temporarily mask bad news. Fifth, Callen and Fang (2013) predict and find that high short interest is related to stock price crashes. The theory underlying this prediction is that short sellers are sophisticated investors who anticipate bad news that is not yet fully reflected in stock prices.

Prior research also indicates that crashes are more likely for stocks with high growth expectations. Bradshaw, Hutton, Marcus and Tehranian (2011) find that stocks with long streaks of past sales growth are more likely to crash. Relatedly, Ak (2015) finds that stocks with high past sales growth are more likely to have large negative cumulative stock returns over the next year. We introduce two new variables in an effort to better measure high growth expectations. Each of our variables uses sell-side analysts' forecasts to identify situations where investors may have optimistic expectations about future earnings. The first variable measures analysts' forecasts of sales growth between the current fiscal year and the next fiscal year. The second variable measures analysts' forecasts of the change in the net margin between the current fiscal year and the next fiscal year. In each case, we predict that higher values of the variable are associated with optimism about future earnings and hence positively related to future stock price crashes.

Data and Variable Measurement. Unless otherwise specified, we obtain the data used in our tests via Factset.[1] Data availability restricts our sample to the period from July 2001 to July 2014. To ensure that our sample includes investable firms, we restrict the sample to firms belonging to the S&P United States BMI with a market capitalization of at least $100 million at the beginning of the period. Following Chen et al., we compute each of our crash measures using daily with dividend stock returns for consecutive six month periods starting on January 1 and July 1 of each calendar year. We adjust each of the daily stock returns for

[1] We also replicated our results using data from CRSP, Compustat and IBES. The results are qualitatively similar to those reported in the paper.

the corresponding with dividend stock return on the Russell 3000 Index so as to focus on firm-specific stock price crashes.

Following Chen et al. (2001), abnormally high trading volume (*DTURNOVER*) is measured as the detrended turnover for the prior six month period. Turnover is measured as the average monthly share turnover, defined as shares traded for the month divided by average shares outstanding for the month. The detrending is done by subtracting the average value of turnover from the 18 months beforehand. Past stock return (*PAST_RET*) is measured as the market-adjusted stock return over the previous six month period. The book-to-market ratio (*BTM*) is measured as the book value per share from the most recent quarterly financial statements divided by the stock price. Analyst coverage (*COVER*) is measured as the number of analysts providing an annual earnings estimate on the stock. We measure accounting opacity (*OPACITY*) using a variant of the accrual volatility measure in Hutton et al. (2009). We measure accruals as the annual change in net operating assets deflated by beginning of year total assets, where net operating assets are defined as non-cash assets less non-debt liabilities. *OPACITY* is then measured as the sum of the absolute value of accruals over the last three consecutive annual reporting periods. Short interest (*SHORT*) is measured as the ratio of the number of shares sold short to the float (number of shares outstanding less closely held shares). We measure forecast sales growth (*SGROW*) as ratio of mean consensus forecast of sales for the next fiscal year to the mean consensus forecast of sales for the current fiscal year minus one. Finally, we measure the forecast change in margin (*NMGROW*) as the difference between the mean consensus forecast of the net margin for the next fiscal year less the mean consensus forecast of the net margin for the current fiscal year, where the net margin is defined as the ratio of net income to sales.

We also include a number of control variables in our empirical analysis. These include the lagged value of the crash measure (*PAST_CRASH*), firm size (*SIZE*), the sample standard deviation of stock returns over the past 6 months (*SIGMA*), and leverage (*LEV*). *SIZE* is measured as the natural logarithm of market capitalization (in $millions) and *LEV* is measured as the ratio of the total liabilities to total assets from the most recently quarterly financial statements. To mitigate the effect of outliers, we winsorize the one-percent tails of each variable.

Results

We present our results in three parts. First, we provide descriptive evidence on our crash measures, including our analysis of the events causing stock price crashes. Second, we present the results for our crash risk forecasting model. Third, we examine the relative investment performance of investment strategies designed to mitigate crash risk.

Describing Stock Price Crashes. We begin with descriptive statistics on each of our three measures of stock price crashes. Recall that each stock price crash measure is signed such that a higher value identifies a larger crash. Table 1 reports descriptive statistics for each measure. The mean value of *CRASH* is 3.62, indicating that the minimum daily return over a six month period averages 3.62 standard deviations. The sample mean for *NCSKEW* is -0.26, indicating the presence of weak positive skewness. Finally, the sample mean for *MINRET* is 8.29%, indicating that the mean minimum daily return within a six month period is -8.29%.

