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Doctoral Dissertation

Essays on Asset Pricing: Distress Risk and Stock Returns

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CYPRUS UNIVERSITY OF TECHNOLOGY

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To my Beloved Parents and my Lovely Wife

ABSTRACT

Financial distress risk is one of the main types of risks that investors and practitioners have to mitigate nowadays. Despite the large body of literature on financial distress and its consequences, many important research questions remain unanswered. This dissertation contributes to this literature through three empirical asset pricing studies that examine the impacts of firm-specific and country-specific financial distress on stock price crashes, stock returns, and foreign investors' returns among others.

The first chapter investigates the relationship between the firms' financial distress and future stock price crashes. Based on monthly changes of distress risk as captured by the Black-Scholes-Merton (1973, 1974) distance-to-default (DD) model, firms which experience an increase in distress risk are more prone to stock price crashes one-month ahead. Using 343,271 monthly observations for the period 1990-2015, I find that this strong positive relationship remains robust for alternative measures of distress risk and stock price crashes. Additionally, changes in distress risk can predict stock price crashes as far as four months ahead. More importantly, I show that the crash-distress relationship is more pronounced when the firms' information asymmetry is higher, as captured by the firms' accounting opacity, stock liquidity, and analysts' dispersion.

In the second chapter, I examine the effects of misvaluation on the well-documented negative relationship between distress risk and stock returns (distress risk anomaly). Findings indicate that distress risk is negatively related to stock returns only in the subset of most overvalued stocks, consistent with the mispricing explanations of prior studies (Dichev, 1998; Griffin and Lemmon, 2002). Moreover, after removing mispricing effects from distress risk, the distress anomaly disappears. The results are robust to alternative specifications of distress risk and mispricing measures.

Lastly, the third chapter focuses on country-specific distress risk, the sovereign risk. More specifically, I examine the rate of return earned by global funds on equity investment in emerging markets (EMs) particularly the role played by sovereign credit risk. Changes in sovereign credit ratings (upgrades/downgrades) influence excess (over risk-free rate) returns earned by foreign investors: lower excess returns are associated with lower risk. The effect of credit upgrades and downgrades, however, is not symmetric. By contrast, credit outlook or credit watch announcements do not seem to influence foreign investors' excess returns. When it comes to abnormal (risk-adjusted) returns, foreign investors treat the information contained in credit rating announcements differently from that in outlook/watch announcements. The differing effect of these two is not evident for the risk-adjusted returns of domestic stock market indexes. There is evidence, however, that the behavior of foreign investors significantly influences the risk-adjusted returns of EM stock market indexes.

Keywords: Distress risk, stock price crash, mispricing, sovereign risk

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LIST OF ABBREVIATIONS

3FF	Fama and French Three-Factor Model
5FF	Fama and French Five-Factor Model
AMEX	American Stock Exchange
BM	Book-to-Market
BSM	Black, Scholes, and Merton
CAPM	Capital Asset Pricing Model
CEO	Chief Executive Officer
CFO	Chief Financial Officer
CO&W	Credit Outlook & Credit Watch
corr.coef	Correlation Coefficient
CR	Credit Ratings
CRSP	The Center for Research in Security Prices
D	Debt
DD	Distance-to-default
DM	Developed Markets
DR	Distress Risk
EMs	Emerging Markets
Eq.	Equation
EPFR	Emerging Portfolio Fund Research
FLOW	Net Flows
GDP	Gross Domestic Product
GFC	Global Financial Crisis

IAPMs	International Asset Pricing Models
KMV	Kealhofer, McQuown and Vasicek
KS	Kolmogorov-Smirnov test
LEV	Leverage
lnGDP	Natural Logarithm
MCAP	Stock Market Capitalization
MDLI	Market Default Likelihood Indicator
ME	Market value of Equity
MIS	Mispricing variable
MOM	Momentum
MSCI	Morgan Stanley Capital International
NCSKEW	Negative Skewness
NYSE	The New York Stock Exchange
Obs.	Number of Observations
OLS	Ordinary Least Squares
R	Monthly Stock Returns
R_f	Risk-free rate
RMKT	Domestic Stock Market Index
RNAV	Changes in Net Asset Value
ROA	Return-on-Assets
ROE	Return-on-Equity
S&P	Standard & Poor's
SE	Standard Errors
Std. Dev.	Standard Deviation

SIC	Standard Industrial Classification
SIZE	Firm's Size (Market Capitalization)
T-bill	Treasury Bill
TNA	Total Net Assets
TOVER	Turnover Ratio
TTM	Trailing Twelve Months
U.S.	United States
V	Firm's Assets Value
VTRAD	Value of Domestic Shares Traded
ΔFX	Changes in Total Assets due to currency fluctuations

INTRODUCTION

Financial distress risk is one of the most crucial types of risks that a company faces. Distress risk is associated with a firm's failure to meet its financial obligations, leading to a worse phenomenon, that of bankruptcy. Distressed firms tend to have low financial flexibility due to high financial constraints, poor profitability and they are more vulnerable to adverse economic conditions (Olper and Titman, 1994). Distress risk is a major threat to capital suppliers, investors, and creditors, as well as to the employees of the financially distressed firms. As a result, scholars recognizing the importance of distress risk, have attempted to quantify the firms' probability of bankruptcy (i.e., Altman, 1968; Merton, 1974; Ohlson, 1980; Crosbie and Bohn, 2003; Bharath and Shumway, 2008) for a good part of the last 60 years.[1] Following the global financial crisis of 2008, financial distress is of high importance for investors and practitioners who want to avoid any financial troubles in the future and understand better the nature of equity markets. On this basis, research delving into specific aspects of financial distress risk is necessary.

Over the last three decades, there has been increasing interest in the relationship between distress risk and stock returns. Several studies examine the impact of distress risk on stock returns and the majority have found a negative relationship termed distress risk anomaly (Dichev, 1998; Griffin and Lemmon, 2002; Campbell, Hilscher and Szilagyi, 2008). On the other hand, Vassalou and Xing (2004) show that the relationship between default risk and stock returns is positive and significant, only in the case of firms that have small market capitalization and/or have high book-to-market ratio; in all other cases the distress-return relation is negligible. Despite the large body of literature on financial distress risk, several questions remain unanswered. More specifically, there is no study that addresses the direct relationship between distress risk anomaly and misvaluation. Also, distress risk is sparingly used by financial studies to explain several financial events. At a first glance, a close relationship of financial distress with various financial events can be easily identified, such

[1] Generally, a company's distress risk is classified into two categories: reduced-form models and structural models (Charitou, Lambertides, and Trigeorgis, 2008). The reduced-form models do not examine the relation between distress risk and firm value explicitly as the structural models do. In addition, the timing of default is not determined based on the firm's value as in the case of structural models, but it is determined as the first jump of an exogenously given jump process (Elizalde, 2005).

as the relationship between distress risk and stock price crashes. This dissertation is designed to fill such gaps by investigating various research questions in the field of distress risk, which are considered to have a high importance for the academic and investment world. Particularly, this Ph.D. dissertation consists of three essays organized into three chapters as follows:

1. Chapter one investigates the relationship between distress risk and crash risk;
2. Chapter two examines the distress-return relation controlling for misvaluation effects
3. Chapter three assesses the impact of distress risk from the country's perspective by examining the relationship between sovereign credit risk and foreign investors returns.

More information, for each of the above three chapters, is provided in the following paragraphs.

The first chapter investigates the relationship between the firm's financial distress and future stock price crashes. Particularly, it investigates how the firm's monthly change of distress risk affects the one-month-ahead occurrence of an extreme negative firm-specific stock return. The primary crash risk measure is a binary variable that takes the value of one when a firm experiences at least one crash week within a certain month estimated from a 52-weeks rolling index model regression inspired by Dimson (1979). The main distress risk measure is given by the Black-Scholes-Merton (1973, 1974) distance-to-default (*DD*) model. The findings show that firms which experience an increase in distress risk are more prone to stock price crashes one-month ahead in the future. The crash-distress relation is strong and economically meaningful after controlling for various crash predictors. Distress risk changes have the ability to forecast future stock price crashes up to four months ahead. The results are robust to alternative specifications of crash risk and distress risk measures. Furthermore, the positive relationship between distress risk changes and future stock price crashes is stronger for firms that are surrounded by high information asymmetry.

Chapter two aims to examine whether the negative distress risk anomaly reported by various studies (e.g., Griffin and Lemmon, 2002; Campbell, Hilscher and Szilagyi, 2008) is driven by mispricing effects. Although prior studies (Dichev, 1998; Griffin and Lemmon, 2002) attribute the distress risk anomaly to mispricing effects, they do not investigate this argument directly and in depth. To examine the interconnection of the distress-mispricing relation, I perform double-sorted portfolio analysis and Fama-MacBeth regression analysis. The primary distress risk measure is defined using the Bharath and Shumway (2008) approach based on Merton's (1974) option pricing model. The primary mispricing measure is the dispersion of earnings expectations (or analysts' disagreement) similar to Johnson (2004) and Sadka and Scherbina (2007). The main contributions of this study are twofold. Firstly, it gives a rational explanation to the "distress risk puzzle", indicating that the distress risk anomaly is driven by overvalued stocks in support of the arguments of prior studies (Dichev, 1998; Griffin and Lemmon, 2002) and secondly, it shows explicitly the relation between distress risk and mispricing. The results of this essay are robust to alternative distress and mispricing measures.

Finally, chapter three examines the impact of a country's distress risk measure, sovereign credit risk, on the rate of return earned by global funds in Emerging Markets. The reason that I investigate this relationship in emerging markets is twofold; first since emerging markets embarked on programs of financial liberalization during the 1990s, they led foreign investors to add stocks from these markets to their portfolios, providing portfolio exposure to these economies as part of strategies aimed at diversification; second, I use a proprietary dataset compiled by EPFR Global to study the factors behind the aggregate rate of return earned by global investment funds making the contribution of this study unique and significant. This chapter makes several contributions. First, to the best of my knowledge, this is the first study to offer a systematic study of sovereign risk along with other factors shaping the performance of global investment funds in EMs. Second, by investigating the role of sovereign credit ratings, it contributes to our understanding of the informational role of announcements by credit rating agencies in international capital markets, especially their effects on foreign equity investors in emerging markets.

Chapter three employs several methodologies comprising of an event study, panel regressions, and two-stage asset pricing models. The results derived from the various analyses of this chapter indicate that changes in sovereign credit ratings (upgrades/downgrades) influence excess returns earned by foreign investors; lower excess returns are associated with lower risk. However, credit outlook or credit watch announcements do not seem to influence foreign investors' excess returns. By analyzing the impact of credit announcements and outlook/watch announcements on abnormal (risk-adjusted) returns of foreign investors, the results show that the informational content of credit ratings (upgrade/downgrade) differs from that of credit outlook (positive/negative). However, this result does not hold when we use the same analysis to model risk-adjusted return of domestic stock market indexes: credit ratings have no explanatory power to explain abnormal stock market returns. This outcome can be attributed to the behavior and the level of sophistication between foreign and domestic stock market participants in emerging markets.

1 The Role of Distress Risk in explaining Stock Price Crashes

1.1 Introduction

Distress risk is associated with the firm's failure to meet its financial obligations and is one of the greatest risks that managers are constantly challenged to handle. This happens because financial distress plays a catalytic role in the firms' ability to raise capital (Diamond, 1991; Whited, 1992; Almeida and Philippon, 2007) and incentivizes managers to manipulate earnings (DeFond and Jiambalvo, 1993; DeAngelo, DeAngelo, and Skinner, 1994; Rosner, 2003; and Charitou, Lambertides, and Trigeofrgis, 2011).[2] Prior literature documents that firms which face high financial distress risk are more vulnerable to adverse economic conditions and tend to have poor profitability and performance (Ohlson 1980; Opler and Titman, 1994, Campbell et al. 2008). As such, managers in these firms face higher incentives to hoard bad news, effectively creating a false sense of positive performance (DeFond and Jiambalvo, 1993; DeAngelo, DeAngelo, and Skinner, 1994; Rosner, 2003; and Charitou, Lambertides, and Trigeorgis, 2011; Andreou, Louca, and Petrou, 2017), likely aiming to camouflage, among other things, the severely adverse consequences that can emerge from heightened financial distress risk positions. Prior studies admit that labor market pressures may lead managers to engage in such moral hazard situations (Fama, 1980; Holmstrom, 1982, 1999; Gibbons and Murphy, 1992) intending to preserve unharmed their wealth and human capital.[3] Persistent hiding and accumulating of bad news, however, will inevitably spill into the market, making investors substantially revise their expectations about the firm's future potential, thereby, triggering an extreme negative idiosyncratic stock return leading to heightened crash risk (Jin and Myers, 2006; Bleck and Liu, 2007; Kim et al., 2011a).

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[2] For instance, DeAngelo, DeAngelo, and Skinner (1994) show that financial distressed firms have large negative accruals (evidence of earnings manipulation) that indend to improve their renegotiation power in the case of bankruptcy event (DeFond and Jiambalvo, 1993).

[3] The relationship between firm performance and manager dismissal is well-established (Hermalin and Weisbach 1998; Lehn and Zhao 2006). Fired managers not only are negatively affected economically in terms of their wealth, but also experience heavily downgraded human capital in the executive labor market (Eckbo et al. 2016). Prior empirical research also provides a strong link between financial distress risk and managerial turnover (Gilson, 1989; Gilson and Vetsuypens, 1993; LoPucki and Whitford 1993; Betker 1995; Novaes, 2002). Thus, in general, the desire of managers to preserve their wealth and human capital makes it highly likely to withhold negative information that otherwise would have lead shareholders and investors to deem the firm as being in a high financial distress risk position.

Stock price crash risk has emerged as an important notion in the literature. The main cause of crash risk is attributed to firms' intention to accumulate bad news for a long period, which leads the stock price to high levels without actually being worth it, creating overvalued stocks and eventually to sudden extreme negative stock returns (Jin and Myers, 2006; Bleck and Liu, 2007; Hutton, Marcus, and Tehranian, 2009; Kothari, Shu, and Wysocki, 2009; Benmelech, Kandel, and Veronesi, 2010; Kim, Li, and Zhang, 2011a; Kim and Zhang, 2016; Andreou et al., 2016). A number of prior studies have examined various factors and conditions (e.g., managerial incentives, corporate governance and capital market transactions) that affect the probability of a future stock price crash (Chen, Hong, and Stein, 2001; Hong and Stein, 2003; Hutton, Marcus, and Tehranian, 2009; Kim and Zhang, 2016; Andreou et al., 2017). Nevertheless, to the best of our knowledge, none of the prior studies have examined the relationship between the firms' financial distress and stock price crash risk.[4] This study indents to fill this gap.

In this vein, this study examines how the firm's distress risk affects the firm's future stock price crash risk. Particularly, it investigates the relationship between *monthly changes in a firm's distress risk and the one-month-ahead occurrence of an extreme negative firm-specific stock return*. Distress risk is measured using the firm-specific probability-to-default as computed with the Black-Scholes-Merton distance-to-default (DD) model (see Black and Scholes 1973; Merton 1973, 1974) (BSM hereafter). We hypothesize that increases in a firm's probability-to-default could signal situations where managers have accumulated negative information about the firm's fundamentals. For instance, the managers of firms who have made wrong investment decisions in the past, failing to reach the expected operating performance, will be inclined to hide this negative information from the firms' financial statements and other reporting to obstruct investors from correctly assessing their firms' financial distress risk position. However, under the efficient market hypotheses, investors should be able to see through the managers' misconduct practices and (eventually) accurately assess, endangering the risk of a stock price crash when the true information is eventually revealed in the market. A notable example is that of Xerox Corp., whose probability-to-

[4] Some studies (e.g. Zhu, 2016; Andreou, Louca, and Petrou, 2017) use the default risk as a control variable in their statistical tests. However, these studies focus on low frequency data using annual basis analyses, failing in this way to capture the dynamic behavior of financial distress risk which becomes evident using a monthly data as in this study.

default increased by 15% (measured using the BSM model) in October of 2000, flagging an early-warning for investors regarding the 2000's Q4 results that were rather disappointing (largest quarterly loss in a decade), leading to a stock price crash (33%) in December of 2000. Figure 1 presents the behavior of firms' distress risk around a stock price crash event. More specifically, this figure illustrates the reaction of crashed firms (or crash group) and their twin non-crashed firms (or untreated group) around a crash event. The event window covers 6-months on either side, before and after the stock price crash. From this figure, it seems that the distress risk of crashed firms is quite lower (<3.5% on average) six months prior the crash event and it increases aggressively close to the crash event. Whereas, after the crash event, the crashed firms do not recover their level of distress risk, indicating that the crash event is not due to a simple stock price shock that may have occurred due to a transitory negative announcement but likely due to a more permanent financial condition caused by severe unexpected announcement of bad news, a consequence of lengthy hoarding of bad news. The untreated sample (non-crashed firms) does not show significant changes in distress risk around a "virtual" crash event.

Figure 1: Crash vs. Non-Crash Group
The figure illustrates the probability of default for two groups based on event study around stock price crashes. The two groups are the Crash group that includes firms that experienced a crash and the second group (Non-Crash group) include firms that did not experience a crash but are most similar firms with crashed firms based on the total similarity measure of Hoberg and Phillips (2016). The crash risk is defined as the extreme negative weekly stock returns similar to Hutton, Marcus, and Tehranian, 2009). The probability of default is estimated similar to Bharath and Shumway (2008). Crashes are marked at month 0.

To investigate the relationship between distress risk and stock price crash we mainly utilize data from Compustat and Center for Research in Security Prices (CRSP) from January 1990 to December 2015.[5] We measure the stock price crash as the extreme negative firm-specific weekly return (Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a and 2011b) within a month, using a rolling procedure to avoid any misclassified crash due to the ex post distribution of stock returns, while the distress risk is the BSM probability to default measure. Our findings indicate a strong positive relationship between distress risk changes and future stock price crash, consistent with our main hypothesis. This crash-distress relation is strong and economically important after controlling for various crash predictors such as detrended level of turnover, negative skewness, and accounting opacity (Chen, Hong, and Stein, 2001; Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a, 2011b; Kim and Zhang, 2016). In addition, distress risk seems to have the ability to predict the probability of stock price crash up to four months before the crash. Our results are robust to alternative specifications of crash risk (Hutton, Marcus, and Tehranian, 2009; Ak et al., 2016) and distress risk measures (Charitou et al., 2013).

Additional analysis shows that the positive crash-distress relation is stronger for firms that are surrounded by high information asymmetry. Specifically, our findings indicate that the impact of distress risk is higher for opaque firms, which is consistent with prior studies (e.g., Hutton, Marcus, and Tehranian, 2009; Kim and Zhang, 2016). We also find that the link between distress risk and crash risk is more pronounced for more illiquid firms and firms that have higher dispersion in their analysts' earnings forecasts.

This study contributes to two literatures, the first about the determinants of stock price crash and the second about the role of the distress risk in capital markets. This is the first study that examines the impact of distress risk on stock price crash directly. The limited literature (e.g., Andreou, Louca, and Petrou, 2017; He and Ren, 2017) that uses distress risk as an auxiliary variable in their tests about stock price crash, failed to find any significant relationship between crash risk and distress risk, possibly due to the use of annual-based analysis and consequently its inability to capture the high frequency dynamics in distress and crash risk proxies. In response, we show in a practical way the importance of such dynamic predictors

[5] The final dataset covers the period from February 1992 to December 2015.

using monthly-based analysis. In addition to this, the findings of this study can be very important for investors and companies, allowing them for dynamic forecasting of a stock price crash. Furthermore, we show how information asymmetry is linked to the distress risk to predict stock price crash through the bad-news-hoarding channel, consistent with the literature (Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009; Chang, Chen, and Zolotoy, 2017). The distress-crash relationship is also related to the distress risk anomaly.[6] As shown in this study, higher distress risk is associated with higher probability of stock price crash. Therefore, the determinants of stock price crash documented in this study (i.e., earnings management, corporate governance, information asymmetry, etc.) are likely potential drivers of the distress risk anomaly.[7]

The remainder of this study proceeds as follows: section 1.2 describes the related literature, section 1.3 describes the data, measurements and the methodology, section 1.4 presents the empirical analysis and section 1.5 provides a robustness analysis. Finally, section 1.6 presents the conclusions of the study.

1.2 Related Literature

The seminal study of Chen, Hong, and Stein (2001) was the inaugural for the direct investigation of stock price crashes, showing that the companies' de-trended level of turnover over the preceding six months tends to have a positive impact on their stock price crash. The de-trended turnover measure is based on the differences-of-the-opinion theory. This theory was widely used by other scholars, directly and indirectly, to explain the crashes connected with the short-sale constraints (Miller, 1977; Diether, Malloy, and Scherbina, 2002; Hong and Stein, 2003). In the same vein, Chang, Chen, and Zolotoy (2017), show that many incentives for bad news hoarding can be derived from capital markets similarly to the seminal study of Chen, Hong, and Stein (2001). Particularly, Chang, Chen, and Zolotoy (2017) show that stocks with high liquidity tend to be more susceptible to crash risk because liquidity induces managers to withhold bad news in order to avoid the selling by transient investors in the case of disclosure. A possible link between distress and crash risk was first documented

[6] The majority of prior studies on distress risk anomaly show that distress risk is negatively related to stock returns (e.g., Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2008; Garlappi and Yan, 2011).

[7] However, we leave this research question for future investigation.

by (Da and Gao, 2010). For instance, Da and Gao (2010) by investigating the negative relation between distress risk and stock returns (known as distress risk anomaly) find that abnormal returns occur only in the first month after the portfolio formation and are concentrated in a small sample of stocks that had recently experienced a crash. Da and Gao (2010) argue that this return reversal derives due to a liquidity shock triggered by a clientele change, which is affected by an increase in a stock's probability of default.[8] Liquidity shocks can also be associated with the reveals of lengthy withholder bad news that can be viewed as public information on liquidity (Bali et al., 2013). From a different perspective, Brogaard, Li, and Xia (2017) find that higher stock liquidity reduces default risk, improving stock price information efficiency and corporate governance by the company's influential shareholders (blockholders). Their findings are consistent with the study of Edmans (2009) who shows that blockholders prefer to invest in highly liquid stocks who can take action upon the negative information. This, in turn, prompts managers to invest (rationally) on long-run growth rather than short-term profit even if their long-term investment behavior burdens short-term earnings (Edmans, 2009). Hence, the high stock market liquidity can lead to better corporate governance reducing the hoarding of bad news and consequently the stock price crash.

A large part of the literature attributes stock price crashes to agency problems that may arise due to the failure of corporate governance to prevent such problems (Kim, Li, and Zhang, 2011a; Callen and Fang, 2013; Andreou et al., 2016; Kim and Zhang, 2016). Kim, Li, and Zhang (2011a), for instance, show that the stock options (incentives) of chief financial officer (CFO) are positively related to the future stock price crashes, but there is a weak relation between crash risk and chief executive officer's options. This paper also indicates that the relation between future crash risk and CFO option sensitivity is more pronounced for firms that have high leverage which can be associated with higher distress risk (Altman, 1968; Ohlson, 1980; Asquith, Gertner, and Scharfstein, 1994). Generally, a weak corporate governance is related to financial distress (Daily and Dalton, 1994; Elloumi and Gueyié, 2001; Lee and Yeh, 2004; Altman and Hotchkiss, 2011) and earnings management (Xie,

[8] An increase in distress risk of stocks that previously were considered in portfolios as healthy and liquid stocks, triggers substantial selling by investors, leading to clientele changes.

Davidson, and Dadalt, 2003; Cornett, Marcus, and Tehranian, 2008; Kothari, Shu, and Wysocki, 2009).

Earnings management is used by managers to hide bad news from investors (Beasley and Beasley, 1996), thus increasing information asymmetry between managers and shareholders (Kothari, Shu, and Wysocki, 2009). Hutton, Marcus, and Tehranian (2009) show that earnings management proxied by opacity is related to stock price crashes especially the years before ex-Sarbanes-Oxley Act. Similarly, Kim, Li, and Zhang (2011b) find that corporate tax avoidance is positively related to firm-specific stock price crash risk. The information asymmetry between managers and shareholders according to Kim and Zhang (2016) is reduced through accounting conservatism which can also decrease the probability of crash. Ertugrul et al. (2017) proxy for earnings management through report readability which shows that firms with the larger annual report and high uncertainty or a tone of doubt tend to have stricter loans' contract and higher probability to crash. In addition to this, DeFond et al. (2015) indicate that IFRS adoption (that leads to increased information quality) decreases crash risk.

Regarding the relation between financial distress and earnings management, there is evidence that managerial behavior is related to firm's financial health (DeFond and Jiambalvo, 1993; DeAngelo, DeAngelo, and Skinner, 1994; Charitou, Lambertides, and Trigeorgis, 2011). For instance, DeFond and Jiambalvo (1993) argue that firms that are close to a bankruptcy event engage in earnings management in order to improve their bargaining position during the renegotiation. Along similar lines, DeAngelo, DeAngelo, and Skinner (1994) argue that executives' accounting choices are based on firms' financial troubles to convince lenders of their willingness to deal with financial problems. Moreover, Charitou, Lambertides, and Trigeorgis (2011) prove that distressed firms have a low level of earnings timeliness for bad news and high level for good news, and they are more prone to earnings management than healthy firms. In a similar vein, Kothari, Shu, and Wysocki (2009) argue that the link between financial distress and management turnover is one of the reasons why managers delay bad news (i.e., through earnings management) with the hope that adverse financial conditions will turnaround.

Overall, prior studies seem to provide substantial evidence to that distress risk may have a vital role in stock price crashes. Particularly, we hypothesize that when firm's financial distress increases, its stock price becomes more vulnerable to stock price crashes. Thus, we expect this relationship to be more pronounced when firms with low financial distress face an immediate increase in distress risk (distress shock), leading transient investors to hedge their positions by selling these stocks.

1.3 Data, Measurements and Methodology

1.3.1 Sample Data

Our sample consists of all U.S. listed firms during the 1990-2015 period with data available on NYSE, AMEX, and NASDAQ in quarterly Compustat and daily Center for Research in Security Prices (CRSP) Databases. Following prior studies (e.g., Kim, Li, and Zhang, 2011a), we exclude financial service firms (SIC 6000-6999) and utilities firms (4900-4999) because these firms have different financial characteristics. Additionally, we exclude firm-year observations with low stock price –if the average price for a year is lower than $2.50; firm-year observations with less than 26 weekly returns; and observations with insufficient financial data to calculate the main variables of our analysis (Hutton, Marcus, and Tehranian, 2009). Our analysis is based on monthly data in order to capture the direct impact of distress risk on stock price crashes.[9] The final sample covers the period from February 1992 to December 2015 and consists of 343,271 firm-month observations that correspond to 4,561 unique firms from various industries.

1.3.2 Crash Risk Measurement

In this study, we employ three different crash risk measures. The primary measure we use, namely *CRASH_1*, is a binary variable indicating whether a crash has occurred within a certain month estimated from a rolling-forward index model. Two more measures are used to complement the analysis, namely *CRASH_2* and *MINRET*. The first is the original Hutton,

[9] Prior studies investigate various crash risk determinants using annual-based analysis. However, since distress risk is very dynamic it would be unable to investigate the impact of distress risk on stock price crash on annual basis. In addition, Chava and Jarrow (2004) show that bankruptcy prediction is improved using monthly observations instead of yearly.

Marcus, and Tehranian (2009) crash measure that is also a binary variable that equals to 1 when a firm experiences at least one crash week during a fiscal year. *MINRET* is a continuous crash measure that is estimated similar to Ak et al. (2016).

To estimate *CRASH_1*, we estimate firm-specific weekly returns using the following 52-weeks rolling index model regression that is inspired by Dimson (1979):

$$r_{i,t} = \alpha_i + \beta_{1,i} r_{m,t-2} + \beta_{2,i} r_{m,t-1} + \beta_{3,i} r_{m,t} + \beta_{4,i} r_{m,t+1} + \beta_{5,i} r_{m,t-2} + \varepsilon_{i,t} \qquad (1.1)$$

where $r_{i,t}$ is return on firm *i* in week t and $r_{m,t}$ is the CRSP value-weighted market index return over week t.[10] The lag and lead returns of the market index allow for infrequent trading (Dimson, 1979). Eq. (1.1) separates the firm returns into two components; general systematic weekly return and firm-specific return captured by the residuals of the regression, $\varepsilon_{i,t}$. Following the literature, we focus on the residuals of this regression, namely, the natural logarithm of one plus the residual return (i.e., $W_{i,t} = ln[1 + \hat{\varepsilon}_{i,t}]$) that defines the firm-specific weekly return for firm i in week t. From this process, the primary crash risk measure takes 1 when firm i faces at least one crash week during the month t and zero otherwise ($CRASH\_1$). A crash week occurs when the firm-specific weekly return ($W_{i,t}$) is 3.09 standard deviations (3.09 standard deviation is chosen to generate a frequency of 0.1% in the normal distribution) below the rolling mean (52-week) of $W_{i,t}$ (Hutton, Marcus, and Tehranian, 2009).[11] Thus, our crash risk measure captures all possible crashes within a year, whereas Hutton, Marcus, and Tehranian (2009) measure identifies the crashes based on the whole fiscal-year returns distribution, leading to possible misclassification due to the possibility to be affected by the post-crash return distribution (Ak et al., 2016).

$CRASH\_2$ is the original Hutton, Marcus, and Tehranian (2009) crash measure. To estimate $CRASH\_2$, we estimate Eq. (1.1) for each (fiscal) year but not using rolling procedure as in $CRASH\_1$. Subsequently, the predicted log-transform residuals from this model are used to estimate the mean value of weekly returns within a fiscal year. $CRASH\_2$ takes 1 when firm i experiences at least one crash week during a specific month. A crash week is defined when

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[10] Weekly firm and market returns are estimated using daily information from CRSP.

[11] We also use various alternative benchmarks, such as 3.2 standard deviations below the rolling mean return for 52-weeks (Chen, Hong, and Stein, 2001; Kim, Li, and Zhang, 2011a and 2011b) where the results are quantitatively similar.

the firm-specific weekly return is 3.09 standard deviations below the average weekly return in a fiscal year. This measure is used in various robustness tests.

