Exploring Stock Price Crashes

An Empirical Study on the European Market

by

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About the Author

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Having completed his primary, middle and high-school in Montemor-o-Velho, he moved to Porto to enter in the Bachelor of Business Administration at Faculdade de Economia do Porto. During this time, he had the opportunity to have a first work experience completing two internships in his finalist year.

After completion, he enrolled in the Master in Finance at Faculdade de Economia do Porto. During this two years program, he had the opportunity to spend one semester as an exchange student at Frankfurt School of Finance & Management, in Germany.

His main interests related to Finance include topics such as asset management and research.

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Abstract

While stock price crashes may be considered rare events, their impacts on companies, financial markets and economies can last for long periods of time hence, it is from the utmost importance to understand their causes.

To do so, this work is divided in two distinct segments. Firstly, using data from firms from 17 different countries across Europe ranging from the beginning of 2003 until the end of 2016, a cross-sectional regression analysis was performed to measure how different firm-related variables can affect stock price crash risk on an individual firm level. Secondly, building up on these findings and previous studies, we applied a simple but useful framework for investors to adapt their stock portfolios to such extreme events. Using a set of previously studied stock price crash predictors, we were able to collect a set of highly statistically significant variables that were then used to group companies into two distinct portfolios, one with "low-crash" likelihood and the other with "high-crash" likelihood. Even though we were able to achieve higher risk-adjusted returns with this simple strategy (Sharpe Ratio of 0.5804 on the low-crash risk portfolio against 0.4986 on the same measure for the high-crash risk portfolio), its essence differs greatly from Ak et al., (2016) work mainly because of two reasons: the way we access stock price crash likelihood and our set of "crash-flags".

Besides offering a new contribute to the scarce empirical literature regarding this topic on European markets and extending Ak et al., (2016) study by using one more crash assessing measure and different stock price predictors, this work also attempts to fill an important gap between academic literature and practical guidance on how to adapt investors' stock portfolios to stock price crashes.

Key-words: Stock Price Crash, Crash Risk, Investment Performance

JEL-Codes: G11, G14

Resumo

Embora *crashes* no preço de ações possam ser considerados raros, o seu impacto nas empresas, mercados financeiros e economias pode perpetuar-se por longos períodos de tempo e, portanto, é impreterível compreender as suas causas.

Para tal, este trabalho está divido em dois segmentos distintos. Em primeiro lugar, utilizando dados de empresas de 17 países europeus com início em 2003 até ao final de 2016, realizámos uma análise seccionada de modo a medir como diferentes fatores relativos às empresas afetam o seu risco de *crash* a um nível individual.

De seguida, com base nos resultados alcançados anteriormente, analisámos uma simples, mas eficaz estratégia, para investidores adaptarem os seus portefólios de ações a tais eventos.

Ao utilizar um conjunto de preditores de *crash* previamente estudados, conseguimos reunir um conjunto de variáveis altamente preditivas de risco de crash que foram de seguida utilizadas para construir dois portefólios, um com "baixo-risco" de *crash* e outro com "elevado-risco" de *crash*. Embora tenhamos conseguido atingir retornos ajustados superiores com esta simples estratégia (Sharpe Ratio de 0.5804 na carteira de "baixo-risco" face a um Sharpe Ratio de 0.4986 na carteira de "alto-risco"), a natureza dos mesmos difere bastante dos resultados de Ak et al., (2016) devido principalmente a dois fatores: o modo como medimos o risco de crash e o conjunto de "*crash-flags*" utilizado.

Para além de contribuir para a escassa literatura relativa a este tópico no mercado europeu e de complementar o estudo de Ak et al., (2016) ao incorporar uma nova variável dependente e diferentes variáveis explicativas, este trabalho procura preencher uma lacuna entre a literatura académica e a sua aplicação prática de como investidores podem adaptar os seus investimentos aos crashes no mercado acionista.

Palavras-chave: Crash no preço de ações, Risco de crash, Performance de investimento

Códigos-JEL: G11, G14

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1. Introduction

When it comes to extreme movements in the stock market, we know that the more abrupt ones of them are drops in price (Chen et al., 2001 - p. 346). These extreme negative movements are known as crashes. During the past, we have seen several of these, both at an aggregate market level (for example, the crash of 1987 or the "tech-bubble burst" of 2001) and on specific companies. This study focuses on the latter.

The main theories behind the existence of stock price crash risk in firms are related to information asymmetry, an agency perspective, between corporate managers and the public (Jin & Myers, 2006). Accordingly, managers tend to hold the release of bad news, for their own benefit, to avoid negative consequences that may arise from it. However, at some point in time, it is impossible to keep hiding information from the market and once it goes public, it goes all at the same time leading up to an abrupt correction through a large negative stock price movement – a crash.

It is unreasonable to guess which companies are withholding bad news from the market in order to predict stock price crash risk. You would need to have inside information regarding the company's situation to be able to know which ones are hiding relevant information from the market.

Even though "unexpected" events such as stock price crashes are believed to be non-diversifiable (Sunder, 2010), growing literature on the topic has found some common factors which are useful to estimate the likelihood of stock price crashes to happen in the future at an individual firm level. In the recent years, academics have found that factors such as past stock returns (Chen et al., 2001), financial reports opacity (Hutton et al., 2009), corporate social responsibility (Y. Kim et al., 2014), short interest (Callen & Fang, 2015b) and the type of strategy pertained to the firm (A. Habib & Hasan, 2017), among others, are associated to the likelihood of a stock experiencing a crash.

However, besides being mainly focused on the United States market, this increasing literature has not been accompanied by useful practical guidance on how to apply these insights on securities selection for portfolio management.

To address this second aspect, *Navigating Stock Price Crashes* (Ak et al., 2016) suggests a strategy which consists in building a portfolio based on stocks which are expected to have lower crash likelihood. They did this by performing a regression in order to find the most significant stock price crash predictors for their sample. After rearranging the data in 5 different groups, in accordance to their crash likelihood, they were able to select the less crash-prone securities and create a portfolio with them. The developed strategy yielded higher returns with lower risk than the considered benchmark. Hence, resulting in a higher Sharpe Ratios in comparison not only to the more crash-prone group but also to the market. Since their strategy is simple and intuitive, we believe it is a good opportunity to test it on the European market as well as to experiment it with other predictive variables.

The pertinence of this study is related to these previous two factors. We aim to fill the existent gap of literature in this field related to the European market and to build up on the previous work from Ak et al., (2016) on how to adapt portfolios to stock price crashes. To do so, we will perform a series of cross-sectional analyses with data from companies included in one of the most well-known European Indexes (STOXX® 600 Europe) to find out which characteristics influence the stock crash likelihood of its constituents. After that, we will develop a framework to apply these same findings on portfolio management in order to investigate whether it is possible to achieve better results than a passive strategy.

Even though our regressions show that most of the previous studied crash influencers in the United States are also applicable in the European market, some of these variables require some kind of adjustment. One flagrant case is financial reporting opacity which, even though it is of great value in the United States related literature, it seems not very useful, as it is, in Europe. Beside this, and with our data limitations, we were able to collect a set of highly significant crash predictors.

However, while performing the second part of this study, even though our strategy resulted in better risk-adjusted returns than our considered benchmark, it did not seem very useful at avoiding companies which are more crash prone. As such, our results greatly differ from the ones in Ak et al., (2016) since they were clearly able to build two distinct portfolios based on the stock price crash risk of each one. We hypothesize three possible explanations for these differences. First, our main variable of interest is not solely focused on the left side (the negative one) of the returns distribution as the measure used by Ak et al., (2016). Second, we considered all the regression variables as possible crash-flags which, as later presented, results in an interesting difference on the regressions conclusions. Thirdly, we did not have access to one of the highest significant variables in Ak et al., (2016) study, short-interest.

Besides this chapter, this dissertation is structured as follows: in chapter 2, a literature review of the topic is made where we will present the main models and theories related to stock price crashes. In chapter 3, a summary of our sample and methodology is presented. In chapter 4, we present the main results of our cross-sectional regressions. In chapter 5, we analyse how the strategy proposed by Ak et al., (2016) performed in our data and chapter 6 contains the conclusions of our study. Lastly, chapter 7 includes the references.

2. Literature Review

A single crash event can not only jeopardise a long investment performance period but also cause reputation losses among the community for active investors that were unfortunate enough to place their bets on those companies (Ak et al., 2016 - p. 28). Given this significant impact price crashes have on stock returns, many researchers tried to find the holy-grail of being able to predict (or at least, understand) stock price crashes.

We now present a review of the literature which is divided in 4 segments. Firstly, we present the main theories for stock price crashes i.e., what intrinsic reasons exist for these to happen. Secondly, we explain the main proxies used to measure crashes. Then, we scrutinise the factors that, so far, are believed to impact the likelihood of stock price crashes to happen. Lastly, we further explain the strategy from Ak et al., (2016) for avoiding high-crash-risk stocks and analyse its results.

2.1. Stock Price Crash Theories

What drives stock price crash risk? There are different theories regarding to which underlying factors impact this measure.

The majority of today's literature relies on the theory of Jin & Myers (2006). This theory endorses the idea that managers tend to withhold bad news from the public by engaging in more opaque reporting systems. According to the authors, opaqueness has both positive and negative effects for corporate insiders. On the positive side, it allows managers to capture more cash flow than they might if investors had all the information. On the other side, once the bulk of bad news is too much to hide, insiders give up and tend to release it all at once, resulting in large negative returns for the stock price. As Kothari et al., (2009) noted, this accumulation of bad news leads to an asymmetric distribution of stock price returns whereas in a scenario where managers release information as it comes, a regular flow of good and bad news regarding the company is expected, leading up to less skewed returns distributions. Corporate insiders tend to hold information because, as the authors explain, "The limits to capture (cash flows) are based on outside investors' perception of the firm's cash flow and value" (Jin & Myers 2006 – p. 258) meaning that, the less the public knows about the company, the more insiders can take advantage of the company's resources in their own benefit hence, managers have incentives to keep information from being released to the general public.

Some other ideas build up on this agency-theory framework and aimed to research the exact nature of this opacity. Benmelech (Benmelech et al., 2010) concluded that managers whose compensation is indexed to stock performance tend to engage in negative NPV (net present value) projects to hide the absence of opportunities that the firm may be facing (providing there are no positive NPV projects available) in order to make it seem that the company has a lot of growing opportunities even though it is, indeed, destroying value. In the same line, as previously concluded by Bleck & Liu (Bleck & Liu, 2007), the existence of historic cost accounting does not allow outsiders to easily access current information about current projects hence reducing market transparency by increasing firm opacity which results in more pronounced asset price crashes (Bleck & Liu, 2007 - p. 252).