Next, we report evidence on the events causing stock price crashes. We manually collect the underlying events by analyzing news reports contemporaneous with the crashes. In order to focus on large crashes, we focus on observations in the top 5% of the distribution for any of our three crash measures. Thus, a crash is defined to have occurred in a period if *CRASH* exceeds 8.29, *NCSKEW* exceeds 2.28 or *MINRET* exceeds 21.14% (i.e., a minimum daily excess return of less than -21.14%). Given the high cost of manually collecting this data, we restrict our analysis to the four 6 month periods beginning on July 1 2012 and ending on June 30 2014. The resulting sample contains over 10,000 observations, of which 686 belong to the top 5% of at least one measure of crash risk. We use the Factset Company News application to identify the cause of each crash. The results of this analysis are tabulated in Table 2. Earnings announcements are by far the most common cause of stock price crashes, causing 67.9% of crashes. Earnings preannouncements are a distant second, causing 9.9% of crashes. Thus, almost 80% of stock price crashes are earnings-related. The only other significant explanation is 'other firm announcement', explaining 9.3% of crashes. The majority of these cases relate to the announcement of disappointing clinical trials for new drugs by healthcare companies.

The evidence in Table 2 is based on a hand-collected sample for a recent two-year period. Figure 1 illustrates the role of earnings announcements in causing stock price crashes over a longer period. This figure is based on earnings announcement dates obtained from Factset. Stock price crashes are classified as being earnings-related if they fall on the earnings announcement date or any of the subsequent two trading days. Figure 1 plots the percentage of earnings-related stock price crashes from 2001 to 2014. The percentage has risen from a low of around 20% in 2001 to a high of almost 70% in 2014, indicating that earnings announcements have been growing in importance as a causal factor in stock price crashes. Note also that the relative importance of earnings announcements temporarily declined during the financial crisis years of 2008 and 2009.

Forecasting Stock Price Crashes. We begin our forecasting analysis by regressing each of our crash measures on the crash forecasting variables. Recall from the previous section that we measure the magnitude of stock price crashes using the distribution of daily returns over six monthly periods and our forecasting variables use information that would have been available to investors at the start of each six month period. Table 3 presents the regression results. Panel A of Table 3 presents the results using *CRASH*, our primary measure of stock price crashes, as the dependent variable. With the exception of past stock return (*PAST_RET*) and forecast change in margin (*NMGROW*), all of the forecasting variables load with the predicted signs and are statistically significant. Short interest (*SHORT*) is the best individual contributor to the forecasting of *CRASH*. The overall explanatory power of the regression, however, is only 4.2%. Thus, while the forecasting variables help to anticipate stock price crashes, they provide far from perfect foresight.

Panel B of Table 3 presents a similar set of results using *NCSKEW* as the measure of stock price crashes. Recall that this crash measure focuses on the left tail of the distribution alone. It helps to identify forecasting variables that only predict stock price crashes, as opposed to those that predict both crashes and positive jumps. We see several significant changes using this alternative measure of crashes. First, there is no evidence that *BTM*, *COVER* and *OPACITY* predict *NCSKEW*. Thus, these variables must predict both extreme crashes and jumps in stock prices, rather than predicting crashes alone. In addition, *PAST_RET* now loads with the predicted positive sign and is statistically significant. It appears that while *PAST_RET* is not particularly good at predicting large crashes, it does help to identify stocks with relatively fatter left-tailed return distributions.

Finally, panel C of Table 3 presents results using *MINRET* as the measure of stock price crashes. These results are broadly consistent with those in panel A. All of the predictive variables except for *PAST_RET* load with the predicted sign. *SHORT* has the greatest statistical significance, while *BTM* becomes statistically insignificant. Note also that the control variable *SIGMA* is highly significant in this regression, but the sign flips from negative in panels A and B to positive in panel C. This result just says that firms with more volatile stock returns in the past are more likely to have bigger negative returns in the future. This result is to be expected and it is why our *CRASH* measure includes lagged volatility in its denominator.