The third crash risk measure is *MINRET*. This proxy, calculated slightly differently from the original measure of Ak et al. (2016), is the negative ratio of the minimum weekly return (instead of daily) over the six-month period (26 weeks) to the sample standard deviation of returns for the previous period.[12] *MINRET* is estimated by the following formula:

$$MINRET_{i,t} = \frac{-Min(r\_adj_{i,t})}{\sqrt{\frac{\sum r\_adj_{i,t-1}^2}{(N-1)}}} \tag{1.2}$$

where r_adj_{it} is the sequence of weekly market-adjusted stock returns to stock *i* during period *t*. The denominator of this equation is the standard deviation of returns for the (previous) period. *N* is the number of weekly stock returns in each period.

1.3.3 Distress Risk

Distress risk is measured using the firm's specific probability-to-default as computed by Black and Scholes (1973) and Merton (1973, 1974) distance-to-default (*DD*) model. More specifically, the distance to default is calculated analogously to Bharath and Shumway (2008) as the probability of default at the debt's maturity, using the following equation:

$$DD\_MRT_{i,m} = \frac{ln\left(\frac{V}{D}\right)+\left(R_{i,m-1}-0.5\sigma_v^2\right)T}{\sigma_{v(BhSh)}\sqrt{T}} \tag{1.3}$$

where *V* is the firm's asset value that equals the firm's market value of equity *(ME)* plus the face value of Debt (*D*).[13] R is the monthly stock returns (CRSP item "ret"). The firm volatility ($\sigma_{v(BhSh)}$) is estimated as the weighted average of the volatilities of a firm's Equity and Debt; $\sigma_{v(BhSh)} = \left(\frac{ME}{(ME+D)}\right)\sigma_E + \left(\frac{D}{(ME+D)}\right)\sigma_D$. Equity volatility ($\sigma_E$) is derived from monthly equity returns, adjusted for cash dividends over a 36-month window: $R_E = ln\left(\frac{E_m+CD_m}{E_{m-1}}\right)$ while debt volatility is estimated using an approximation formula $\sigma_D = 0.05 + 0.25\sigma_E$. T is

[12] Similar to Chen, Hong, and Stein (2001) we use a six-month period of weekly market-adjusted stock returns (weekly stock return minus weekly market return). The weekly stock return instead of daily stock returns allow as to avoid largely an overreaction stock returns in a single day.
[13] All the variables used in this paper are described in the Appendix I.

the debt's maturity which is set equal to 1 year similarly to other studies (e.g., Bharath and Shumway, 2008).

Subsequently, the probability of default arises by the normal distribution of negative distance to default similar as in Merton's (1974) model:[14]

$$DR\_MRT_{i,m} = N(-DD\_MRT_{i,m}) \quad (1.4)$$

Thereupon we utilize the probability to default to define the month *m-2* to month m-1 change of distress risk ($\Delta DR\_MRT_{i,m-1}$) as follows:

$$\Delta DR\_MRT_{i,m-1} = DR_{i,m-1} - DR_{i,m-2} \quad (1.5)$$

For completeness, we use an alternative distress risk proxy that is based on Charitou et al. (2013) model (DR_MRTALT). The firm's volatility ($\sigma_{v(CDLT)}$) in Charitou et al. (2013) DD_MRTALT is derived from the volatility of the total firm's return; $R_V = ln\left(\frac{V_m+D_m}{V_{m-1}}\right)$, where D_m is the total firm payout which is equal to cash dividends plus interest expenses.[15] Thus, the Eq. (1.3), (1.4), and (1.5) are as follows:

$$DD\_MRTALT_{i,m} = \frac{ln\left(\frac{V}{B}\right)+\left(R_{i,m-1}-0.5\sigma^2_{v(CDLT)}\right)T}{\sigma_{v(CDLT)}\sqrt{T}} \quad (1.3a)$$

$$DR\_MRTALT_{i,m} = N(-DD\_MRTALT_{i,m}) \quad (1.4a)$$

$$\Delta DR\_MRTALT_{i,m-1} = DR_{i,m-1} - DR_{i,m-2} \quad (1.5a)$$

For further robustness, we also use the percentage change of *DR_MRT (%DR_MRT)* from month m-2 to the month m-1. However, due to the extreme values, observations with *%DR_MRT* higher than 100% are replaced with the maximum value of 100%.

[14] Notice that DR_MRT is not the "actual" firm's probability to default because it does not correspond to the true probability of default in large samples since we apply the cumulative normal distribution (Bharath and Shumway, 2008). In contrast, Crosbie and Bohn (2003) in their KMV model use a large dataset of bankrupt companies creating their own statistical distribution that is applied for the estimation of the default probabilities.

[15] R_V is slightly modified by using the maximum of actual firm value return (R_V) and the risk-free rate ($\max(R_V, R_f)$) (Charitou et al., 2013).

1.3.4 Control Variables

We use a number of control variables found in prior studies to be related to distress risk (default probability) and stock crash risk dynamics. We use five distress-related variables that capture a wide range of a firm's distress behavior. These variables are: market default likelihood indicator (*MDLI*) (Andreou, 2015) to control for market-wide distress risk;[16] inverse current ratio (*CL/CA)* to proxy for firm-specific financial liquidity; leverage (*LEV*) to control for leverage effects; return-on-assets (*ROA*) to control for profitability issues; a dummy variable (*INCLOSS*) that takes 1 for firms with negative net income for the last two consecutive years, to capture firm's financial trouble. Further, we control for financial constraints using the size-age (*SA)* index of Hadlock and Pierce (2010) defined as follows:

$$SA = -0.737 \times ME + 0.043 \times ME^2 - 0.040 \times AGE \qquad (1.6)$$

where *ME* is the firm's market capitalization and *AGE* is the number of years since the firm's listing in Compustat.

Following the literature, we include additional control variables such as a firm's size (*SIZE*), calculated as the natural logarithm of the firm's market capitalization; research and development to total sales (*R&D/SALES*); a firm's growth proxy *(M/B)*. We also use the *TOBIN'S_Q* ratio as a potential proxy for mispricing (Tobin, 1969; Tobin, Brainard, & others, 1977). In addition, we use a binary variable for the firm's age (*AGE_10*) that takes 1 if the firm's age is lower than 10 years and 0 if the firm's age is equal or higher than 10. Previous studies (Chen, Hong, and Stein, 2001; Jin and Myers, 2006; Kim et al., 2011a, 2011b; Kim et al., 2016) indicate that firms with high negative skewness of the previous year's weekly returns $(W_{i,t})$ are positively related to stock price crashes. Therefore, we include the negative weekly skewness (third moment) of the previous year (lags 12 months) using the following formula:

$$NCSKEW_{i,t} = \frac{-\left[n(n-1)^{\frac{3}{2}} \sum W_{i,t}^3\right]}{(n-1)(n-2)\left(\sum W_{i,t}^2\right)^{\frac{3}{2}}} \qquad (1.7)$$

[16] The aggregate firm-specific probability to default (*MDLI*) is calculated as the average value of firms' probability to default included in the S&P500 Index Portfolio. The distress risk for each firm is estimated using the Merton (1974) model.

We also control for past monthly returns as Chen, Hong, and Stein (2001) show that high past returns (using annual lags) tend to be more prone to crash risk. However, high past monthly (rather than annual) return may be associated with an upward stock price momentum that is less likely to be crashed in the current month. This means, in contrast to Chen, Hong, and Stein (2001), that the relation between past monthly returns and crash risk may be negative. To control for the general stock price momentum, we use the market adjusted return (*MA_Ret*) that is equal to a firm's stock return minus the CRSP value-weighted market index return.

Hong and Stein (2003) show that stock price crashes are more pronounced around periods of heavy trading volume. Similarly, Chen, Hong, and Stein (2001) show empirically that firms that have experienced an increase in trading volume relative to trend over the prior six months face more crashes. Thus, we control for investors' difference in opinion using Chen, Hong, and Stein (2001) proxy, *DTURN*.

We also control for earnings management and information asymmetry between managers and shareholders using the accounting opacity measure (*OPACITY*) of Hutton, Marcus, and Tehranian (2009) who show a positive relationship between accounting opacity and stock price crashes (consistent with the findings of Jin and Myers, 2006). *OPACITY* is estimated as the three-year moving sum of the absolute value of annual discretionary accruals where accruals are estimated based on the modification model of Jones (1991).

1.3.5 Model Specification

The main empirical analysis is based on a logit model where the dependent variable, CRASH_1, is a binary variable that equals 1 if stock price crash occurs and zero otherwise. The main logit model is as follows:

$$CRASH\_1_{i,m} = \alpha_0 + a_1 \Delta DR\_MRT_{i,m-1} + \sum_{k=2}^{K} a_k Distress\_Vars_{i,m-1} + \sum_{l=K+1}^{L} a_l Controls_{i,m-1} + e_{i,m} \quad (1.8)$$

where *Distress_Vars* includes the distress-related variables while Controls consist of control variables of crash risk based on prior literature.

All independent variables are lagged by one-period (month) apart from the *NCSKEW* that is used with a lag of one year (12 months). All logit models include industry and year fixed effects to control for unobservable events. For industry effects, we use the 48 industry classifications of Fama and French (1997). Furthermore, standard errors are estimated through the clustering procedure to account for autocorrelated and heteroskedastic standard errors.

Ordinary least squared (OLS) regression analysis is used in robustness analysis to examine the impact of distress risk on stock price crash using our continuous crash risk measure (*MINRET*). The OLS model is as follow:

$$MINRET_{i,m} = \alpha_0 + a_1 \Delta DR\_MRT_{i,m-1} + \sum_{k=2}^{K} a_k Distress\_Vars_{i,m} + \sum_{q=K+1}^{Q} a_q Controls_{i,m-1} + e_{i,m} \qquad (1.9)$$

The standard errors (SE) in Eq. (1.9) are estimated using the Driscoll and Kraay (1998) standard errors that are heteroskedasticity consistent and robust to general forms of cross-sectional (spatial) and temporal dependence (autocorrelation) due to the fact that our sample has large time dimension and regression errors. In addition, $MINRET_{i,m}$ is calculated using similar information with some of the independent variables such as size and market-adjusted returns where errors have a high probability of autocorrelation, hence Driscoll-Kraay SE is an ideal process. In Eq. (1.9) we do not include industry and year fixed effects due to the SE estimation method of Driscoll and Kraay (1998), which does not allow for such examination. We use 12 months as the maximum lag in the autocorrelation structure.

1.4 Empirical Analysis

1.4.1 Summary Statistics

Table 1 presents yearly descriptive statistics of the main stock crash measure (*CRASH_1*) and the corresponding distress risk change (*ΔDR_MTR*) of the month before the crash event.[17] It shows also the mean of stock returns for crashed and non-crashed firms in the crashed month. Our sample includes 5965 (17.27%) crash incidents which is consistent with previous

[17] First, we show yearly statistics of crash events to allow relative comparison with prior studies.

studies (Hutton, Marcus, and Tehranian, 2009; Kim et al., 2016).[18] The highest percentage of crashes, 35.77%, is observed in 2008 during the global financial crisis. The average change of distress risk (*ΔDR_MRT*) is positive for all years under consideration and the average *ΔDR_MRT* of 0.7% per month. In addition, the difference of *ΔDR_MRT* between the firms that faced a crash and those that did not during a year is positive and significantly different, indicating that firms that had experienced a crash faced an increase in their distress risk in the month before the crash. The average return on the month of the crash event is -17.1% while the average monthly return for non-crash firms is 1.9%. The impact of crashes on stock returns indicate the substantial adverse effects on shareholders wealth.

Table 2 reports summary statistics (Panel A) and Pearson correlation matrix (Panel B) for the main variables of the study.[19] Panel A shows that the monthly mean of *CRASH_1* is 1.9%, slightly higher than 1.7% of *CRASH_2*. As discussed in sub-section 3.2, the original crash measure is unable to capture crashes that are misclassified (as non-crash) due to the extremely negative post-crash return distribution. The primary explanatory variable, *ΔDR_MRT*, has mean value of 0.1% and standard deviation of 5.2%. *%DR_MRT* has a mean value of 20.5% that seems to be concentrated in the fourth quartile. The summary statistics of control variables are quantitatively similar with those of previous studies (Chen, Hong, and Stein, 2001; Hutton, Marcus, and Tehranian, 2009; Callen and Fang, 2013; Andreou et al., 2016; Chang, Chen, and Zolotoy, 2017) despite the different time-frequency and time period.

[18] According to the assumption that firm-specific returns were normally distributed, then 5.07% ($1-(1-0.001)^{52}=0.0507$) of the firms were expected to crash during the year. However, the actual percentage of stock price crashes over the year is much higher than the expected value, 17.27% vs. 5.07%.

[19] All continuous variables have been winsorized at the 1st and 99th percentiles to mitigate possible data errors.

Table 1: Yearly stock price crashes statistics, distress risk changes and stock returns between crash months and non-crash months

This table presents the yearly statistics of Crash measure along with some related statistics of ΔDR_MRT and stock returns. "$Avg\_\Delta DR\_MRT_{i,t-1}$ on crash (C)" provides the average value of ΔDR_MRT for crashed companies while the "$Avg\_\Delta DR\_MRT_{i,t-1}$ for non-crash (NC)" for non-crashed companies. The column "NC-C" reports the difference between the ΔDR_MRT for crashed and non-crashed firms. The last two columns provide the average return values for crashed and non-crashed companies, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Year	Number of Observations	Number of Crashes	Percentage of Crashes	$Avg\_\Delta DR\_MRT_{i,m-1}$ on crash (C)	$Avg\_\Delta DR\_MRT_{i,m-1}$ for non-crash (NC)	*NC-C*	Avg_Return on crash	Avg_Return for non-crash
1992	1118	111	9.93%	0.006	0.001	-0.005***	-0.188	0.018
1993	1252	166	13.26%	0.000	-0.002	-0.002**	-0.165	0.019
1994	1351	140	10.36%	0.004	0.001	-0.003*	-0.161	0.007
1995	1507	195	12.94%	0.007	0.000	-0.007***	-0.186	0.026
1996	1581	181	11.45%	0.002	0.000	-0.003**	-0.165	0.023
1997	1699	209	12.30%	0.001	-0.001	-0.002	-0.167	0.021
1998	1655	326	19.70%	0.014	0.006	-0.008***	-0.194	0.009
1999	1559	249	15.97%	0.008	0.000	-0.007***	-0.179	0.029
2000	1504	260	17.29%	0.013	0.002	-0.011***	-0.249	0.027
2001	1361	131	9.63%	0.005	-0.002	-0.006**	-0.205	0.046
2002	1450	222	15.31%	0.008	-0.001	-0.009***	-0.203	0.003
2003	1482	242	16.33%	0.001	-0.004	-0.005**	-0.126	0.040
2004	1626	234	14.39%	0.003	0.001	-0.002*	-0.157	0.024
2005	1643	341	20.75%	0.003	-0.001	-0.004***	-0.166	0.012
2006	1604	313	19.51%	0.001	-0.001	-0.002**	-0.175	0.022
2007	1539	313	20.34%	0.004	0.001	-0.003**	-0.159	0.008
2008	1451	519	35.77%	0.022	0.015	-0.007***	-0.226	-0.033
2009	1133	216	19.06%	0.004	-0.005	-0.008**	-0.178	0.046
2010	1335	132	9.89%	0.003	-0.001	-0.004***	-0.124	0.035
2011	1357	207	15.25%	0.007	0.001	-0.005***	-0.161	0.003
2012	1330	300	22.56%	0.003	-0.001	-0.003***	-0.144	0.022
2013	1347	298	22.12%	0.000	-0.002	-0.003***	-0.118	0.038
2014	1342	287	21.39%	0.007	0.000	-0.006***	-0.128	0.011
2015	1315	373	28.37%	0.008	0.003	-0.005***	-0.155	0.000
Total	34541	5965	17.27%	0.007	0.000	-0.006***	-0.171	0.019

Panel B of Table 2 shows a high correlation between our stock price crash $CRASH\_1$ and the alternative crash measure of Hutton, Marcus, and Tehranian (2009), *CRASH_2*. The correlation between the change in distress risk, ΔDR_MRT, and the three crash risk measures is positive and significant. Among all variables, the highest correlation coefficient, 0.588, is between age (*AGE_10*) and firm's financial constraints (*SA*). In general, our variables exhibit low bivariate correlation coefficients.[20]

Table 2: Descriptive Statistics

This table presents in Panel A the descriptive statistics of various variables for 343271 firm-month observations that correspond to 4561 firms from various industries. Panel B presents the Pearson correlation. $CRASH\_1$ and $CRASH\_2$ are binary variables that equal to 1 when a firm experiences at least one crash week during the month t. $MINRET$ is a continuous measure of crash risk that is estimated as the negative ratio of minimum weekly return over the six-month period to the sample standard deviation of weekly returns for the previous period. ΔDR_MRT and $\%DR\_MRT$ are the changes of distress risk and the percentage changes of distress risk, respectively. *MDLI* is the average monthly default risk of the firms that are included in the S&P500 Index Portfolio. $DTURN$ is the detrended average weekly stock trading volume. SA is the measure of financial constraints. Opacity is the three-year moving sum of the absolute discretionary accruals. *AGE_10* is a binary variable that equals to 1 if firm's age is below 10 years and zero otherwise. Size is the firms' market capitalization (stock price multiply by the number of shares outstanding), M/B is the market to book ratio) market capitalization to book value of equity), *TOBIN'S_Q* is the ratio of total firm value (Market capitalization plus total liabilities) over total assets, MA_Ret is the firms' market adjusted returns that is equal to the company's total stock return minus market's value weighted return (CRSP value-weighted market return). *R&D/SALES* is calculated as the research and development over the total sales, *INCLOSS* is a binary variable that equals to 1 if the firm's earnings are negative for the last two years. *NCSKEW* is the negative conditional skewness that is estimated by Eq. (1.6).

Panel A. Summary Statistics

Variables	Mean	Median	Min	Q1	Q3	SD	Max
$CRASH\_1_{i,m}$	0.019	0.000	0.000	0.000	0.000	0.136	1.000
$CRASH\_2_{i,m}$	0.017	0.000	0.000	0.000	0.000	0.129	1.000
$MINRET_{i,m}$	0.482	0.417	-0.153	0.306	0.578	0.301	23.427
$\Delta DR\_MRT_{i,m-1}$	0.001	0.000	-0.997	0.000	0.000	0.052	0.986
$\%DR\_MRT_{i,m-1}$	0.007	0.000	-1.000	-0.773	1.000	0.765	1.000
$MDLI_{i,m-1}$	0.003	0.002	0.000	0.001	0.003	0.003	0.018
$DTURN_{i,m-1}$	0.001	-0.001	-0.321	-0.022	0.021	0.069	0.342
$SA_{i,m-1}$	-3.914	-3.867	-4.637	-4.164	-3.620	0.353	-3.257
$\mathrm{OPACITY}_{i,m-1}$	0.380	0.187	0.026	0.109	0.327	0.783	8.939
$AGE\_10_{i,m-1}$	0.175	0.000	0.000	0.000	0.000	0.380	1.000
$SIZE_{i,m-1}$	8.578	8.412	8.412	8.412	8.412	0.543	13.346
$M/B_{i,m-1}$	2.668	1.963	-33.024	1.239	3.161	5.072	42.274
$TOBIN'S\_Q_{i,m-1}$	1.799	1.444	0.454	1.121	2.009	1.353	66.579
$MA\_Ret_{i,m-1}$	0.003	-0.003	-0.920	-0.062	0.058	0.126	9.312
$R\&D/SALES_{i,m-1}$	0.080	0.000	0.000	0.000	0.020	0.459	5.400
$CL/CA_{i,m-1}$	0.606	0.513	0.028	0.352	0.735	0.473	35.044
$LEV_{i,m-1}$	0.531	0.522	0.017	0.384	0.651	0.235	9.268
$ROA_{i,m-1}$	0.021	0.042	-8.249	0.005	0.076	0.148	0.342
$INCLOSS_{i,m-1}$	0.226	0.000	0.000	0.000	0.000	0.418	1.000
$NCSKEW_{i,m-12}$	-0.026	-0.069	-5.134	-0.469	0.339	0.844	6.620

[20] *VIF* tests also confirm no multicollinearity among variables (*VIF*<5).

Panel B. Pearson Correlation Coefficient

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. $\mathbf{CRASH\_1_{i,m}}$	1.000																			
2. $\mathbf{CRASH\_2_{i,m}}$	0.668**	1.000																		
3. $\mathbf{MINRET_{i,m}}$	0.237**	0.205**	1.000																	
4. $\boldsymbol{\Delta DR\_MRT}_{\mathbf{i,m-1}}$	0.024**	0.016**	0.097**	1.000																
5. $\%\boldsymbol{\Delta DR\_MRT}_{\mathbf{i,m-1}}$	0.017**	0.013**	0.131**	0.220**	1.000															
6. $\mathbf{MDLI_{i,m-1}}$	0.017**	0.012**	0.126**	0.009**	0.016**	1.000														
7. $\mathbf{DTURN_{i,m-1}}$	0.015**	0.004*	0.137**	0.027**	0.034**	0.009**	1.000													
8. $\mathbf{SA_{i,m-1}}$	-0.001	-0.002	0.072**	0.005**	0.003*	-0.086**	-0.017**	1.000												
9. $\mathbf{Opacity_{i,m-1}}$	0.004*	0.002	0.019**	0.007**	0.002	0.030**	0.016**	-0.037**	1.000											
10. $\mathbf{Age\_10_{i,m-1}}$	0.001	-0.000	0.055**	0.005**	0.005**	-0.044**	-0.007**	0.588**	-0.010**	1.000										
11. $\mathbf{Size_{i,m-1}}$	-0.001	0.001	-0.093**	-0.007**	-0.015**	0.029**	-0.013**	-0.161**	0.040**	-0.114**	1.000									
12. $\mathbf{M/B_{i,m-1}}$	0.006**	0.005**	-0.010**	0.002	0.014**	-0.015**	0.035**	0.012**	0.017**	0.009**	0.123**	1.000								
13. $\mathbf{TOBIN'S\_Q_{i,m-1}}$	0.010**	0.012**	0.005**	-0.004*	0.021**	-0.032**	0.055**	0.112**	0.030**	0.075**	0.153**	0.357**	1.000							
14. $\mathbf{MA\_Ret_{i,m-1}}$	-0.032**	-0.029**	-0.120**	-0.175**	-0.266**	0.012**	0.015**	0.002	0.001	0.000	0.006**	-0.009**	-0.016**	1.000						
15. $\mathbf{R\&}\boldsymbol{D/SALES}_{\mathbf{i,m-1}}$	0.005**	0.005**	0.048**	-0.001	0.002	0.001	-0.009**	0.114**	0.008**	0.096**	-0.022**	0.075**	0.268**	0.001	1.000					
16. $\mathbf{CL/CA_{i,m-1}}$	-0.001	-0.006**	-0.015**	-0.000	0.004*	0.005**	0.029**	-0.027**	0.053**	0.001	0.091**	0.008**	-0.044**	-0.005**	-0.105**	1.000				
17. $\mathbf{LEV_{i,m-1}}$	0.003	-0.002	-0.001	0.015**	0.027**	0.005**	0.032**	-0.083**	0.013**	-0.023**	0.052**	-0.024**	0.016**	-0.002	-0.034**	0.371**	1.000			
18. $\mathbf{ROA_{i,m-1}}$	0.001	0.005**	-0.086**	0.001	-0.002	-0.012**	0.040**	-0.130**	0.002	-0.123**	0.125**	0.009**	-0.200**	0.001	-0.440**	-0.038**	-0.179**	1.000		
19. $\boldsymbol{INCLOSS}_{\mathbf{i,m-1}}$	-0.003	-0.007**	0.077**	-0.010**	-0.006**	-0.008**	-0.030**	0.136**	0.010**	0.114**	-0.126**	-0.001	0.062**	0.009**	0.232**	0.021**	0.120**	-0.515**	1.000	
20. $\mathbf{NCSKEW_{i,m-12}}$	0.008**	0.006**	-0.008**	-0.014**	-0.020**	0.016**	-0.043**	-0.018**	0.010**	-0.002	0.023**	-0.005**	-0.017**	-0.000	0.005**	-0.004*	-0.004*	-0.010**	0.009**	1.000

1.4.2 Distress Risk and Crash Risk

We first show univariate evidence regarding the relationship between the change in distress risk from month *m-2* to *m-1* (*ΔDR_MRT*) and corresponding stock price crashes one month ahead (*CRASH_1*). Each month stocks are sorted into five portfolios based on previous month's *ΔDR_MRT* (whereby the 1st portfolio consists of stocks with the lowest *ΔDR_MRT* and the 5th portfolio the highest *ΔDR_MRT* stocks) and calculate the percentage of stock price crashes for each of these portfolios. Figure 2 illustrates the results. The per-month number of crashes in the lowest *ΔDR_MRT* portfolio is close to 1.4% and increases almost monotonically to approximately 2.3% in the highest *ΔDR_MRT* portfolio. The monthly crash difference between the highest and lowest *ΔDR_MRT* portfolios is 0.84% and is highly significant (p-value < 0.01). This figure suggests that distress risk is related positively with the probability of stock price crashes.

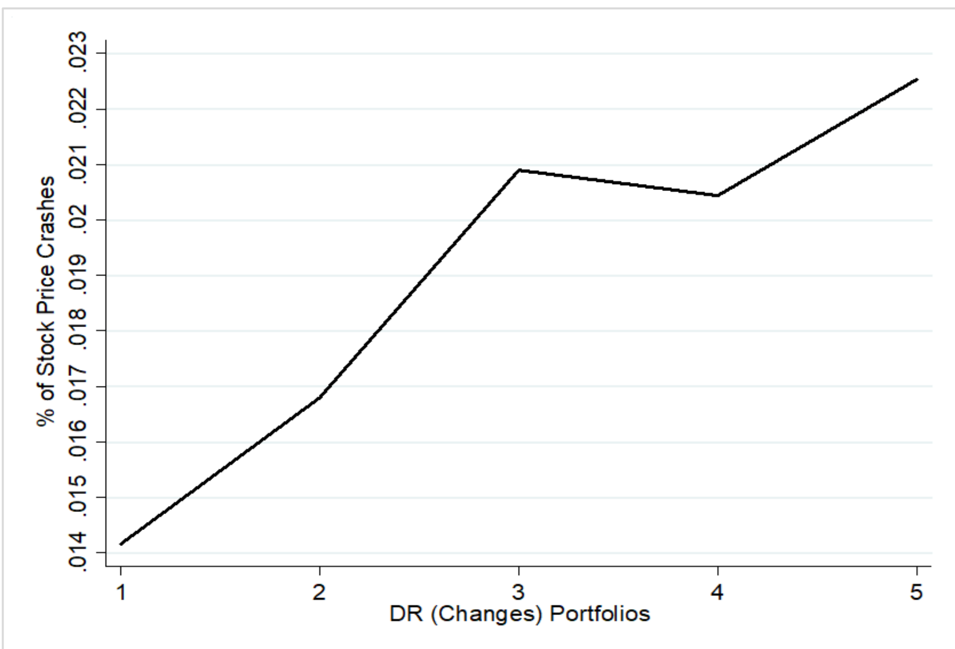

Figure 2: Percentage of stock price crashes across *ΔDR_MRT* quintiles
This figure displays the monthly percentage of stock price crashes across *ΔDR_MRT* quintiles. For each *ΔDR_MRT* quintile, the percentage of stock price crashes is the number of firm-month crashes divided by the total number of firm-month observations in that quintile.

We further investigate the relationship between distress risk and stock price crashes using multivariate analysis. Table 3 presents the results from the logit model as described by Eq. (1.8). The dependent variable is stock price crash risk (*CRASH_1*) in month m, whereas all independent variables are lagged by one month. All continuous variables are standardized to 0 mean and 1 standard deviation to avoid potential influences due to scaling differences.

Model (1) presents the univariate relationship between changes in distress risk (*ΔDR_MRT*) and the occurrence of stock price crash one month ahead. The coefficient of *ΔDR_MRT* is positive and statistically significant (p-value < 0.01), consistent with our hypothesis that firms with an increase in distress risk are more likely to experience a future stock price crash. In terms of economic significance, a one standardized unit increase of *ΔDR_MRT* increases the probability of a stock price crash by 14.34%. Model (2) includes a number of variables to control for various distress information likely related to stock price crashes. Despite the inclusion of these variables, *ΔDR_MRT* remains positive and highly significant while its economic impact on the probability of stock price crash is slightly lower, at 13.08%. *MDLI* is also positive and highly significant in predicting stock price crash, confirming the important role of an aggregate market default risk measure in asset pricing (Andreou, 2015). *SA* is positive and highly significant consistent with He and Ren (2017) who find that firm's financial constraints play a key role in future stock price crashes. In contrast with prior studies (Callen and Fang, 2013; Andreou et al., 2017), *SIZE* is negative and significant, suggesting that firms with high market capitalization tend to have a lower probability to crash. The difference most likely is due to the different data frequency (i.e., monthly vs. annual) used in this study. *M/B* is positive and significant only in Model (2).

Models (3) and (4) of Table 4 include additional control variables used by prior studies to predict stock price crashes. Again *ΔDR_MRT* remains significant in predicting stock price crash beyond these controls. Regarding controls, investors' heterogeneity (DTURN) is positive and significant consistent with prior studies (Chen, Hong, and Stein, 2001, Kim et al., 2011b). Consistent with Andreou et al. (2016) but in contrast to Hutton, Marcus, and Tehranian (2009), the financial opacity is not significant to predict stock price crash. *TOBIN'S_Q* is positively related to future stock price crashes, which indicates that potentially overvalued stocks (high *TOBIN'S_Q*) tend to have a higher probability to crash. As expected, market-adjusted return, MA_Ret, is significantly negatively related to stock price crashes, in contrast to prior studies (e.g., Chen, Hong, and Stein, 2001, Kim et al., 2011b). Also, higher conditional skewness (NCSKEW) leads to significant higher likelihood of stock price crash, consistent with prior studies (Chen, Hong, and Stein, 2001, Kim and Zhang, 2015; Andreou, Louca, and Petrou, 2017).