Another theory for stock price crashes, which supports the theoretical background of the seminal study by Chen (Chen et al., 2001), is the theory developed in 1999 by Hong and Stein (Hong & Stein, 1999). According to the latter, the difference of opinion between investors is the main cause for price crashes. Their reasoning goes as follows: imagine a scenario (similar to Miller, 1977) with two different groups of investors, one is bullish about the future of the firm (it believes the stock price will go up) and another has a bearish sentiment (it believes the stock price will go down). Now, inside each of these groups, there is heterogeneity between investors and, as such, some of them are short-sale constricted (for example, mutual funds). This restriction obstructs some bearish investors from acting on their beliefs and thus, their information is kept outside of the market meaning that, there may be a slight overvaluation of the stock. Hence, if for some reason (for example, new unexpected information comes out) the more bullish investors may change their minds about the future of the stock and decide to exit the market, the bearish investors, that were impeded to act on their information, become the marginal buyers leading up to a decrease in price to the level at which these are willing to buy resulting, usually, in a price crash. The authors published a more developed study of their theory in 2003 (Hong & Stein, 2003).

Regarding once again to investors' heterogeneity, Cao et al., (2002) developed a theory based on the way different investors act based on fixed setup trading costs. Accordingly, to be willing to trade, investors sometimes need to verify their information by assessing other informed investors' trades in order to have greater confidence of their ability to recover these costs. This need for validation, holds them from trading which diminishes market participation and hence, results in an information-blockage between these side-lined investors and the market. Thus, once the information is confirmed by other investors' trades, it is so related to past price movements. Hence, "(…) return distributions exhibit conditional skewness, becoming more negatively skewed following positively trending prices (…)" (Cao et al., (2002) - p. 643).

Stock returns' volatility is also considered by some authors a source of stock price risk. Campbell and Hentschel (Campbell & Hentschel, 1992) conclude that volatility feedback in stock returns can explain part of the returns skewness (which can be used as a proxy for stock price crash risk). As it was later pointed, this increase in stock returns' volatility leads investors to reassess upwards the required risk premium hence, resulting in a price drop that generates negative skewness (Hutton et al., 2009 - p. 68).

2.2. Stock Price Crash Measures

As noted in Ak et al. study "Navigating Stock Price Crashes" (Ak et al., 2016), there are two ways of defining a stock price crash: one relative to the ex-post returns of the stock that has experienced the crash, and another one (used by those same authors) regarding ex-ante returns. Ak et al., (2016) define a crash simply as a "large and abrupt negative stock return relative to the distribution of returns leading up to the crash." (Ak et al., 2016 - p. 28).

On the other hand, stock price crash risk may be defined as the likelihood a stock has of suffering a price crash, i.e., "the likelihood of observing extreme negative values in the distribution of firm-specific returns" (Habib & Hasan, 2017 - p. 391).

Previous literature on the topic already defined several proxies for assessing stock price crash risk.

Chen (Chen et al., 2001) defines two different measures of crash propensity: NCSKEW and DUVOL.

NCSKEW, which stands for "negative coefficient of skewness", allows us to compare the shape of the left (negative) tail of the distribution of returns to the shape of the right (positive) one and thus conclude that higher values of this indicator result in a longer left tail meaning that the stock is more prone to crash than another one with smaller left tail.

$$\mathrm{NCSKEW}_{it} = -\left(n(n-1)^{3/2}\sum R_{it}^{3}\right) \Big/ \left((n-1)(n-2)\left(\sum R_{it}^{2}\right)^{3/2}\right)$$

Equation a - NCSKEW

DUVOL (meaning "down-to-up volatility") compares the magnitude of the returns below the period's mean return to the magnitude of the returns above the mean return. It classifies these periods as "down" periods if their return in below the period average return and "up" periods if they are above. Once again, higher values on this indicator represent a more left-skewed distribution and thus, higher crash possibility.

$$\mathrm{DUVOL}_{it} = \log\left\{(n_{\mathrm{u}}-1)\sum_{\mathrm{DOWN}} R_{it}^{2} \Big/ \left((n_{\mathrm{d}}-1)\sum_{\mathrm{UP}} R_{it}^{2}\right)\right\}.$$

Equation b - DUVOL

Later, Hutton (Hutton et al., 2009) used CRASH (CRASH_COUNT) a binary variable which takes the value 1 if, in that week, the return is 3.09 standard deviations below the yearly mean return and 0 if it is above that threshold. The 3.09 value regarding standard deviations is chosen in order to include the 0.1% of returns in each tail of an assumed normal distribution of that firm-stock returns meaning that, any observation included in those 0.1% are considered extreme events (whether a crash or a jump depending on which side it is located). Also with this variable, a higher value represents a higher crash frequency in the returns distribution.

Ak et al., (2016) argue that the some of the previous measures contain problems. First, regarding NCKSEW, the authors argue that it can be influenced not by crashes (long left tail) but by several negative returns (fat left tail) and secondly, that this measure excludes both crash and jump prone stocks (Ak et al., 2016 - p. 29). Regarding the previous CRASH measure (from Hutton et al., 2009), they claim that due to its binary

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

Equation c - CRASH

logic, it ignores the magnitude of the crash. Taking these limitations into consideration, the authors created a modified version of CRASH.

Besides CRASH, and for simplicity, Ak et al., (2016) study also uses MINRET (which stands for (negative of) minimum return of the period) as a crash measure. Inspired by previous work (for example, Bates, 2000) , in J.-B Kim and Zhang (J.-B. Kim & Zhang, 2014), the measurement variable was defined as "implied volatility smirks". This measures the implied volatility of an option (IV-SKEW) as the difference between implied volatility out-of-the-money puts (IVOTMP) and the at-the-money calls (IVATMC). Again, higher values, that is, higher steepness of the smirk, represents higher risk of crash.

$$IV\text{-}SKEW_{jt} = IV_{jt}^{OTMP} - IV_{jt}^{ATMC}$$

Equation d – IV-SKEW

As it is noticeable, all the available measures of crash are different in its essence and thus, all of them try to capture different associations among what causes these crashes. Nevertheless, even though the vast majority of studies rely on NCKSEW and DUVOL as main proxies for stock price crash risk, there is not, presently, a consensus on which of these variables is the most correct one to assess crash likelihood (Ahsan Habib et al., 2017 - p. 7).

2.3. *Stock Price Crash Determinants*

The main goal of crash risk literature is trying to understand which factors influence stock price crashes. These factors can be grouped in distinct segments such as i) capital market related factors, ii) company related factors, iii) management related factors and iv) other factors.

i. Capital market factors

Starting in 2001, we have a central study by Chen (Chen et al., 2001) in which the authors set the structure for all the following studies regarding stock price crashes. Using data from the U.S. market, the authors concluded about the existence of a positive relation between trading volume on the previous 6 months and stock price crash risk. Also, with this work, they found a positive relation between positive returns 36 months prior the event and firm size (measure through market capitalization) to stock price crash risk. These last two conclusions go against previous studies (for example, Harvey & Siddique, 2000).

Even though some literature concludes on the existence of negative relation between stock liquidity and default risk (for example, Brogaard et al., 2017 - p. 502), concerning stock performance, Chang et al., (2017) found that higher stock liquidity is related to higher stock price crash risk. Their argument relies on the fact that managers of highly liquid companies tend to withhold bad news from the public because, due to its higher liquidity on the market, investors would promptly sell their stocks, leading up to a crash.

Callen and Fang (Callen & Fang, 2015b) shed some light on short-sellers' ability to predict subsequent drops in price by concluding about the existence of a positive relationship between short-interest and one-year ahead stock price crash risk. The authors conclude that short-sellers are able to predict ex-ante bad news hoarding which leads to price crashes (Callen & Fang, 2015b – p. 192). However, even though they are believed to predict negative returns, the variables they use to do it are also related to other influencers of stock price crashes such as poor earnings quality (Desai et al., 2006) and financial misconduct (Karpoff & Lou, 2010).

ii. Company factors

Hutton et al., (2009), concluded that firms which present more opaque financial reporting, measured through discretionary accruals, have higher crash risk. Also, Zhu (Zhu, 2016) concluded the same results and states that managers use accruals to hoard bad news from outsiders. This conclusions goes in line with the theoretical framework presented earlier by Jin & Myers (2006) which claims information asymmetry on agency relationships as the main cause for stock price crashes. Also, there is a positive relation between real earnings management and stock crash in the following year as well as between deviations from real operations and stock price crash risk (Francis et al., 2016).

Tax avoidance is also related to stock crashes. In J.-B. Kim et al., (2011) there is evidence that corporate tax avoidance is positively related to stock price crash at a firm-level. The authors, however, conclude that this effect is mitigated when companies are more widely followed by analysts and better external monitored.

Conservative accounting practices are negatively related to stock price crash risk (J.-B. Kim & Zhang, 2016). This consequence is related to the fact that conservatism decreases information asymmetry in the market (LaFond & Watts, 2008 - p. 474) thus, avoiding negative surprises to investors.

A. Habib & Hasan, (2017), following Bentley et al., (2013) previous measures of "strategy ranks", were able to conclude that firms with higher strategy rankings, i.e., prospector-type of firms in combination with long-term equity incentives are more prone to bad news hoarding by managers which reflects in higher probability to experience stock price crashes than defender-type ones.

Y. Kim et al., (2014), following previous work on the corporate social responsibility topic (for example, Chatterji et al., 2009) and using a similar modelling framework as in Chen et al., (2001), find out that firms that have higher corporate social responsibility ratings, tend to have lower stock price crash risk thus, concluding that corporate social responsibility practices help to mitigate this risk.

iii. Management factors

Since management is a crucial factor in firm performance, it is important to understand how they can influence stock price crashes.

J.-B. Kim et al., (2016) found that companies with overconfident CEOs tend to overestimate projects' returns as well to disregard negative feedback regarding their actions leading to higher crash likelihood. Also, more confident CEOs tend to present less conservative financial statement (Ahmed & Duellman, 2013) which is positively related to stock price crash.

Another interesting finding present in another study is that CEO's age is also related with future stock crashes. Unfortunately, for younger executives, the literature shows evidence that younger CEOs are related to higher crash probability (Andreou et al., 2016).

Regarding CFOs' equity incentives, J.-B. Kim et al., (2011) conclude about the existence of a significant positive relation between CFOs' stock options and stock price crash risk while no significant relation was found regarding CEOs' options. As the authors say, in accordance with Benmelech et al., (2010), these type of equity incentives lead managers to withhold bad news from the public in order to maximize their possible returns. However, later, Andreou et al., (2016) show that CEO stock options can also increase future crashes.

Board size also influences stock price crashes. As Andreou et al., (2016) conclude, higher the number of member in the board of a company results in fewer stock price crashes.

iv. Other factors

Besides these previous major groups, there are other factors that are believed to influence stock price crash likelihood.

Religion is appointed as a predictor for stock price crash. Callen & Fang (2015a) conclude that companies with headquarters located in counties with higher levels of religiosity present lower crash risk.

Also, companies with institutional investors which have a stable presence in the company while conducting a monitoring role, have lower stock price crash risk (for example, Callen & Fang, (2013) or An & Zhang, (2013)).

Companies where insiders have a higher proportion of ownership also tend to have lower future crashes (Andreou et al., 2016).

Analysts' expectations also perform an important role in this topic. As shown in Ak et al., (2016), companies for which sell-side analysts have very optimistic prospects about future sales and net margin tend to have higher crash risk propensity.