Five of the variables in Table 3 consistently have the hypothesized sign and are statistically significant in at least one panel. These five variables are *DTURNOVER*, *BTM*, *OPACITY*, *SHORT* and *SGROW*. Each of these variables also contains distinct information in the quest to predict stock price crashes. *DTURNOVER* captures disagreement among investors, as reflected by increased trading activity. *BTM* captures rich valuations relative to the underlying fundamentals. *OPACITY* captures the potential use of subjective accounting assumptions in past earnings. *SHORT* reflects the negative sentiment of short sellers, usually sophisticated investors specializing in identifying overpriced stocks. Finally, *SGROW* identifies stocks for which sell-side analysts have optimistic expectations about future earnings. We further note that each of these five variables is either directly or indirectly related to subsequent earnings announcements. *BTM*, *OPACITY* and *SGROW* relate directly to the accounting numbers underlying the stock price, while *DTURNOVER* and *SHORT* often relate to investor disagreement about future earnings. Thus, earnings announcements are a likely future catalyst that links these variables to future stock price crashes.

Investment Implications. Having identified the key predictors of crash risk, we next investigate how positioning a portfolio to avoid crashes impacts investment performance. We naturally expect to reduce the incidence of future cashes, but we also expect such a portfolio to yield higher returns and lower risk. Previous research indicates that several of the variables that we use to predict crashes are also negatively related to future stock returns. In particular, future stock returns have been shown to be positively related to the book-to-market ratio (see Fama and French, 1992), and negatively related to short interest (see Asquith and Meulbroek 1995), accruals (see Sloan, 1996) and growth expectations (see Dechow and Sloan 1997).

In order to investigate the investment implications of avoiding stocks with high crash risk, we develop and test a simple set of investment rules. First, we rank stocks on each of the five predictors of crashes at the beginning of each period. Next, we select the top 20% of stocks that are most likely to crash based on each predictor. So we take the top 20% of stocks ranked on *DTURNOVER*, *OPACITY*, *SHORT* and *SGROW* and the bottom 20% ranked on *BTM*. Finally, we examine the relative performance of investment strategies that avoid high crash-risk stocks. We limit these investment tests to stocks in the Russell 3000 universe and use the returns on the Russell 3000 index to benchmark investment performance.

Table 4 presents the equal-weighted mean value of various investment performance statistics for the six month period following the classification of firms into high crash risk groupings. We designate an observation that is in the top 20% of a crash predictor as having a 'crash flag'. With five predictors in total, each observation can have anywhere between 0 and 5 crash flags. Observations with more crash flags are predicted to be more likely to crash. Consistent with this prediction, each of the three crash measures, *CRASH*, *NCSKEW* and *MINRET* are increasing in the number of crash flags. The results for *MINRET* are the easiest to interpret. For stocks with 0 crash flags, the mean minimum daily return over the next 6 months is only -6.68%. As we increase the number of crash flags, the mean minimum daily return becomes more negative, reaching -14.42% with five crash flags. The next column in Table 4 reports the mean active stock return over the next 6 months. The active return is monotonically decreasing as the number of crash flags increases, from 1.15% with 0 crash flags to -6.00% with 5 crash flags. The final column of Table 4 reports the mean of the daily tracking error relative to the Russell 3000 over the subsequent 6 months. The tracking error is monotonically increasing is the number of crash risk flags, from a low of 2.03% with 0 flags to a high of 3.67% with 5 crash risk flags. Thus, avoiding stocks with a high number of crash risk flags not only mitigates future crashes, but also eliminates stocks with lower future returns and higher future risk.

Based on the results in Table 4, a robust strategy for minimizing crash risk would be to avoid stocks with at least three crash risk flags. Note that *CRASH*, our primary measure of crashes, increases at a lower rate beyond 3 crash flags. Future active returns, moreover, are significantly negative for stocks with 3 or more crash flags. Finally, such a strategy eliminates only 10% of stocks from consideration, and so does not impose excessive restrictions on the investment universe.

In order to better understand the potential benefits from implementing such a strategy, we simulate the strategy over our sample period. At the beginning of each 6 month period, we form two portfolios. The first portfolio contains stocks with 2 or fewer crash flags at the beginning of the period ('low crash risk' portfolio). The second portfolio contains stocks with 3 or more crash flags at the beginning of the period ('high crash risk' portfolio). We reconstitute each portfolio at the end of every 6 month period. We then track the crash frequencies of the underlying stocks and investment performance of each of these portfolios over our sample period.