Table 3: The Impact of Distress Risk Changes on Stock Price Crashes

This table presents the results of logit regressions, having as dependent variable the primary stock price crash dummy ($Crash_{i,m}$). All models include constant, control variables, industry and year effects. All variables are defined in Appendix I. The standard errors are clustered at the firm level. Z-values (t-statistics) are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Constant	-4.664***	-4.666***	-4.669***	-4.649***
	(-16.85)	(-17.69)	(-17.86)	(-18.04)
$\mathbf{\Delta DR\_MRT_{i,m-1}}$	0.134***	0.123***	0.084***	0.085***
	(13.46)	(12.11)	(7.89)	(7.91)
$\mathbf{MDLI_{i,m-1}}$		0.150***	0.137***	0.138***
		(7.98)	(7.44)	(7.46)
$\mathbf{SA_{i,m-1}}$		0.067***	0.056***	0.056***
		(4.29)	(3.02)	(3.03)
$\mathbf{SIZE_{i,m-1}}$		-0.025**	-0.024**	-0.024**
		(-2.22)	(-2.07)	(-2.15)
$\mathbf{M/B_{i,m-1}}$		0.028**	0.008	0.009
		(2.14)	(0.65)	(0.68)
$\mathbf{CL/CA_{i,m-1}}$		0.015	0.016	0.016
		(0.92)	(1.04)	(1.08)
$\mathbf{LEV_{i,m-1}}$		0.017	0.015	0.015
		(1.14)	(1.04)	(1.06)
$\mathbf{ROA_{i,m-1}}$		0.028	0.063**	0.064**
		(1.13)	(2.39)	(2.43)
$\boldsymbol{INCLOSS}_{\mathbf{i,m-1}}$		-0.045	-0.039	-0.041
		(-1.28)	(-1.10)	(-1.15)
$\mathbf{DTURN_{i,m-1}}$			0.095***	0.097***
			(6.66)	(6.84)
$\mathbf{OPACITY_{i,m-1}}$			-0.009	-0.008
			(-0.75)	(-0.72)
$\mathbf{AGE\_10_{i,m-1}}$			0.009	0.009
			(0.50)	(0.48)
$\boldsymbol{TOBIN'S\_Q_{i,m-1}}$			0.065***	0.068***
			(3.13)	(3.28)
$\mathbf{MA\_Ret_{i,m-1}}$			-0.281***	-0.281***
			(-13.46)	(-13.45)
$\mathbf{R\&}\boldsymbol{D/SALES}_{\mathbf{i,m-1}}$			0.028	0.028
			(1.30)	(1.32)
$\mathbf{NCSKEW_{i,m-12}}$				0.052***
				(4.47)
Time Effects	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes
Obs.	343271	343271	343271	343271
Wald Chi-square	1231.81	1383.16	1717.2	1759.01
Log Pseudolikelihood	-31726.285	-31681.557	-31515.925	-31507.126
Pseudo R2	0.0161	0.0175	0.0226	0.0229

1.4.2.1 *Robustness Analysis*

Because the measure of distress risk contains market data information that may create endogeneity and multicollinearity issues, we perform several tests to alleviate these concerns. Particularly, we re-estimate model (4) of Table 3 using changes in distress risk at different lagged periods. Through this analysis, we also investigate the time-span predictability of distress risk. For instance, Model (4a) of Table 4 examines the impact of the *ΔDR_MRT* at the month m-2, which is calculated as the difference of distress risk from the month m-3 to the month m-2. Results reported in Table 4 show that *ΔDR_MRT* is still positive and statistically significant at the 1% level up to 4 four months before. This suggests that changes in distress risk can predict stock price crash as far as four months before the crash, diminishing also any concern with regards to endogeneity and multicollinearity. The change in distress risk turns insignificant to predict stock price crashes in five months in the future (Models (4d)-(4f)).

For further robustness test, we estimate the orthogonal measure of distress risk (*RES_ ΔDR_MRT)* using the following (monthly) rolling 36-month window regression model:

$$\Delta DR\_MRT_{i,m} = \alpha + b_{SA}SA_{i,m} + b_{size}SIZE_{i,m} + b_{MB}M/B_{i,m} + b_{MA\_RET}MA\_Ret_{i,m} + b_{\Delta PO}\Delta PO_{i,m} + v_{i,m} \qquad (1.10)$$

Our focus is on the residuals ($v_{i,m}$) of Eq. (1.10). Particularly, *RES_ ΔDR_MRT* derived from the predicted residuals ($\widehat{v_{i,m}}$) reflecting the "pure" distress risk changes measure, which captures the change in distress risk after controlling for standard firm characteristics and alternative accounting-based distress risk measure, ΔPO.[21] Model (4g) in Table 4 shows that the new distress risk measure, *RES_ ΔDR_MRT*, is positive and statistically significant (*p*-value < 0.01) consistent with our previous findings.

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[21] We use the Ohlson (1980) accounting-based distress proxy since five of our distress-related control variables (*SIZE*, *CL/CA*, *LEV*, *ROA*, and *INTOW*) are its determinants. The other four variables that are used in the estimation of O-Score are: 1) working capital to total assets; 2) a binary variable that takes one if the total liabilities exceed total assets and zero otherwise; 3) funds provided by operations over total liabilities (FUO/TL); 4) net income difference over the summation of the absolute values of the net income of the last two periods $-\left(\frac{(NI_t - NI_{t-1}}{|NI_t| + |NI_{t-1}|}\right), NIC$. This measure is estimated using the original coefficients of Ohlson (1980) but we also use the updated coefficients of Hillegeist et al. (2004) for robustness. The results are quantitatively similar (untabulated).

1.4.2.2 Crashed Vs. Non-Crashed Firms

In this section, we examine whether our findings are biased to market-wide characteristics and whether are similar to non-crashed firms. To do, we investigate whether *ΔDR_MRT* and other firm-specific and market-wide explanatory variables exhibit similar behavior in the month prior to crash events. Each crashed firm is matched with a non-crashed firm using the total similarity measure of Hoberg and Phillips (2016).[22] Results presented in Table 5 show that *ΔDR_MRT* is higher for crashed firms than that of non-crashed firms. Specifically, the crashed sample has a mean *ΔDR_MRT* of 0.9% while the matched only 0.3%.[23] The difference is statistically significant. This finding lends credence to our main hypothesis as it precludes the possibility our findings are driven by firm-specific characteristics or market-wide effects. Regarding other variables, the negative skewness (lagged twelve months) is positive (0.030) for the crashed firms but negative (-0.025) for the non-crashed firms (p-value < 0.01), consistent with our previous results. The crashed firms also have higher and significantly different mean values of *SA* index and *AGE_10* than the non-crashed firms, which connotes that crashed firms have more financial constraints and they are younger than their corresponding non-crashed firms. Market-adjusted return (*MA_RET*) is -2.2% for the crashed sample and -0.1% for the matched sample. This difference (-2.1%) is statistically significant at the 1% level, confirming that stocks following a bullish trend during the month before crash are less likely to crash, but stocks on a bearish trend have a higher probability to crash. This is also linked with distress risk as more sophisticated investors may identify at an early stage which firms may experience serious financial difficulties when new announcements are received in near future.

[22] The total similarity measure of Hoberg and Phillips (2016) is based on words that companies use to describe their products in 10-K annual filings where for each firm a pairwise word similarity score is computed. Our analysis is also applied using the firms' size as the matching measure for each month and industry (Fama & French, 1997, 48 industry classifications), where the results are quantitatively similar.
[23] The *t*-tests are computed using Welch's (1947) formula.

Table 4: Multicollinearity and Endogeneity Robustness Tests

This table presents the logit results of Model (4) from Table 3 under various modifications of the main explanatory variable, *ΔDR_MRT*. Particularly, Models (4a) to (4f) use lags values of *ΔDR_MRT* up to 12 months. In model (4g), *ΔDR_MRT* is replaced with *RES_ ΔDR_MRT* that represents the isolated information of *ΔDR_MRT* derived by Eq. (1.10). All models include constant, control variables, industry and year effects. The standard errors are clustered at the firm level. Z-values (t-statistics) are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(4)	(4a)	(4b)	(4c)	(4d)	(4e)	(4f)	(4g)
Constant	-4.649***	-4.643***	-4.629***	-4.628***	-4.624***	-4.609***	-4.625***	-5.022***
	(-18.04)	(-17.89)	(-17.79)	(-17.69)	(-17.60)	(-17.45)	(-16.85)	(-16.44)
$\boldsymbol{\Delta DR\_MRT_{i,m-1}}$	0.085***							
	(7.91)							
$\boldsymbol{\Delta DR\_MRT_{i,m-2}}$		0.057***						
		(4.29)						
$\boldsymbol{\Delta DR\_MRT_{i,m-3}}$			0.048***					
			(3.80)					
$\boldsymbol{\Delta DR\_MRT_{i,m-4}}$				0.035***				
				(2.92)				
$\boldsymbol{\Delta DR\_MRT_{i,m-5}}$					-0.007			
					(-0.50)			
$\boldsymbol{\Delta DR\_MRT_{i,m-6}}$						0.002		
						(0.19)		
$\boldsymbol{\Delta DR\_MRT_{i,m-12}}$							0.017	
							(1.17)	
$\boldsymbol{RES\_\ \Delta DR\_MRT_{i,m-1}}$								0.060***
								(4.87)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	343271	338514	332656	328073	323635	319494	294876	313343
Wald Chi-square	1759.01	1609.24	1555.21	1527.9	1497.5	1477.62	1427.91	1539.05
Log Pseudolikelihood	-31507.126	-31156.149	-30702.906	-30415.611	-29972.847	-29550.684	-27268.442	-28911.834
Pseudo R2	0.023	0.022	0.022	0.021	0.021	0.022	0.022	0.023

Table 5: Crashed Vs. Non-Crashed Firms

This table illustrates the average values of various firms' characteristics for two different sub-samples (crashed and non-crashed firms) and their comparison tests. The first sub-sample (Crashed Firms) consists the firm-month observations of crashed firms while the second sub-sample (Non-Crashed Firms) include the closest non-crashed firms to the crashed firms during their crash event. t-statistic is computed with degrees of freedom that use Welch's (1947) formula. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Crashed Firms (C)	Non-Crashed Firms (M)	Difference ($C-M$)	t-statistic
$\Delta DR\_MRT_{i,m-1}$	0.009	0.003	0.006***	4.794
$NCSKEW_{i,m-12}$	0.030	-0.025	0.055***	3.211
$DTURN_{i,m-1}$	0.003	0.005	-0.002	-1.446
$SA_{i,m-1}$	-3.944	-3.973	0.029***	3.997
$\mathrm{OPACITY}_{i,m-1}$	0.426	0.439	-0.013	-0.728
$AGE\_10_{i,m-1}$	0.164	0.133	0.032***	4.424
$SIZE_{i,m-1}$	8.596	8.615	-0.019	-1.601
$M/B_{i,m-1}$	2.919	2.981	-0.063	-0.548
$TOBIN'S\_Q_{i,m-1}$	1.919	1.894	0.025	0.862
$MA\_Ret_{i,m-1}$	-0.022	-0.001	-0.021***	-7.836
$R\&D/SALES_{i,m-1}$	0.107	0.101	0.006	0.521
$CL/CA_{i,m-1}$	0.599	0.600	-0.001	-0.126
$LEV_{i,m-1}$	0.537	0.530	0.007	1.498
$ROA_{i,m-1}$	0.021	0.021	0.000	0.014
$INCLOSS_{i,m-1}$	0.216	0.219	-0.003	-0.354

Our results thus far indicate that changes in firms distress risk is significantly and positively related to a future stock price crash and is robust after controlling for various control variables, robust statistical tests, and alternative matched sample. This distress-crash relationship is attributed to various reasons: 1) distress risk reflects market and accounting based information that is not easily revealed by other factors and presents a comprehensive view of firms' financial condition which is not likely to be affected by low financial opacity; 2) active investors sell these stocks when they identify the financial difficulties of the firms. The distress-crash relationship is expected to be more pronounced when there is high information asymmetry between firms' managers and shareholders (Kothari, Shu, and Wysocki, 2009) because a market-based distress risk measure cannot be easily manipulated by accounting practices. Our findings support this argument: they show the changes in distress risk contain useful financial information up to four months before a stock price crash. In the following analysis, we examine the impact of the distress risk on the probability of stock crash under specific information asymmetry conditions.

1.4.2.3 *Distress Risk and Stock Price Crash under Information Asymmetry*

In this section, we examine under what conditions the distress risk and stock price crash relationship becomes more pronounced. There is prior evidence that information asymmetry plays a key role in forecasting stock crash (Kothari, Shu, and Wysocki, 2009; Hutton, Marcus, and Tehranian, 2009; Kim and Zhang, 2016). Thus, the underlying factor under investigation in this section is information asymmetry. We employ segregation analysis by replacing our main explanatory variable *ΔDR_MRT* in Eq. (1.8) by three new interaction terms that utilize three binary variables based on firm's information asymmetry level. The two extreme binary variables, P_1 and P_4, take the value of one for firms in the lowest (1st quartile) and highest (4th quartile) information asymmetry portfolios and zero otherwise, respectively. The middle binary variable, P_{2+3}, takes one for firms in the second and third quartiles of information asymmetry. The interactions terms multiply the binary variables by *ΔDR_MRT*. The information asymmetry in this study is proxied by three variables; the Opacity measure as in Hutton, Marcus, and Tehranian (2009), the Amihud's (2002) illiquidity measure (*AILLIQ*), and Analysts' dispersion (Ajinkya and Gift, 1985).[24] The first measure (OPACITY) captures the information asymmetry (between managers and shareholders) derived by earnings management, while the other two measures (*AILLIQ* and analysts' dispersion) capture the information asymmetry between investors. Eq. (1.8) is modified as follows:

$$Crash_{i,m} = \alpha_0 + a_1(P_1 \times \Delta DR\_MRT_{i,m-1}) + a_2(P_{2+3} \times \Delta DR\_MRT_{i,m-1}) + a_3(P_4 \times \Delta DR\_MRT_{i,m-1}) + \sum_{m=4}^{M} a_m Distress\_Vars_{i,m} + \sum_{n=M+1}^{N} a_n Controls_{i,m-1} + e_{i,m} \quad (1.11)$$

Table 6 presents the results. Model (1) shows the results based on the opacity measure. The model indicates that the impact of *ΔDR_MRT* on the probability of stock price crash is higher for the firms with higher accounting opacity. Specifically, for the highest opacity portfolio ($P_4 \times \Delta DR\_MRT$) an increase of one standardized unit of *ΔDR_MRT* leads to a significant increase of 12.19% the probability of stock price crash. For the middle opacity portfolio ($P_{2+3} \times \Delta DR\_MRT$) the impact of *ΔDR_MRT* on the probability of stock price crash is by

[24] The portfolios for financial opacity are sorted based on the whole sample while the portfolios for *AILLIQ* and Dispersion are sorted using monthly and industry rebalancing due to the different investor preferences. Because of missing values for analysts' dispersion the sample for this analysis is reduced to 158,932.

approximately 8.55% and for the lowest opacity portfolio ($P_1 \times \Delta DR\_MRT$) the impact of *ΔDR_MRT* is 4.71%. These findings are consistent with Hutton, Marcus, and Tehranian (2009) who find that firms with opaque financial reports tend to have a higher stock crash risk.

Models (2) and (3) examine how the stock market liquidity and analysts' dispersion affect the magnitude of the *ΔDR_MRT* impact on stock price crash. The results of model (2) show that *ΔDR_MRT* has a greater impact for more illiquid ($P_4 \times \Delta DR\_MRT$) firms while for high liquidity stocks ($P_1 \times \Delta DR\_MRT$) ΔDR_MRT has no significant effect. Further, the difference of coefficients between the low liquidity ($P_4 \times \Delta DR\_MRT$) and high liquidity ($P_1 \times \Delta DR\_MRT$) stocks is 0.091 and statistically significant. These findings are consistent Brogaard, Li, and Xia (2017) who show that firms with enhanced liquidity have lower default risk due to higher information efficiency and stronger corporate governance credited mainly to blockholders. The more information efficiency and stronger corporate governance lead to a lower likelihood of stock price crash since new information (bad or good news) is released via a timely fashion to the public. Furthermore, model (3) shows that the impact of *ΔDR* on stock price crash is significant for stocks with high dispersion of analysts' earnings forecasts ($P_4 \times \Delta DR\_MRT$). This result is also consistent with Avramov et al. (2009) who show that the negative cross-sectional relation between analysts' dispersion and future stock returns is driven mainly by firms' financial distress.[25]

Table 6: The impact of Distress Risk on Crash Risk under Asymmetry Conditions

This table presents the logit regression results where *ΔDR_MRT* is replaced with its interaction terms with three dummies variables that are created from portfolio formations based on three different information asymmetry variables in each of the three models. Specifically, in model (1) the three dummies that constitute the interaction terms are the portfolios based on stocks' accounting opacity ($OPACITY$) where P_4 takes one if the stocks are included in high opacity portfolio and zero otherwise, similarly P_{2+3} takes 1 if the stocks are included in the second and third opacity portfolios while the P_1 takes 1 if stocks are included in the lowest opacity portfolios. In the same manner, P_4, P_{2+3}, P_1 in model (2) are defined based on the Amihud (2002) illiquidity measure (*AILLIQ*). While the binary variables in Model (3) are constructed based on investors' dispersion (*DISPERSION*) that is defined as standard deviation of analysts' estimates. The standard errors are clustered at the firm level. T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$\mathbf{OPACITY_{i,m-1}}$ (1)	$\mathbf{AILLIQ_{i,m-1}}$ (2)	$\mathbf{DISPERSION_{i,m-1}}$ (3)
Constant	-4.645***	-4.645***	-4.525***
	(-17.96)	(-17.97)	(-10.18)

[25] Sadka and Scherbina (2007) show that the negative dispersion-return relation is more pronounced for illiquidity stocks, highlighting the interconnection between dispersion and illiquidity.

$(\boldsymbol{P_1} \times \boldsymbol{\Delta DR\_MRT_{i,m-1}})$	0.046**	0.013	-0.076
	(2.04)	(0.41)	(-1.05)
$(\boldsymbol{P_{2+3}} \times \boldsymbol{\Delta DR\_MRT_{i,m-1}})$	0.082***	0.081***	0.034
	(5.31)	(5.90)	(1.05)
$(\boldsymbol{P_4} \times \boldsymbol{\Delta DR\_MRT_{i,m-1}})$	0.115***	0.104***	0.066**
	(6.80)	(6.25)	(2.56)
⋮	⋮	⋮	⋮
Time Effects	Yes	Yes	Yes
Industry Effects	Yes	Yes	Yes
$(\boldsymbol{P_4} \times \boldsymbol{\Delta DR\_MRT_{i,m-1}}) - (\boldsymbol{P_1} \times \boldsymbol{\Delta DR\_MRT_{i,m-1}})$	0.069**	0.091***	0.142*
Chi-square	6.31	7.1	3.44
Prob > Chi-square	0.012	0.0077	0.0638
N	343271	343271	158932
Wald Chi-square	1757.38	1783.93	896.22
Log Pseudolikelihood	-31504.263	-31503.897	-14834.1
Pseudo R2	0.023	0.023	0.0238

In sum, changes in distress risk have a higher impact (predictive ability) on stock price crash for firms with higher information asymmetry, either between managers and shareholders or among investors. As prior studies show that information asymmetry and earnings management relationship is more pronounced for firms in financial troubles (DeFond and Jiambalvo, 1993; DeAngelo, DeAngelo, and Skinner, 1994; Charitou, Lambertides, and Trigeorgis, 2011), we concur that *ΔDR_MRT* conveys useful information in predicting stock price crash when the practice of hoarding bad news reaches a critical threshold level (Kothari, Shu, and Wysocki, 2009; Hutton, Marcus, and Tehranian, 2009).

1.5 Additional Tests

In this section, we provide additional tests using alternative measures of stock price crash and distress risk. To alleviate concerns over the definition of our primary stock price crash measure, we re-estimate Model (4) of Table 3 using two alternative measures of stock price crash as defined in subsection 3.2. These alternative crash measures are 1) *CRASH_2* that is the original version of crash risk as estimated in Hutton, Marcus, and Tehranian (2009), and 2) MINRET which is the continuous crash risk measure of Ak et al. (2016). We also use an alternative distress risk measure estimated in Charitou et al. (2013) as described in subsection 3.3 (*DR_MRTALT*). We keep a common sample in all models' results for a consistent comparison. The results are reported in Table 7. For brevity, table 7 tabulates only the coefficients of *ΔDR_MRT, ΔDR_MTRALT, and %DR_MTR.*

Our results show that in all model specifications, both measures of the distress risk change are positive and significant in predicting stock price crash for all three alternative measures of crash risk. Overall, the results from this analysis suggest that our findings are robust to alternative modifications and tests, highlighting the key role of distress risk in predicting stock price crash.

Table 7: The Impact of Distress Risk Changes on Stock Price Crashes: Additional Analysis

Table 7 presents the results from additional robustness tests. More specifically, Table 7 provides the results from logit (first six columns) and ordinary least squares (last three columns) models using alternative measures of crash risk and ΔDR_MRT. The alternative measures of crash risk are 1) the original version of crash risk (CRASH_2) as it is estimated by Hutton, Marcus, and Tehranian (2009) and 2) the continues crash risk measure (MINRET) of Ak et al. (2016). While the alternative proxies for ΔDR_MRT are 1) the changes of distress risk as measured by Charitou et al. (2013), ΔDR_MRTALT, and 2) the percentage change of distress risk (%DR_MRT, based on our standard distress risk measure of Bharath and Shumway, 2008). All models include the control variables similar to the Model (4) of Table 3. Model (1) is similar to the Model (4) of Table 3, having a difference only about the sample size, where here the sample is based on the available information of the new *DR* measure, *ΔDR_MRTALT*. The standard errors that derived from logit models (Model (1)-(6)) are clustered at the firm level. The standard errors of OLS models (Model (7)-(9)) are heteroskedasticity consistent and robust to general forms of cross-sectional (spatial) and temporal dependence, estimating Driscoll and Kraay (1998) standard errors, specifying 12 months as lagged values to be considered in the autocorrelation structure. T-statistics are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$\mathbf{CRASH\_1}_{i,t}$			$\mathbf{CRASH\_2}_{i,t}$			$\boldsymbol{MINRET}_{i,t}$ ($\boldsymbol{OLS}$)		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Constant	-4.649***	-4.650***	-4.653***	-4.995***	-4.995***	-4.999***	0.489***	0.489***	0.489***
	(-17.95)	(-17.93)	(-17.85)	(-14.83)	(-14.82)	(-14.77)	(44.39)	(44.78)	(45.58)
$\mathbf{\Delta DR\_MRT_{i,m-1}}$	0.077***			0.069***			0.023***		
	(6.81)			(5.28)			(4.82)		
$\mathbf{\Delta DR\_MRTALT_{i,m-1}}$		0.076***			0.060***			0.026***	
		(6.45)			(4.44)			(5.12)	
$\mathbf{\%DR\_MRT_{i,m-1}}$			0.034**			0.040***			0.029***
			(2.55)			(2.80)			(7.62)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Industry Effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
N	342454	342454	342454	342454	342454	342454	342454	342454	342454
Wald chi2	713.770	1697.740	1594.210	1054.000	1039.184	1022.990			
Log-Pseudolikelihood	-31387.631	-31389.404	-31407.600	-28642.116	-28645.823	-28651.709			
Pseudo R2	0.023	0.023	0.022	0.018	0.017	0.017			
R2 (OLS)							0.075	0.077	0.079

1.6 Conclusion

This study investigates the direct relationship between changes in firms' distress risk and future stock price crash. We show that an increase in a firm's distress risk increases the probability of stock price crash in the following month. The predictive ability of the distress risk change persists up to four months before the crash event. The impact of distress risk on stock price crash is robust to alternative distress risk and crash risk measures.

Our findings are consistent with a theory that a stock price crash is driven mainly by practices used by managers to hoarding bad news for a long period (Jin and Myers, 2006). A firm in financial troubles has higher incentives to manipulate its financial results (Charitou, Lambertides, and Trigeorgis, 2011) mainly to have access to external financing. When the true financial condition of the firm is revealed, a stock price crash is a natural consequence. Hence, in this study, we argue that distress risk can convey important risk-related information that can be used to signal future stock price crash. This hypothesis is supported by our findings on the role of information asymmetry on the magnitude of the impact of distress risk on stock price crash. Particularly, the results indicate that the impact of distress risk on future stock price crash is higher for firms with higher accounting opacity, less liquidity and higher dispersion of analysts' earnings forecasts.

Our findings are highly important for market practitioners as they provide a dynamic measure (distress risk) to forecast future stock price crash. If investors use the distress risk as a possible predictor of crash risk, they can benefit by early warning signs, thus possibly avoiding to a large extent the crash-related investment errors.

2 Distress Risk Anomaly and Misvaluation

2.1 Introduction

The relationship between distress risk and stock returns has been the subject of increasing scholarly interest over the past two decades.[26] Most studies reveal a negative impact of distress risk on stock returns (Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2008; Garlappi and Yan, 2011). This anomalous distress-return relation is in direct contradiction to the risk-reward trade-off in financial markets, which predicts that financially distressed firms compensate investors for bearing this type of risk (Fama and French, 1995; Chen and Zhang, 1998). A rational justification of distress anomaly is that highly distressed companies earn lower returns due to the inability of investors to accurately price distressed stocks (Dichev, 1998; Griffin and Lemmon, 2002). Although prior studies concur that the distress anomaly is due to mispricing effects, they do not investigate this argument in depth. For example, in order to support the mispricing explanation, Griffin and Lemmon (2002) show that the anomaly is stronger during earnings announcements; there is no prior research, however, that investigates the mispricing argument explicitly. Prior studies have generally relied on indirect mispricing mechanisms and arguments to explain the distress anomaly. Our study intends to fill this gap using direct proxies of mispricing to examine whether the distress risk anomaly is driven by mispricing effects.

To date, research has linked mispricing with dispersion in analysts' earnings forecasts (Diether, Malloy, and Scherbina, 2002; Johnson, 2004; Sadka and Scherbina, 2007) and bad earnings quality (e.g., Jensen, 2005). For instance, Johnson (2004) used the dispersion of earnings expectations to proxy for mispricing (similar to Sadka and Scherbina, 2007) and to show a negative relationship between dispersion of earnings expectations and stock returns that is more pronounced for more financially-levered firms. This result is consistent with our hypothesis that the negative distress-return relation is driven primarily by misvalued stocks. Other studies argue that financially distressed firms have higher incentives to manipulate their financial performance in order to conceal (to some extent) their financial distress (DeAngelo, DeAngelo, and Skinner, 1994; Rosner, 2003; Lee and Yeh, 2004; Charitou,

[26] Distress risk is associated with a firm's failure to meet its financial obligations.

Lambertides, and Trigeorgis, 2011).[27] Highly distressed firms that engage in such practices shift their stock price away from fair (intrinsic) value. Jensen (2005) shows that managers of overvalued stocks engage in earnings management practices to sustain overvaluation. Chi and Gupta (2009) and Badertscher (2011) concur with Jensen's (2005) findings: Badertscher (2011) finds that the longer a firm is overvalued, the more likely it is to engage in earnings management practices.

Earnings management is unsustainable, because negative financial information can only be withheld until it reaches an arbitrary level. Once this level is reached, firms experience a stock price crash (Kothari, Shu, and Wysocki, 2009). For example, Hutton, Marcus, and Tehranian (2009) show that firms with high accounting opacity (proxied by earnings management) have a higher probability of stock price crash, which is another form of risk.

One way to measure for distress risk is to use the option pricing model outlined by Black and Scholes (1973) and Merton (1974). The model views equity as an option on the firms´ assets with exercise price the face value of debt. This measure, in contrast to the alternative reduced form models of Altman (1968) and Olhson (1980), is a forward-looking measure of a firm's likelihood to default (Vassalou and Xing, 2004).[28] We proxy mispricing by analysts' disagreements similar to Johnson (2004) and Sadka and Scherbina (2007). For robustness, we utilize two alternative mispricing measures: the first is the proxy of Rhodes-Kropf, Robinson, and Viswanathan (2005) derived from the decomposition of market-to-book multiple and the second is abnormal returns (alpha) derived from the five-factor asset pricing model by (Fama & French, 2015). Our findings show that the distress risk anomaly is driven primarily by mispriced (overvalued) stocks, which supports findings by prior studies (Dichev, 1998; Griffin and Lemmon, 2002). More specifically, we show that the negative distress-return relationship is primarily the result of overvaluation of highly distressed stocks, which are more likely to have lower or even negative returns in subsequent month(s), compared to low distress risk stocks. Our findings are robust to alternative distress and mispricing measures.

[27] Other studies show that earnings shenanigans are used by firms to keep financial constraints at low levels (Lamont, Polk, and Saa-Requejo, 2001; Livdan, Sapriza, and Zhang, 2009).
[28] Our primary distress risk measure is based on the naïve approach of Bharath and Shumway (2008).

The main contribution of this study is twofold; first, we give a rational explanation to the "distress risk puzzle", indicating that the distress risk anomaly is driven by overvalued stocks (a systematic feature of highly distressed stocks) and second, we model explicitly the relationship between distress risk and mispricing..

The remainder of the paper is organized as follows: Section 2.2 contains the relevant literature review, section 2.3 describes the data, the measurements of our variables and methodology. Section 2.4 discusses our empirical results and section 2.5 is the conclusion.

2.2 Literature Review

Several studies use financial distress (Chan and Chen, 1991; Fama and French, 1996) to explain certain key asset pricing anomalies (e.g., size, value, asset growth, momentum). For instance, Fama and French (1992, 1993) argue that the value premium can be explained by financial distress. This argument, however, goes against the majority of studies on the reported impact of distress risk on stock returns. Dichev (1998) demonstrates a negative relation between default risk and stock returns using the Altman (1968) and Ohlson (1980) scores of probability of default. He analyzes this anomaly as the inability of investors to accurately price distress risk, but does not examine this argument in detail. Griffin and Lemmon (2002) show that firms with high distress risk tend to have the largest return reversals around earnings announcements, a fact that can be interpreted as an implicit justification of the mispricing hypothesis. Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011) explain the distress risk anomaly through the renegotiation options available to shareholders close to a bankruptcy event. Likewise, Trigeorgis, Lambertides, and Del Viva (2015) argue that the reorganization (put) options lead firms to higher (returns) skewness which result in lower stock returns. Conrad, Kapadia, and Xing (2014) argue that the negative distress-return relationship arises due to the high probability of extreme positive outcomes (jackpots) of distressed firms.