Table 1
Summary of the main stock price crash predictors

First column presents the study, second column the study' sample, third column illustrates the main variable of interest and the fourth the impact of an increase in value of the variable of interest.

Study	Sample	Main variable(s) of interest	Expected impact on crash likelihood
Chen et al., (2001)	All NYSE and AMEX firms from July 1965 - 1998	Trading volume	+
		Past returns	+
		Size	+
Chang et al., (2017)	58,533 firm-year observations from the United States from 1993 - 2010	Stock liquidity	+
Callen & Fang (2015b)	40,660 firm-year observations from the United States from 1981 - 2011	Short Interest	+
Hutton et al., (2009)	40,882 firm-year observations from 1991 - 2005	Financial reporting opacity	+
Zhu (2016)	108,104 firm-year observations from 1965 - 2013	Accruals	+
J.-B. Kim et al., (2011)	87,162 firm-year observations from the United States from 1995 - 2008	Corporate tax avoidance	+
J.-B. Kim & Zhang (2016)	114,548 firm-year observations from the United States from 1964 - 2007	Accounting conservatism	-
A. Habib & Hasan (2017)	68,604 firm-year observations from 1969 - 2012	Strategy score	+
Y. Kim et al., (2014)	12,978 firm-year observations from the United States from 1995 - 2009	Corporate Social Responsibility	-
J.-B. Kim et al., (2016)	17,562 firm-year observations from S&P 1500 Index from 1993 - 2010	CEO overconfidence	+
Andreou et al., (2016)	18,649 firm-year observations from 1995 - 2013	CEO age	-
J.-B. Kim et al., (2011)	29,638 firm-year observations from the United States from 1993 - 2009	CFO equity incentives	+
Callen & Fang (2015a)	80,404 firm-year observations from 1971 - 2000	County level of religiosity	-
Callen & Fang (2013)	61,705 firm-year observations from 1981 - 2008	Institutional investor stability	-

Table 1 – Summary of the main stock price crash predictors

2.4. *Exploring Stock Price Crash Risk*

The motivation for exploring the impact of stock price crash predictors on portfolio performance comes from the study from Ak et al., (2016). As far as we are aware, this is one of the first studies where a framework was developed in order to apply the insights from stock crash literature to portfolio management. Using CRASH as the main dependent variable and a sample from S&P United States BMI ranging from July 2001 to July 2014, the authors concluded that the main 5 crash influencers (according to their variable) were detrended stock turnover, financial statement opacity, short-interest, forecasted sales growth and book-to-market value.

The developed framework is very simple and intuitive. They separated the predictors that positively contributed to stock price crash (the first four previously mentioned) from the ones that reduce crash likelihood (book-to-market value). Then, all the 6-month period observations were ranked relative to these main predictors and a simple rule was applied. Thus, if a stock was among the top 20% of each of the positive influencers, it was considered to have a "crash-flag". The same happened for the stocks that were in the bottom 20% of the book-to-market ratio value.

Hence, for each 6-month period, a stock could have between 0 and 5 crash-flags being that the higher the number of crash-flags associated, the more likely the stock was to crash in the subsequent period.

Therefore, to analyse the impact of these crash-flags, at the beginning of each 6-month period, the authors created two different portfolios. The first one, considered to be "low-crash-risk" was constituted by stock with 0, 1 or 2 crash-flags at the beginning of the period. The other, "high-crash-risk" portfolio, had stocks with over 3 or more crash-flags at the beginning of the period. After running these portfolios for the period, both on a value and equal-weighted basis, their conclusions were enlightening

The results from the value-weighted portfolio revealed three important facts. Firstly, the "high-crash-risk" portfolio (annualized excess return = 2.08%) underperformed the "low-crash-risk" one (annualized excess return = 4.33%) and the benchmark (annualized excess return = 4.26%). Secondly, the "high-crash-risk" portfolio presented higher volatility (volatility = 24.62%) than the "low-crash-risk" (volatility = 15.17%) and the benchmark (volatility = 15.40%) hence, leading to a lower Sharpe Ratio than the "low-crash-risk" portfolio and the benchmark. Lastly, the "low-crash-risk” portfolio is similar to the benchmark due to the fact that, being value-weighted, only a small fraction of companies belonged to the “high-crash-risk” portfolio thus, about 90% of the benchmark was made of “low-crash-risk” holdings. (Ak et al., 2016 - p. 36).

Using equal-weighted portfolios, the results are even more pronounced. In this situation, the “high-crash-risk” portfolio achieved a negative Sharpe Ratio of -0.2191 whereas the “low-crash-risk” portfolio performed with a ratio of 0.4142 (Ak et al., 2016 - p. 36).

In conclusion, with this simple strategy aimed at avoiding high-crash-risk stocks, the authors demonstrated that is it possible to achieve higher returns with lower risk.

3. Data & Methodology

3.1. Data

The data is entirely retrieved from Thomson Reuters DataStream.

In order to achieve a wide representation of the main European economies, we based our sample on the STOXX® Europe 600 index. Our initial sample comprises all the companies included in STOXX ® Europe 600 index at the beginning of each of the 28 considered semesters. This index includes companies from 17 different countries across Europe with small to large market capitalization' companies.

As in previous literature, we divide our analysis in 6-month periods (for example, Chen et al., (2001) or Ak et al., (2016)) . Thus, because the index components are not static over time, we collected its constituents at the beginning of each period (i.e., 1st January and 1st July) and assume that these will remain part of the index until the beginning of the subsequent period. Since we will be using the Index return as benchmark, we understand that fixing the companies ex-ante may not be the most correct approach however, since the main constituents remain fairly constant over each 6-months period, the only problem this method will comprise is that it will retrieve a smaller amount of data since most of the companies that are delisted from the index were either acquired or bankrupt.

Due to data limitations, the initial data ranges from January 2003 until July 2016, consisting in 16,801 observations divided in 28 periods (semesters).

As in many indexes, our sample contains companies from different industries. We classify the firms in accordance to Thomson Reuters General Industry Classification. It divides companies in 6 distinct industry codes: 1 - Industrial, 2- Utility, 3- Transportation, 4- Banks/Saving & Loan, 5- Insurance, 6- Other Financial. Below we present the frequency table for the industry codes.

Table 2

Industry Code

The table contains the frequency and percentages of the industries contained in our sample. "Missing" represents the number of observations (companies) for which no industry code was retrieved. "Valid Percent" represents the percentage of each industry on the overall industry population. Industry legend: 1- Industrial, 2- Utility, 3-Transporation, 4- Banks/Saving & Loan, 5- Insurance, 6- Other Financial.

Industry Code

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	11079	65.9	66.2	66.2
	2	1437	8.6	8.6	74.8
	3	484	2.9	2.9	77.7
	4	1643	9.8	9.8	87.5
	5	901	5.4	5.4	92.9
	6	1193	7.1	7.1	100.0
	Total	16737	99.6	100.0	
Missing	System	64	0.4		
Total		16801	100.0		

Table 2 – Initial sample industry codes

Size is an important factor for stock price crash literature. As Chen et al., (2001) concluded, small-caps are more positively skewed in terms of returns than large caps (Chen et. al., 2001 - p. 379). Hence, as we compare our average value for SIZE (3.836) with Chen et al., (2001) study (5.177), we realize that we are dealing with a different type of sample which may certainly result in lower values for our crash measures and thus, lower variable significance. Also, as we can see from the graph below, we have a slightly higher propensity of smaller firms represented by a lower median (3.752) than the mean.

Figure 1

Company' size distribution

"Size" is measured as the log of the company's market capitalization. "Frequency" is the number of companies.

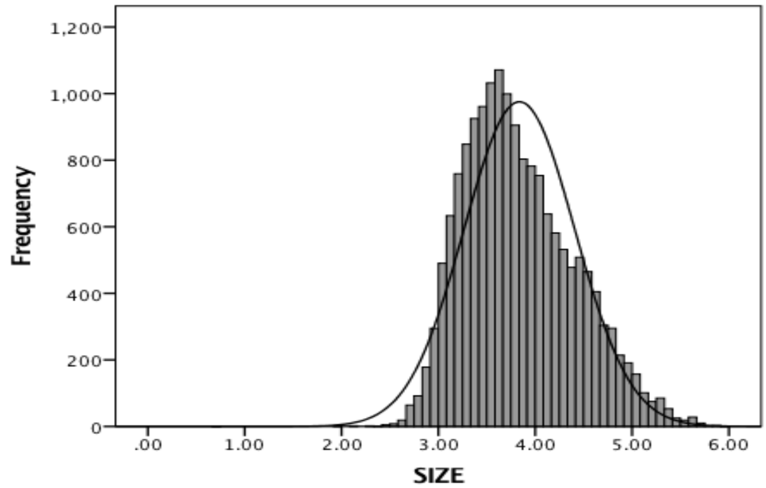

Figure 1- Company size frequency distribution

3.2. Methodology

In order to understand what impacts the stock price crash likelihood in our sample, we perform a series of cross-sectional regressions.

Our dependent variables, measures of stock price crash risk, include DUVOL, NCSKEW, CRASH and MIN.RET (all previously explained in chapter 2). All the returns used in the calculation of these variables are market adjusted. Note that every variable is constructed in a way that a higher value represents a higher stock crash measure.

CRASH and MIN.RET were chosen mainly for two reasons. Firstly, as Ak et al., (2016) mention, these measures focus only on the left side of the returns distribution whereas others such as DUVOL or NCSKEW focus on the overall distribution. Secondly, MIN.RET was chosen because of its ease of interpretation. DUVOL and NCSKEW were chosen because of their importance on the overall stock price crash literature.

However, from all the above, DUVOL will be our main variable of interest because firstly, it is one of the most commonly used measures for stock price crash studies and secondly, it is more intuitive to understand than NCSKEW.

Our independent variables include several factors which previously literature already defined. It is imperative to state that the data for every measure of our independent variables is taken before the period in consideration, i.e., to explain the stock price crash on period t+1 (next 6-month period), we use data that would be available to the investor the period before t (current 6-month period). Hence, all explanatory variables are available in the previous period relative to the explained variables.

Following Callen & Fang, (2015b) we use detrended turnover (DTURNOVER) as a measure for trading volume which can be considered a proxy for investors disagreement. Turnover is measured as the average monthly traded volume divided by the average monthly shares outstanding for the previous 6 months. In order to detrend, we subtract the previous 6 months' turnover value. We use a 6-month period measure instead of the 12-months period to be in line with our previous sample division.

As in Chen et al., (2001) past stock return (PAST_RETURN) is defined as the cumulative return of the company stock during the previous 6-month period. This return is measured as a log change in the return index of the stock provided on the database and is then market-adjusted by the contemporaneous STOXX® Europe 600 cumulative return. Market-to-book (MTB) ratio is the market capitalization divided by the latest available book value of equity provided by the database on the last day of the previous 6-month period.

Analyst coverage (COVERAGE) is measured as the logarithm of 1 plus the number of analysts following the company at the beginning of the period in analysis. The number of analysts following each company is measured by the number of earnings per share forecasts for the next year before the considered period, provided by the I/B/E/S database.