Figure 2 plots the distribution of realized future crashes for stocks in each of the two portfolios. For ease of interpretation, we use *MINRET* as our measure of crash magnitude (recall that *MINRET* is the negative of the minimum daily return over the next 6 months). As expected, the distribution of future crashes for the high crash risk portfolio lies significantly to the right of the corresponding distribution for the low crash risk portfolio.

Figure 3 plots the investment performance of the two portfolios over the sample period. Panel A plots the performance of value-weighted portfolio returns while panel B plots the performance of equal-weighted portfolio returns. Each plot also includes the (value weighted) return on the Russell 3000 index for comparative purposes. Panel A reveals three key facts. First, the high crash risk portfolio significantly underperforms both the low crash risk portfolio and the Russell 3000. Second, the high crash risk portfolio exhibits higher volatility than the low crash risk portfolio and the Russell 3000. Third, the performance of the low crash risk portfolio is almost identical to that of the Russell 3000. The reason for the latter result is that only about 10% of stocks belong to the high crash risk portfolio, and these stocks tend to have relatively low market capitalizations.

Given that low capitalization stocks appear to be more crash-prone, panel B reports portfolio performance using equal-weighted returns. The performance differential is much greater using equal-weighted returns. The high crash risk portfolio has negative cumulative returns, while the low crash-risk portfolio significantly outperforms the Russell 3000. Thus, it appears that our crash risk flags are particularly good at predicting crashes in lower capitalization stocks.

Table 5 provides investment performance statistics for the portfolios plotted in Figure 3. Excess returns are computed by subtracting the yield on the 10 Year Treasury Note. On a value-weighted basis, the low crash-risk portfolio performs similarly to the Russell 3000. The high crash risk portfolio, in contrast, has lower excess returns and higher volatility, resulting in a Sharpe ratio less than one third of that of the Russell 3000. The high crash risk portfolio also has a beta significantly greater than 1. On an equal-weighted basis, the performance differentials are much greater. The low crash risk portfolio outperforms the Russell 3000 by 4.41%, while the high crash risk portfolio underperforms by -10.36%. The high crash risk portfolio continues to have higher volatility, higher beta and higher tracking error. In sum, our strategy for avoiding high crash risk stocks not only mitigates future crashes, it also results in higher portfolio returns and reduced portfolio risk.

Conclusion

Stock price crashes are a major source of concern for active investment managers. We have demonstrated, however, that investors can be proactive in positioning their portfolios to avoid stock price crashes. We identify five flags that are useful for forecasting crashes. Incorporating these flags into portfolio construction also leads to higher returns with lower risk. While the predictive ability of these flags is far from perfect, each of the flags has an intuitive interpretation that can provide the starting point for deeper fundamental analysis. For example, the measure of accounting opacity identifies firms with earnings that have been heavily influenced by subjective accounting decisions. As such, the flags provide a guide for deeper fundamental analysis that should further enable active investors to shield their portfolios from stock price crashes

References

Ak, B. 2015. “Predicting Large Negative Stock Returns: The Trouble Score”, Working Paper, University of California, Berkeley.

Asquith, P., and L. Meulbroek. 1995. “An Empirical Investigation of Short Interest”, Working Paper, Harvard Business School.

Bradshaw, M., A. Hutton, A. Marcus, A. J., and H Tehranian. 2011. “Opacity, Crash Risk, and the Option Smirk Curve”, Working Paper, Boston College.

Callen, J. and F. Fang. 2014. “Short Interest and Stock Price Crash Risk”, Working Paper, Rotman School of Management.

Chen, J., H. Hong and J. Stein. 2001. “Forecasting Crashes: Trading Volume, Past Returns and Conditional Skewness in Stock Prices”, *Journal of Financial Economics* 61, 345-381.

Dechow, P. and R. Sloan. 1997. “Returns to Contrarian Investment Strategies: Tests of Naive Expectations Hypotheses”, *Journal of Financial Economics*, 43 , 3-27.

Fama, E. 1965. “The Behavior of Stock-Market Prices”, *Journal of Business* 38, 34-105.