On the other hand, some prior studies do not find evidence on the distress risk anomaly. For instance, Vassalou and Xing (2004) show that the relationship between default risk and stock returns turns positive for firms with small market capitalization and high book-to-market ratio. Da and Gao (2010) on the other hand, demonstrate that the positive relationship between stock returns and default risk occurs only in the first month following portfolio formation but, two months later, the default risk premium disappears. They also argue that this positive relationship is driven by short-term reversals instead of systematic default risk. The majority of studies, however, favor the negative distress-return relation.

Regarding the impact of mispricing on stock returns, Sadka and Scherbina (2007) use analysts' disagreement as a proxy for mispricing to show that stocks diverge from their intrinsic values when the trading costs are high, a finding consistent with prior studies (e.g., De Long et al., 1990; Pontiff, 1996; Shleifer, 2000). Diether, Malloy, and Scherbina (2002) use the same mispricing measure to show a negative relation between mispricing and subsequent stock returns. Johnson (2004) provides an explanation for this phenomenon based on firms' financial leverage. Specifically, he argues that the negative dispersion-return relationship is more pronounced when firms have high levels of debt. Prior studies (Altman, 1968; Ohlson, 1980; Campbell, Hilscher and Szilagyi, 2008) show that firms' (book or market) leverage is a significant determinant offinancial distress and, most likely, distress risk and analysts' disagreement are directly correlated. Along the same lines, Avramov et al. (2009) show that the profitability of dispersion-based (mispricing) trading strategies is driven by the worst-rated firms directly associated with financial distress. Overall, there is evidence to support that stock mispricing and financial distress are interconnected, a factor that should be investigated in the context of distress anomaly. This is what this chapter aims to do in what follows.

2.3 Data, Measurements and Methodology

2.3.1 Sample Data

Our sample includes 4,374 U.S. firms from January 1976 to December 2015, and the data are from the Compustat (Quarterly) and CRSP databases (excluding financial firms with 4-digit SIC codes between 6000 and 6999).[29] To ensure that accounting variables are announced before the monthly market data (e.g., returns), we match quarterly accounting data with stock returns three months after the release of the quarterly results. Our analysis is

[29] All the quarterly variables derived from Income statements and Cash Flows are calculated based on Trailing Twelve Months (TTM), thus the variables are all seasonally adjusted.

based on monthly observations, which allows us to capture the dynamic effects of distress risk (Chava and Jarrow, 2004).

2.3.2 Distress Risk

The most appropriate proxy of distress risk for this research question is the Black and Scholes (1973) and Merton (1974) (hereafter BSM) option-based probability to default. The default risk measures based on option models have an advantage over the reduced-form models because of their ability to capture the market default-related information through the market prices (Trigeorgis, Lambertides, and Viva, 2015). Option pricing models enable the construction of a measure of distress risk that contains forward-looking information (since market prices reflect investors' expectations about a firm's future performance). This is more appropriate for estimating the market´s assessment of the likelihood of a firm exercising its default option in the future than historical estimates. Unlike accounting-based models, the volatility of asset is a key input in such option pricing models.[30]

In this paper, distress risk is measured using the Bharath and Shumway (2008) approach. Specifically, we use the distance to default (hereafter *DD*) that is derived from Merton *DD* equation.

$$DD_{BhSh_{i,t}} = \frac{ln\left(\frac{V}{B}\right)+\left(R_{i,t-1}-0.5\sigma^2_{v(BhSh)}\right)T}{\sigma_{v(BhSh)}\sqrt{T}} \qquad (2.1)$$

where *V* is the firms' asset value that equals the firm's market value of equity (*ME*) plus the face value of its debt (*B*). The market value of equity (*ME*) is the number of shares outstanding (CRSP item shout) multiplied by the market price of shares (CRSP item "PRC"), while the face value of debt is estimated using the debt in one year (Compustat item "dd1"), plus half long-term debt (Compustat item "dltt") which is the same debt variable that is used

[30] For the past half century, scholars, have recognized the importance of bankruptcy probability and have attempted to find the most efficient way to measure it. These measures are separated into two main categories: reduced-form models and structural models (Charitou, Lambertides, and Trigeorgis, 2008). The most widely used reduced-form models are those using Altman's (1968) and Ohlson's (1980) scores. The seminal study by Black and Scholes (1973) and Merton (1974) was the trigger for many scholars to investigate default probabilities and their consequences using option pricing-based models. The BSM model is considered to be the first structural model.

by Crosbie and Bohn (2003) in their KMV model.[31] R is the monthly stock returns (CRSP item "ret"). The firms' volatility ($\sigma_{v(BhSh)}$) is estimated as a weighted average of the volatilities of a firm's equity and debt: $\sigma_{v(BhSh)} = \left(\frac{ME}{(ME+B)}\right)\sigma_E + \left(\frac{B}{(ME+B)}\right)\sigma_B$. Equity volatility ($\sigma_E$) is the standard deviation derived from monthly equity returns, adjusted for cash dividends[32] over a 36-month window: $R_E = ln\left(\frac{ME_t+CD_t}{ME_{t-1}}\right)$, while debt volatility is estimated using an approximation formula $\sigma_B \approx 0.05 + 0.25\sigma_E$. T is the maturity time of the firm's debt, which is set to 1 year.

We also use the Charitou et al. (2013) measure of default risk (DD_{CDLT}) for robustness tests. The difference between this measure and Eq. (2.1) is the estimation of firm's volatility ($\sigma_{v(CDLT)}$). In particular, $\sigma_{v(CDLT)}$ is estimated from the firm value return, which is obtained as $R_V = ln\left(\frac{V_t+D_t}{V_{t-1}}\right)$, where D_t is the total firm payout that equals to cash dividends plus interest expenses (Compustat item "xint"). Following Charitou et al. (2013), we modified R_V and use the maximum between firm's total value return and risk-free rate (1-month U.S. Treasury bill rate), $\max(R_V, R_f)$. We estimate volatility $\left(\sigma_{v(CDLT)}\right)$ as standard deviation from a 36-month window. Both measures of distress risk are estimated at a monthly frequency.

2.3.3 Mispricing measures

Our primary mispricing measure is the analysts' disagreement (or forecasts dispersion), $\mathrm{MIS}_{\mathrm{DIS}}$. This has been used widely by prior studies (i.e., Diether, Malloy, and Scherbina, 2002; Johnson, 2004; Sadka and Scherbina, 2007). Following previous studies (Diether, Malloy, and Scherbina, 2002; Johnson, 2004; Sadka and Scherbina, 2007), we define analysts' disagreement as the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year over the absolute value of the mean outstanding earnings forecasts (zero values of the average forecasts are excluded).[33] This measure is calculated only if a firm is covered by at least two analysts.

[31] KMV model is based on the structural approach to calculate the firm's probability of default.
[32] ME_t is the firm's market capitalization and CD_t is cash dividends (Compustat item "dvpsx")
[33] Analyst earnings forecasts are taken from the U.S. Institutional Brokers Estimate System, known as I/B/E/S.

For robustness, we use two alternative proxies to reduce bias inferences that may occur due to a potential measurement error. The first alternative mispricing measure is based on the decomposition method of a firm's market-to-book multiple developed by Rhodes-Kropf, Robinson, and Viswanathan (2005). Specifically, we decompose the firm's natural logarithm of market-to-book equity ratio [$\ln(M/B)$] into two components: the misvaluation (market value to intrinsic value of equity) and the growth option (intrinsic value to book value of equity) components (Hertzel and Li, 2010). The decomposition is as follows:

$$ln\left(\frac{M}{B}\right) = ln\left(\frac{M}{V}\right) + ln\left(\frac{V}{B}\right) \tag{2.2}$$

where M is stock market capitalization, B is the book value of common equity, and V represents the intrinsic value of equity; V needs to be estimated. In contrast to other studies (Lee, Myers, and Swaminathan, 1999; Dong, Hirshleifer, & Richardson, 2006), Rhodes-Kropf, Robinson, and Viswanathan (2005) relax the residual income model to estimate V (by excluding analysts' forecasts), thus greatly reducing the bias level of the estimations. The residual income specification is as follows:

$$ln(M_{i,t}) = a_{0,j,t} + a_{1,j,t} \times ln(B_{i,t}) + a_{2,j,t} \times ln(|NI_{i,t}|) + a_{3,j,t}I^{-}ln(|NI_{i,t}|) + a_{3j,t}(LEV)_{i,t} + \varepsilon_{i,t} \tag{2.3}$$

where $|NI_{it}|$ is the absolute value of net income (Compustat item "ni") of firm i at time t. I^{-} is a binary variable that equals to one for firms with negative net income and zero otherwise. *LEV* is the market leverage ratio that equals the firm's total liabilities over its market value. The firm's market value is equal to the firm's market capitalization + book assets (Compustat item "at") – deferred taxes (Compustat item "txdb") – Book value of common equity (Compustat item "ceq"). Subscript j refers to industry. ε_{it} captures the difference between the observed market value of equity and intrinsic value. This is the proxy for misvaluation and is abbreviated as $MIS_{RRV,i,t}$ in empirical analysis. Eq. (2.3) is estimated cross-sectionally for each industry and month. We use the 12-industry classification scheme by Fama and French (1997). The model specification can explain within-industry cross-sectional variation in market capitalization ($M_{i,t}$) by an average of over 89% for all industries. This misvaluation measure has also been employed by other studies (Hertzel and Li, 2010 and Fu, Lin and Officer, 2013).

Our second alternative mispricing proxy is abnormal returns (alpha) derived from the five-factor asset pricing model by Fama and French (2015). A stock is assumed to be overvalued in relation to a specific model if its estimated alpha is negative, meaning that the stock fails to generate a return at (or above) the required rate of return. Conversely, if alpha is positive, the stock is undervalued. The five-factor asset pricing model specification is as follows:

$$EXRET_{i,t} = MIS_{\alpha\_5FF_{i,t}} + \beta_{MRP_{i,t}} \times MRP_t + s_{SMB_{i,t}} \times SMB_t + s_{HML_{i,t}} \times HML_t + r_{RMW_{i,t}} \times RMW_t + c_{CMA_{i,t}} \times CMA_t + \varepsilon_{i,t} \qquad (2.4)$$

where $EXRET_{i,t}$ is the firm's i excess return (over one-month risk-free rate) for the month t and MRP is market risk premium. *SMB* is the small-minus-big and *HML*, the high-minus-low factors that account for the return difference between small- and big-sized firms, and value and growth stocks, respectively. *RMW* (robust minus weak) is the profitability factor and *CMA* (conservative minus aggressive) is the investment factor.[34] Alpha ($MIS_{\alpha\_5FF_{i,t}}$) in Eq. (2.4) captures the abnormal or risk-adjusted returns that cannot be explained by risk factors. For each firm, we estimate Eq. (2.4) with rolling regressions and a 36-month window to yield time-variant firm-specific estimates of alpha. In our analysis, estimated alphas are multiplied by -1; so that higher (positive) reported alphas correspond to more overvalued stocks and lower (negative) alphas to undervalued stocks.

2.3.4 Methodology

Our methodology consist of a portfolio analysis and Fama-MacBeth (1973) regression analysis. The preliminary, univariate portfolio analysis aims to show the existence of distress anomaly. In the double-sorted portfolio analysis, we identify potential interconnections between stock mispricing and distress risk. In the single-sort portfolio analysis, stocks are sorted into ten portfolios based on distress risk measures. In the double-sort portfolio analysis, stocks are first sorted into five portfolios based on mispricing measures, and then, within each mispricing portfolio, stocks are sorted into five portfolios based on distress risk.

In the second part, we estimate Fama and MacBeth (1973) regressions by augmenting the standard Fama and French (1992) model with distress risk, mispricing, and interaction terms:

[34] The Fama-French risk factors, along with the risk-free interest rate are obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html .

$$EXRET = f(Beta, Size, BM, ROE, MOM, DR, MIS, Interactions) \qquad (2.5)$$

where *Beta (β)* represents the firm's systematic risk estimated over the previous 36 months, using the capital asset pricing model (CAPM). Size is the firm's monthly market capitalization estimated as the natural logarithm of *ME* (which is equal to a stock's price multiplied by the number of shares). *BM* is book-to-market ratio estimated as the book value of common equity divided by *ME*. *ROE* is the ratio of return-on-equity estimated as a firm's net income to book value of common equity. *MOM* stands for momentum calculated as the cumulative monthly return of the previous 12 months leaving one month as a gap. *DR* is distress risk, the negative distance-to-default (DR_{BhSh}), as derived from Eq. (2.1).[35] *MIS* is the mispricing variable measured by MIS_{DIS}, MIS_{α_5FF} and MIS_{RRV}. All explanatory variables are lagged one month (t-1). To avoid sensitivity of our results to extreme observations we perform the analysis winsorizing the top and bottom 1% (1st and the 99th percentiles, respectively) of observations for each independent variable.

2.4 Empirical Analysis

Subsection 2.4.1 presents summary statistics of our key variables, along with portfolio analysis, to investigate distress anomaly; subsection 2.4.2 presents Fama-MacBeth (1973) analysis; and the final subsection, 2.4.3, provides robustness analysis. If our hypothesis that distress risk anomaly is driven by overvalued stocks is valid, then after controlling for mispricing effects, the distress anomaly should be eliminated.

2.4.1 Summary Statistics and Portfolio Analysis

Table 8 reports descriptive statistics (Panel A) and correlation coefficients (Panel B) for our key variables. Beta is the systematic risk and is close to 1 (mean=1.15 and median=1.09). The average size (ln(ME)) is 6.38, ranging from 0.45 to 10.09. *BM* has an average value equal to 0.62 which is close to other studies (e.g., Kothari and Shanken, 1997; Trigeorgis and Lambertides, 2014). The mean values of *ROE* and *MOM* are equal to 8.04% and 14.89%, respectively. Mean *DR* is -6.85, which is quantitatively similar to other studies that use a similar *DR* measure (e.g., Bali et al., 2017). MIS_{DIS} has a mean of 0.21, while its median is

[35] Similarly, the negative DD_{CDLT} is abbreviated as DR_{CDLT}.

close to zero (=0.047), indicating that the analysts' expectations for almost half the stocks do not have a great dispersion. Panel B shows that Size is negatively correlated with BM (-0.266) and DR (-0.337). In general, all bivariate correlation coefficients are relatively small ($|corr.coef.| \leq$ 33.7%).

Table 8: Summary Statistics of Key Explanatory Variables

This table presents summary statistics (Panel A) and correlation coefficients (Panel B) for the key variables that are included in the asset pricing model specified by Eq. (2.5). *RET* is monthly stock returns derived from CRSP Database. Beta is estimated using the CAPM over a 36-month period. Size is the natural logarithm of market capitalization (number of shares outstanding × price per share). Book-to-Market (*BM*) ratio is the book value of common equity divided by market capitalization. *ROE* (Return-on-Equity) is equal to net income over book value of common equity. MOM (Momentum) is estimated as the cumulative monthly return of the previous 12 months leaving a one-month gap. DR_{BhSh} is the negative distance to default which is estimated by Eq. (2.1). MIS_{DIS} refers to the mispricing measures that are calculated as the standard deviation of all outstanding earnings-per-shares forecasts for the current fiscal year, over the absolute value of the mean outstanding earnings forecasts. Panel B presents the Pearson correlation coefficients. ** and * represent statistically significant at 1% and 5% respectively.

Panel A. Summary Statistics

	RET	***Beta***	***Size***	***BM***	***ROE***	***MOM***	DR_{BhSh}	MIS_{DIS}
Mean	0.0122	1.1523	6.3770	0.6199	0.0804	0.1489	-6.8557	0.2055
Median	0.0083	1.0935	6.2500	0.5286	0.1180	0.0935	-5.8254	0.0469
Min	-0.9737	-0.7096	0.4543	-112.3932	-4.4779	-0.9450	-24.0715	0.0000
Q1	-0.0510	0.7222	5.0673	0.3255	0.0526	-0.1133	-9.0679	0.0200
Q3	0.0699	1.4975	7.5745	0.8061	0.1701	0.3251	-3.4998	0.1154
Max	9.3736	3.8629	10.0866	29.8519	2.6400	8.7264	1.6906	197.0000
Std. Dev.	0.1242	0.6651	1.7562	0.6937	0.4185	0.4473	4.9420	1.2999
N	347255	347255	347255	347255	347255	347255	347255	347255

Panel B. Pearson Correlation Coefficients

	RET	***Beta***	***Size***	***BM***	***ROE***	***MOM***	DD_{BhSh}	MIS_{DIS}
RET	1							
Beta	-0.002	1						
Size	-0.019**	-0.101**	1					
BM	0.021**	-0.033**	-0.266**	1				
ROE	0.007**	-0.071**	0.120**	-0.066**	1			
MOM	0.002	0.028**	0.093**	-0.189**	0.047**	1		
DR_{BhSh}	0.006**	0.194**	-0.337**	0.239**	-0.119**	-0.269**	1	
MIS_{DIS}	-0.005**	0.037**	-0.080**	0.059**	-0.056**	-0.054**	0.088**	1

Table 9 presents a single and double-sorted portfolio analysis. Panel A shows value-weighted returns based on two different distress measures, DR_{BhSh} and DR_{CDLT}. Stocks are sorted based on their distress risk of the previous month and the value-wieghted return of each DR portfolio is reported (with monthly rebalancing). Consistent with prior studies, we find a negative relationship between distress risk and stocks returns (e.g., Campbell, Hilscher, and

Szilagyi, 2008; Garlappi and Yan, 2011). The return difference between the highest and lowest DR portfolios are -0.73 (t-stat$= -2.53$) and -0.59% (t-stat$= -2.09$), using DR_{BhSh} and DR_{CDLT} respectively.

To examine the role of mispricing in distress risk anomaly, we perform double-sort portfolio analysis in Panel B of Table 9. Stocks are first sorted into five portfolios based on the mispricing measure (MIS_{DIS}) of the previous month and subsequently into five distress risk portfolios.[36] Panel B of Table 9 shows that the distress risk anomaly exists only in the portfolio of the most overvalued stocks or highest (5th) MIS_{DIS} portfolio. The return difference between the lowest and highest distressed stocks is -0.83% (or 10.43% per annum), and is significant at 5% level. These findings explicitly set out the mispricing hypothesis of distress risk anomaly in that the latter seems to be the outcome of market correction of highly distressed stocks.

Table 9: Portfolio Analysis

This table presents the value-weighted returns of portfolios derived from univariate and double-sorted analysis. Particularly, Panel A presents the value-weighted returns of portfolios formed monthly based on firms' distress risk of the previous month. The portfolio analysis is applied based on two different distress risk measures based on Bharath and Shumway (2008) and Charitou et al. (2013) as they are described in section 2.3.2. Panel B presents the value-weighted returns of double-sorted portfolios based on distress effect controlled by analysts' disagreement (our primary mispricing proxy). Portfolios are formed from February of 1976 to December of 2015, when the data are available. Particularly, stocks are sorted into five portfolios based on their mispricing measure of the previous month. Within each mispricing portfolio, stocks are sorted into five portfolios based on their distress risk variables. Highest-Lowest column/row are the return difference between the highest and lowest distress portfolios. t-statistic is used to determine if the two-sample means (e.g., Highest-Lowest) are equal. *, **, *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A. Univariate Analysis

	V.W. Return	
DR Port.	DD_{BhSh}	DD_{CDLT}
1-Lowest	0.0097	0.0095
2	0.0104	0.0105
3	0.0097	0.0099
4	0.0097	0.0100
5	0.0097	0.0089
6	0.0094	0.0103
7	0.0111	0.0105
8	0.0104	0.0098
9	0.0092	0.0106
10-Highest	0.0025	0.0036
Highest-Lowest	-0.0073**	-0.0059**
T-statistics	-2.5308	-2.0888

[36] The distress risk portfolios are formed based on stock distress risk in the previous months, similar to the mispricing measure.

Panel B. Double-Sorted Portfolio Analysis: Distress effect controlled by Analysts' Disagreement								
		DR_{BhSh}						
		1-Lowest	2	3	4	5-Highest	Highest-Lowest	t-statistic
	1-Lowest	0.0106	0.0111	0.0121	0.0118	0.0141	0.0035	1.4513
	2	0.0087	0.0076	0.0096	0.0108	0.0099	0.0013	0.5983
MIS_{DIS}	3	0.0098	0.0095	0.0116	0.0103	0.0096	-0.0002	-0.0865
	4	0.0101	0.0079	0.0099	0.0119	0.0096	-0.0004	-0.1564
	5-Highest	0.0125	0.0122	0.0078	0.0078	0.0042	-0.0083**	-2.3054

Portfrolio Analysis suggests that mispriced stocks are a key factor for distress anomaly, which is consistent with our initial hypothesis. It seems that the distress anomaly is due to the price correction of extremely overvalued distressed stocks. The interconnection of stock mispricing and distress risk is investigated further in the next section with multivariate Fama-MacBeth regressions.

2.4.2 Fama-MacBeth regression analysis

In this section, we examine whether distress risk explains subsequent stock returns beyond standard Fama and French (1992) variables, along with some additional control variables using Fama-MacBeth (1973) regressions. The Fama-MacBeth analysis is presented in Table 10.[37] The benchmark Models (1) and (2) confirm the role of standard variables (e.g., beta, Size, B/M) in a basic Fama-French (1992) type analysis (including *ROE* and *MOM*). Then we proceed with our extended analysis of the incremental role of distress risk in explaining subsequent equity returns. Consistent with prior studies both *Size* and *BM* are significant factors explaining subsequent returns. *ROE* and *MOM* are also positive and highly significant. Model (3) confirms that distress risk (DR_{BhSh}) exhibits a significant *negative* relation with subsequent equity returns: a unit increase in DR_{BhSh} implies a lower average return equal to 2.4%. Model (4) examines the impact of distress risk on subsequent returns after controlling for mispricing. Consistent with prior studies, MIS_{DIS} is negative and highly significant (e.g., Diether, Malloy and Scherbina, 2002) that is, stocks with high analysts' disagreement (overvalued stocks) tend to have a lower subsequent return. The inclusion of $\mathrm{MIS}_{\mathrm{DIS}}$ in Model (4) reduces the size of DR_{BhSh} but remain significant. DR_{BhSh} becomes

[37] Reported t-statistics in our Fama-MacBeth regressions are estimated based on Newey and West (1987) standard errors using 3-month time-lags.

insignificant in Model (5), which includes the interaction between DR_{BhSh} and MIS_{DIS}. The negative and significant interaction effect (coef.$= -0.091$, t-stat$= -3.04$) in Model (5) shows distressed firms that are more overvalued tend to have lower average returns.

In Panel B of Table 10, we further investigate the relation between DR_{BhSh} and stock returns by estimating Fama-MacBeth regressions for each of the five portfolios sorted by mispricing measure (MIS_{DIS}).[38] The results for the first three low mispricing portfolios, models (3i)-(3iii), show that DR_{BhSh} is not significant in explaining subsequent stock returns. On the other hand, in the high mispricing portfolios (most overvalued stocks), models (3iv) and (3v), results show that DR_{BhSh} is negative and significant. These results corroborate our previous findings that the distress risk anomaly is mostly driven by overvalued distressed stocks.

2.4.3 Robustness Analysis

First, we provide robustness tests by re-estimating the double-sorted portfolio and Fama MacBeth analyses using alternative proxies for distress risk and mispricing. Table 11 presents the double-sorted portfolio analysis using the alternative distress and mispricing measures. Panel A and B provide additional evidence on the interconnection between distress risk and stock mispricing. In Panel A, we replace DR_{BhSh} by DR_{CDLT}, and the results indicate that the distress anomaly exists only within the most overvalued portfolio, confirming the previous results. The results of Panel B in Table 11 are also quantitatively similar to the results of Panel B in Table 9.[39]

[38] The results are quantitatively similar regardless of the mispricing measure.

[39] The untabulated results are quantitatively similar using alphas derived from CAPM (Sharpe, 1964; Lintner, 1965a, 1965b) and the three-factor model (Fama and French, 1993).

Table 10: Extended Fama and French Type Regressions

This table presents the Fama-MacBeth regressions. Beta is estimated over a 3-year period using the CAPM. *Size* is the natural logarithm of market value of equity. Book-to-Market (*BM*) ratio is the book value of common equity divided by market value of equity. *ROE* (Return-on-Equity) is equal to net income over book value of common equity. *MOM* (Momentum) is calculated as the cumulative monthly return of the previous 12 months leaving a one-month gap. DD_{BhSh} is the negative distance to default which is estimated similar to Bharath and Shumway (2008) (Eq. 2.1). MIS_{DIS} is measured as the standard deviation of all outstanding earnings-per-share forecasts for the current fiscal year over the absolute value of the mean outstanding earnings forecasts. $DD_{BhSh} \times MIS_{DIS}$ is the interaction term between DD_{BhSh} and MIS_{DIS}. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively, using Newey-West (1987) adjusted t-statistics.

	Panel A					Panel B				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(3i)**	**(3ii)**	**(3iii)**	**(3iv)**	**(3v)**
	FF3	**FF3-Extended**	**FF3-Extended**	**FF3-Extended**	**FF3-Extended**	$\mathbf{P_1}$	$\mathbf{P_2}$	$\mathbf{P_3}$	$\mathbf{P_4}$	$\mathbf{P_5}$
Constant	1.361***	1.057**	0.956**	1.072**	1.075**	1.063**	0.657	0.957**	0.640	0.358
	(3.25)	(2.58)	(2.23)	(2.53)	(2.54)	(2.25)	(1.47)	(2.01)	(1.20)	(0.63)
Beta	-0.010	-0.041	-0.012	0.003	0.001	0.125	-0.102	0.064	0.098	-0.070
	(-0.07)	(-0.33)	(-0.09)	(0.02)	(0.01)	(0.87)	(-0.68)	(0.43)	(0.65)	(-0.49)
Size	-0.092**	-0.098**	-0.114***	-0.122***	-0.117***	-0.136***	-0.100**	-0.107**	-0.113**	-0.052
	(-2.10)	(-2.36)	(-2.80)	(-3.04)	(-2.92)	(-3.06)	(-2.27)	(-2.41)	(-2.20)	(-0.85)
BM	0.079	0.240**	0.271**	0.306***	0.317***	0.600***	1.103***	0.406*	0.449***	0.142
	(0.70)	(2.19)	(2.53)	(2.83)	(2.93)	(2.92)	(5.86)	(1.86)	(2.79)	(1.00)
ROE		0.786***	0.751***	0.648***	0.648***	1.422***	0.985**	0.250	0.662	0.579**
		(3.45)	(3.31)	(2.99)	(2.93)	(2.81)	(2.13)	(0.47)	(1.36)	(2.13)
MOM		0.903***	0.822***	0.794***	0.775***	0.730**	0.503	0.842***	0.636**	0.684*
		(3.42)	(3.24)	(3.17)	(3.12)	(2.23)	(1.52)	(2.68)	(2.27)	(1.69)
$\boldsymbol{DR_{BhSh}}$			-0.024**	-0.019*	-0.011	-0.007	-0.009	-0.005	-0.039**	-0.054***
			(-2.34)	(-1.93)	(-1.12)	(-0.59)	(-0.74)	(-0.36)	(-2.21)	(-2.64)
$\boldsymbol{MIS_{DIS}}$				-0.341***	-0.646***					
				(-3.03)	(-4.36)					
$\boldsymbol{DR_{BhSh} \times MIS_{DIS}}$					-0.091***					
					(-3.04)					
Obs.	347255	347255	347255	347255	347255	69917	69455	69459	69325	69099
R-Squared	0.045	0.059	0.062	0.066	0.068	0.116	0.108	0.105	0.101	0.096

Table 11: Robustness Double-Sorted Portfolio Analysis

This table presents the value-weighted return of double-sorted portfolios based on alternative distress and mispricing variables' specifications, which are divided into two panels. Panel A presents the distress risk effect controlled by analysts' disagreement and Panel B shows the results of distress effect controlled by alternative mispricing measures. Portfolios are formed from February of 1976 to December of 2015, when the data are available. Specifically, stocks are sorted into five portfolios based on their mispricing measure of the previous month. Within each mispricing portfolio, stocks are sorted into five portfolios based on their distress risk variables. As mispricing measures we use three different approaches, 1) analysts' disagreement (MIS_{DIS}), that is equal to the earnings forecasts dispersion, 2) the mispricing measure (MIS_{RRV}) of Rhodes-Kropf, Robinson, and Viswanathan (2005), and 3) the negative alpha ($-MIS_{\alpha\_5FF}$) derived from five-factor asset pricing model of Fama and French (2015). The distress risk proxies are based on Bharath and Shumway (2008), DR_{BhSh} (primary distress risk), and Charitou et al. (2013), DR_{CDLT} (alternative distress risk), as described in section 2.3.2. Highest-Lowest column are the return difference between the highest and lowest distress portfolios. t-statistic is used to determine if the two-sample means (e.g., Highest-Lowest) are equal. *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

Panel A. Distress effect controlled by Analysts' Disagreement

		DR_{CDLT}						
		1-Lowest	2	3	4	5-Highest	Highest-Lowest	t-statistic
MIS_{DIS}	1-Lowest	0.0103	0.0114	0.0117	0.0121	0.0137	0.0034	1.4665
	2	0.0085	0.0084	0.0091	0.0106	0.0107	0.0023	1.1003
	3	0.0094	0.0101	0.0108	0.0099	0.0096	0.0002	0.0940
	4	0.0103	0.0078	0.0106	0.0100	0.0094	-0.0009	-0.3171
	5-Highest	0.0134	0.0115	0.0083	0.0091	0.0049	-0.0084**	-2.4374

Panel B. Distress effect controlled by alternative mispricing proxies ($\mathbf{MIS_{RRV}}$ and $-\mathbf{MIS}_{\alpha_{5FF}}$)

		DR_{BhSh}						
		1-Lowest	2	3	4	5-Highest	Highest-Lowest	t-statistic
MIS_{RRV}	1-Lowest	0.0142	0.014	0.0139	0.0134	0.0135	-0.0007	-0.1969
	2	0.0106	0.0097	0.0125	0.0122	0.0116	0.0011	0.4162
	3	0.0075	0.0104	0.0094	0.011	0.0101	0.0026	1.0215
	4	0.0103	0.0094	0.0103	0.0077	0.0109	0.0006	0.2162
	5-Highest	0.0092	0.0098	0.0087	0.0115	0.002	-0.0072**	-2.1838
		DR_{BhSh}						
		1-Lowest	2	3	4	5-Highest	Highest-Lowest	t-statistic
$-MIS_{\alpha_{5FF}}$	1-Lowest	0.0117	0.0099	0.0116	0.0095	0.0114	-0.0002	-0.0867
	2	0.0089	0.0106	0.0088	0.0108	0.0115	0.0026	1.0057
	3	0.0094	0.0114	0.0111	0.0099	0.0112	0.0018	0.8201
	4	0.0103	0.0105	0.0108	0.0137	0.0093	-0.0010	-0.2917
	5-Highest	0.0126	0.0110	0.0093	0.0076	0.0002	-0.0125***	-2.5850

Table 12 illustrates the results of Models (3) and (4) of Table 10, using the alternative distress and mispricing measures.[40] Consistent with Table 10, the coeficient of DR_{CDLT} in Model (3') is negative and significant (t-stat= -1.93). However, when the mispricing variable is added in model (4'), DR_{CDLT} is not significant. Model (4'') and (4''') include the alternative mispricing measures. MIS_{RRV} in Model (4'') is negative and significant and causes a

[40] Table 12 also presents the results from Table 10 for comparison.

reduction in statistical significance of DR_{BhSh} by 10%. MIS_{α_5FF}, in Model (4''') is insignificant.