To proxy opacity (OPACITY) we use the scaled accruals measure used by Bhattacharya Uptal et al., (2003). According to the authors, higher values of scaled accruals represent higher values of earnings aggressiveness which can be thought of as an opacity measure. To do so, we sum the change in current assets for year t minus the change in current liabilities for year t minus change in cash for year t plus the change in current portion in long-term debt minus depreciation in year t plus the change in income taxes payable for year t. All this is then scaled by the value of total assets for year t-1. One advantage of this measure opposed to others is that it can be used in multiple countries (Bhattacharya Uptal et al., 2003 - p. 646). We chose this measure instead of the variant from Ak et al., (2016) of the more commonly used accrual volatility measure of Hutton et al., (2009) because doing so would result in a much smaller sample due to data limitations.

In order to measure liquidity (ILLIQUIDITY), we use the same approach as Huberman & Halka, (2001) in constructing a spread/price ratio. To do so, we compute, for each trading day, the ratio of the bid-ask spread to its midpoint. Then as in Chang et al., (2017), in order to construct the variable, we take the arithmetic mean of this daily measure for the 12 months before the considered period. Note that a higher value on this measure, represents a larger percentage of the bid-ask spread relative to its price meaning that, the stock is less liquid (more illiquid) than an otherwise lower value. We are aware of the existence of other liquidity proxies believed to be better representative of this property however, we lacked data on money-value-traded-volume for most European countries in order to calculate a more complete measure like in Amihud, (2002) as suggested in Goyenko et al., (2009).

Corporate social responsibility (CSR) was measured with a variant from the work of Y. Kim et al., (2014). ASSET4 Environmental, Social and Corporate Governance Data, through Thomson Reuters DataStream, provides an equal weighted average score to assess how well the company acts in areas such as environmental, social and corporate governance. The higher the value, the better the company performs in the respective area being that 100 is the maximum value. Hence, higher values on this variable represent companies that are viewed as companies with better environmental, social and corporate governance practices. We use this measure as a percentage thus, every CSR score provided by ASSET4 is divided by 100.

Forecasted sales growth (SGROW) is measured the same way as in Ak et al., (2016). To do so, on the day before the start of the period, we collected the mean estimate for company sales for the next year (FY1) and for the year after (FY2) on I/B/E/S database. The variable is the ratio between FY2 estimate and FY1, minus 1. Forecasted net margin growth (NMGROW) is measured as the forecasted net margin two years from the starting date minus the forecasted net margin one year after the starting period date.

Size (SIZE) is the logarithm of the market capitalization of the company on the day before the starting period.

Leverage (LEVERAGE) is measured as the ratio on total liabilities to total assets on the preceding day of period start.

Returns' volatility is measured by the sample standard deviation of the daily logarithmic returns on the previous 6 months before the period starting date (SIGMA).

DUVOL t-1 is the value of DUVOL (our main dependent variable) for the previous 6-month period.

At the end, we get 11,200 data points with values for every variable (list-wise) to be included in the regressions. We understand that this is a smaller number than most studies performed on this topic which may (and will) influence the results. However, this is a particularity we have to adapt to in order to have the diversity supplied on an index such as STOXX® 600 Europe. Also, due to data limitations on variables such as corporate social responsibility (CSR), we are forced to start analysis in 2003 because no data is available prior to that. The last year of the analysis, 2016, is also a necessity since no data on accruals is available for 2017.

Table 3
Summary Statistics – Independent Variables

The sample period is from January 2003 to December 2016. DTURNOVER is the monthly average value of the traded volume dividing by the number of shares outstanding for the previous 6-month period detrended by the same measurement on the 6 months before. PAST_RETURN is the cumulative return of the company stock during the previous 6-month period. BTM is the inverse of the market-to-book value provided by the database on the last day of the previous 6-month period. COVERAGE is the log of 1 plus the number of analysts following the company at the beginning of the period in analysis. OPACITY is measured through scaled accruals. ILLIQUIDITY is measured as the average bid-ask spread scaled by its mean. CSR is the score provided by ASSET4 divided by 100 (%). SGROW is the ratio of the sales forecast for the next fiscal year divided by the sales forecast for the present fiscal year minus one. NMGROW is the forecasted change in margin for the next fiscal year. SIZE is measured as the logarithm of the market capitalization for the starting period date. LEVERAGE is the ratio of total liabilities to total assets. SIGMA represents the sample standard deviation of returns for the previous period. DUVOL t-1 is the measure of DUVOL variable for the previous period.

Summary Statistics

				Percentiles		
	N	Mean	Std. Deviation	25	50	75
DTURNOVER	16417	0.0011	0.0473	-0.0126	0.0004	0.0133
PAST_RETURN	16753	0.0019	0.0888	-0.0398	0.0063	0.0508
MTB	16290	2.8494	45.8424	1.2300	2.0300	3.3600
COVERAGE	16654	1.2033	0.2682	1.1139	1.2553	1.3802
ILLIQUIDITY	16720	0.0030	0.0045	0.0010	0.0017	0.0032
OPACITY	12597	-0.0415	0.0941	-0.0737	-0.0400	-0.0088
CSR	15247	0.7055	0.2701	0.5485	0.8248	0.9169
SGROW	16416	0.0605	0.1435	0.0272	0.0496	0.0785
NMGROW	16367	0.0020	4.2483	0.0008	0.0045	0.0108
SIZE	16800	3.8360	0.5724	3.4052	3.7516	4.2163
LEVERAGE	16611	0.6488	0.2333	0.5075	0.6409	0.7976
SIGMA	16753	0.0085	0.0045	0.0056	0.0073	0.0099
DUVOL t-1	16751	-0.1327	0.4172	-0.3621	-0.1301	0.1001

Table 3 - Summary statistics - Independent Variables

Comparing our sample and methodology with Ak et al., (2016) we realize some differences.

To start, their analysis is performed in the United States market whereas our is from European companies. Even though both studies applied the 6-month period framework, Ak et al., (2016) sample ranges from July 2001 – July 2014 whereas our ranges from January 2003 until July 2016.

There are also some differences concerning variable construction and variable usage.

First, we contribute to another dimension of the work by adding DUVOL as a new dependent variable.

On what is concerning to explanatory variables, their detrended turnover measure follows Chen et al., (2001) measured as the monthly share turnover for the previous 6-month period detrended by subtracting the average turnover value for the 18 months beforehand. Our variable is an adaption of the simpler, but equally predictable, measure from Callen & Fang (2015b).

Financial reporting opacity is also different. Ak et al., (2016) uses a "variant of the accrual volatility measure in Hutton et al., (2009)." (Ak et al., 2016 – p. 30). Such variable would eliminate most of our sample because of lacking data. Hence, we decided to use the above mentioned scaled accrual measure.

Also, to try to keep the variables in such a way that expected higher values increase stock price crash, we use the market-to-book ratio instead of the book-to-market ratio from Ak et al., (2016).

Even though we were not able to use short interest in our regressions (SHORT), we included two extra variables studied in previous works. These include a stock liquidity measure (ILLIQUIDITY) and corporate social responsibility score (CSR).

Finally, since our main dependent variable is different from Ak et al., (2016), our lagged value of stock price crash likelihood is measured through DUVOL t-1 instead of CRASH t-1.

Besides these differences, we also add another set of variables to their regression. Below, we present a table with the used variables in each study.

Table 4
Stock price crash variables – comparison

Comparison of the variables used in each study.

Our study		Ak et al., (2016)	
Dependent variables	Independent variables	Dependent variables	Independent variables
NCSKEW	DTURNOVER	NCSKEW	DTURNOVER
DUVOL	PAST_RETURN	CRASH	PAST_RETURN
CRASH	MTB	MIN.RET	BTM
MIN.RET	COVERAGE		COVER
	ILLIQUIDITY		OPACITY
	OPACITY		SHORT
	CSR		SGROW
	SGROW		NMGROW
	NMGROW		SIZE
	SIZE		LEVERAGE
	LEVERAGE		SIGMA
	SIGMA		CRASH t-1
	DUVOL t-1		

Table 4 - Stock price crash variables - comparison

4. Empirical Results

We now present the results divided in 2 different parts. Firstly, we will present descriptive statistics of the crash risk measures. Then, we will analyse the results of our model regressions.

4.1. Stock price crash measures

Table 5
Summary Statistics – Dependent Variables

The sample period is from January 2003 to December 2016. All the formulas for the dependent variables have been previously explained.
DUVOL (Equation b), NCSKEW (Equation a), CRASH (Equation c).

Summary Statistics					
		DUVOL	NCSKEW	CRASH	MIN.RET
N	Valid	16793	16801	16751	16800
	Missing	8	0	50	1
Mean		-0.144	0.015	3.682	2.50%
Median		-0.131	-0.033	2.938	1.90%
Std. Deviation		0.507	1.253	2.876	2.49%
Maximum		6.160	10.171	90.757	66.50%
Percentiles	5	-0.779	-1.556	1.520	0.90%
	95	0.522	1.898	8.169	6.00%

Table 5 - Summary statistics - Dependent variables

We start by analysing our dependent variables.

Table 3 provides descriptive statistics of the dependent variables used in our regressions. DUVOL has a sample mean value of -0.144 which is higher than the value obtained by Chen et al., (2001) (mean value of -0.190) but much lower than the results of Y. Kim et al., (2014) (mean value of -0.002). Surprisingly, our DUVOL measure is very similar to Francis et al., (2016) values of -0.141 for the mean and 0.505 for standard deviation. Clearly, this is just a coincidence because, even though the authors do not explain where their data comes from, the time period is different (which ranges from 1989 to 2009). Nevertheless, the main conclusion we can take from DUVOL is that, according to this measure, given that it has a negative mean value, stock returns for the sample present a positive skewness.

NCSKEW has a mean value of 0.015. When comparing our 95% percentile (1.898) to Ak et al., (2016) value (2.28), we realize we have a smaller incidence of extreme values than their study.

CRASH, conceived by Ak et al., (2016), has a mean value of 3.682. This means, according to the authors, that the minimum daily return over a 6-month period averages 3.682 standard deviations. Comparing to the authors' value of 3.62, we realize we have a more volatile sample. This conclusion is supported by the differences in standard deviation (2.876 versus 2.39).

MIN.RET even though included for ease of interpretation, provides some great insights for comparison. As we can see, the mean value for minimum return over a 6-month period is -2.50%. This value greatly differs from the one presented in Ak et al., (2016) (mean value of -8.29%). Besides this, we also notice the discrepancy not only between our standard deviation value (2.49%) and the previous authors' standard deviation (7.29%), but also between our median (-1.90%) and theirs (-6.17%) and the 95^{th} % percentile value (-6.00%) and theirs (-21.14%) (Ak et al., 2016 – p. 31).

Figure 2
Distribution of minimum returns (MIN.RET)

The sample period is from January 2003 to December 2016. Minimum returns (MIN.RET) is measured as the log change in the value of the return index (RI) measure from Thomson Reuters Dastream.