Fama, E. and K. French. 1992. The cross-section of expected stock returns, *Journal of Finance*, 47, 427-465.

Hutton, A., A. Marcus and H. Tehranian. 2009. “Opaque Financial Reports, R2 and Crash Risk”, *Journal of Financial Economics* 94, 67-86.

Skinner, D. and R. Sloan. 2001. “Earnings Surprises, Growth Expectations and Stock Returns or Don’t Let an Earnings Torpedo Sink Your Portfolio”, *Review of Accounting Studies* 7, 289-312.

Sloan, R. 1996. “Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?” *Accounting Review* 71, 289-315.

Figure 1

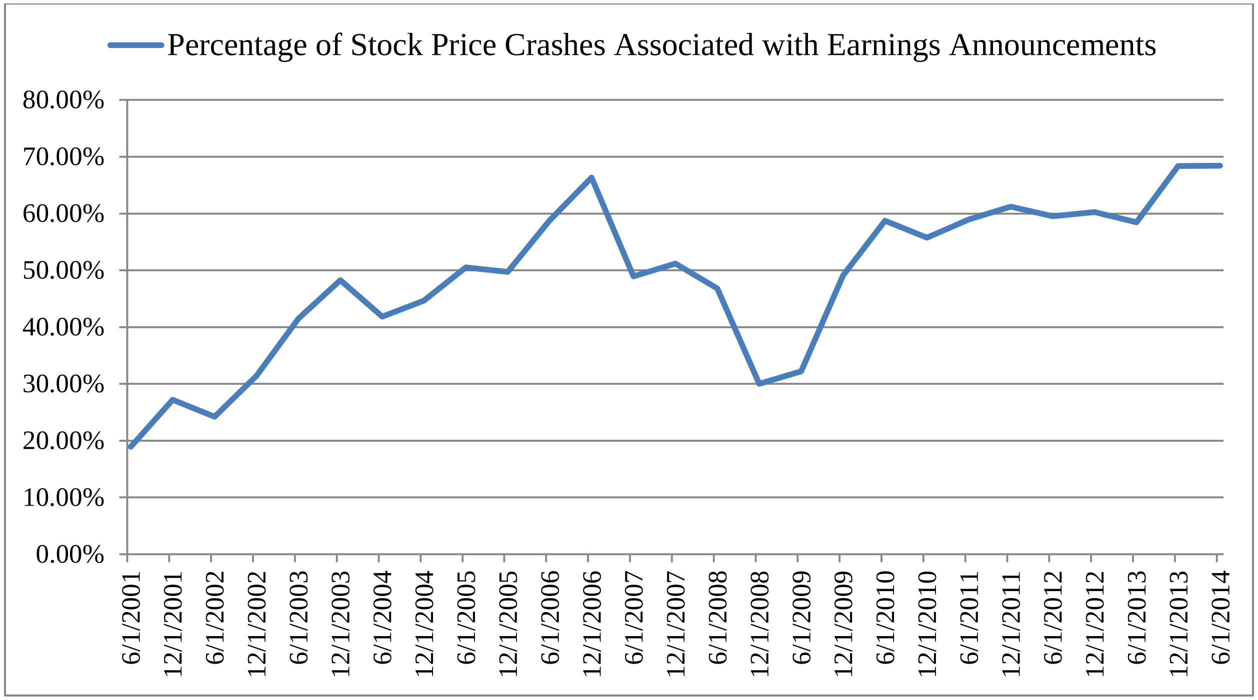

Percentage of Stock Price Crashes Associated with Earnings Announcements
80.00%
70.00%
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
6/1/2001
12/1/2001
6/1/2002
12/1/2002
6/1/2003
12/1/2003
6/1/2004
12/1/2004
6/1/2005
12/1/2005
6/1/2006
12/1/2006
6/1/2007
12/1/2007
6/1/2008
12/1/2008
6/1/2009
12/1/2009
6/1/2010
12/1/2010
6/1/2011
12/1/2011
6/1/2012
12/1/2012
6/1/2013
12/1/2013
6/1/2014