Table 12: Robustness on DR-Return Relation

This table provides the robustness Fama-MacBeth regression results based on alternative distress risk and mispricing measures. The alternative distress risk measure is DR_{CDLT} and the alternative mispricing measures are MIS_{RRV} and $-MIS_{\alpha\_5FF}$. The control variables are Beta, Size, BM, ROE, and MOM, which are common in all models. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, using Newey-West (1987) adjusted t-statistics.

	(3)	(3')	(4)	(4')	(4'')	(4''')
Constant	0.976**	1.024**	1.091***	1.135***	0.902**	0.919**
	(2.30)	(2.40)	(2.60)	(2.70)	(2.26)	(2.18)
Beta	-0.015	-0.021	0.000	-0.005	0.013	-0.010
	(-0.12)	(-0.17)	(0.00)	(-0.04)	(0.10)	(-0.08)
Size	-0.112***	-0.112***	-0.120***	-0.120***	-0.090**	-0.100**
	(-2.74)	(-2.76)	(-2.99)	(-3.02)	(-2.29)	(-2.51)
BM	0.269**	0.234**	0.304***	0.273**	0.241*	0.249**
	(2.51)	(2.14)	(2.81)	(2.45)	(1.73)	(2.34)
ROE	0.755***	0.727***	0.651***	0.620***	0.610***	0.822***
	(3.32)	(3.21)	(2.99)	(2.89)	(2.67)	(3.74)
MOM	0.836***	0.787***	0.807***	0.758***	0.877***	0.863***
	(3.30)	(3.09)	(3.22)	(3.02)	(3.56)	(3.40)
DR_{BhSh}	-0.019**		-0.015*		-0.015*	-0.018**
	(-2.21)		(-1.78)		(-1.79)	(-2.13)
DR_{CDLT}		-0.018*		-0.014		
		(-1.93)		(-1.53)		
$MIS_{DIS,i,t}$			-0.343***	-0.361***		
			(-3.05)	(-3.27)		
$MIS_{RRV,i,t}$					-0.260***	
					(-2.98)	
$MIS_{\alpha\_5FF,i,t}$						-0.028
						(-1.21)
Obs.	347255	344954	347255	344954	337119	341475
R-Squared	0.062	0.062	0.066	0.066	0.068	0.066

To investigate our hypothesis further, we isolate the pure component of distress risk from potential (undesired) mispricing effects. If our hypothesis is true, we expect the new "pure" distress risk to be insignificant in explaining subsequent stock returns. To do this decomposition, we regress DR_{BhSh} on MIS_{DIS} using the following OLS regression:[41]

$$DR_{BhSh_{i,t}} = a + \delta MIS_{DIS_{i,t-1}} + \varepsilon_{i,t} \tag{2.6}$$

The "pure" *DR* is derived from the estimated residuals ($\widehat{\varepsilon_{i,t}}$) of Eq. (2.6) that capture the information contained by the measure of distress risk that is not explained by mispricing. We

[41] We estimate each regression for each month and industry in order to capture the industry-specific distress characteristics that play a key role in distress risk determination (Chava and Jarrow, 2004). The same exists for mispricing measures within each industry (Alford, 1992; Liu, Nissim and Thomas, 2002).

apply this method for the alternative measures (MIS_{RRV} and MIS_{a_FF5}) of distress risk and mispricing.

The robustness results are presented in Table 13. The first two models in Table 13 include the ("contaminated") distress risk measures, DR_{BhSh} and DR_{CDLT}. Models (3) and (4) replace DR_{BhSh} and DR_{CDLT} with orthogonal components, DR_{BhSh}^{DIS} and DR_{CDLT}^{DIS}. The estimated coefficients are not significant, confirming that by removing mispricing-related information from *DR*, the negative distress-return relation is no longer present. The results remain unchanged when alternative mispricing measures (DR_{BhSh}^{RRV} and DR_{BhSh}^{FF5}) are used in Models (5) and (6).

Table 13: Robustness on *DR*-Return Relation

This table provides the robustness Fama-MacBeth regression results based on "pure" distress risk measures (DR_{BhSh}^{DIS}, DR_{CDLT}^{DIS}, DR_{BhSh}^{RRV}, and DR_{BhSh}^{5FF}) derived from Eq. (2.6). Models (3) and (4) use as a mispricing variable the analysts' disagreement in the decomposition method. Analysts' disagreement equals to the standard deviation of all outstanding earnings-per-shares forecasts for the current fiscal year over the absolute value of the mean outstanding earnings forecasts. Model (5) uses as mispricing measure for the decomposition method, the mispricing proxy of Rhodes-Kropf, Robinson, and Viswanathan (2005), MIS_{RRV}. In the final model (6), *DR* is decomposed using $-MIS_{\alpha\_5FF}$ derived from the 5-Factor model by Fama and French (2015). All the control variables in this table are similar to those in Table 12. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively, using Newey-West (1987) adjusted t-statistics.

	"Contaminated" *DR* Measures		"Pure" *DR* Measures			
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.897**	0.930**	1.035**	1.037**	1.035***	1.038***
	(2.14)	(2.23)	(2.58)	(2.58)	(2.59)	(2.60)
Beta	-0.022	-0.030	-0.059	-0.060	-0.050	-0.045
	(-0.18)	(-0.24)	(-0.49)	(-0.49)	(-0.41)	(-0.37)
Size	-0.104**	-0.101**	-0.090**	-0.090**	-0.094**	-0.095**
	(-2.57)	(-2.51)	(-2.22)	(-2.22)	(-2.35)	(-2.35)
BM	0.311**	0.301**	0.243*	0.240*	0.264*	0.261*
	(2.35)	(2.28)	(1.82)	(1.80)	(1.96)	(1.95)
ROE	0.685***	0.691***	0.718***	0.719***	0.716***	0.709***
	(3.04)	(3.07)	(3.19)	(3.20)	(3.19)	(3.15)
MOM	0.730***	0.740***	0.793***	0.791***	0.773***	0.777***
	(2.80)	(2.83)	(3.00)	(2.99)	(2.92)	(2.92)
DR_{BhSh}	-0.021**					
	(-2.55)					
DR_{CDLT}		-0.018**				
		(-2.23)				
DR_{BhSh}^{DIS}			0.004			
			(0.72)			
DR_{CDLT}^{DIS}				0.006		
				(0.88)		
DR_{BhSh}^{RRV}					-0.005	

					(-0.69)	
DR^{5FF}_{BhSh}						-0.007
						(-1.13)
Obs.	328091	328091	328091	328091	328091	328091
R-Squared	0.064	0.064	0.063	0.063	0.063	0.063

Overall, the results provide evidence that the distress risk anomaly is likely due to overvalued distressed stocks that their prices tend to decline in the following month(s). Consistent with this notion, Sadka and Scherbina (2007) argue that the mispricing of stocks with high earnings dispersion tends to be short-lived. Hence, if we control for the mispricing effect, the distress risk anomaly is no longer present, supporting the arguments of prior studies that distress anomaly can be explained by mispricing of stocks (Dichev, 1998; Griffin and Lemmon, 2002).

2.5 Conclusion

Several studies suggest that distress risk is negatively related to stock returns (e.g., Campbell, Hilscher, and Szilagyi, 2008; Garlappi and Yan, 2011). Our study investigates this anomalous relation and contributes to the existing literature by examining directly whether distress-return relationship is affected by mispricing effects. Our argument is also motivated by the fact that prior studies relied upon indirect mispricing justifications to explain distress anomaly (Dichev, 1998; Griffin and Lemmon, 2002). To investigate the interconnection between distress risk and stock mispricing, we perform double-sorted portfolio analysis and Fama-MacBeth regression analyses.

Our findings suggest that the distress anomaly is driven by mispriced (overvalued) stocks, a finding consistent with prior studies (Dichev, 1998; Griffin and Lemmon, 2002) that try to explain distress anomaly through the inability of investors to accurately price distress risk. More specifically, our results provide evidence that the negative distress-return relation exists only within the portfolio of the most overvalued stocks; a finding that is also supported by Fama-MacBeth regression analysis. Furthermore, by decomposing the mispricing effects from distress risk, we find that the "pure" (net of mispricing effects) distress risk does not have any significant effect on stock returns, confirming our hypothesis that distress risk anomaly is driven by mispricing effects. The results are robust to alternative specifications of distress risk, mispricing proxies, and approaches.

3 Equity Investment by Global Funds: Return and Sovereign Risk

3.1 Introduction

During the 1990s many emerging markets (EMs) embarked on programs of financial liberalization, especially the opening of stock markets to foreign investment. This has led foreign investors to add EM stocks to their portfolios, providing portfolio exposure to these economies as part of strategies aimed at diversification. A substantial literature has developed on the consequences of liberalization for stock market returns in EMs and the factors that drive international portfolio capital flows to these economies.[42] The performance of stock markets in EMs and their comparison to stock markets of developed countries has been thoroughly examined in the literature (e.g., Diamonte, Liew, and Stevens, 1996; Fama and French, 1998; Griffin, Kelly, and Nardari, 2010). There is, however, very little study of the performance of foreign equity investors in EMs. The purpose of this paper is to study the returns earned by global investment funds on their equity investments in emerging economies. We examine the factors that have played an important role in the returns earned by global funds in EMs, paying special attention to the impact of sovereign credit rating announcements on the return of foreign equity holdings. Sovereign credit ratings are considered an important determinant of access to international capital markets by EMs (Reinhart, 2002) because they are one important source of information that foreign investors can use to assess the level of riskiness in EMs.

In this study, we use a proprietary dataset compiled by *EPFR Global* to study the factors behind the aggregate rate of return earned by global investment funds in EMs during 1998-2013. Figure 3 shows the MSCI Emerging Market (MSCI EM) and Developed Market (MSCI DM) total return index during 1999-2013 (rebased to January 1999). The figure shows that stock markets in EMs have outperformed those of DMs during this period: while the MSCI DM index doubled it increased fivefold in MSCI EMs. The outperformance of DM stock markets by EMs has been well documented. Figure 3 also presents an index of the

[42] Studies include, *inter alia*, Bekaert and Harvey (2000), Edison and Warnock (2008) and Thapa and Poshakwale (2012). The literature is discussed in greater detail in the next section.

performance of global investment funds in EMs (Fund Index).[43] It shows that global investment funds have narrowly outperformed the MSCI EM index during this period. Our study focuses on the return of global funds and looks into the factors behind their outperformance of EM stock market indexes, particularly the role played by sovereign credit risk.

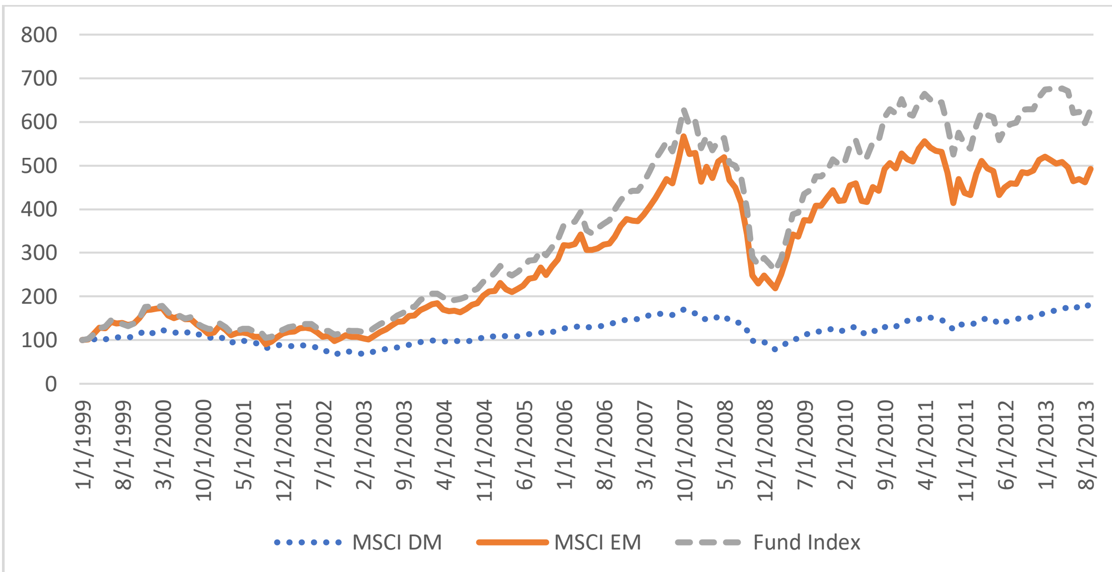

Figure 3: Stock Indexes (Jan. 1999 = 100)
The figure illustrates the MSCI Emerging Market index (MSCI EM), MSCI Developed Market index (MSCI DM) and the Global investment fund index during 1999-2013 (rebased to January 1999). The Global investment fund index is calculated as the average monthly return of foreign investment funds in 16 EMs. The MSCI indexes are from DataStream.

Figure 4 shows the annual rate of return earned by global investment funds in sixteen EMs (left axis) and the amount of net foreign equity capital invested in the same EMs by global funds (right axis). The rate of return has generally been positive, with notable exceptions during the early years of the opening of EM stock markets (2000-02) and the height of the global financial crisis (GFC). The figure also shows that, starting from low levels in the early 2000s, equity inflows to EMs increased continuously to reach $10bn by 2006. While there was a small net outflow during the early stages of the GFC in 2008, flows rebounded in 2009-10 to reach $20bn in 2009. As many commentators have argued, while investors shunned DMs in the early phases of the GFC, EMs were increasingly seen as attractive destinations

[43] We computed the global fund return index with monthly data on the aggregate rate of return earned by global investment funds in 16 EMs. The data used in the calculation of this index are described in Section 3.3.

due to the perception of strong fundamentals and the “decoupling” hypothesis: the economic fate of EMs came to be seen as differing from that of DMs. Net capital flows turned negative in 2011 and especially in 2013 as the first signs of the reversal of quantitative easing policies especially in the US (“taper tantrum”) appeared.

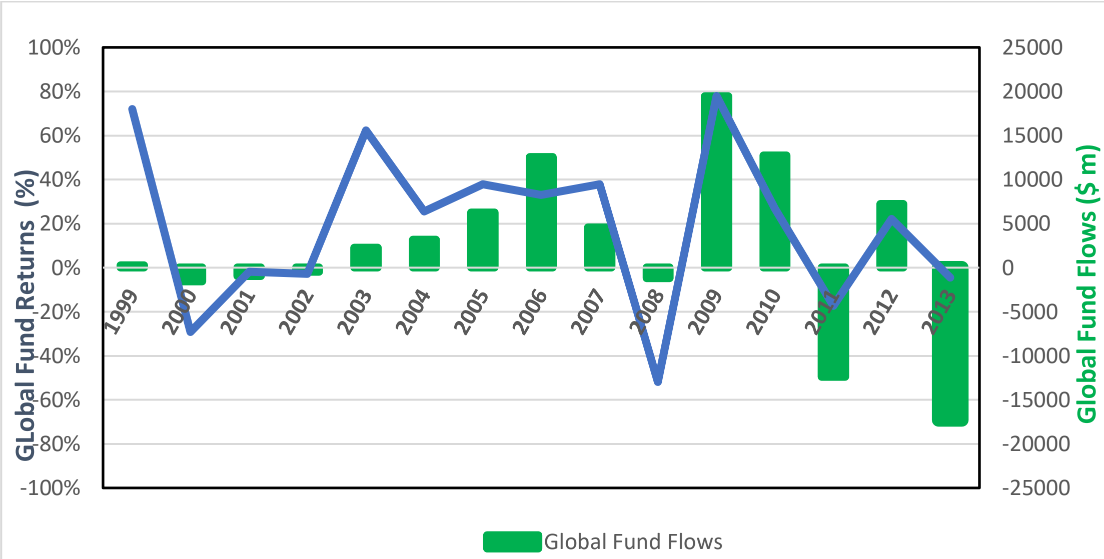

Figure 4: Annual Rate of Return of Foreign Investors and Net Capital Flows to EMs

The figure presents the annual returns of the global investment fund index (left axis) and the amount of global equity fund flows (right axis) in sixteen EMs during the period 1999 - 2013. The annual global fund returns are the average annualized returns (using monthly returns from EFPR Global) for sixteen EMs. Global fund flows are equal to the total amount of net foreign equity capital invested in the same (sixteen) EMs.

This paper makes several contributions. First, to the best of our knowledge, this is the first paper to offer a systematic study of sovereign risk along with other factors shaping the performance of global investment funds in EMs. By studying the determinants of the rate of return, it provides an assessment of the factors behind portfolio investment decisions by global investors in EMs. Second, by investigating the role of sovereign credit ratings, it contributes to our understanding of the informational role of announcements by credit rating agencies in international capital markets. To achieve this we employ several methodologies comprising event study, panel regressions, and two-stage asset pricing models. Event studies are mainly used to examine the behavior of foreign investors’ and stock market returns around credit rating events.[44] They reveal a distinct pattern between credit rating announcements and foreign investors' returns, consistent with studies on the relation between bond ratings and stock returns (e.g., Odders-White and Ready, 2006; Almeida *et al.*, 2017). The event methodology results are supported by panel estimates of the determinants of foreign investors' rate of return. The panel regression results show that a credit-rating upgrade is associated with lower excess (over risk-free rate) returns for foreign investors, consistent with the fundamental risk-return relationship in finance. On the other hand, announcements of change in credit outlook are unrelated to investors' returns. Third, we study the abnormal (risk-adjusted) returns of both foreign investors and stock markets in EMs. We follow a two-stage asset pricing procedure. In the first stage, three global asset pricing models, the augmented international CAPM (ICAPM) and the augmented three- and five-factor models of Fama and French (1993, 2015) are employed, to obtain risk-adjusted returns both for foreign investors and the broad stock markets. In the second stage, we estimate the determinants of risk-adjusted returns. We find that the informational content of credit rating upgrade/downgrade differs from that of credit outlook (positive/negative). This result holds for the risk-adjusted returns of investors but not the broad stock market. We attribute this finding to differences in behavior and level of sophistication between foreign and domestic stock market participants in EMs. Finally, our study examines the role of foreign equity flows by global funds on the rate of return. We find evidence of "return chasing", i.e., investment flows to countries where investors anticipate higher risk-adjusted returns.

The following section provides a brief review of the literature on stock returns and sovereign credit ratings in EMs. Section 3.3 describes the data and measurement of variables. The following section outlines panel estimation results of the determinants of investors' excess returns and the relationship to sovereign credit ratings. Section 3.5 investigates the abnormal (risk-adjusted) return of foreign investors and for stock markets in EMs. The last section concludes.

[44] In this paper a credit rating event refers to announcements of both credit upgrade/downgrade and credit outlook/watch. We study both types of announcements and focus on the distinct impact of the two on stock market and foreign investor returns.

3.2 Background Literature

When constructing their portfolio, international investors seek to maximize their return/risk tradeoff. Given the level of risk, investors tend to raise their investment in markets that are expected to provide higher returns and retreat from markets where expected returns are low (Bohn and Tesar, 1996). EMs have come to constitute an important component of international portfolios. International investors consider a number of factors or risks that may influence portfolio allocation across markets such as stock market development, stock market liquidity, exchange rate return, and sovereign credit ratings by the various rating agencies (S&P, Moody's and Fitch).

Levine and Zervos (1996) show that greater stock market development (higher market capitalization to GDP) is positively related to long-run economic growth. This can act to attract long-term foreign investors but may be also be a disincentive for foreign investors that look for short-term returns because a more mature stock market (higher capitalization) is associated with lower economic uncertainty or risk and, consequently, lower returns. Regarding the relation between equity and exchange rate returns, Hau and Rey (2006) show that the correlation structure of equity market and exchange rate returns is related to the level of equity market development (market capitalization to GDP). Specifically, they find that in countries with higher equity market development, the more negative the correlation of equity returns and exchange rate returns.

A notable difference between emerging and developed equity markets is the relative illiquidity of EMs, an important consideration for international investors, as noted by Amihud *et al.* (2015). Chuhan (1994) argues that market liquidity is an important factor for international investors in allocating their funds and low EM liquidity is a discouraging investment factor. Thapa and Poshakwale (2012) show that investors prefer to invest more in larger developed markets with more liquidity that have a higher degree of market efficiency. Liquidity risk is an important factor in asset pricing models (Amihud and Mendelson, 1986; Amihud, 2002). The impact of liquidity on stock returns in EMs is studied by Bekaert, Harvey and Lundblad (2007) whose main liquidity measure has strong predictive power on stock returns, much more so than the local market risk.[45]

There is extensive research of the relationship between corporate bond rating changes and common stock returns in developed markets (Holthausen and Leftwich, 1986; Zaima and McCarthy, 1988; Hsueh and Liu, 1992; Goh and Ederington, 1993; Almeida *et al.,* 2017).[46] However, there is little study of the effects of sovereign credit ratings on stock market returns, especially in EMs. Reisen and Von Maltzan (1999) find a significant impact of credit-rating changes on stock markets in EMs. Brooks *et al.* (2004) indicate that a downgrade of EMs may lead to a negative impact on local stock returns. Kaminsky and Schmukler (2002) show that sovereign credit rating changes influence not only the related financial instruments (government bonds), but also stock market returns. In addition, they show that the effects of credit ratings changes are stronger during crises. Dittmar and Yuan (2008) show that the impact of sovereign ratings on local stock returns can be more pronounced for companies that have bonds in their capital structure. Almeida *et al.* (2017) show that sovereign ratings affect corporate policies that are difficult to explain by unobservable firm characteristics and/or macroeconomic conditions. They find that sovereign ceiling policies apply (Borensztein, Cowan, and Valenzuela, 2013) and argue that these policies may affect corporate investment and financial policies.[47]

The application of international asset pricing models (IAPMs) to developed and emerging markets (Grauer, Litzenberger, and Stehle, 1976; Stulz, 1981; Cho, Eun, and Senbet, 1986; Griffin, Kelly, and Nardari, 2010; Hou, Karolyi, and Kho, 2011; Fama and French, 2012 and 2017) is an area that has attracted considerable interest, especially after the liberalization of EM financial markets (Bekaert and Harvey, 2000; Chaieb and Errunza, 2007). Widely-used models are the international capital asset pricing model and arbitrage-pricing-theory based models similar to the three-factor model of Fama and French (1993).[48] Specifically, Fama

[45] Their main liquidity measure is the proportion of daily zero stock returns for corporations in EMs averaged over the month.
[46] Durbin and Ng (2005) examine the impact of countries' credit ratings on corporate bonds ratings in EMs and show that corporate bond spreads in EMs are not always higher than government bond spreads. This implies that the so-called "sovereign ceiling" is not always applicable in EMs.
[47] The sovereign ceiling policy is when there is no company that can receive a credit rating higher than that of the country's sovereign rating.
[48] The Fama & French (1993) three-factor model is a leading asset pricing model. The three-Factor model includes, along with the market risk premium, two risk-factors relating to firm size and book-to-market equity.

and French (2012) advocate the application of global risk factors to develop three- and four-factor global capital asset pricing models to explain global and regional returns. Fama and French (2015) expand the three-factor model to include two additional risk factors, investment and profitability, and apply this to a global framework (Fama and French, 2017). It should be noted that most global asset pricing models ignore exchange rate risk.

Following on developments in asset pricing models, several studies have shown that the risk factors that can forecast expected stock returns in developed markets such as size, value and momentum can also explain expected returns in EMs. According to Rouwenhorst (1999), risk factors that imitate size and value strategies also exist in EMs and can be used to forecast expected stock returns. Kaminsky, Lyons, and Schmukler, (2004) show that a momentum strategy is evident in EM stock market returns because investors systematically buy winning stocks and sell losers, especially during crises. Harvey (1995) shows that the global capital asset pricing models cannot explain the cross-section of average returns in EMs and that these markets are influenced more by local information such as sovereign credit ratings. Cakici, Tang, and Yan, (2016) show that size and momentum strategies do not lead to superior returns in EMs.

All the studies outlined above relate to returns either of individual corporations or the broad stock market indexes ignoring the important role of foreign investors. In this paper we draw on previous studies, to study the determinants of stock returns for global funds in EMs. Specifically, central to our analysis is the role of sovereign credit ratings. We test the significance of credit ratings after controlling for various determinants of the cross-section of EM returns. We also make use of the global asset pricing models discussed above to investigate the risk-adjusted (abnormal) returns of both foreign investors and the broad stock markets of EMs.

3.3 Data Measurement and Sources

The main purpose of this paper is to examine the behavior of equity returns by global funds in EMs. Our main sample consists of monthly information about returns on equity holding

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Hou, Karolyi, and Kho, (2011) developed a global three-factor model that includes factor-mimicking portfolios of momentum and cash flow-to-price along with a global market factor. They claim that their model performs better than the Fama/French global three-factor model.

by global investment funds in 16 EMs for the period May 1998 - September 2013. The countries are: Brazil, Chile, China, Czech Republic, Egypt, India, Indonesia, South Korea, Malaysia, Mexico, Philippines, Russia, South Africa, Taiwan, Thailand and Turkey.

In the rest of this section, we describe the data for the variables central to our analysis. We begin with a description of the data on the rate of return of global equity funds in EMs. Subsequently, we describe the construction of credit rating events. Finally, we describe the construction of the remaining variables.

3.3.1 Rate of Return Earned by Global Investment Funds in Equity Investment

Our data on the rate of return earned by global investment funds in EMs come from a proprietary dataset compiled by *EPFR Global* (http://www.epfr.com). This source provides information on the aggregate rate of return achieved by global funds in various EMs. As of mid-2014, *EPFR Global* tracked 17,732 global funds with over $5tn in equity assets. The funds tracked are registered globally (not just in the US) and thus the data track the performance of global portfolio investors in EMs. *EPFR Global* collects aggregate data for each EM during each month on the following variables: (i) total net assets (*TNA*) in each EM at the end of each month; (ii) changes in net asset value (*RNAV*) or the rate of return between the end of the previous month and the current month; and, (iii) for funds not denominated in U.S. dollars, changes in total assets due to currency fluctuations (ΔFX).[49,50] These data are the basis for the calculation of net flows (*FLOW*) or investor contributions/redemptions to each emerging market during each month as follows:

$$FLOW_{i,t} = TNA_{i,t} - (1 + RNAV_{i,t}) \times TNA_{i,t-1} - \Delta FX_{i,t} \tag{3.1}$$

where i represents each EM and t each month. The rate of return funds earn in each EM ($RNAV_{i,t}$) is the central variable of our study. We also make use of the data on fund flows ($FLOW_{i,t}$) and total net assets ($TNA_{i,t}$).

[49] According to *EPFR Global* it has established direct data feeds "…by the investment management firms or by their fund administrators that have been given the responsibility for tracking individual security pricing, calculating the net asset value of the fund, and conveying this information on to shareholders, regulatory bodies, securities exchanges, and third-party data vendors".

[50] Fund providers that track funds denominated in currencies other than the US dollar are required, according to *EPFR Global*, "…to database currency rates and calculate each fund's base currency fluctuation against the USD".

3.3.2 Credit Rating Events

One of the important variables in our analysis is EM credit rating assessment by international agencies. Three major agencies (Standard & Poor's, Fitch and Moody's) provide information about sovereign debt creditworthiness based on maturity (short-term vs. long-term) and currency denomination (foreign vs. local currency). In our study, we use foreign-currency long-term issuer ratings compiled by Standard & Poor's (S&P) and assembled from their document *S&P Sovereign Rating and Country T&C Assessment Histories*. We have chosen the foreign-currency long-term ratings because they are the most relevant for foreign fund investors.[51] The choice of S&P ratings is because it is the lead among rating agencies (e.g., Kaminsky and Schmukler, 2002; Brooks et al., 2004; Almeida et al., 2017).[52]

S&P provides general-purpose letter sovereign credit ratings as well as additional information in the form of special-purpose ratings (what are termed credit actions). Special-purpose ratings consist of announcements on credit outlook and credit watch. According to S&P, credit outlook announcements provide an assessment of "the potential direction of a long-term rating over the intermediate term (typically six months to two years)". Credit outlook announcements take one of three forms: positive, negative, or stable. A positive outlook implies a country rating may be raised, a negative the opposite, while a stable outlook implies the country rating is most likely to be unchanged. The second type of special-purpose rating or credit rating action is a credit watch announcement. This is S&P's "opinion regarding the potential direction of a short-term or long-term rating." Credit watch actions place a country either on a positive watch or negative watch.