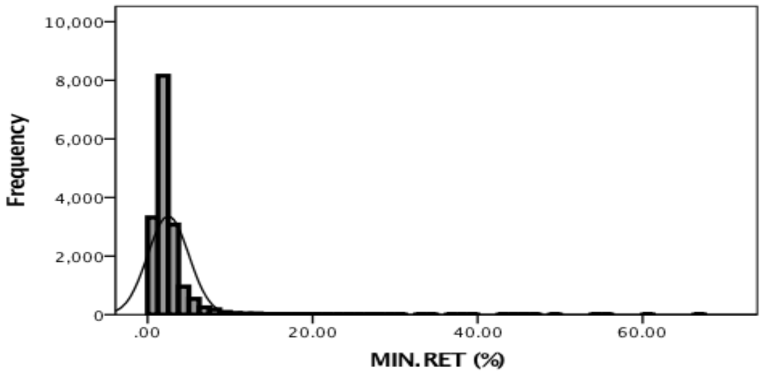

Figure 2 – Minimum return (%) frequency distribution

This comparison allows us to conclude that we are dealing with a much different sample than Ak et al., (2016). As it is easy to see, their sample presents a much higher incidence of extreme negative returns (measured by MIN.RET). There may be a lot of explanations for these differences (geography, time period, industry selection, etc.). The descriptive analysis also shows the minimum return over the 6-month period in our data is -66.50%. As expected, the correlation between all crash measures are positive and significant. Since DUVOL and NCSKEW measure stock price crash likelihood through a different logic than the others, their correlation to the other two variables is the lowest. CRASH and MIN.RET have a high correlation (0.780) because both focus on the same section of returns distribution, the left tail. Correlation between CRASH and MIN.RET is slightly higher in our sample than Ak et al., (2016) correlation of 0.71 (Ak et al., 2016 – p. 31).

Table 6
Correlations – Dependent Variables

The sample period is from January 2003 to December 2016. All the formulas for the dependent variables have been previously explained.
DUVOL (Equation b), NCSKEW (Equation a), CRASH (Equation c).

Correlations

	DUVOL	NCSKEW	CRASH	MIN.RET
DUVOL	1			
NCSKEW	.663**	1		
CRASH	.365**	.576**	1	
MIN.RET	.259**	.485**	.780**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6 - Correlations - Dependent variables

Nevertheless, we realize that NCSKEW (in Ak et al., (2016)), is less correlated to CRASH and MIN.RET (0.55 to the first and 0.39 to the latter) than in our sample.

4.2. Regression analysis

We start our analysis by looking at the correlations between the variables which provides us with some important insights about our sample.

Table 7
Correlations – Independent Variables

The sample period is from January 2003 to December 2016. DTURNOVER is the monthly average value of the traded volume dividing by the number of shares outstanding for the previous 6-month period detrended by the same measurement on the 6 months before. PAST_RETURN is the cumulative return of the company stock during the previous 6-month period. BTM is the inverse of the market-to-book value provided by the database on the last day of the previous 6-month period. COVERAGE is the log of 1 plus the number of analysts following the company at the beginning of the period in analysis. OPACITY is measured through scaled accruals. ILLIQUIDITY is measured as the average bid-ask spread scaled by its mean. CSR is the score provided by ASSET4 divided by 100 (%). SGROW is the ratio of the sales forecast for the next fiscal year divided by the sales forecast for the present fiscal year minus one. NMGROW is the forecasted change in margin for the next fiscal year. SIZE is measured as the logarithm of the market capitalization for the starting period date. LEVERAGE is the ratio of total liabilities to total assets. SIGMA represents the sample standard deviation of returns for the previous period. DUVOL t-1 is the measure of DUVOL variable for the previous period.

Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
NCSKEW (1)	1																
DUVOL (2)	.663**	1															
CRASH (3)	.576**	.365**	1														
MIN.RET (4)	.485**	.259**	.780**	1													
DTURNOVER (5)	0.006	-.023**	-.021**	.041**	1												
PAST_RETURN (6)	.025**	.064**	-.052**	-.166**	-.130**	1											
MTB (7)	.018*	0.003	.055**	.068**	-0.007	0.013	1										
COVERAGE (8)	.035**	.065**	.021**	-.038**	-.033**	-.025**	0.003	1									
ILLIQUIDITY (9)	-0.005	-.060**	-.060**	.081**	.049**	0.006	-0.013	-.274**	1								
OPACITY (10)	-0.004	-0.004	-0.001	-0.012	0.010	.026**	.023**	-.020*	-.041**	1							
CSR (11)	0.015	.029**	.021*	-.054**	-.046**	-0.012	-.024**	.406**	-.219**	-0.008	1						
SGROW (12)	.018*	0.013	.031**	.056**	0.014	.050**	0.010	-.028**	.043**	.042**	-.086**	1					
NMGROW (13)	0.006	0.000	0.008	0.013	0.001	-0.009	0.000	0.007	-0.001	0.016	-0.012	.049**	1				
SIZE (14)	.034**	.097**	.027**	-.120**	-.024**	.093**	.016*	.362**	-.265**	0.003	.304**	-0.015	-0.006	1			
LEVERAGE (15)	-.025**	-.028**	0.008	.036**	.018*	-.073**	-0.001	.041**	.037**	-.088**	.056**	-.068**	0.005	.020*	1		
SIGMA (16)	-0.003	-.083**	-.103**	.343**	.118**	-.251**	-0.011	-0.008	.179**	-0.008	-.058**	.025**	0.008	-.184**	.065**	1	
DUVOL t-1 (17)	.023**	.069**	.038**	.027**	.037**	-.342**	-0.007	.058**	-.072**	-0.011	.042**	-0.012	0.009	.035**	-.027**	-0.003	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 7 - Correlations - Independent variables

As we can denote right away, NCSKEW and DUVOL have very low correlation with SIGMA. This result supports the idea that forecasting returns skewness is different from forecasting volatility (Chen et al., - p. 359). However, the same can't be said regarding MIN.RET. This conclusion was somewhat expected due to its inherent simplicity. Another result which goes in line with Chen et al., (2001) is the negative correlation between firm size (SIZE) and return volatility (SIGMA). This result was also expected since lower market capitalization firms tend to have more volatile returns. This last result is linked to the positive correlation between illiquidity and returns' volatility.

This result is supported on the premise that higher market capitalization stocks (higher SIZE) tend to have higher liquidity (lower ILLIQUIDITY) which is reinforced by the negative correlation coefficient between these two last measures.

Past returns (PAST_RETURN) and past returns' volatility (SIGMA) presents a correlation of -0.251. The correlation between returns and volatility has been widely studied by the academy and while classic models defend a positive relationship between stock returns and volatility (for example, Sharpe (1964)), others state the existence of a negative relationship (for example, Li et al., (2005) or Bae et al., (2007)).

The negative coefficient between corporate social responsibility (CSR) and opacity (OPACITY) is also an expected result due to the fact that financial reporting is a parameter used to calculate the CSR score hence, higher values of opacity should result in lower CSR scores.

Other expected results include the fact that bigger companies tend to have more sell-side analysts following them (positive correlation between SIZE and COVERAGE) and that more closely followed companies tend to have higher corporate social responsibility scores (our highest correlation coefficient is between COVERAGE and CSR).

Lastly, an important result is the fact that DUVOL and DUVOL t-1 have present a low coefficient which assures us that no autocorrelation issues exist between these two measures.

We now present the results of our regressions. As previously explained, we regressed all of our dependent variables to the factors that previous literature concluded to impact stock price crash likelihood.

Firstly, due to their importance, we analyse the results from DUVOL and NCSKEW as dependent variables.

Table 8
Regression results with DUVOL and NCSKEW as dependent variables

The sample period is from January 2003 to December 2016. DTURNOVER is the monthly average value of the traded volume dividing by the number of shares outstanding for the previous 6-month period detrended by the same measurement on the 6 months before. PAST_RETURN is the cumulative return of the company stock during the previous 6-month period. BTM is the inverse of the market-to-book value provided by the database on the last day of the previous 6-month period. COVERAGE is the log of 1 plus the number of analysts following the company at the beginning of the period in analysis. OPACITY is measured through scaled accruals. ILLIQUIDITY is measured as the average bid-ask spread scaled by its mean. CSR is the score provided by ASSET4 divided by 100 (%). SGROW is the ratio of the sales forecast for the next fiscal year divided by the sales forecast for the present fiscal year minus one. NMGROW is the forecasted change in margin for the next fiscal year. SIZE is measured as the logarithm of the market capitalization for the starting period date. LEVERAGE is the ratio of total liabilities to total assets. SIGMA represents the sample standard deviation of returns for the previous period. DUVOL t-1 is the measure of DUVOL variable for the previous period. All the estimates are standardized coefficients. Intercept not shown. ***, **, * are used to flag estimates statistically significant at 1%,5% and 10%, respectively.

	Panel A		**Panel B**	
	Dependent variable = DUVOL		Dependent variable = NCSKEW	
Variable (Pred.)	Estimate	t-statistic	Estimate	t-statistic
DTURNOVER (+)	0.020**	2.057	0.018*	1.936
PAST_RETURN (+)	0.076***	7.298	0.030***	2.848
MTB (+)	0.028***	3.013	0.045***	4.808
COVERAGE (+)	0.027**	2.401	0.026**	2.329
ILLIQUIDITY (-)	-0.019*	-1.901	0.013	1.256
OPACITY (+)	-0.013	-1.380	-0.009	-0.928
CSR (-)	-0.003	-0.291	-0.001	-0.097
SGROW (+)	0.024**	2.496	0.018*	1.877
NMGROW (+)	0.005	0.555	0.009	0.923
SIZE (+)	0.045***	4.112	0.013	1.153
LEVERAGE (-)	-0.016*	-1.689	-0.025***	-2.614
SIGMA (-)	-0.059***	-5.944	-0.012	-1.226
DUVOL t-1 (+)	0.041***	4.077	0.038***	3.789
Adjusted R^2	0.018		0.005	

Table 8 - Regression results with DUVOL and NCSKEW as dependent variables

Panel A shows the regression estimates for our main variable of interest, DUVOL. Denote that, the predicted signs of the independent variables are based on previous studies concerning DUVOL and NCSKEW. As expected, detrended turnover (DTURNOVER), past return (PAST_RETURN), market-to-book value and company size (SIZE) load with positive signs and high significance. These results were expected since previous studies using DUVOL as dependent measure, achieved the same results (for example, Chen et al., (2001), Callen & Fang, (2013) or Callen & Fang, (2015b)). This means that higher values on these measures, imply a higher crash likelihood. Returns' volatility (SIGMA) also loads with the expected negative signs and high significance. Our results for DUVOL shows 3 other measures with p-values below 10%. Analyst coverage (COVERAGE) goes in line with the results from Chen et al., (2001) however, their results have higher t-statistic (3.288 vs 2.401). There may be many justifications for this however, the one that seems more reasonable is on what is related to market dynamics. The U.S. stock market (from where their sample comes from) is much more vibrant than European markets and thus, analysts are more critical in driving opinions than in Europe. Nevertheless, this is just a possibility and further studies would be needed to validate it. Sales growth (SGROW) loads with positive sign (the same predicted in Ak et al., (2016)). Leverage (LEVERAGE), loads with negative sign meaning that increases in leverage reduce crash likelihood. Our variable for financial opacity (OPACITY) did not provide any relevant results since besides loading with a negative coefficient, it is not statistically significant. Stock market illiquidity (ILLIQUIDITY) loads with the predicted sign but low significance. Also, as expected, DUVOL t-1 loads with positive sign and high significance meaning that more crash-prone stocks in the past, will remain more crash-prone in the future.