Figure 2
Crash Risk Density Plot using Negative of Minimum Daily Return

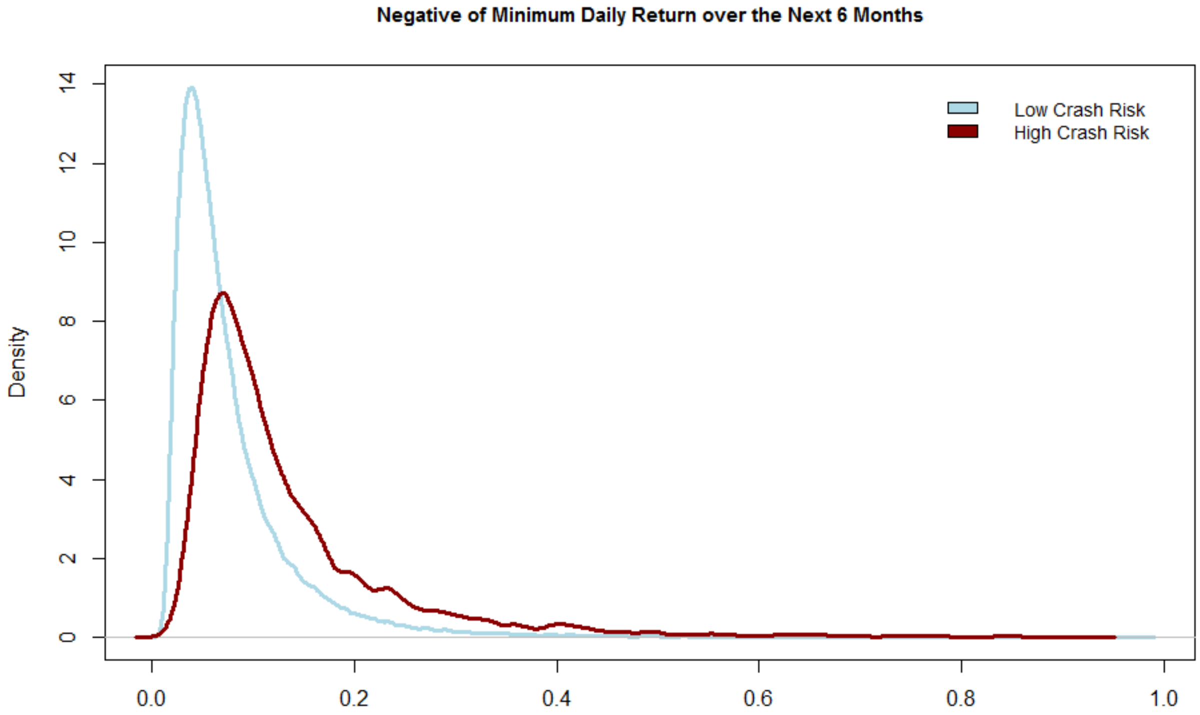
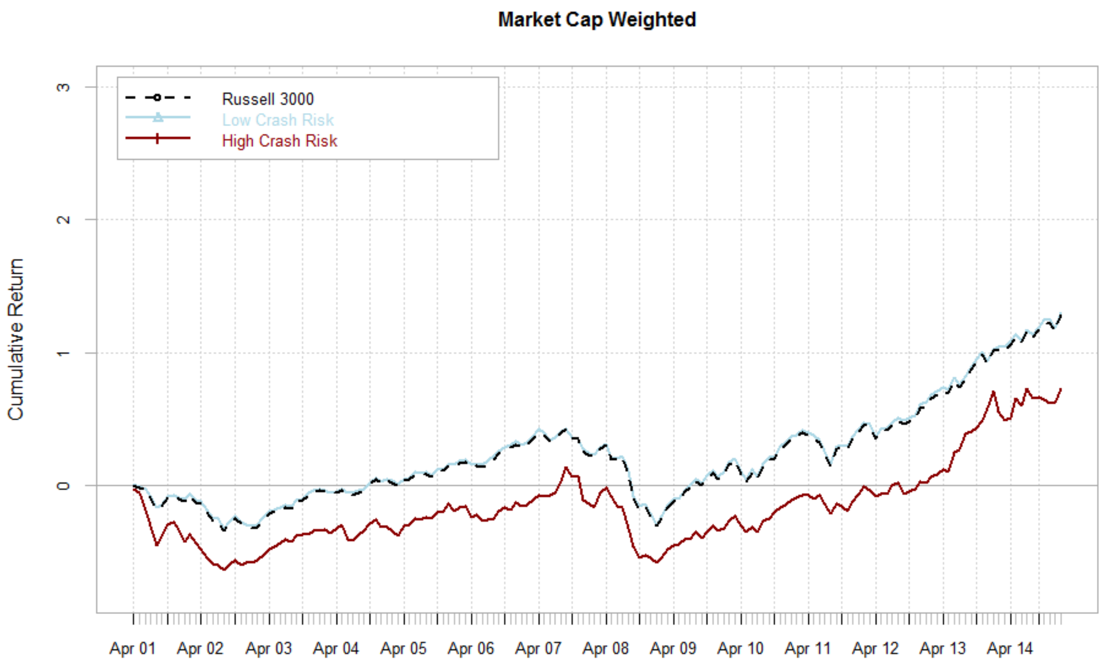