Table 14 shows the frequency of rating announcements by country during our sample period. Upgrades (improvements in letter grade) outnumber downgrades by a factor of 2:1. Positive and negative outlook announcements occur at roughly the same frequency.[53] The country

[51] Although short-term ratings may also be relevant for foreign investors with a different time horizon, these ratings have a shorter history than longer-term ratings.

[52] Gande and Parsley (2014) show that ratings among agencies are highly correlated and test whether there exists a leader/follower relationship between the rating agencies. The Gande/Parsley test showed the "leader" rating agency to be S&P. Using their result and the fact that ratings do not differ significantly between rating agencies, we focus on S&P rating announcements.

[53] The table does not present information on credit watch announcements because there were only 8 (negative) credit watch announcements during the sample period. Nevertheless, credit watch announcements are used to compute the credit outlook and watch score of each country (described in the next paragraph).

with the highest number of events[54] was Russia (20) and the countries with the lowest were the Czech Republic, Taiwan and Thailand (5 each).

Table 14: S&P Credit Rating Announcements (May 1998 – September 2013)

This table presents credit ratings announcements (upgrade, positive outlook, downgrade and negative outlook) for each country. The credit rating announcements are collected by S&P.

Country	Upgrade	Positive Outlook	Downgrade	Negative Outlook
Brazil	6	5	2	3
Chile	3	3	0	0
China	5	2	1	1
Czech Rep.	2	2	1	0
Egypt	0	0	7	4
India	2	3	1	4
Indonesia	8	3	4	3
South Korea	6	1	0	0
Malaysia	3	3	2	1
Mexico	4	3	1	1
Philippines	3	2	2	4
Russia	9	3	5	2
South Africa	3	1	1	2
Taiwan	0	0	2	3
Thailand	2	1	0	2
Turkey	6	6	2	4
Total	62	38	31	34

Our empirical analysis consists, in the first place, of an event study to examine the behavior of several variables around credit events: upgrades/downgrades and positive/negative outlook announcements. We proceed with various econometric tests of the relationship between credit events and equity returns. For the latter purpose, we create two variables that incorporate information on credit events provided by S&P. The first variable, the credit rating variable (CR), converts the letter credit ratings assigned by S&P to a numerical scale (see, e.g., Gande and Parsley, 2005 and 2014; Almeida et al., 2017; for a similar conversion). Countries that have defaulted on their obligations are coded 0 while countries with the highest rating, triple A ("AAA"), are coded 21.[55] The second variable includes information about credit outlook and credit watch announcements ($CO\&W$). Specifically, $CO\&W$ combines this information as follows: it assigns the value -1 for a negative outlook announcement, 0 for stable outlook, and +1 for a positive outlook, and assigns the value 0.5 for credit watch

[54] In this paper an event denotes a change in letter grade or outlook or watch.

[55] The numerical transformation of credit ratings is provided in Appendix II.

positive announcement and -0.5 for credit watch negative. [56] We summarize the ratings information provided by S&P into two distinct variables because we are interested in the differential effect (if any) of the information content of these two on foreign investors' returns.

3.3.3 Country-specific Variables

The first variable is the rate of return of each EM's domestic stock market index (*RMKT*). This index serves as a yardstick by which to compare the rates of return achieved by global funds. It is computed as the logarithmic difference of the main stock market index of each EM. We also compute several indicators widely used in the literature on stock market development. The ratio of stock market capitalization to GDP (*MCAP/GDP*) is thought to be a measure of market size and maturity (Levine and Zervos, 1996 and 1998). Stock market capitalization (*MCAP*) is the value (in local currency) of shares of domestic companies listed on the stock exchange at the end of each month. Given that GDP data (in local currency) are not available at monthly frequency, we use quarterly GDP data and assign the same value for each month in a quarter. Annual GDP for a specific month is then obtained as the sum of the last four quarterly GDP values. Second is a measure of stock market liquidity, the turnover ratio (*TOVER*), defined as the value of domestic shares traded divided by market capitalization (Levine and Zervos, 1996). To compute a monthly figure for the numerator of this variable, we use daily data on the value of shares traded adjusted for the numbers of trading days and normalized to 21 (the average number of trading days in a month), or

$$TOVER_{i,t} = \frac{\sum_{j=1}^{N_{i,t}} VTRAD_{i,j,t} \times \left(\frac{21}{N_{i,t}}\right)}{MCAP_{i,t}} \qquad (3.2)$$

where $VTRAD_{i,j,t}$ is the value (in local currency) of domestic shares traded on day *j* of month *t* on the stock exchange of country i, $N_{i,t}$ is the number of trading days, and $MCAP_{i,t}$ is stock market capitalization at the end of month *t*. Additional variables included in the empirical analysis are the size of the domestic economy, inflows of foreign equity capital and exchange

[56] Previous studies (e.g., Gande and Parsley, 2005 and 2014; Almeida et al., 2017), have focused only on letter ratings or combined the information in letter ratings and credit outlook/watch into a comprehensive measure of credit ratings (using the scoring method adopted here). Our contention (and empirical tests) is that the information content of these two has quite different implications for returns.

rate risk. Economic size (ln*GDP*) is measured by the (logarithm) of domestic GDP in US dollars (for comparison across countries). Foreign capital flow (*FLOW*/*TNA*) is the ratio of equity capital flows during a specific month relative to total net foreign assets at the end of each month (*FLOW* and *TNA* were defined in (3.3.1)). Finally, exchange rate variability (*ERV*) is measured as the rolling standard deviation (with a 36-month window) of exchange rate returns relative to the US dollar.

The source of data for the stock market variables (*RMKT*, *VTRAD*, *MCAP*) is DataStream. Data on GDP in local currency and the exchange rate are from the *International Financial Statistics* of the IMF. Data on *FLOW* and *TNA* are from *EPFR Global*.

3.4 Empirical Analysis

3.4.1 Descriptive Statistics

Table 15 presents the mean, standard deviation and Sharpe ratio for foreign investors' and local stock market returns by country.[57] Foreign investors achieved the highest mean (monthly) return in Turkey (1.8%) but volatility (standard deviation) associated with it was also the highest (14.1%). The lowest rate of return was earned in Taiwan. The highest Sharpe ratio was for Korea (13.4%) and the lowest for Taiwan (1.1%). By comparison, the highest mean stock market return was achieved by Turkey's Borsa Istanbul 100. Turkeys' stock market index also experienced the second highest standard deviation (Russia the highest). The highest Sharpe ratio was achieved by the Mexican Bolsa IPC index and the lowest by Taiwan's Stock Exchange Index. The performance of foreign investors compares favorably to the local stock market. The mean return of foreign investors across all EMs was 1.1% and that of domestic stock markets 0.8%. The monthly difference between the two is 0.28% and significant (*t*-statistic = 3.560). Foreign investors' rate of return was higher than the stock market return in all but two EMs (Egypt and Mexico). On the other hand, the variability of foreign investors' returns was generally higher (for all but three countries) compared to that of the market. In sum, the performance of foreign investors, as measured by the Sharpe ratio,

[57] The Sharpe ratio is the average return in excess of the risk-free rate (one-month US T-bill rate) divided by the standard deviation of returns.

is superior to that of the domestic stock market index (mean Sharpe ratio for foreign investors was 9.8% compared to 6.7% for the domestic stock markets).

Table 15: Investors and Stock Market Performance (May 1998 – September 2013)

This Table shows the mean, standard deviation and Sharpe ratio of foreign investors' returns and local market returns for each country. The Sharpe ratio is the average return in excess of the risk-free rate (one-month US T-bill rate) divided by standard deviation.

	Investors' Rate of Return (*RNAV*)			**Market Rate of Return (*RMKT*)**		
Country	Mean	Std. Dev.	Sharpe ratio	Mean	Std. Dev.	Sharpe ratio
Brazil	0.013	0.099	0.108	0.008	0.090	0.067
Chile	0.009	0.066	0.115	0.008	0.046	0.125
China	0.011	0.085	0.106	0.003	0.081	0.008
Czech Rep.	0.004	0.053	0.040	0.004	0.074	0.022
Egypt	0.005	0.066	0.044	0.009	0.090	0.075
India	0.012	0.088	0.111	0.010	0.084	0.091
Indonesia	0.017	0.116	0.127	0.012	0.081	0.125
Korea	0.014	0.093	0.134	0.008	0.081	0.080
Malaysia	0.010	0.064	0.130	0.006	0.065	0.057
Mexico	0.010	0.075	0.105	0.011	0.067	0.138
Philippines	0.008	0.088	0.070	0.006	0.073	0.051
Russia	0.014	0.111	0.106	0.008	0.142	0.044
South Africa	0.010	0.069	0.119	0.010	0.060	0.129
Taiwan	0.003	0.077	0.011	-0.000	0.073	-0.027
Thailand	0.012	0.090	0.114	0.007	0.084	0.055
Turkey	0.018	0.141	0.117	0.016	0.130	0.105
Mean	0.011	0.089	0.098	0.008	0.086	0.067

Table 16 reports the summary statistics and Pearson correlation coefficients (some variables contain fewer observations due to lack of data). The mean (median) credit rating (*CR*) is 12.6 (13.0), a number that translates to an average rating of triple B (BBB). Mean stock market capitalization relative to GDP (*MCAP*/*GDP*) is 44%, and its volatility is 34.5%; these values are comparable to those reported elsewhere (e.g., *World Development Indicators* of the World Bank). On average, EMs experienced a small monthly outflow of foreign equity funds relative to total net assets (−0.4% and median outflow of −0.1%). Fund flows are volatile with a monthly standard deviation of 20.3%. Monthly turnover relative to market capitalization is 2.8% and its volatility is low (standard deviation is 3.8%).[58] Panel B of Table 16 indicates that none of the cross-correlations is sufficiently high to raise concerns over multicollinearity in our main statistical analysis.

[58] The three indicators of risk reported in Table 3 (Political, Economic and Financial) are used as control variables in robustness analysis and will be explained in a subsequent section.

3.4.2 Credit Ratings and Equity Investments in EMs: An Event Study

In this section, we analyze the impact of negative announcements (a downgrade or negative outlook) and positive announcements (an upgrade or positive outlook) on market-specific variables through an event study.[59] The variables considered are *RNAV*, *RMKT*, *FLOW*/*TNA*, *MCAP*/*GDP*, and *TOVER*.

3.4.2.1 Negative Announcements by S&P

Figure 5 presents event-study results with a 3-month window either side of a negative announcement. The first column of Figure 5 (Figures 5a – 5e) shows the behavior of market-specific variables surrounding a credit downgrade, while the second column (Figures 5a′ – 5e′) shows the same for negative outlook announcements.

Figures 5a and 5a′ show foreign investors' rate of return (*RNAV*). We note that during the period before the negative announcement, when sovereign creditworthiness is judged low by credit rating agencies, foreign investors earn negative returns. Following a negative announcement (downgrade or negative outlook), the rate of return earned by foreign investors is higher, a finding consistent with finance theory that higher (lower) risk should be rewarded by higher (lower) returns (Sharpe, 1964; Lundblad, 2007). As investors adjust to higher risk their required rate of return increases. This finding is reaffirmed by test results in Table 17: Panel A shows results for a two-sample *t*-test and Panel B for the Kolmogorov-Smirnov (KS) test.[60] The average rate of return the three months following a downgrade is 6.1% higher than the three preceding months (and the difference is significant at the 0.01 level).

Similarly, the difference either side of a negative outlook is 6.3% (also significant). Figures 5b and 5b′ present the market rate of return (*RMKT*) around negative announcements. The results are similar to those for investors' rate of return. Before the negative announcement, markets earn negative returns, whereupon provided increased returns to compensate for higher risk. In this case, the difference in returns is 6.9% and 3.4%, respectively (both

[59] The event study considers downgrade/upgrade and positive/negative outlook announcements but not positive/negative watch announcements because there were only 8 of these during the sample period. In the econometric analysis of subsequent sections these two (outlook and watch) were combined in the variable *CO&W* as described in the previous section.

[60] Two-sample *t*-tests examine the hypothesis of equality of means for two samples - before and after the credit event announcement. The *t*-tests are computed using Welch's (1947) formula. Kolmogorov-Smirnov (KS) is a nonparametric test that compares the equality of distributions of the two samples.

significant). There seems to be a differential impact on the rate of return for the two announcements, a conjecture explored more formally in the following sections.[61]

Figure 5c shows that during periods surrounding a downgrade (either before or after the announcement) net fund flows are negative as investors withdraw funds from markets about to be or recently downgraded. The same holds true for the period around negative credit outlook (Figure 5c′, with exceptions one month before and the month of the negative credit outlook). However, there is no evidence of significant changes in capital flows around these events (Table 17). Finally, there is no evident pattern concerning stock market development (Figures 5d and 5d′) and stock market liquidity (Figures 5e and 5e′) around negative announcements.

[61] Table 17 also shows test results for the difference between foreign investor returns and stock market returns. While foreign investors' returns generally fare better than domestic markets, the difference is generally not significant.

Table 16: Summary Statistics and Correlation Coefficients

This table reports summary statistics (Panel A) and Pearson correlation coefficients (Panel B). *RNAV* is foreign investors' return and *RMKT* is domestic market return. *CR* and *CO&W* represent credit ratings and credit outlook/ watch, respectively. *MCAP/GDP* represents the stock market development. *TOVER* refers to stock market liquidity defined as the value of domestic shares traded over the market capitalization. ln(GDP) is the natural logarithm of *GDP*, a proxy for the economic size of each country. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month. Political Risk, Economic Risk and Financial Risk are aggregate indicators of various types of risk measured by the PRS Group. * and ** indicate significance at the 5% and 1% levels, respectively.

Panel A. Summary Statistics

	RNAV	*RMKT*	*CR*	*CO&W*	*MCAP /GDP*	*TOVER*	*ln(GDP)*	*FLOW/TNA*	*Political Risk*	*Economic Risk*	*Financial Risk*
Mean	0.011	0.008	12.577	0.010	0.440	0.028	15.9654	-0.004	67.211	36.855	39.545
Median	0.014	0.011	13.000	0.000	0.334	0.020	15.87686	-0.001	67.500	37.000	40.000
Minimum	-0.530	-0.825	0.000	-1.000	0.001	0.000	11.15915	-10.340	40.000	16.000	22.000
Q1	-0.037	-0.034	10.000	0.000	0.207	0.000	14.65	-0.017	61.500	34.500	37.000
Q3	0.060	0.054	15.000	0.000	0.625	0.040	17.319	0.015	74.250	40.000	43.000
SD	0.089	0.086	3.480	0.568	0.345	0.038	1.979648	0.203	8.403	4.484	4.749
Maximum	0.619	0.587	20.000	1.000	1.771	0.328	21.07043	0.417	83.000	45.500	48.500
Obs.	2960	2960	2960	2926	2421	2040	2748	2960	2960	2960	2960

Panel B. Pearson Correlation Coefficients

	RNAV	*RMKT*	*CR*	*CO&W*	*MCAP/ GDP*	*TOVER*	*ln(GDP)*	*FLOW/TNA*	*Political Risk*	*Economic Risk*	*Financial Risk*
RNAV	1.000										
RMKT	0.832**	1.000									
CR	-0.043*	-0.042*	1.000								
CO&W	-0.009	-0.017	-0.016	1.000							
MCAP/GDP	0.020	0.006	0.540**	-0.097**	1.000						
TOVER	0.030	0.039	0.031	0.227**	-0.314**	1.000					
ln(GDP)	-0.027	-0.040*	0.441**	0.063**	0.062**	-0.034	1.000				
FLOW/TNA	0.065**	0.055**	-0.007	0.009	0.048*	0.050*	-0.011	1.000			
Political Risk	-0.023	-0.025	0.755**	0.121**	0.361**	-0.018	0.363**	-0.019	1.000		
Economic Risk	-0.073**	-0.065**	0.617**	0.227**	0.463**	0.093**	0.427**	-0.009	0.528**	1.000	
Financial Risk	-0.011	-0.015	0.616**	0.017	0.466**	0.089**	0.388**	0.017	0.268**	0.606**	1.000

Downgrade Announcement

Figure 5a

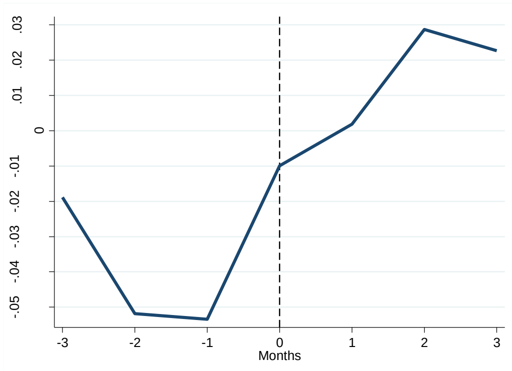


Figure 5b

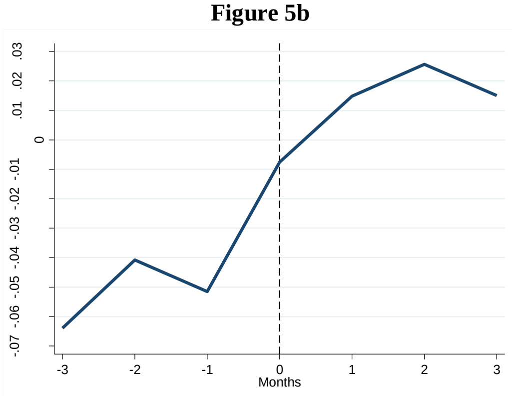
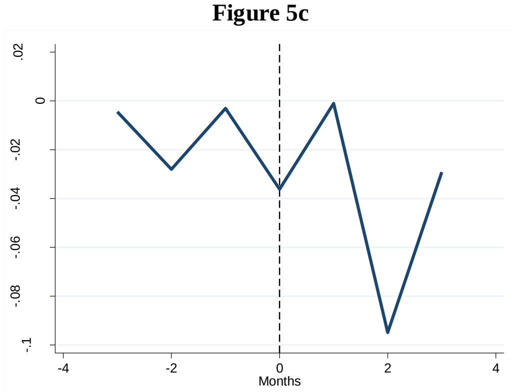


Figure 5c



Negative Credit Outlook Announcement

Figure 5a′

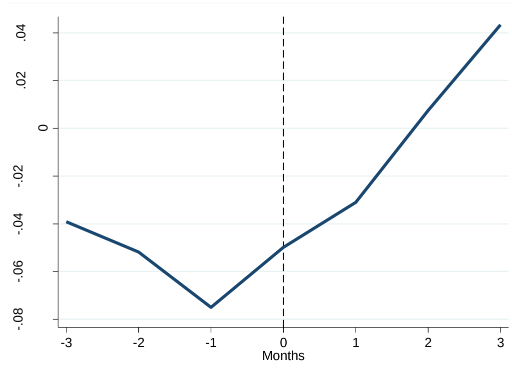


Figure 5b′

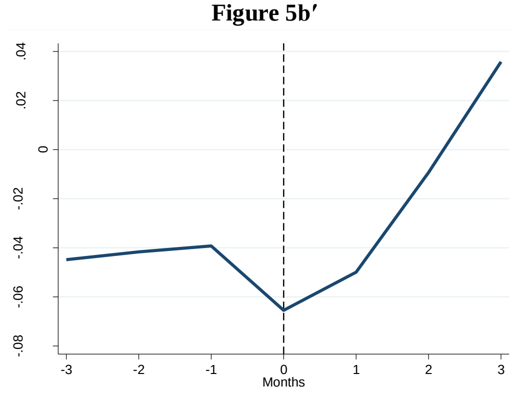


Figure 5c′

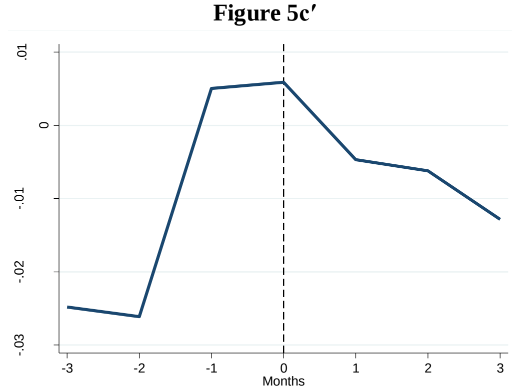


Figure 5d

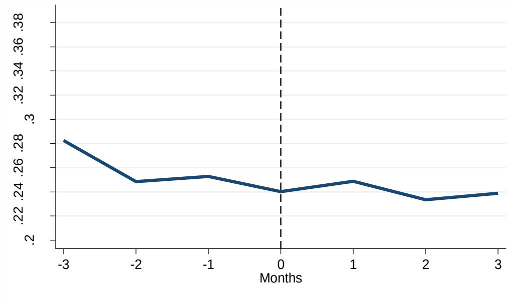


Figure 5d′

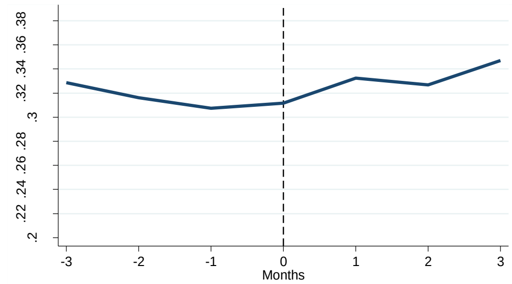


Figure 5e

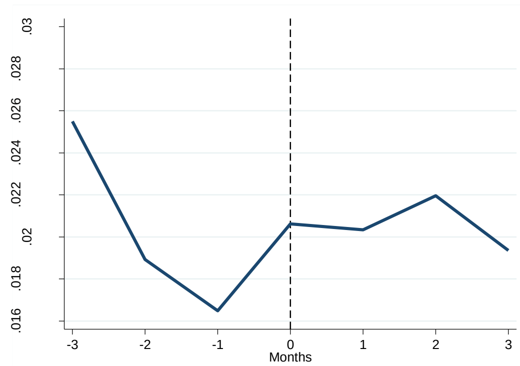


Figure 5e′

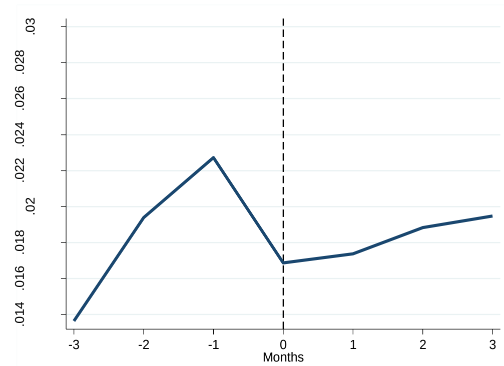


Figure 5: Downgrade and Negative Credit Outlook Announcements
The figures present event studies around announcements by S&P of a sovereign downgrade (Figures 5a – 5e) or negative credit outlook (Figures 5a′ – 5e′). Events are marked month 0 in both cases. The variables considered are *RNAV*, *RMKT*, *FLOW/TNA*, *MCAP/GDP*, and *TOVER*. *MCAP/GDP* represents stock market development. *TOVER* refers to stock market liquidity defined as the value of domestic shares traded relative to market capitalization. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month.

Table 17: Tests of Difference around Negative Announcements

Panel A presents the means for several variables before and after (downgrade or negative credit outlook) announcement and two sample *t*-tests for the difference in means (the *t*-ratio in parentheses is computed with degrees of freedom that use Welch's (1947) formula). Panel B presents the results of the nonparametric Kolmogorov-Smirnov test for differences in distribution around negative events. The parentheses in Panel B are probability values. *RNAV* is foreign investors' return and *RMKT* is domestic market return. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month. *MCAP/GDP* represents the stock market development. *TOVER* refers to stock market liquidity defined as the value of domestic shares traded over the market capitalization. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A. Two Sample *t*-test

	Downgrade Announcement						Negative Credit Outlook Announcement					
Time period	***RNAV***	***RMKT***	***RNAV-RMKT***	***FLOW/TNA***	***MCAP/GDP***	***TOVER***	***RNAV***	***RMKT***	***RNAV-RMKT***	***FLOW/TNA***	***MCAP/GDP***	***TOVER***
Avg. 3-months Before	-0.044	-0.051	0.007	-0.013	0.248	0.020	-0.056	-0.042	-0.014	-0.015	0.317	0.019
Avg. 3-months After	0.017	0.018	-0.001	-0.042	0.260	0.021	0.007	-0.008	0.014	-0.008	0.322	0.019
Avg. 3-mo. after - Avg. 3-mo. before	0.061*** (3.017)	0.069*** (3.095)	-0.008 (0.549)	-0.029 (-0.900)	-0.012 (-0.2930)	0.001 (0.192)	0.063*** (3.557)	0.034* (1.873)	0.028*** (2.851)	0.007 (0.813)	0.005 (0.101)	-0.000 (-0.040)

Panel B. Kolmogorov-Smirnov test

	Downgrade Announcement					Negative Credit Outlook Announcement				
	RNAV	***RMKT***	***FLOW/TNA***	***MCAP/GDP***	***TOVER***	***RNAV***	***RMKT***	***FLOW/TNA***	***MCAP/GDP***	***TOVER***
Combined K-S	0.202* (0.099)	0.224** (0.049)	0.098 (0.869)	0.167 (0.441)	0.137 (0.650)	0.244*** (0.007)	0.192* (0.061)	0.151 (0.227)	0.139 (0.491)	0.099 (0.899)

3.4.2.2 Positive Announcements by S&P

Next, we consider positive announcements: the first column of Figure 6 (Figures 6a-6e) refers to announcements of credit upgrade while the second (Figures 6a′-6e′) to positive credit outlook. Figures 6a and 6a′ present results for investors' rate of return (*RNAV*) around positive events. We note that foreign investors earn positive returns during the period before and after a positive announcement. Following the positive announcement, the rate of return decreases: during the three months after the announcement the rate of return is 1.8% lower (upgrade) and 3.1% lower (positive outlook). The same pattern is observed for stock market returns (*RMKT*) in Figures 6b and 6b′. Comparing the rates of return for foreign investors and stock markets following a downgrade and an upgrade, a possible asymmetry can be deduced from the event study. The change in the rate of return is large (in absolute value) and significant the period following a downgrade. By comparison the change in return is small (absolute value) and insignificant (according to the K-S test results) during the period following an upgrade. This apparent asymmetry between changes in rates of return following a credit upgrade or downgrade is a conjecture that we test in the following section.

Figures 6c and 6c′ present equity capital flows. Net capital flows are positive during periods surrounding positive announcements. The difference between average equity flows before and after an upgrade is not significant whereas after the positive outlook it is -1.6% and significant (Table 18). Finally, we find no significant changes in market development (*MCAP*/*GDP*) or liquidity (*TOVER*) following negative announcements. Combining these results with those of negative announcements, we find no observable pattern for equity capital flows, stock market development and market liquidity during periods surrounding credit events.

The overall preliminary evidence from the event study is that rates of return for foreign investors and stock markets behave differently around periods surrounding credit rating events. This is consistent with a hypothesis that foreign investors allocate funds to EMs taking into account, among other factors, sovereign credit risk. More specifically, foreign investors before a potential downgrade (upgrade) intend to avoid (exploit) any potential negative (positive) outcome before the event occurs but thereafter adjust their portfolios based on the new information. In the case of an upgrade event, rationally, foreign investors' returns are reduced adjusting to lower risk, while in the case of a downgrade, their required returns are increased adjusting to higher risk. To examine the validity of this and other hypotheses, we proceed with multivariate analysis.