Panel B provides the results for NCSKEW as dependent variable. The results remain fairly consistent with the ones from DUVOL (except for ILLIQUIDITY). An interesting result, which is a consequence of the high correlation between NCSKEW and DUVOL is that DUVOL t-1 is also very useful in predicting negative conditional skewness. As result, higher values of past DUVOL result in more significant negative skewness measured with NCSKEW.

Table 9
Regression results with CRASH and MIN.RET as dependent variables

The sample period is from January 2003 to December 2016. DTURNOVER is the monthly average value of the traded volume dividing by the number of shares outstanding for the previous 6-month period detrended by the same measurement on the 6 months before. PAST_RETURN is the cumulative return of the company stock during the previous 6-month period. BTM is the inverse of the market-to-book value provided by the database on the last day of the previous 6-month period. COVERAGE is the log of 1 plus the number of analysts following the company at the beginning of the period in analysis. OPACITY is measured through scaled accruals. ILLIQUIDITY is measured as the average bid-ask spread scaled by its mean. CSR is the score provided by ASSET4 divided by 100 (%). SGROW is the ratio of the sales forecast for the next fiscal year divided by the sales forecast for the present fiscal year minus one. NMGROW is the forecasted change in margin for the next fiscal year. SIZE is measured as the logarithm of the market capitalization for the starting period date. LEVERAGE is the ratio of total liabilities to total assets. SIGMA represents the sample standard deviation of returns for the previous period. DUVOL t-1 is the measure of DUVOL variable for the previous period. All the estimates are standardized coefficients. Intercept not shown. ***, **, * are used to flag estimates statistically significant at 1%,5% and 10%, respectively.

	Panel C		**Panel D**	
	Dependent variable = CRASH		Dependent variable = MIN.RET	
Variable (Pred.)	Estimate	t-statistic	Estimate	t-statistic
DTURNOVER (+)	-0.004	-0.384	0.008	0.854
PAST_RETURN (+)	-0.067***	-6.519	-0.080***	-8.193
MTB (+)	0.097***	10.459	0.131***	14.867
COVERAGE (+)	-0.004	-0.354	-0.028***	-2.672
ILLIQUIDITY (-)	-0.044***	-4.435	-0.003	-0.292
OPACITY (+)	-0.006	-0.651	-0.017*	-1.914
CSR (-)	-0.003	-0.335	-0.027***	-2.809
SGROW (+)	0.041***	4.287	0.063***	7.039
NMGROW (+)	0.006	0.672	0.006	0.696
SIZE (+)	-0.021*	-1.911	-0.048***	-4.601
LEVERAGE (-)	-0.002	-0.261	0.004	0.420
SIGMA (-)	-0.139***	-14.166	0.288***	31.094
DUVOL t-1 (+)	0.002	0.175	-0.004	-0.404
Adjusted R^2	0.033		0.134	

Table 9 - Regression results with CRASH and MIN.RET as dependent variables

Panel C provides the results for CRASH as dependent variable. In this case, with our set of data, detrended turnover (DTURNOVER) does not provide relevant explanatory power. Our main reason for this is the fact that our turnover variable is not the same as CRASH authors used thus, it may not capture variations the same way. Surprisingly, financial opacity (OPACITY) loads with a negative sign and high explanatory power. We cannot see any reason for this to happen besides the fact that this measure is clearly not appropriate for our sample. Past returns (PAST_RETURN) and leverage (LEVERAGE), even though loading with a different sign than the predicted one and high significance, the same happens in Ak et al., (2016). DUVOL t-1 is now not statistically significant. This happens because, as previously explained, DUVOL focus on a different dispersion of returns from CRASH and MIN.RET which only focus on the negative side.

Panel D presents the results for MIN.RET as dependent variable. As explained, this measure is included only for ease of interpretation however, there are some conclusions we can take from it. Analyst coverage (COVERAGE) loads with high significance and opposite sign than it was predicted. Remember that MIN.RET is the highest negative return for the considered period. A possible explanation for this is that, higher number of analysts following the company allow a more evenly distribution of news (both bad and good) hence, given this constant information flow, the stocks are less prone to really extreme movements. This seems a plausible explanation however it would need further investigation to be corroborated. A very interesting result is the sign of the corporate social responsibility (CSR) measure. Accordingly, and in line with previous studies, higher values of this measure result in lower crash probability. This is the case with this measure. Once again, DUVOL t-1 loses its explanatory power and SIGMA now loads with the opposite sign, in line with Ak et al., (2016).

As shown by the results, the majority of our variables load with the predicted signs from previous studies.

There is, however, an important conclusion arising from these results. Firm size (SIZE), loads with positive sign for DUVOL and NCSKEW and negative for CRASH and MIN.RET. Even though they are, in each case, in line with previous studies, it is well-known that lower capitalization stocks are more crash-prone. There are several theories supporting both sides of the equation. Our goal, however, is to see how this factor impacts the overall portfolio performance, using our main dependent variable as crash measure.

Below, we present tables comparing our results with DUVOL as dependent variable with Ak et al., (2016) results with both CRASH (their main variable of interest) and NCSKEW as explained variables.

Note that the scale differences between estimates is due to the fact that ours are the standardized coefficients retrieved by the estimation output.

Table 10
Regressions comparison – Ak et al., (2016) (1)

Comparison of DUVOL regression results with CRASH regression results from Ak et al., (2016). Intercept not shown. ***, **, * are used to flag estimates statistically significant at 1%,5% and 10%, respectively. Source for Panel F data from Ak et al., (2016). Panel F sample data is from S&P United States BMI firms with market capitalization above $100 million ranging from July 2001 to July 2014 comprising 59,489 observations included in the final regressions.

	Panel A		**Panel F**	
	Dependent variable = DUVOL		Dependent variable = CRASH	
Variable (Pred.)	Estimate	t-statistic	Estimate	t-statistic
DTURNOVER (+)	0.020**	2.057	0.580***	6.12
PAST_RETURN (+)	0.076***	7.298	-0.328***	-8.22
MTB (+)	0.028***	3.013		
BTM			-0.137***	-5.18
COVERAGE (+)	0.027**	2.401	0.160***	7.83
OPACITY (+)	-0.013	-1.380	0.550***	4.91
SGROW (+)	0.024**	2.496	0.421***	6.84
NMGROW (+)	0.005	0.555	0.119	1.55
ILLIQUIDITY (-)	-0.019*	-1.901		
CSR (-)	-0.003	-0.291		
SHORT			2.400***	22.13
SIZE (+)	0.045***	4.112	-0.122***	-12.15
LEVERAGE (-)	-0.016*	-1.689	-0.213***	-5.46
SIGMA (-)	-0.059***	-5.944	-36.372***	-38.48
DUVOL t-1 (+)	0.041***	4.077		
CRASH t-1			0.026***	5.34
Adjusted R^2	0.018		0.042	

Table 10 - Regressions comparison – Ak et al., (2016) (1)

Even though different in their dependent variables, both regressions present similar results. The main differences are related to the difference in sign for past returns

(PAST_RETURNS) which was not predicted beforehand by Ak et al., (2016) and size (SIZE) for which the authors did not provide any prediction at all. As we can see, short interest (SHORT) is very useful at explaining stock price crashes. On what financial opacity (OPACITY) is concerned, it shows good value to predict stock price crashes.
It is also important to notice that lagged values of both dependent variables show great contribution to forecast crash likelihood hence, we conclude that previously crash-prone firms tend to continue so in the future.

Table 11
Regressions comparison – Ak et al., (2016) (2)

Comparison of DUVOL regression results with NCSKEW regression results from Ak et al., (2016). Intercept not shown. ***, **, * are used to flag estimates statistically significant at 1%,5% and 10%, respectively. Source for Panel F data from Ak et al., (2016). Panel F sample data is from S&P United States BMI firms with market capitalization above $100 million ranging from July 2001 to July 2014 comprising 59,489 observations included in the final regressions.

	Panel A		**Panel G**	
	Dependent variable = DUVOL		Dependent variable = NCSKEW	
Variable (Pred.)	Estimate	t-statistic	Estimate	t-statistic
DTURNOVER (+)	0.020**	2.057	0.308***	5.15
PAST_RETURN (+)	0.076***	7.298	0.273***	10.34
MTB (+)	0.028***	3.013		
BTM			-0.015	-0.88
COVERAGE (+)	0.027**	2.401	-0.001	-0.09
OPACITY (+)	-0.013	-1.380	0.010	0.13
SGROW (+)	0.024**	2.496	0.164***	4.18
NMGROW (+)	0.005	0.555	-0.126***	-2.56
ILLIQUIDITY (-)	-0.019*	-1.901		
CSR (-)	-0.003	-0.291		
SHORT			0.178**	2.56
SIZE (+)	0.045***	4.112	0.030***	4.73
LEVERAGE (-)	-0.016*	-1.689	-0.095***	-3.82
SIGMA (-)	-0.059***	-5.944	-6.891***	-11.75
DUVOL t-1 (+)	0.041***	4.077		
CRASH t-1			0.018***	3.63
Adjusted R^2	0.018		0.008	

Table 11 - Regressions comparison – Ak et al., (2016) (2)

Nevertheless, the comparison between DUVOL and CRASH provides us with more interesting insights. Being that they are more similar to each other than to CRASH, as evidenced by our correlation analysis, we expected that the impact of each variable on the dependent variables would be, at least, in the same direction.

This happens for the majority of our predictors except for net margin growth (NMGROW) however, our estimate is not significant.

Another interesting result is that analyst coverage (COVERAGE) becomes not significant for Ak et al., (2016). This is somehow unexpected since previous studies found a positive relation between both these measures (for example, Chen et al., (2001)).

Financial opacity (OPACITY) also becomes statistically non-significant.

According to the authors, the fact that these variables (BTM, COVERAGE and OPACITY) become statistically non-significant means that "these variables must predict both extreme crashes and jumps in stock prices, rather than predicting crashes alone" (Ak et al., (2016) – p. 32).

This last conclusion will have impact in the second segment of this study since market-to-book (the inverse of book-to-market) will be used as a crash-flag predictor for our asset-allocation strategy.

5. Investment implications

5.1. Strategy

The most stimulating insight from any empirical study is to understand how the results can be applied. To do so, we hypothesized whether it is possible to achieve better risk-adjusted results by applying a set of investment rules aiming at reducing the incidence of high crash-prone stocks in a portfolio. Inspired by Ak et al., (2016) framework, we will backtest our results to see what effect an ex-ante trading strategy would produce.

For this, we start by identifying according to our main dependent variable (DUVOL), the more significant crash predictors. Our regressions estimated 10 variables with high statistical significance. Below, we rank them by predictive power.