Figure 3. Cumulative Returns for Low Crash Risk and High Crash Risk Portfolios.
Panel A: Value-Weighted Returns



Panel B: Equal-Weighted Returns

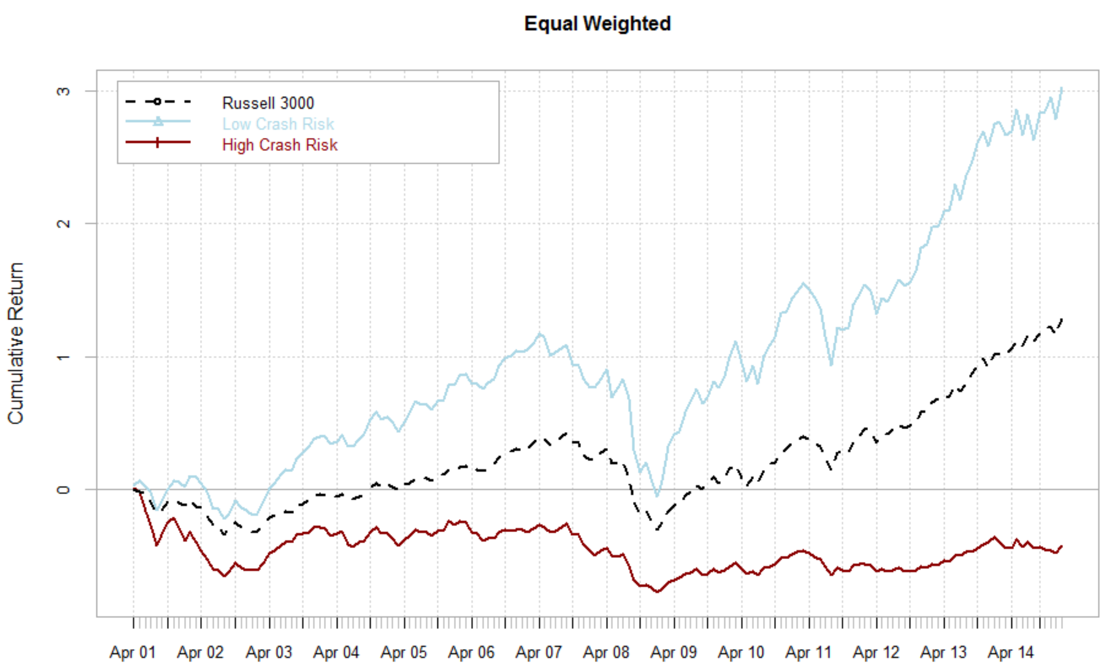


Table 1
Descriptive Statistics on Stock Price Crash Measures. Sample consists of 59,489 observations from July 2001 to June 2014.

	CRASH MEASURE		
	CRASH	NCSKEW	MINRET (%)
Mean	3.62	-0.26	8.29
Std. Dev.	2.39	1.53	7.29
5%	1.45	-2.71	2.38
Median	2.91	-0.24	6.17
95%	8.29	2.28	21.14

Table 2
Events Causing Stock Price Crashes from July 2012 to June 2014

CODE	EXPLANATION	Frequency	%
1	EARNINGS ANNOUNCEMENT	466	67.9
2	EARNINGS PREANNOUNCEMENT/UPDATED GUIDANCE	68	9.9
3	ADVERSE LEGAL RULING	11	1.6
4	ADVERSE REGULATORY RULING (E.G., FDA)	16	2.3
5	MANAGEMENT CHANGE	6	0.9
6	OTHER FIRM ANNOUNCEMENT	64	9.3
7	OTHER	40	5.8
8	NOT AVAILABLE	15	2.2

Table 3
Regressions of Crash Variables Measured Over the Subsequent Six Months on Crash Forecasting Variables. Sample consists of 59,489 observations from July 2001 to June 2014.