Upgrade Announcement | **Positive Credit Outlook Announcement**

Figure 6a

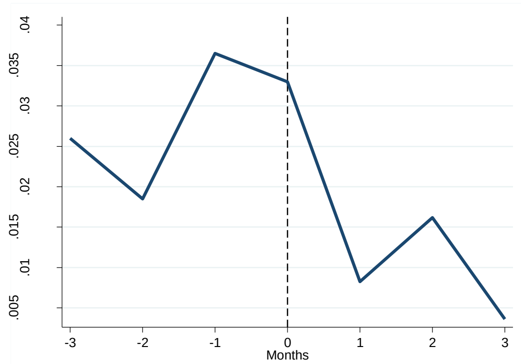


Figure 6a′

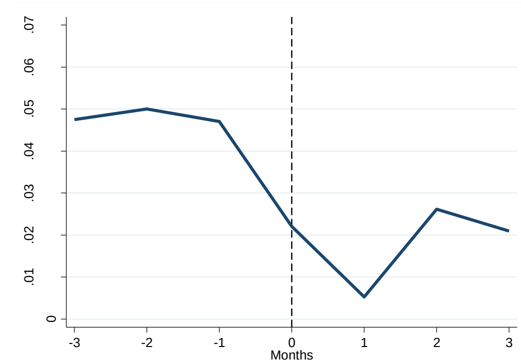


Figure 6b

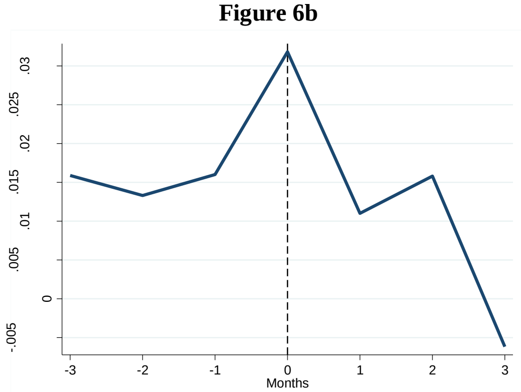


Figure 6b′

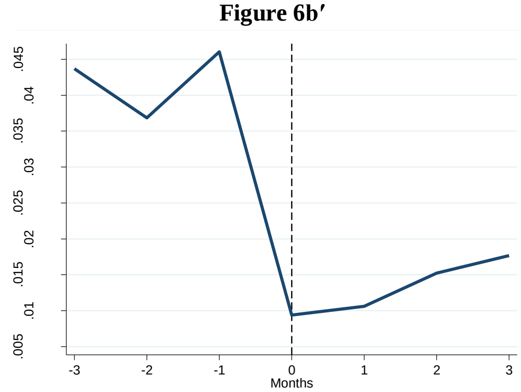


Figure 6c

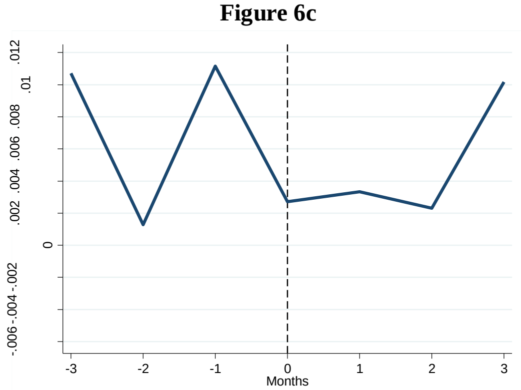


Figure 6c′

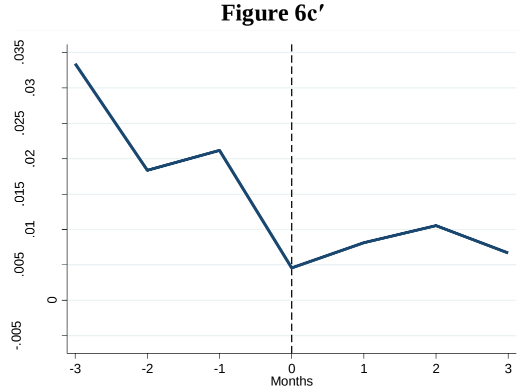


Figure 6d

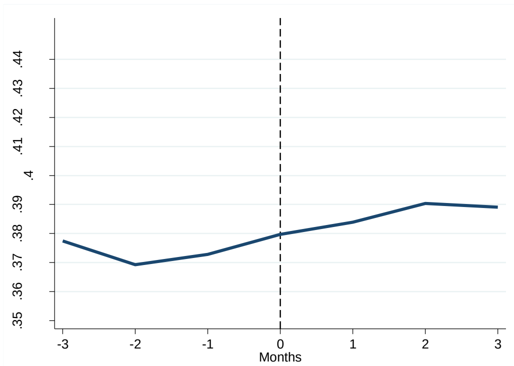


Figure 6d′

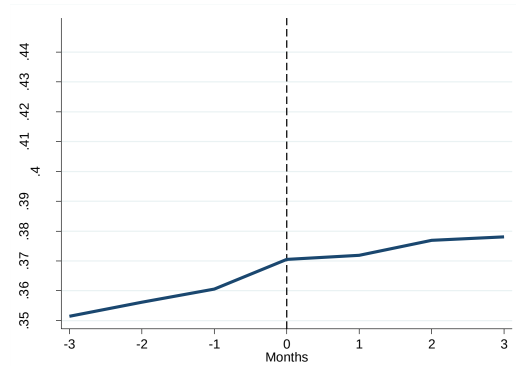


Figure 6e

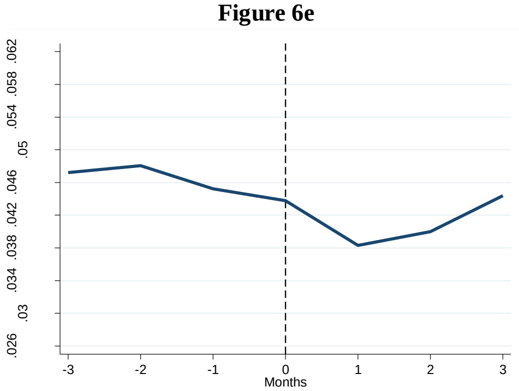


Figure 6e′

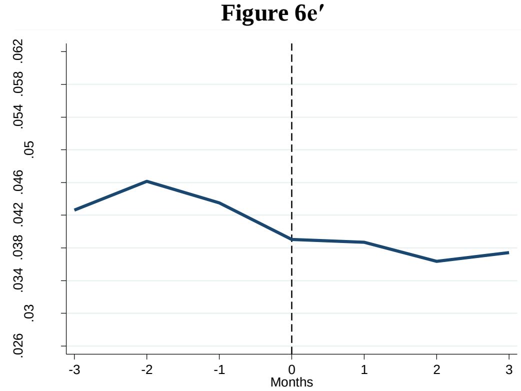


Figure 6: Upgrade and Positive Credit Outlook Announcements
The figures present event studies around announcements by S&P of a sovereign upgrade (Figures 6a – 6e) or positive credit outlook (Figures 6a′ – 6e′). Events are marked month 0 in both cases. The variables considered are *RNAV*, *RMKT*, *FLOW/TNA*, *MCAP/GDP*, and *TOVER*. *MCAP/GDP* represents stock market development. *TOVER* refers to stock market liquidity defined as the value of domestic shares traded relative to market capitalization. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month.

Table 18: Tests of Difference around Positive Announcements

Panel A presents the means for several variables before and after (upgrade or positive credit outlook) announcement and two sample *t*-tests for the difference in means (the *t*-ratio in parentheses is computed with degrees of freedom that use Welch's (1947) formula). Panel B presents the results of the nonparametric Kolmogorov-Smirnov test for differences in distribution around positive events. The parentheses in Panel B are probability values. *RNAV* is foreign investors' return and *RMKT* is domestic market return. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month. *MCAP/GDP* represents the stock market development. *TOVER* refers to stock market liquidity defined as the value of domestic shares traded over the market capitalization. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A. Two Sample *t*-test

	Upgrade Announcement						**Positive Credit Outlook Announcement**					
Time period	***RNAV***	***RMKT***	***RNAV-RMKT***	***FLOW/TNA***	***MCAP/GDP***	***TOVER***	***RNAV***	***RMKT***	***RNAV-RMKT***	***FLOW/TNA***	***MCAP/GDP***	***TOVER***
Avg. 3-months Before	0.027	0.015	0.012	0.008	0.370	0.047	0.048	0.042	0.006	0.024	0.35	0.044
Avg. 3-months After	0.009	0.007	0.002	0.005	0.388	0.041	0.017	0.014	0.003	0.008	0.370	0.037
Avg. 3-mo. before	-0.018**	-0.008	-0.010*	-0.003	0.015	-0.006	-0.031***	-0.028**	-0.003	-0.016**	0.020	-0.007
- Avg. 3-mo. after	(-2.013)	(-0.948)	(-1.85)	(-0.443)	(0.528)	(-0.946)	(-2.580)	(-2.533)	(0.003)	(-1.991)	(0.507)	(-0.824)

Panel B. Kolmogorov-Smirnov test

	Upgrade Announcement					**Positive Credit Outlook Announcement**				
	RNAV	***RMKT***	***FLOW/TNA***	***MCAP/GDP***	***TOVER***	***RNAV***	***RMKT***	***FLOW/TNA***	***MCAP/GDP***	***TOVER***
Combined K-S	0.129	0.065	0.086	0.086	0.079	0.172*	0.157	0.202**	0.159	0.087
	(0.099)	(0.844)	(0.515)	(0.674)	(0.909)	(0.073)	(0.125)	(0.020)	(0.207)	(0.957)

3.4.3 Credit Ratings and Investor Excess Returns

3.4.3.1 Panel Methodology

In this section, we examine the effect of the two credit risk variables (*CR* and *CO&W*) on the excess rate of return (or market premium) earned by foreign investors in a panel-regression framework. We estimate the following model:

$$\left(RNAV_{i,t} - RF_t\right) = \gamma_i + \delta_t + \theta_1 CR_{i,t-1} + \theta_2 CO\&W_{i,t-1} + \boldsymbol{\zeta} \boldsymbol{Z}'_{\boldsymbol{i,t-1}} + u_{i,t} \qquad (3.3)$$

where RF_t refers to the global risk-free rate[62] and $\boldsymbol{Z}$ is a vector of explanatory variables. All explanatory variables are lagged one period for two reasons. We are interested in the impact of various factors along with credit ratings events on expected returns and, second, lagging the explanatory variables mitigates any endogeneity effects. The estimated model includes country- and time-specific parameters to control for unobservable country characteristics and time effects. The elements of $\boldsymbol{Z}$ are market-specific and country-specific variables. Stock market development (*MCAP*/*GDP*) is known to affect foreign investors' decisions (Thapa, Paudyal, and Neupane, 2013). Net flow of foreign capital (*FLOW*/*TNA*) examines the hypothesis that aggressive investment behavior (return chasing) by foreign investors affects returns. The final market-specific variable is the liquidity proxy, *TOVER*. Country-specific variables include a measure of economic activity (the log of GDP) by way of accounting for a country's economic size on returns and a measure of exchange rate variability (*ERV*) to account for the effects of currency risk on returns. For each EM, *ERV* is estimated as the rolling standard deviation of exchange rate returns (relative to the US dollar) with a 36-month estimation window.

Table 19 presents estimation results. Column (1) is the partial correlation model between investor excess returns and credit ratings or outlook/watch. An increase (decrease) in credit rating or a positive (negative) outlook/watch is related to lower (higher) required rates of return. The finding regarding increases (decreases) in ratings remains robust after the introduction of a number of controls. On the other hand, the finding regarding credit outlook/watch is not significant after adding controls. Specifically, equity investments in

[62] Following the methodology of Fama/French the global risk-free rate is measured as the one-month US T-bill rate.

countries with higher credit ratings (higher *CR* or lower risk) tend to receive a lower rate of return, a finding that is consistent with the risk-return trade-off (Ghysels, Santa-Clara, and Valkanov, 2005; Lundblad, 2007) and with the event study conclusions. An increase in value for *CR* by one unit (an upgrade by one notch) is associated with a reduction in investors' excess rate of return by 0.38% (monthly). This result is consistent for all specifications of Table 19 and is further explored in the next section.

Table 19: Foreign Investors' Excess Rate of Return

The table presents panel estimation results with country- and time-specific effects for the period May 1998 - September 2013. The dependent variable in all models is foreign investors' excess rate of return ($RNAV - R_f$). CR and CO&W represent credit ratings and credit outlook/ watch, respectively. MCAP/GDP captures the stock market development. TOVER refers to stock market liquidity defined as the value of domestic shares traded over the market capitalization. ln(GDP) is the natural logarithm of GDP a proxy for the economic size of each country. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month. ERV or exchange rate risk is estimated as the rolling standard deviation (with a 36-month window) of exchange rate returns relative to the US dollar. All explanatory variables are lagged by one month. The *t*-statistics are presented in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	(1)	(2)	(3)	(4)
$\boldsymbol{CR_{t-1}}$	-0.434***	-0.382***	-0.301**	-0.385***
	(-4.30)	(-3.08)	(-2.44)	(-3.03)
$\boldsymbol{CO\&W_{t-1}}$	-0.476**	-0.275	-0.127	-0.280
	(-1.99)	(-1.07)	(-0.45)	(-1.07)
$\boldsymbol{ln(GDP_{t-1})}$		-2.274***	-2.374***	-2.278***
		(-3.32)	(-2.71)	(-3.32)
$(\boldsymbol{MCAP/GDP})_{t-1}$		-3.726***	-3.153***	-3.729***
		(-3.13)	(-2.68)	(-3.13)
$(\boldsymbol{FLOW/TNA})_{t-1}$		0.951	0.001	0.949
		(0.55)	(0.00)	(0.55)
$\boldsymbol{TOVER_{t-1}}$			4.232	
			(0.66)	
$\boldsymbol{ERV_{t-1}}$				-1.016
				(-0.11)
Time Effects	Yes	Yes	Yes	Yes
Country Effects	Yes	Yes	Yes	Yes
Obs.	2910	2395	1845	2395
R-Squared	0.520	0.544	0.590	0.544

Regarding the remaining explanatory variables, the size of national economies (as measured by GDP) is negatively related to returns indicating that investors in larger economies expect to receive lower returns; alternatively, higher economic size may allow for a reduction in market risk and consequently lower excess return. Foreign investors' returns tend to be lower in more developed stock markets (higher *MCAP/GDP*). This is consistent with the notion of lower rates of return in more mature markets as profit opportunities are reduced. Finally, foreign investor returns do not seem to follow higher equity capital flows, i.e. there is no evidence of return chasing. This result, however, will be re-examined in subsequent sections.

The results remain unchanged when additional control variables are introduced in columns (3) and (4). The additional explanatory variables, stock market liquidity and exchange rate variability, are insignificant determinants of investor excess returns.[63] Next, we examine whether the effects of downgrades and upgrades are symmetric.

3.4.3.2 Are Credit Downgrades and Upgrades Asymmetric?

The event study raised the possibility that the effect of downgrades and upgrades on returns may not be symmetric and the effects of downgrades may be more pronounced. There is some evidence in the literature (Kaminsky and Schmukler, 2002; Brooks et al., 2004; Avramov et al., 2009) that downgrades and upgrades have different effects on stock returns. To test this proposition, we estimate modified versions of the model (3.3) as follows:

$$\left(RNAV_{i,t} - RF_t\right) = \gamma_i + \delta_t + \theta_2 CO\&W_{i,t-1} + \theta_3 DOWN_{i,t-1} + \theta_4 UP_{i,t-1} + \boldsymbol{\zeta Z'_{i,t-1}} + u_{i,t} \tag{3.4}$$

$$\begin{aligned}\left(RNAV_{i,t} - RF_t\right) = \gamma_i + \delta_t + \theta_1 CR_{i,t-1} + \theta_2 CO\&W_{i,t-1} + \theta_3 DOWN_{i,t-1} + \\ \theta_4 UP_{i,t-1} + \theta_5 (CR \times DOWN)_{i,t-1} + \theta_6 (CR \times UP)_{i,t-1} + \boldsymbol{\zeta Z'_{i,t-1}} + u_{i,t}\end{aligned} \tag{3.5}$$

where $DOWN$ is a binary variable that indicates whether a downgrade has occurred (equal to 1 and zero otherwise) and similarly UP is a binary variable that records upgrades. Model (3.4) examines the direct effect of upgrades/downgrades on investors' returns and can be used to gauge possible asymmetry between the two ($\theta_3 \neq \theta_4$). In addition to asymmetry, model (3.5) allows the effects of upgrades/downgrades to depend on a country's current

[63] It should be noted that the inclusion of *TOVER* reduces sample size because stock market turnover (the numerator of *TOVER*) is available for a limited number of countries/time periods. We also estimated three additional (unreported) models that include the International Country Risk Guide (ICRG) measures of the PRS group (http://www.prsgroup.com/about-us/our-two-methodologies/icrg). The ICRG measures summarize several metrics to arrive at aggregate indicators of economic, political and financial risk. These risks are measured on a scale of 0 to 100 with higher values indicating lower risk (see Table 16 for descriptive statistics for these variables). The results (untabulated) show that these indicators are not significant, but all our other conclusions remain unchanged.

credit rating and serves to test whether asymmetric effects have a different impact on investor returns when countries are graded higher (receive higher letter grades) or lower by S&P.

We estimate models (3.4) and (3.5) using the specification in column (2) of Table 19.[64] The results are in Table 20. Columns (1) and (2) present estimates of models (3.4) and (3.5), respectively, and columns (3) and (4) estimate the same models but the dependent variable in this case is the two-period ahead cumulated excess return. We find evidence of an asymmetric effect for downgrades and upgrades: downgrades are associated with significantly higher excess returns for foreign investors, whereas upgrades do not influence significantly investors' excess returns. Moreover, column (2) indicates that the asymmetric effect depends on a country's current credit rating: the coefficient of the interaction effect ($CR \times DOWN$) is negative and significant indicating that downgrades have a larger effect on investors' returns when a country's credit rating is low. On the other hand, the interaction effect with upgrades is insignificant. In addition, the total effect of credit ratings on investors' excess returns is negative and significant, confirming the results of the previous section.[65] The total effect of downgrades is positive but (in comparison to the partial) is insignificant. All these conclusions hold when instead of looking at one-period ahead returns, we investigate two-period-ahead returns. In conclusion, we find evidence that the effect of downgrades and upgrades on foreign investors' returns is asymmetric and the effect is stronger in magnitude when sovereign ratings are low.

The results so far have examined the effects of credit events on the excess return (over the risk-free rate) of foreign investors. Next, we turn to foreign investors' risk-adjusted returns and examine the link between sovereign credit ratings and risk-adjusted or "abnormal" returns.

[64] Results with the other specifications of Table 19 are similar.
[65] All total effects (and corresponding significance tests) presented in this paper are evaluated at the mean value of the relevant variables.

Table 20: Credit Ratings Asymmetry

Panel A presents panel-estimation results with country- and time-specific effects for the period May 1998 - September 2013. The dependent variable in columns (1) and (2) is foreign investors' excess rate of return (*RNAV* – R_f) and in columns (3) and (4) is the two-month ahead cumulative excess return. *CR* and *CO&W* represent credit ratings and credit outlook/ watch, respectively. *MCAP/GDP* captures the stock market development. *TOVER* refers to stock market liquidity defined as the value of domestic shares traded over the market capitalization. ln(GDP) is the natural logarithm of GDP a proxy for the economic size of each country. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month. *DOWN* is a binary variable that equals to one when a downgrade has occurred and zero otherwise and similarly *UP* is a binary variable that records upgrades. Panel B presents estimates of the total effect of *CR*, *DOWN*, and *UP* evaluated at the relevant means. All explanatory variables are lagged by one month. The *t*-statistics are presented in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A. Credit Ratings Asymmetry and Foreign Investors' Excess Returns				
	(1)	**(2)**	**(3)**	**(4)**
Dependent Variable	**Excess Return**	**Excess Return**	**Cumulative Excess Return**	**Cumulative Excess Return**
$\boldsymbol{CR_{t-1}}$		-0.290**		-0.342***
		(-2.30)		(-3.87)
$\boldsymbol{CO\&W_{t-1}}$	-0.174	-0.183	-0.109	-0.141
	(-0.67)	(-0.71)	(-0.61)	(-0.78)
$\boldsymbol{DOWN_{t-1}}$	4.475***	13.560***	2.066**	4.392*
	(3.22)	(3.73)	(2.14)	(1.74)
$\boldsymbol{UP_{t-1}}$	0.362	2.541	0.252	1.012
	(0.39)	(0.73)	(0.39)	(0.42)
$\boldsymbol{ln(GDP_{t-1})}$	-2.974***	-2.352***	-2.619***	-1.964***
	(-4.60)	(-3.44)	(-5.80)	(-4.11)
$\boldsymbol{(MCAP/GDP)_{t-1}}$	-4.152***	-3.743***	-4.130***	-3.645***
	(-3.53)	(-3.15)	(-5.03)	(-4.40)
$\boldsymbol{(FLOW/TNA)_{t-1}}$	1.017	0.849	1.951	1.793
	(0.59)	(0.49)	(1.63)	(1.50)
$\boldsymbol{(CR \times DOWN)_{t-1}}$		-0.976***		-0.291
		(-2.86)		(-1.23)
$\boldsymbol{(CR \times UP)_{t-1}}$		-0.172		-0.054
		(-0.61)		(-0.28)
Time Effects	Yes	Yes	Yes	Yes
Country Effects	Yes	Yes	Yes	Yes
Obs.	2395	2395	2380	2380
R-Squared	0.544	0.548	0.611	0.614
Panel B. Total Effects				
$\boldsymbol{CR_{t-1}}$		-0.3017***		-0.219***
		(-2.41)		(-2.45)
$\boldsymbol{DOWN_{t-1}}$		1.161		0.443
		(-0.68)		(0.36)
$\boldsymbol{UP_{t-1}}$		0.352		0.293
		(-0.37)		(0.41)

3.5 Risk-Adjusted Rates of Return

3.5.1 The Risk-Adjusted Rate of Return Earned by Foreign Investors

The results in section 3.4 indicate a significant relationship between foreign investors' excess rate of return and sovereign credit ratings. We investigate further the information content of credit events on returns in EMs after controlling for standard asset pricing factors. More specifically, we employ a two-stage procedure similar to Wermers (2000). In the first stage, we estimate three global asset pricing models: the augmented international CAPM (ICAPM) and the augmented three- and five-factor models of Fama & French (1993, 2015).[66] The estimated models are used to generate risk-adjusted returns (alphas) specific to each country. In the second stage, we estimate the effect of sovereign credit events and other variables on the risk-adjusted rate of return earned by foreign investors.

The International CAPM and the three- and five-factor Fama-French models are given by

$$\left(RNAV_{i,t} - RF_t\right) = \alpha_{i,t} + \beta_{DMRP_{i,t}} \times DMRP_t + \beta_{GMRP_{i,t}} \times GMRP_t + \varepsilon_{i,t} \qquad (3.6)$$

$$(RNAV_{i,t} - RF_t) = \alpha_{it} + \beta_{DMRP_{i,t}} \times DMRP_t + \beta_{GMRP_{i,t}} \times GMRP_t + s_{GSMB_{i,t}} \times GSMB_t + s_{GHML_{i,t}} \times GHML_t + \varepsilon_{i,t} \qquad (3.7)$$

$$(RNAV_{i,t} - RF_t) = \alpha_{i,t} + \beta_{DMRP_{i,t}} \times DMRP_t + \beta_{GMRP_{i,t}} \times GMRP_t + s_{GSMB_{i,t}} \times GSMB_t + s_{GHML_{i,t}} \times GHML_t + r_{GRMW_{i,t}} \times GRMW_t + c_{GCMA_{i,t}} \times GCMA_t + \varepsilon_{i,t} \qquad (3.8)$$

Model (3.6) is the augmented International CAPM. It includes the domestic market risk premium (*DMRP* or the domestic stock market return minus the risk-free rate) and the global market risk premium $GMRP$ (global market index return minus global risk-free rate) to capture systematic risk with the local and global market. The augmented three- and five-

[66] The three-factor model includes, apart from the market risk premium, the small-minus-big and high-minus-low (SMB and HML) factors. These account for the return difference between small- and big-sized firms and the spread in returns between value and growth companies. The size proxy used for the development of the SMB factor is the natural logarithm of firm's market capitalization while for the HML factor the auxiliary variable is the book-to-value ratio. The five-factor model includes two additional risk-factors, the profitability factor, RMW (robust minus weak), and the investment factor, CMA (conservative minus aggressive). The RMW factor uses as profitability proxy the firm's annual revenue minus cost of goods sold, interest expense and selling general and administrative expenses all divided by book equity at the end of the previous fiscal year. The investment variable in CMA factor is the growth of total assets estimated as the percentage of total assets between the end of year *t-2* and *t-1*.

factor models in (3.7) and (3.8) include additionally the global risk factors of Fama and French (1993, 2015): small minus big ($GSMB$), high minus low ($GHML$), robust minus weak ($GRMW$) and conservative minus aggressive ($GCMA$).[67] The models in (3.6)-(3.8) are estimated for each country separately by rolling regressions with a 36-month window to yield time-variant country-specific estimates of risk-adjusted returns (alphas).

In the second stage, we estimate the determinants of the risk-adjusted returns in a panel framework. We allow for asymmetric effects of downgrades/upgrades and employ a framework similar to models (4) and (5). Specifically, we estimate the following models:

$$\widehat{\alpha_{i,t}} = \gamma_i + \delta_t + \varphi_2 CO\&W_{i,t-1} + \varphi_3 DOWN_{i,t-1} + \varphi_4 UP_{i,t-1} + \boldsymbol{\eta H'_{i,t-1}} + \epsilon_{i,t} \quad (3.9)$$

$$\widehat{\alpha_{i,t}} = \gamma_i + \delta_t + \varphi_1 CR_{i,t-1} + \varphi_2 CO\&W_{i,t-1} + \varphi_3 DOWN_{i,t-1} + \varphi_4 UP_{i,t-1} + \varphi_5 (CR \times DOWN)_{i,t-1} + \varphi_6 (CR \times UP)_{i,t-1} + \boldsymbol{\eta H'_{i,t-1}} + \epsilon_{i,t} \quad (3.10)$$

where alphas ($\widehat{\alpha_{i,t}}$) are generated from models (3.6) – (3.8) and $\boldsymbol{H}$ is a vector of explanatory variables.

The results are in Table 21. Columns (1) and (2) are the estimates of models (3.9) and (3.10), respectively, when the alphas were generated by model (3.6). Column (3) estimates the model in (3.10) when the dependent variable is the two-period ahead cumulated return. The variables included in $\boldsymbol{H}$ are those in the specification of column (3) of Table 19.[68] The remaining columns of Table 21 repeat estimation of these three with alphas generated by the 3-factor model (columns (4) – (6)) and 5-factor models (columns (7) – (9)). Table 21 also reports the mean (and *t*-test for its significance) of the risk-adjusted returns (alphas) calculated by models (3.6) – (3.8). The mean risk-adjusted return is significantly different from zero in all three cases. Moreover, as we move from the ICAPM to the five-factor model, the mean return decreases from 0.30% to 0.16%, a finding that is consistent with numerous previous applications of factors contribution in asset pricing literature.

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[67] The Fama/French global risk factors along with the global risk-free interest rate are obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[68] The results of Table 21 employ the specification of column (3) of Table 19 in order to examine the effect of stock market turnover (*TOVER*) on risk-adjusted returns. This comes at the expense of a substantial reduction in sample size (compared to the specification in column (2) of Table 19 and in Table 20) because this variable is unavailable for a number of country/month combinations. Excluding *TOVER* and using the larger sample leaves our main conclusions in Table 21 unchanged.

There is a negative and significant (both partial and total effect) relation between sovereign credit ratings (*CR*) and foreign investors' abnormal returns for all the specifications estimated in Table 21. Investments in higher-rated EMs have lower risk-adjusted returns for foreign investors than lower-rated EMs. In contrast to foreign investors' excess returns, the estimate of credit outlook and watch (*CO&W*) is positive and significant in all specifications indicating that the information content of *CO&W* is potentially different from that of *CR*. We ascribe this to the forward-looking nature of *CO&W* compared to *CR*. Credit outlook/watch announcements frequently precede upgrade/downgrade announcements, or contain information about future potential changes to *CR*, something that foreign investors can use to benefit earning higher abnormal returns. The estimates for asymmetric effects of downgrades/upgrades are generally insignificant. The total effect of downgrades on abnormal returns is insignificant whereas, for the ICAPM and three-factor models, the total effect of credit upgrades is positive and significant. This could indicate that, after adjusting for risk, foreign investors treat upgrades less as an indicator of lower credit risk, but more as a stamp of approval by credit rating agencies on structural and other reforms undertaken by EMs that will increase the future productivity of EM investments and corporate profitability.

By comparison with the results for excess returns, stock market development (*MCAP/GDP*) is positively and significantly related to abnormal returns. Holding economic size constant and accounting for risk factors, more mature EM stock markets offer possibilities for higher abnormal returns for foreign investors. Equity capital flows to EMs (*FLOW/TNA*) are positively and significantly related to investors' risk-adjusted returns: foreign investors have pursued policies of actively chasing higher abnormal returns in EMs. Finally, in most specifications market liquidity (*TOVER*) is negatively and significantly related to abnormal returns: higher turnover reduces foreign investors' opportunities for abnormal returns, a finding consistent with many studies of stock market liquidity in developed markets.

Table 21: Foreign Investors' Risk-Adjusted Rate of Return

The table reports panel-estimates of a two-stage procedure for the determinants of foreign investors' risk-adjusted returns. In the first stage, three asset pricing models (International CAPM and the three- and five-factor models of Fama and French (1993, 2015)) are estimated to generate country-specific foreign investors' risk-adjusted rates of return. In the second stage, the risk-adjusted returns (alphas) are used as dependent variables. The explanatory variables in the second stage are lagged by one month. *CR* and *CO&W* represent credit ratings and credit outlook/watch, respectively. *MCAP/GDP* captures the stock market development. *TOVER* refers to stock market liquidity defined as the value of domestic shares traded over the market capitalization. ln(GDP) is the natural logarithm of *GDP* a proxy for the economic size of each country. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month. *DOWN* is a binary variable that equals to one when a downgrade has occurred and zero otherwise and similarly UP is a binary variable that records upgrades. Panel B presents estimates of the total effect of *CR*, *DOWN*, and *UP* evaluated at the relevant means. *t*-statistics are presented in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: Panel-estimates: Foreign Investors' Risk-Adjusted Rate of Return

	(1) ICAPM	(2) ICAPM	(3) Cum-ICAPM	(4) 3-Factor	(5) 3-Factor	(6) Cum-3-Factor	(7) 5-Factor	(8) 5-Factor	(9) Cum-5-Factor
CR_{t-1}		-0.138***	-0.144***		-0.128***	-0.133***		-0.092***	-0.095***
		(-12.01)	(-12.53)		(-9.44)	(-9.78)		(-6.68)	(-6.90)
$CO\&W_{t-1}$	0.227***	0.199***	0.185***	0.130***	0.105***	0.093***	0.094***	0.077***	0.065**
	(8.74)	(7.97)	(7.51)	(4.30)	(3.55)	(3.18)	(3.12)	(2.58)	(2.20)
$DOWN_{t-1}$	0.327**	-0.125	-0.179	0.277*	-0.001	-0.106	0.197	0.165	0.084
	(2.44)	(-0.41)	(-0.59)	(1.78)	(-0.00)	(-0.30)	(1.27)	(0.45)	(0.23)
UP_{t-1}	0.220**	0.497	0.308	0.166	0.648*	0.468	0.043	0.222	0.049
	(2.44)	(1.55)	(0.97)	(1.58)	(1.70)	(1.25)	(0.41)	(0.58)	(0.13)
$ln(GDP_{t-1})$	-0.679***	-0.360***	-0.356***	-0.342***	-0.041	-0.042	-0.162*	0.055	0.047
	(-8.41)	(-4.43)	(-4.41)	(-3.64)	(-0.43)	(-0.43)	(-1.73)	(0.56)	(0.48)
$(MCAP/GDP)_{t-1}$	0.135	0.378***	0.386***	0.750***	0.976***	0.976***	0.590***	0.750***	0.752***
	(1.24)	(3.58)	(3.70)	(5.93)	(7.80)	(7.87)	(4.67)	(5.92)	(6.00)
$(FLOW/TNA)_{t-1}$	0.532***	0.460***	0.445***	0.594***	0.524***	0.513***	0.552***	0.506***	0.502***
	(3.52)	(3.19)	(3.14)	(3.39)	(3.07)	(3.05)	(3.15)	(2.93)	(2.95)
$TOVER_{t-1}$	-2.133***	-2.000***	-1.835***	0.306	0.418	0.737	-1.252*	-1.162*	-0.862
	(-3.51)	(-3.44)	(-3.21)	(0.43)	(0.61)	(1.09)	(-1.77)	(-1.67)	(-1.26)
$(CR \times DOWN)_{t-1}$		0.018	0.020		0.001	0.010		-0.017	-0.011
		(0.60)	(0.70)		(0.03)	(0.28)		(-0.49)	(-0.31)
$(CR \times UP)_{t-1}$		-0.018	-0.004		-0.035	-0.020		-0.011	0.002
		(-0.71)	(-0.18)		(-1.17)	(-0.70)		(-0.38)	(0.07)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1635	1635	1623	1635	1635	1623	1635	1635	1623
R-Squared	0.355	0.414	0.416	0.371	0.409	0.414	0.377	0.397	0.401
Mean of alphas (%)	0.301***	0.301***	0.301***	0.179***	0.179***	0.179***	0.161***	0.161***	0.161***
***t*-statistic (alpha=0)**	(19.01)	(19.01)	(19.01)	(10.48)	(10.48)	(10.48)	(9.207)	(9.207)	(9.207)

Panel B. Total Effects									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
CR_{t-1}		-0.138***	-0.144***		-0.129***	-0.134***		-0.092***	-0.095***
		(-12.09)	(-12.60)		(-9.54)	(-9.86)		(-6.75)	(-6.94)
$DOWN_{t-1}$		0.106	-0.184		0.014	0.021		-0.062	-0.056
		(0.63)	(-1.17)		(0.07)	(-0.10)		(-0.30)	(-0.28)
UP_{t-1}		0.263***	0.299***		0.191**	0.199**		0.074	0.077
		(2.99)	(3.63)		(1.83)	(1.93)		(0.70)	(0.74)

3.5.2 The Risk-Adjusted Rate of Return of Domestic Stock Markets

Thus far we have examined the role of credit risk announcements on foreign investors' returns. In this section, we look at the impact of credit risk announcements on returns for the broad domestic stock market index of EMs. We postulate that the activities of foreign investors are expected to have a significant impact on domestic stock market returns in EMs, especially during periods of credit rating announcements since foreign investors make use of such information in their portfolio strategy.[69] To examine whether foreign investors influence the behavior of stock market returns in EMs and the role played by sovereign credit risk we use the same two-stage procedure as in the previous section with two main differences: the return in the first-stage models of (3.6) – (3.8) refers to return of the domestic stock market index (net of the risk free rate) for each EM[70] and in the second-stage models (3.9) and (3.10), the vector of explanatory variables includes the return of foreign investors (*RNAV*) and its interactions with credit rating (*CR*). The results are in Table 22.