Table 12
Crash-flags ranking

Variables presented in this tables are the ones that loaded with the predicted sign. They are ranked according to their statistical significance in the regression with DUVOL as dependent variables.

Rank	Variable
1	PAST_RETURN (+)
2	SIGMA (-)
3	SIZE (+)
4	DUVOL t-1 (+)
5	MTB (+)
6	SGROW (+)
7	COVERAGE (+)
8	DTURNOVER (+)
9	ILLIQUIDITY (-)
10	LEVERAGE (-)

Table 12 - Crash-flags ranking

To perform the asset allocation analysis, we will use the same 5 crash-flag framework as Ak et al., (2016). As we can see from the above table, the top 5 crash predictors are PAST_RETURN, SIGMA, SIZE, DUVOL t-1 and MTB. Our objective, in order to minimize stock price crash risk, is to avoid stocks with high values of the variables that contribute to higher crash risk and buy stocks with high values for variables that help mitigate this likelihood.

To do this, we select the top 20% of stocks on each crash predictor. Hence, we select the top 20% stocks based on PAST_RETURN, SIZE, DUVOL t-1 and MTB. Analogously, we select the bottom 20% stocks on SIGMA. Hence, if a stock belongs to one of these groups, we classify it has having one crash-flag. Thus, a stock can have between 0 and 5 crash-flags being that, the more crash-flags a stock has, the more crash-prone it is. After selecting all companies with values for all the considered predictors, we end up with 16,240 observations for the overall 28 semesters.

Figure 3
Frequency of crash-flags

This graph shows the frequency analysis for the observations with 0, 1, 2, 3,4 or 5 crash-flags. On the left Y-axis, we have the frequency of each observation by number of crash-flags. On the right Y-axis, we have the cumulative percentage of the number of crash flags by observation

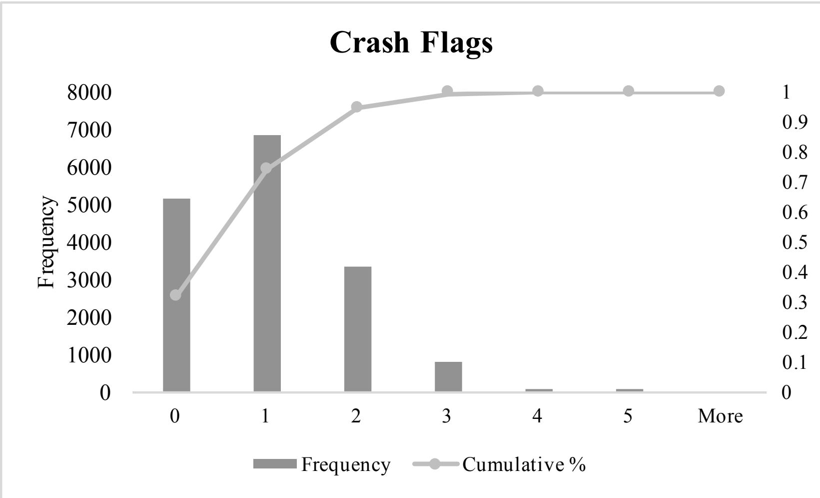

Figure 3 – Crash flags frequency and cumulative percentage distribution

As we can see, we have a much higher percentage of observations with 0 or 1 flags (32% and 42%) with only about 26% of the sample having 2 or more crash flags.

In order to see how the flags system can help us to minimize stock price crash risk, we divided them into distinct groups and computed an equal-weighted mean value for the different crash risk measures.

Table 13
Mean Investment performance over the next 6-months

All the formulas for the dependent variables have been previously explained. DUVOL (Equation b), NCSKEW (Equation a), CRASH (Equation c).

Mean Value of Crash Measures For the next 6 Months

Crash Flags	Observations	DUVOL	NCSKEW	CRASH	MIN.RET
0	31.786%	-0.167	-0.042	3.581	-2.741%
1	42.309%	-0.139	0.029	3.672	-2.470%
2	20.554%	-0.126	0.059	3.797	-2.225%
3	4.865%	-0.084	0.082	3.865	-2.088%
4	0.474%	-0.082	0.236	4.051	-1.824%
5	0.012%	0.066	0.148	4.162	-1.850%

Table 13 - Mean Investment performance over the next 6-months

For all the distribution based measures, the higher the number of flags, the higher the crash measure is for the majority of the observations. We are aware that NCSKEW decreases from group 4 to group 5 however, we believe that this is a consequence of the low percentage of observations in group 5 (0.012% or 2 observations). This means that, by using only these 5 predictors, we can build our portfolio in such a way that it, according to our variables, avoids more crash-prone stocks for the next 6-month period.
However, there is a surprising result. As shown, the minimum return (MIN.RET) measure decreases as the number of crash-flags increases. We don't know any particular reason for this unexpected result however, there is something we can infer from the previous regression tables. As documented, returns' volatility (SIGMA) is extremely significant for explaining minimum return whereas, in line with previous studies, the other measures are negatively associated with returns' volatility. Hence, since we will be using SIGMA as a crash-flag (due to its high negative significance with the other variables), we can see right away that our portfolio selection strategy will be highly influenced by this parameter. This is because, even though NCSKEW, DUVOL and CRASH assess the crash-risk based on its distribution, MIN.RET simply utilizes the minimum negative return which, plain simply, is what impacts the portfolio's performance. We hope, however, that our simple strategy can surpass this factor. Thus, we already have a very different result from Ak et al., (2016). Even though in their regressions, returns' volatility (measured by SIGMA), loaded with high significances (-38.48 for CRASH, -11.75 for

NCSKEW and +48.21 for MIN.RET (Ak et al., 2016 - p. 33)), the authors decided not to use it as a crash-flag. In order to check if this difference is due to SIGMA, we performed the same analysis using a different set of crash predictors (excluding SIGMA) and MIN.RET behaved as expected, decreasing as the number of crash-flags increased.

To test whether our predictive variables can provide some useful guidance to portfolio's management activities, we design a similar analysis to Ak et al., (2016).

We start by organizing, at the beginning of each 6-month period, all the stocks according to their crash-flags. Then, in order to isolate them, we create two distinct portfolios, a "high-crash-risk" portfolio and a "low-crash-risk" portfolio. In order to select which stocks belong to each portfolio, we analysed the percentage change value in DUVOL in each group. As in Ak et al., (2016), we separate the portfolios on each period at the 3-flag threshold.

Once the portfolios are built, we assume that the they will remain constant over the next 6 months. Then, at the beginning of the next period, the portfolios are rebalanced in order to accommodate the changes of the predictors. In order to magnify the impact of our strategy, based on Ak et al., (2016) results, we will use equal-weighted portfolios. On the other hand, the market portfolio will be value-weighted in order to reflect the natural benchmark.

5.2. Results

Below, we show the results from the portfolio selection strategy.

Figure 4
Portfolio Performances

Returns were calculated as % change of the return index (RI) retrieved by Thomson Reuters DataStream.

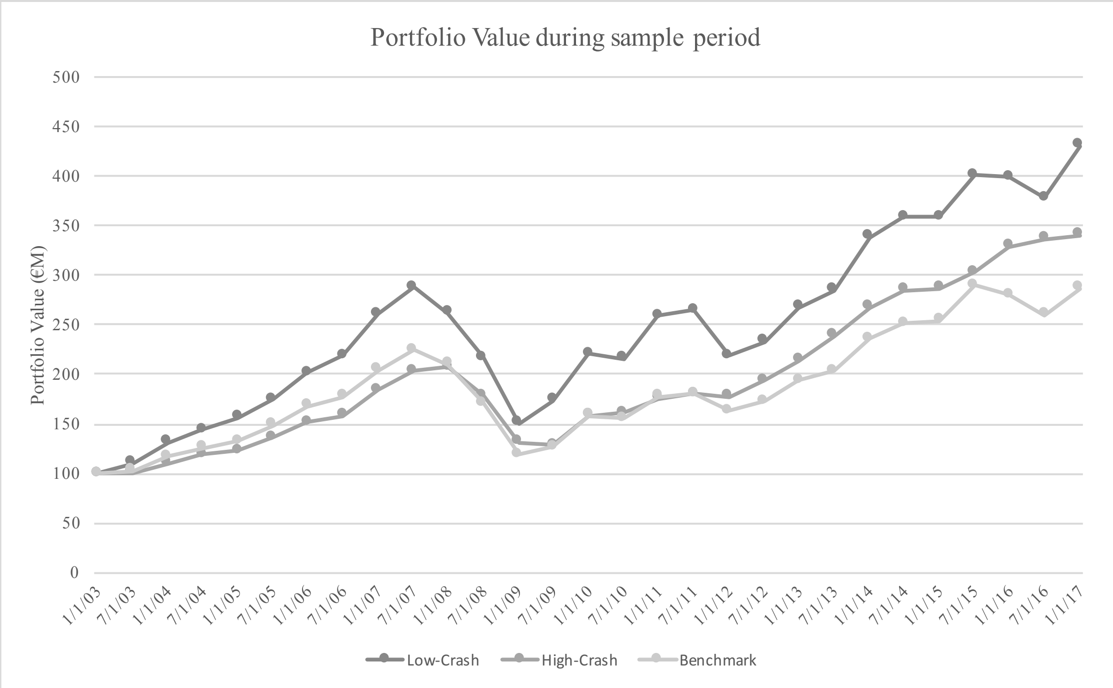

Figure 4 – Portfolios performance over sample period

As we can see in the above graph, the selection methodology of the low-crash portfolio provided higher absolute returns than both the high-crash and benchmark. More specifically, 100M€ invested in each portfolio, rebalanced at the beginning of each semester ignoring transaction costs, would result in approximately 430€M for the low-crash portfolio, 340€M for the high-crash portfolio and 287€M for the STOXX 600® Europe benchmark.

Even though this strategy allowed for a better portfolio performance than simply replicating the market portfolio (which was expected), provided us with more interesting understandings. As we can quickly conclude, just by looking at the graph, the strategy didn't particularly avoid "crashes" per se. Looking for example at the period ranging from July 2011 to January 2012, the "low-crash" portfolio's return was an impressive -17.5% whereas the "high-crash" (which, in theory, would have a lower return) only lost about -1.1%. More precisely, the low-crash portfolio performed negatively for 4 different periods where the high-crash showed positive returns. The same happened to the high-crash portfolio only once (January 2009 to July 2009).

Hence, as we compare our portfolios' evolution to the cumulative return distribution in Ak et al., (2016) study, we can see obvious differences.