	Panel A: Dependent Variable = *CRASH*				Panel B: Dependent Variable= *NCSKEW*				Panel C: Dependent Variable = *MINRET*		
Variable (Predicted Sign)	Estimate	t value	Pr(>|t|)		Estimate	t value	Pr(>|t|)		Estimate	t value	Pr(>|t|)
Intercept (?)	5.129	69.75	0.000		-0.313	-6.71	0.000		0.067	35.52	0.000
Forecasting Variables:											
DTURNOVER (+)	0.580	6.12	0.000		0.308	5.15	0.000		0.021	8.85	0.000
PAST_RET (+)	-0.328	-8.22	0.000		0.273	10.34	0.000		-0.007	-7.25	0.000
BTM (-)	-0.137	-5.18	0.000		-0.015	-0.88	0.377		-0.001	-1.05	0.292
COVER (+)	0.160	7.83	0.000		-0.001	-0.09	0.927		0.005	10.27	0.000
OPACITY (+)	0.550	4.91	0.000		0.010	0.13	0.893		0.031	10.96	0.000
SHORT (+)	2.400	22.13	0.000		0.178	2.56	0.011		0.078	28.19	0.000
SGROW (+)	0.421	6.84	0.000		0.164	4.18	0.000		0.018	11.19	0.000
NMGROW (+)	0.119	1.55	0.122		-0.126	-2.56	0.010		0.006	3.24	0.001
Controls:											
PAST_CRASH (?)	0.026	5.34	0.000		0.018	3.63	0.000		0.044	6.83	0.000
SIZE (?)	-0.122	-12.15	0.000		0.030	4.73	0.000		-0.006	-22.65	0.000
SIGMA (?)	-36.372	-38.48	0.000		-6.891	-11.75	0.000		1.521	48.21	0.000
LEV (?)	-0.213	-5.46	0.000		-0.095	-3.82	0.000		-0.005	-5.25	0.000
Adjusted R-squared	0.042				0.008				0.227		
Number of Obs.	59,489				59,489				59,489		

Table 4
Investment Performance for Stocks Classified by Number of Crash Risk Flags. Sample consists of 59,489 observations from July 2001 to June 2014.

Number of Crash Flags	Mean Investment Performance Over the Next 6 Months					
	% of Observations	CRASH	NCSKEW	MINRET	Active Return Versus Russell 3000	Daily Tracking Error
0	45	3.54	-0.27	6.68%	1.15%	2.03%
1	30	3.62	-0.27	8.25%	0.89%	2.42%
2	15	3.71	-0.27	10.38%	-0.41%	2.97%
3	7	3.80	-0.23	11.92%	-2.43%	3.29%
4	2	3.86	-0.19	13.33 %	-4.66 %	3.57%
5	1	3.92	-0.02	14.42%	-6.00%	3.67%

Table 5

Investment Performance (Annualized) for Portfolios Formed on Crash Risk Flags. Sample consists of 59,489 observations from July 2001 to June 2014.

(Low Crash Risk=2 or Fewer Flags, High Crash Risk =3 to 5 Flags)

		Value-Weighted Portfolio		Equal-Weighted Portfolio	
	Russell 3000	Low Crash Risk	High Crash Risk	Low Crash Risk	High Crash Risk
Excess Return	4.26%	4.33%	2.08%	8.61%	-5.98%
Volatility	15.40%	15.17%	24.62%	20.79%	27.29%
Sharpe Ratio	0.2764	0.2854	0.0847	0.4142	-0.2191
Versus Russell 3000:					
Beta		0.9840	1.3514	1.2643	1.5908
Active Return		0.07%	-2.19%	4.41%	-10.36%
Tracking Error		0.67%	14.22%	8.34%	15.07%
Information Ratio		0.1084	-0.1541	0.5291	-0.6876