Figure 5
Cumulative returns for low-crash-risk and high-crash-risk portfolios on an equal weighted basis – Source: Ak et al., (2016) – p.35

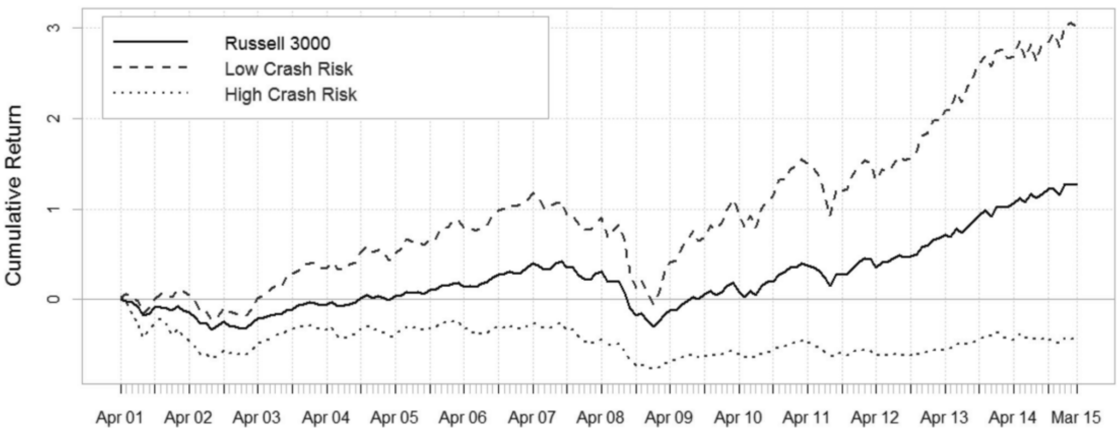

Figure 5 – Comparison Returns for Low-Crash-Risk and High-Crash-Risk Portfolios

Comparing both graphs, we can see that the high-crash-risk portfolio performed worse than the Russell 3000 (benchmark used in Ak et al., (2016) study) having not once crossed its line. Nevertheless, even though the low-crash-risk portfolio is constructed in a way to avoid crashes, we can quickly see in the graph that the equal weighted low-crash-risk portfolio performed worse than both the others (year 2008 and 2011). We believe this is an aspect that should be further studied.

Table 14
Average Annualized Investment Performance for Portfolios based on Crash-Flag strategy (1)

Excess Return is calculated as the average annualized return for each period subtracted by the corresponding 3-month UK bill as risk-free rate. Volatility is measured as the annualized value of the daily standard deviation of the portfolio returns. Sharpe ratio is the ratio between the two previous measures.

	Low-Crash Risk Portfolio	High-Crash Risk Portfolio
Excess Return	12.06%	8.51%
Volatility	20.78%	17.06%
Sharpe Ratio	0.5804	0.4986

Table 14 - Average Annualized Investment Performance for Portfolios (1)

The table above was constructed based on the investment performance of each portfolio. Excess return, following Ak et al., (2016), is calculated by subtracting the annualized 3-month risk-free rate to the portfolio's return.

Taking a closer look at the investment performance of each portfolio, we realize that besides achieving a higher return in absolute terms, the low-crash risk portfolio also performed better on a risk-adjusted basis measured by the Sharpe Ratio. This result was expected since in Ak et al., (2016), the low-crash risk portfolio also achieved as higher Sharpe Ratio than the high-crash risk one.

However, there is an extreme difference between our results and the ones presented on their study.

Table 15
Average Annualized Investment Performance for Portfolios based on Crash-Flag strategy
Excess return measure calculated by subtracting the corresponding 3-month Treasury bill. Source: Ak et al., (2016) – p. 36

	Low-Crash Risk Portfolio	High-Crash Risk Portfolio
Excess Return	8.61%	-5.98%
Volatility	20.79%	27.29%
Sharpe Ratio	0.4142	-0.2191

Table 15 - Average Annualized Investment Performance for Portfolios (2)

As we can see from the previous two tables and graphs, even though both the low-crash risk portfolios are somewhat comparable, the high-crash risk portfolios differ greatly from each other.

We hypothesise that this difference is, partly, a result of the crash-flag predictors. As shown in Table 13, our minimum return variable (MIN.RET) decreases in value as the perceived riskiness from the crash-flag strategy increases. According to Ak et al., (2016) results, this is an unexpected conclusion since, in their study, all variables move in the same direction (Ak et al., 2016 – p. 34). The reason for this, as previously mentioned, is the fact that the previous authors chose not to use returns' volatility (SIGMA) as a predictor (despite of its high significance in all their regressions) whereas we used it. Even more, we used it, as the results for the DUVOL regression leads us to, with a negative impact on the stock price crash measure (meaning that, higher values of SIGMA, reduce future stock price crash risk) (Table 6 – Panel A). Clearly, given the fact that

SIGMA loads with the opposite sign in the regression which uses minimum return (Table 7 – Panel D) as dependent variable, it is expected that the fact that higher numbers of crash-flags require lower values of SIGMA, it results in a decreasing change of the MIN.RET variable. Besides returns' volatility (SIGMA), the second highest significant crash predictor in Ak et al., (2016) study is short interest (SHORT). Unfortunately, due to data availability limitations, we were not able to include this variable in our regressions thus, even though we believe the results would be different, we cannot be certain of its impact in DUVOL.

However, the predictors do not explain everything. As we can see, both from the annualized portfolio performance graphs (Figures 4 and 5) and from comparing our "high-crash" portfolio excess return to Ak et al., (2016) values (8.51% vs -5.98%), there is a clear difference between the type of asset allocation in both studies. This difference arises mainly from our dependent variable choice and crash predictors selection.

Ak et al., (2016) use CRASH as the main dependent variable being the one they use to select and rank the crash-flag predictors. Given the fact that the numerator of this variable is the negative of the minimum return of each stock for the current period, it is expected that this crash-flag strategy, applied with the CRASH variable as the main crash-risk measure, will avoid the majority of the more extreme negative returns. The rationale behind this measure is very strong because, as they argue, a crash is a large negative return (i.e., long left tail) which is captured by the variable's numerator whereas a measure like DUVOL, has a stronger focus on the asymmetries of the returns distribution, the skewness of the returns (i.e., fat left tail) (Ak et al., 2016 - p. 29).

Thus, even though DUVOL is a widely used measure in the stock price crash literature, using it as a basis for a strategy like this one, in the European markets, does not seem to be effective at avoiding stock price crashes.

Nevertheless, even though apparently our strategy was not successful at avoiding crashes, it was still able to "beat the market".

Table 16
Investment performance of each portfolio in relation to STOXX 600 ® Europe

	Low-Crash Risk Portfolio	High-Crash Risk Portfolio
Beta	1.135	0.734
Alpha	5.12%	4.84%
Tracking Error	6.78%	10.82%

Table 16 - Investment performance relative to benchmark

Due to the large number of stocks included in the low-crash risk portfolio, a Beta close to 1 related to the benchmark was expected. Regarding the high-crash risk portfolio, based on Ak et al., (2016) study, it was expected a higher Beta value than the low-crash one however, as we can see, it presented a Beta lower than 1.

Interestingly, an equal-weighted strategy applying these crash-flags results in positive active returns (measured through Alpha) of 5.12% and 4.84% for each portfolio.

6. Conclusion

We proposed to investigate stock price crashes dynamics in the European market. Even though published literature does not provide any relevant work regarding this topic in Europe (Ahsan Habib et al., 2017 - p. 36), we hypothesized if the stock price crash causes between our geography of interest and previous studies were similar.

We concluded with our regressions that, despite all the differences between the two markets, most of the variables used in the United States to forecast stock price crashes can be used to explain stock price crash likelihood in Europe. Variables such as past return, market-to-book ratio, size or past return's volatility proved to be very useful at estimating future stock price crash likelihood measured by future negative skewness of returns. However, this first segment of the study has two big limitations. First, our sample is considerably smaller than in similar studies. This happens for two reasons: 1) we did not want to focus our analysis in individual countries (it would require a different approach since each country has its own specificities) hence, we used an index which is limited to 600 companies. This was a necessary approach to achieve a broad basket of economies inside Europe and 2) variables limitations (for instance, we did not have access to short interest in the European market). This variable limitation, which is related to the second limitation of this first segment, forced us to use some proxies that, even though are not the ones present in most studies, were the ones we were able to retrieve from our database in order not to reduce even more our sample. Nevertheless, despite these limitations, overall, the forecasting results were as expected.

Then, building up on these previous findings and the work of Ak et al., (2016), we applied the crash-flag framework to avoid highly crash-prone stock and construct a more efficient stock portfolio. Even though our strategy provided higher risk-adjusted returns than the benchmark, it was not able to isolate stock price crashes in the high-crash portfolio as in Ak et al., (2016). There are three possible explanations for this difference and each one affects the result in its own manner.

Firstly, our choice of crash risk measure (DUVOL) is very different in its nature than theirs (CRASH). It is so because CRASH only focus on the left side of returns' distribution since it includes the minimum return of each firm in the numerator and thus, it focuses on the effect from longer left-side tail of returns' distribution. On the other hand, DUVOL, our crash risk measure, takes into consideration both sides of the returns' distribution hence, it incorporates the effect of fatter left-tails which may result not from extreme negative movements in price ("crashes") but instead, a higher propensity for less extreme but still negative returns in comparison to the positives.

Secondly, we considered all variables in the regression as possible crash-predictors whereas Ak et al., (2016) uses past crashes, size, returns' volatility and leverage as controls without a sign prediction. We did not feel the need to use control variables since there are plenty of studies that analyse the impact of these variables in our main variable of interest, DUVOL. Hence, following this slightly different framework, our crash-flag strategy ended up including two variables (size and previous return volatility) that were not considered in Ak et al., (2016). The implication of this choice relies on the past returns' volatility (SIGMA) impact on the dependent variables. As shown, SIGMA has a negative (and high statistically significant) impact on stock price crash measured by all dependent variables except minimum return (MIN.RET). Thus, using SIGMA (with a negative sign) as crash-flag, led us to include in the high-crash risk portfolio, some of the companies with the lowest negative returns (in absolute terms) meaning that, some of the stock with more pronounced crashes were included in the low-risk portfolio.

Lastly, in Ak et al., (2016) study, short interest has the second highest statistical significance (only behind returns' volatility (SIGMA)) on both regressions focused only on the left side of the returns' distribution. As we do not include this variable due to lack of data on short interest for the European markets, we believe we are missing an important dimension on the stock price predictors.

We believe that in a time where information flows instantly, stock price crash literature is more pertinent than ever. Since most regressions in this field have very little explanatory power (measure by R^2), we think there is a lot of room for improvement. We propose three lines for further research.

First, now that behavioural finance is increasing its importance in the financial literature, we think it would be interesting to take a step back from the already studied stock price crash variables such as financial reporting, managerial characteristics, governance and capital market data and develop a framework to include behavioural characteristics as stock price crash predictors.

Secondly, the lack of literature in the European market regarding this topic opens a great opportunity for researchers to explore whether the common crash risk measures are adequate or not. Also, it would be interesting to test, individually, which explanatory variables can be adapted to Europe and how their explanatory power differs among the different countries due to their inherent differences (financial reporting and market dynamics to name a few).

Lastly, even though there are lots of literature on this topic in the United States, Ak et al., (2016) is the only one (at least, that we know of) that offers some guidance on how to adapt the “academia knowledge” to the investment profession. However, even though their strategy proved to be useful in avoiding more crash-prone stocks, it is a simple strategy and can be greatly improved.

7. References

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