The mean abnormal return for domestic stock markets is positive and significant and declines as additional factors included, a pattern similar to foreign investors' risk-adjusted returns (section 3.5.1). The impact of credit ratings (*CR*) is either insignificant or positive and significant (3-factor model). This is different from the result for investors' risk-adjusted returns: foreign investors treat changes in credit ratings differently from domestic investors. The local stock markets in EMs are dominated by possibly less sophisticated local investors that do not account for sovereign credit rating changes in their investment decisions.

The information contained in credit outlook/watch (*CO&W*) is priced by EM stock markets, a finding reinforcing the results for foreign investors' adjusted returns. The forward-looking nature of the information contained in credit outlook/watch influences both local and foreign investors' risk perception. The effect of credit downgrades is negative (and significant for

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[69] The role of foreign investors in stock markets of EMs and the relative information advantage that such investors may possess is a subject for debate. The evidence is mixed. For instance, Froot, O'Connell, and Seasholes (2001) and Bailey, Mao, and Sirodom (2007) find that foreign investors have a relative information advantage compared to local investors in EMs. Others (e.g., Choe, Kho and Stulz, 2005; and Teo, 2009) find that local investors are better informed. Ferreira et al., (2017) find that though there is an information advantage for local investors, there is no significant difference in the performance of local and foreign investors. Their study, however, is not confined to EMs but includes 32 countries most of which are developed economies.

[70] Thus in (6)-(8) we replace *RNAV* with *RMKT* and of course, *DMRP* no longer appears as an explanatory variable.

the models without *CR*). This is additional evidence that the broad stock market treats announcements of credit rating changes differently from private investors. Announcements of downgrades are not treated as indications of reduced creditworthiness and domestic stock market expected returns do not increase accordingly. In the model with *CR*, the partial effect of downgrades continues to be negative and significant, though the total effect is insignificant. Finally, there is no evidence that domestic stock market returns respond to announcements of upgrades.

The results in Table 22 include as explanatory variable the return of foreign investors (*RNAV*) and its interactions with sovereign ratings. The effect (partial and total) of *RNAV* on abnormal stock-market returns is positive and significant. We interpret this as evidence that investments by foreign investors contribute to an improved performance for the local stock markets as well, and as indirect evidence that foreign investors possess a different information set and operate differently from local investors, a factor that contributes to higher returns for the whole of the domestic stock market. We find no evidence that the performance effect of foreign investors on domestic stock returns depends on assessments of sovereign credit risk: the interaction effect between foreign investor returns and credit ratings is not significant.

Market liquidity (*TOVER*) is positively and significantly related to stock-market abnormal returns. This would seem to indicate that, during periods of increased stock market turnover, market abnormal returns are on average higher, a counterintuitive finding and in contrast to the experience of developed-market abnormal returns (Amihud and Mendelson, 1989; Brennan, Chordia, and Subrahmanyam, 1998; Acharya and Pedersen, 2005). A possible explanation is the differing behavior of domestic and foreign investors. Local investors (especially retail) in EMs lack experience compared to foreign investors and may consist of noise traders. Thus, increased turnover may in fact be the outcome of activities by noise traders or new or optimistic traders that enter/exit stock markets during prosperous/crisis periods that lead to the positive relationship between turnover and local stock returns. Finally, there is no evidence that foreign equity capital flows chase returns in the broader stock market.

Table 22: Domestic Stock Market Risk-Adjusted Rate of Return

The table reports panel-estimates of a two-stage procedure for the determinants of stock market returns risk-adjusted returns in 16 EMs. In the first stage, three asset pricing models (International CAPM and the three- and five-factor models of Fama and French) are estimated to generate country-specific domestic stock market risk-adjusted rates of return. In the second stage, the risk-adjusted returns (alphas) are used as dependent variables. The explanatory variables in the second stage are lagged by one month. *CR* and *CO&W* represent credit ratings and credit outlook/ watch, respectively. *MCAP/GDP* captures the stock market development. *TOVER* refers to stock market liquidity defined as the value of domestic shares traded over the market capitalization. *ln(GDP)* is the natural logarithm of *GDP* a proxy for the economic size of each country. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month. *DOWN* is a binary variable that equals to one when a downgrade has occurred and zero otherwise and similarly *UP* is a binary variable that records upgrades. *RNAV* is foreign investors' return. Panel B presents estimates of the total effect of *CR*, *RNAV*, *DOWN*, and *UP* evaluated at the relevant means.*t*-statistics are presented in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: Panel-estimates: Domestic Stock Market Risk-Adjusted Rate of Return

	(1) ICAPM	(2) ICAPM	(3) 3-Factor	(4) 3-Factor	(5) 5-Factor	(6) 5-Factor
CR_{t-1}		0.033		0.092***		-0.021
		(1.52)		(3.82)		(-0.80)
$CO\&W_{t-1}$	0.290***	0.291***	0.219***	0.234***	0.117**	0.109*
	(6.11)	(6.09)	(4.19)	(4.45)	(2.12)	(1.95)
$DOWN_{t-1}$	-0.853***	-1.415**	-0.890***	-1.191*	-0.766***	-1.563**
	(-3.50)	(-2.40)	(-3.31)	(-1.84)	(-2.69)	(-2.27)
UP_{t-1}	0.156	0.642	0.054	-0.394	0.041	-0.516
	(0.94)	(1.04)	(0.30)	(-0.58)	(0.22)	(-0.72)
$lnGDP_{t-1}$	-0.160	-0.235	0.263	0.042	0.716***	0.744***
	(-1.08)	(-1.51)	(1.62)	(0.24)	(4.15)	(4.09)
$(MCAP/GDP)_{t-1}$	3.313***	3.282***	3.313***	3.162***	3.272***	3.319***
	(16.67)	(16.17)	(15.13)	(14.18)	(14.10)	(13.98)
$(FLOW/TNA)_{t-1}$	0.117	0.113	0.342	0.383	0.520	0.524
	(0.42)	(0.41)	(1.12)	(1.26)	(1.60)	(1.61)
$TOVER_{t-1}$	8.628***	8.612***	9.346***	9.279***	9.481***	9.557***
	(7.75)	(7.74)	(7.62)	(7.59)	(7.30)	(7.34)
$RNAV_{t-1}$	0.020***	0.036***	0.021***	0.029**	0.021***	0.024*
	(4.50)	(3.25)	(4.16)	(2.39)	(4.01)	(1.82)
$CR_{t-1} \times RNAV_{t-1}$		-0.001		-0.001		-0.000
		(-1.50)		(-0.64)		(-0.26)
$CR_{t-1} \times DOWN_{t-1}$		0.070		0.054		0.081
		(1.23)		(0.87)		(1.23)
$CR_{t-1} \times UP_{t-1}$		-0.041		0.033		0.045
		(-0.85)		(0.62)		(0.81)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1635	1635	1635	1635	1635	1635
R-Squared	0.423	0.425	0.367	0.375	0.329	0.330
Mean of alphas (%)	0.432***	0.432***	0.144***	0.144***	0.099***	0.099***
***t*-statistic (alpha=0)**	(15.057)	(15.057)	(4.945)	(4.945)	(3.306)	(3.306)

Panel B: Total Effects

	(1) ICAPM	(2) ICAPM	(3) 3-Factor	(4) 3-Factor	(5) 5-Factor	(6) 5-Factor
CR_{t-1}		0.032		0.093***		-0.019
		(1.46)		(3.86)		(-0.75)
$RNAV_{t-1}$		0.019***		0.021***		0.020***
		(4.02)		(4.06)		(3.78)

$DOWN_{t-1}$	-0.497 (-1.53)	-0.480 (-1.35)	-0.495 (-1.30)
UP_{t-1}	0.105 (0.62)	0.037 (0.20)	0.079 (0.40)

3.5.3 Foreign Investors' Risk-Adjusted Rate of Return in Excess of the Market

In the introductory section, we noted that the rate of return earned by foreign investors is generally in excess of the domestic stock market. In this section, we investigate the role of credit rating events in explaining this difference. We follow the same two-step procedure as before but the difference in returns in models (3.6) – (3.8) is the difference between foreign investors' and domestic stock market return (*RNAV* – *RMKT*). The alphas in models (3.9) and (3.10) can now be termed the risk-adjusted return of foreign investors in excess of domestic stock returns. They are the lower compared to previous models in Tables 8 and 9. The estimation results are in Table 23.

Credit ratings are negatively (and significantly) related to excess risk-adjusted returns. Increases in *CR* are associated with lower excess returns for foreign investors. On the other hand, announcements of positive outlook/watch are viewed differently than changes in credit risk. Announcements of positive outlook/watch are accompanied by higher returns for foreign investors compared to market returns. A possible rationale for the finding is, as outlined earlier, that foreign investors treat information contained in outlook/watch announcements differently from participants in the broader stock market. Foreign investors act on information contained in positive outlook/watch as precursors of upgrades and exploit this information to earn higher returns relative to the market. There is generally no evidence of differing effects of credit downgrades and upgrades: the total effect for either is insignificant. Increased liquidity reduces the risk-adjusted returns of foreign investors relative to the domestic market. Finally, there is evidence that return chasing increases the return advantage of foreign investors over the domestic market and this advantage is more pronounced in less mature EM markets.

Table 23: Risk-Adjusted Returns of Foreign Investors in Excess of the Stock Market

The table reports panel-estimates of a two-stage procedure for the determinants of risk-adjusted returns of foreign investors in excess of stock market returns in 16 EMs. In the first stage three asset pricing models (International CAPM and the three- and five-factor models of Fama and French) are estimated to generate country-specific risk-adjusted rates of returns of foreign investors in excess of domestic stock market returns. In the second stage, the risk-adjusted returns (alphas) are used as dependent variables. The explanatory variables in the second stage are lagged by one month. *CR* and *CO&W* represent credit ratings and credit outlook/ watch, respectively. *MCAP/GDP* captures the stock market development. *TOVER* refers to stock market liquidity defined as the value of domestic shares traded over the market capitalization. *ln(GDP)* is the natural logarithm of *GDP* a proxy for the economic size of each country. *FLOW/TNA* is the ratio of net equity capital flows during each month relative to total net foreign assets at the end of each month. *DOWN* is a binary variable that equals to one when a downgrade has occurred and zero otherwise and similarly *UP* is a binary variable that records upgrades. Panel B presents estimates of the total effect of *CR*, *DOWN*, and *UP* evaluated at the relevant means.*t*-statistics are presented in parentheses. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Panel A: Panel-estimates: Risk-Adjusted Returns of Foreign Investors in excess of the Stock Market

	(1) ICAPM	(2) ICAPM	(3) 3-Factor	(4) 3-Factor	(5) 5-Factor	(6) 5-Factor
CR_{t-1}		-0.131***		-0.191***		-0.119***
		(-8.24)		(-10.92)		(-6.20)
$CO\&W_{t-1}$	0.201***	0.177***	0.169***	0.132***	0.150***	0.127***
	(5.75)	(5.13)	(4.31)	(3.47)	(3.57)	(3.05)
$DOWN_{t-1}$	0.484***	0.352	0.472**	0.002	0.300	0.062
	(2.69)	(0.83)	(2.34)	(0.00)	(1.39)	(0.12)
UP_{t-1}	0.024	-0.457	-0.099	-0.569	-0.145	-0.779
	(0.20)	(-1.03)	(-0.73)	(-1.16)	(-0.99)	(-1.45)
$lnGDP_{t-1}$	-0.777***	-0.480***	-0.411***	0.021	-0.368***	-0.101
	(-7.15)	(-4.28)	(-3.37)	(0.17)	(-2.82)	(-0.74)
$(MCAP/GDP)_{t-1}$	-0.677***	-0.450***	-0.288*	0.046	-0.609***	-0.402**
	(-4.62)	(-3.08)	(-1.76)	(0.28)	(-3.47)	(-2.27)
$(FLOW/TNA)_{t-1}$	0.538***	0.487**	0.577**	0.497**	0.532**	0.489**
	(2.65)	(2.45)	(2.53)	(2.26)	(2.18)	(2.03)
$TOVER_{t-1}$	-6.674***	-6.502***	-6.938***	-6.702***	-8.743***	-8.575***
	(-8.14)	(-8.11)	(-7.55)	(-7.58)	(-8.89)	(-8.82)
$CR_{t-1} \times DOWN_{t-1}$		-0.015		0.007		-0.001
		(-0.38)		(0.16)		(-0.03)
$CR_{t-1} \times UP_{t-1}$		0.043		0.044		0.055
		(1.25)		(1.16)		(1.32)
Time Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1635	1635	1635	1635	1635	1635
R-Squared	0.255	0.290	0.247	0.305	0.237	0.258
Mean of alphas (%)	0.200***	0.200***	0.153***	0.153***	0.095***	0.095***
***t*-statistic (alpha=0)**	(10.570)	(10.570)	(7.562)	(7.562)	(4.360)	(4.360)

Panel B. Total Effects

	(2) ICAPM	(4) 3-Factor	(6) 5-Factor
CR_{t-1}	-0.129***	-0.189***	-0.118***
	(-8.25)	(-10.93)	(-6.19)
$DOWN_{t-1}$	0.149	0.099	0.042
	(0.64)	(0.38)	(0.15)
UP_{t-1}	0.110	0.012	-0.0545
	(0.91)	(0.09)	(-0.37)

3.6 Conclusion

The information contained in sovereign credit ratings (letter grades) by S&P influences excess (over the risk-free rate) returns earned by foreign investors on equity investment in EMs. Foreign investors require a lower excess return for lower risk. On the other hand, after taking into account the determinants of excess returns, information contained in announcements of credit outlook/watch by S&P does not seem to influence the excess returns of foreign investors. The effect of credit upgrades and downgrades is asymmetric. Downgrades appear to influence foreign investors' returns and the effect is more pronounced when EMs are assigned lower credit ratings by S&P. On the other hand, there is no evidence that upgrades have a significant effect on excess returns.

When it comes to foreign investors' abnormal or risk-adjusted returns, the information contained in credit ratings and credit outlook/watch is treated differently. Announcements of a positive credit outlook/watch by S&P are associated with higher abnormal returns while an increase in the credit rating with lower. The contrasting effect of credit ratings with credit outlook/watch is related to the forward-looking nature of credit outlook announcements that foreign investors take into account and modify their investment strategy accordingly.

The effect of credit ratings on abnormal returns for the broad stock market index of EMs differs from that for foreign investors: the effect on stock market returns is generally insignificant. On the other hand, announcements of positive credit outlook/watch have similar effects on abnormal stock market returns: the estimated coefficient is positive and significant. The domestic market treats the information content in a similar way to foreign investors. We ascribe this to the importance of foreign investors in driving abnormal returns in EMs. This conjecture is reinforced by strong evidence that foreign investor returns exert a positive and significant influence on stock market abnormal returns. The trading behavior of foreign investors differs from that of locals in that stock market liquidity has a negative (and significant) effect on foreign investors' abnormal returns but (counter intuitively) a positive (and significant) effect on abnormal stock market returns, such that, in the latter case, higher trading turnover is associated with higher returns. Local investors who may be relatively unsophisticated trade noisily thus generating both higher turnover and higher abnormal returns.

While credit rating agencies have come under heavy criticism especially since the advent of the global financial crisis, our results show that their announcements provide important signals that foreign investors may exploit in formulating their investment strategies in EMs. On the other hand, domestic investors appear immune to announcements of credit rating changes. Their trading activities may contribute to generating opportunities for abnormal returns that foreign investors can pursue.

CONCLUSIONS

This dissertation aims at investigating some of the consequences of financial distress through three innovative chapters. In brief, the first chapter examines the impact of distress risk on stock price crash; the second chapter investigates the relationship between distress risk anomaly and mispricing effects; chapter three examines the impact of a country's sovereign credit risk, on returns earned by foreign investors on equity investment in EMs.

The first chapter examines the direct relationship between firms' distress risk and future stock price crash. More specifically, I show that an increase in a firm's distress risk change, increases the probability of stock price crash in the following month(s). The forecasting ability of the distress risk change continues up to four months prior the crash event. The relationship between distress risk and stock price crash is robust to alternative distress risk and crash risk measures. The findings derived from this chapter are consistent with the theory that stock price crash is driven mainly by managers' practices of hoarding bad-news for a long period (e.g., Jin and Myers, 2006). This argument is supported by the results on the role of information asymmetry in the magnitude impact of distress risk on stock price crash. Particularly, these results show that the impact of distress risk on future stock price crash is higher for firms with higher accounting opacity, less liquidity and higher dispersion of analysts' earnings forecasts.

Chapter two examines stock misvaluation as the primary reason for the occurrence of the well-documented distress risk anomaly, namely that high distress risk is negatively related with stock return. To investigate the relationship between distress risk and stock mispricing, I perform double-sorted portfolios analysis and Fama-MacBeth regression analysis. My findings show that distress risk anomaly is driven by mispriced (overvalued) stocks, which support the mispricing explanations of previous studies (Dichev, 1998; Griffin and Lemmon, 2002). This chapter is differentiated from previous studies such as that of Griffin and Lemmon (2002) on the basis that the effects of stock mispricing are examined directly on distress risk. The results are supported by the use of alternative specifications of distress risk, mispricing proxies, and approaches.

Chapter three, focusses on the impact of distress risk information at a country-specific level. Particularly, the final chapter examines the impact of sovereign credit ratings information (credit risk, credit outlook, and credit watch) on returns earned by foreign investors on equity investment in EMs. The results show that foreign investors require a lower excess return (over the risk-free rate) for lower risk that is consistent with finance theory (Sharpe, 1964; Lundblad, 2007). However, credit outlook/watch by S&P does not seem to influence the excess returns of foreign investors. Also, the effect of credit upgrades and downgrades is asymmetric. When analyzing foreign investors' abnormal or risk-adjusted returns, I find that the information contained in credit ratings and credit outlook/watch is treated differently. More specifically, announcements of a positive credit outlook/watch by S&P are associated with higher abnormal returns on the one hand while an increase in the credit rating with lower abnormal returns on the other. This contrasting effect of credit ratings with credit outlook/watch is attributed to the forward-looking nature of credit outlook announcements which foreign investors take into consideration and then adjust their investment strategy accordingly. Regarding the impact of credit ratings on abnormal returns for the broad stock market index of EMs, the results show that the effect of credit ratings on stock market returns is generally insignificant, but the announcements of positive credit outlook/watch have similar effects on abnormal stock market returns: the estimated coefficient is positive and significant. Overall, the results of the third chapter show that credit rating announcements provide important signals that foreign investors may exploit in formulating their investment strategies in EMs. On the other hand, domestic investors appear immune to announcements of credit rating changes where their trading activities may contribute to generating opportunities for abnormal returns that foreign investors can pursue.

In general, the three chapters of this dissertation stress the importance of distress risk (in firm-specific and country-specific level) in the investment world. More specifically, chapters one and two employ firm-specific distress risk measures, showing how distress risk is associated with stock price crash and mispricing respectively. Chapter three uses country-specific distress information (sovereign credit ratings), presenting the effects of credit ratings and credit outlook/watch on foreign (and local) investors returns on equity investment in EMs. All three chapters are of great interest to investors and market practitioners who look to avoid bad performance as well as to managers who want to manage their firms as efficiently as possible attracting the interest of the investors.

This dissertation has, of course, a number of possible limitations. For instance, a research limitation that is common in the first two chapters is the limited number of alternative distress risk measures due to the unavailability, such as the distress risk measure derived from the KMV model of Crosbie and Bohn (2003). Also, the analysis of the first chapter covers the period from 1990 to 2015 that is already a long period sufficient for the purpose of the study but future studies may extend their time period further. The last chapter (three) has a limited number of countries and time periods under investigation due to the restricted common data available from various databases.

The findings of this dissertation give the opportunity for future research on the field of financial distress risk. Particularly, the first chapter can be extended by investigating the factors that lead distress risk to increase and consequently to a stock price crash, contributing further to the related literature. Chapter 2 does not examine the factors that lead to overvaluation of the distressed stocks. A further study towards this direction can give substantial support to the chapter's hypothesis, giving thus a narrowest/more accurate explanation for distress risk anomaly. A possible extension of chapter three can be a comparison of the impact of the sovereign credit risk on emerging and developing countries where the differences between the two market-groups are very possible due to the noise that may arise from domestic investors in these markets.

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APPENDIX I

This appendix lists all the variables' definitions used in the first chapter.

CRASH_1 is a binary variable that equals 1 when a firm experience at least 1 crash week during a month and zero otherwise. To estimate weekly crashes, we examine whether the firm-specific weekly return derived from Eq. (1.1) (running rolling 52-week) is 3.09 standard deviations (3.09 standard deviation is chosen to generate a frequency of 0.1% in the normal distribution) below the rolling mean of the previous 52 weeks return.
CRASH_2 is the crash measure based on Hutton, Marcus and Tehranian (2009), which is an indicator that takes 1 if the firm experiences at least 1 crash week during the fiscal year, and zero otherwise. The crash week is defined in same way as in ***CRASH_1*** with the difference that, now, the firm-specific weekly return is estimated again by Eq. (1.1) but not using a 52-week rolling procedure, but it is regressed fiscal year by fiscal year, and the crash is defined if the firm-specific weekly return is 3.09 standard deviations below the average of the firm-specific return for the fiscal year.
MINRET is the negative ratio of the minimum weekly return over the six-month period (26 weeks) to the sample standard deviation of returns for the previous period.
$\boldsymbol{W}$ is the natural logarithm of residuals derived from Eq. (1.1), which defines the firm-specific weekly return.
ME is market value of equity that is equal to the number of shares outstanding (CRSP item shout) multiplied by the market price of shares (CRSP item “prc”)
D *is the* face value of debt is estimated using the Debt in one year (Compustat item “dd1q”) plus half long-term debt (Compustat item “dlttq”) which is the same debt variable that is used by Crosbie and Bohn (2003) in their KMV model.
$\boldsymbol{V}$ is the firm’s assets value that equals to the firm’s market value of equity *(ME)* plus the face value of Debt (*D*).
$\boldsymbol{CD}$ is cash dividends (compustant item “dvpsx”).
$\boldsymbol{R_E}$ is monthly equity returns, adjusted for cash dividends over a 36-month window. $\boldsymbol{R_E}$ is given by the following equation: $\mathrm{R_E} = \ln\left(\frac{\mathrm{E_t}+\mathrm{CD_t}}{\mathrm{E_{t-1}}}\right)$
$\mathbf{R}_{\boldsymbol{V}}$ is the total firm’s return used for the estimation of $\mathrm{DD_{CDLT}}$ that is given by:

$\mathbf{R}_V = \mathbf{ln}\left(\frac{\mathbf{V_t+D_t}}{\mathbf{V_{t-1}}}\right)$, where $\mathbf{D_t}$ is the total firm payout at month t which is equal to cash dividends plus interest expenses (Compustat item "xintq").

$\boldsymbol{\sigma_{v(BhSh)}}$ is the firm's volatility used in the estimation of $\boldsymbol{DD_{BhSh}}$. $\boldsymbol{\sigma}_{\mathbf{v(BhSh)}}$ is estimated as:

$$\sigma_{v(BhSh)} = \left(\frac{ME}{(ME+D)}\right)\sigma_E + \left(\frac{D}{(ME+D)}\right)\sigma_D,$$

where $\boldsymbol{\sigma_E}$ is equity volatility derived from monthly equity returns ($\boldsymbol{R_E}$), adjusted for cash dividends over a 36-month window. While debt volatility ($\boldsymbol{\sigma_D}$) is estimated using an approximation formula $\boldsymbol{\sigma}_{\mathbf{D}} = 0.05 + 0.25\sigma_{\mathrm{E}}$. $\boldsymbol{T}$ is the maturity time of a firm's equity option which is set equal to 1 for consistency.

$\boldsymbol{DD\_MRT}$ is the "naïve" distance-to-default of Bharath and Shumway (2008) inspired by Merton's (1974) model.

$\boldsymbol{DR\_MRT}$ is the probability of default based on the normal distribution of negative $\boldsymbol{DR\_MRT}$ similar as in Merton's model.

$$\boldsymbol{DD\_MRT_{i,t}} = \frac{\ln\left(\frac{\mathrm{V}}{\mathrm{D}}\right) + \left(\mathrm{R}_{i,t-1} - 0.5\sigma^2_{\mathrm{v(BhSh)}}\right)\mathrm{T}}{\sigma_{\mathrm{v(BhSh)}}\sqrt{\mathrm{T}}}$$

$\boldsymbol{\sigma}_{\mathbf{v(CDLT)}}$ is the firm's volatility used in the estimation of $\boldsymbol{DD\_MRTALT}$. $\boldsymbol{\sigma}_{\mathbf{v(CDLT)}}$ is derived from the volatility of the total firm's return ($\boldsymbol{R_V}$)

$\boldsymbol{DD\_MRTALT}$ is the distance-to-default of Charitou et al. (2013) Model that is given by the following equation:

$$\boldsymbol{DD\_MRTALT_{i,t}} = \frac{\ln\left(\frac{\mathrm{V}}{\mathrm{D}}\right) + \left(\mathrm{R}_{V_{i,t-1}} - 0.5\sigma^2_{\mathrm{v(CDLT)}}\right)\mathrm{T}}{\sigma_{\mathrm{v(CDLT)}}\sqrt{\mathrm{T}}}$$

$\boldsymbol{DR\_MRTALT}$ is the probability of default based on the normal distribution of negative $\boldsymbol{DD\_MRTALT}$

$\boldsymbol{\Delta DR\_MRT}$ and $\boldsymbol{\Delta DR\_MRTALT}$ is change of distress risk from month t-2 to month t-1 for $\boldsymbol{DR\_MRT}$ and $\boldsymbol{DR\_MRTALT}$ respectively.

RES_ ΔDR_MRT is the "pure" distress risk measure derived from Eq. (1.10).
MDLI (Market default likelihood indicator) that is equal to the aggregate firm-specific probability to default (Andreou, 2015). The aggregate firm-specific probability to default is calculated as the average value of firms' probability to default included in the S&P500 Index Portfolio. The distress risk for each firm is estimated using the Merton (1974) model.
CL/CA is the company's inverse current ratio that is equal to current liabilities to total assets.
LEV (Leverage) is total liabilities (compustat item "lt") to total assets (compustat item "at")
ROA *(*Return-on-Assets) is net income (compustat item "ni") to total assets
INCLOSS takes 1 for firms with negative net income (Compustat item "ni") for the last two consequtive years
WC/TA is the ratio of working capital (Compustat item "wcapq") to total assets.
TLHTA is a binary variable that equals to one if the firm's total liabilities (Compustat item "lt") exceed total assets and zero otherwise.
FUO/TL represents the company's funds that are provided by operations (Compustat item "pi" plus "dp") divideded by total liabilities.
NIC net income difference over the summation of the absolute values of the net income of the last two periods $-\left(\frac{(NI_t - NI_{t-1}}{\lvert NI_t \rvert + \lvert NI_{t-1} \rvert}\right)$. ***NIC*** captures change in net income.
SA index is calcualted using the model of Hadlock and Pierce (2010) defined as: $$\boldsymbol{SA} = -0.737 \times \mathrm{ME} + 0.043 \times \mathrm{ME}^2 - 0.040 \times AGE$$ where ***ME*** is the firm's market capitalization and ***AGE*** is the decimal number of years since the firm's listing in Compustat.
SIZE *is* calculated as the natural logarithm of the firm's market capitalization
R&D/SALES is the research and development (compustat item "rd") to total assets calculated.

M/B is calculated as a firm's market capitalization (ME) over the book value of common equity (**BE**) (Compustat item "ceq")
TOBIN'S_Q ratio is equal to the market value of a company (ME+$Total\ Liabilities$) divided by the firm's total assets.
MA_Ret that is equal to a firm's stock return minus the CRSP value-weighted market index return.
AGE_10 equal to 1 if the firm's age is lower than 10 years and 0 if the firm's age is equal or higher than 10.
DTURN is estimated as the detrended average weekly stock trading volume during the fiscal year.
OPACITY is equal to the three-year moving sum of the absolute discretionary acrruals derived from a modified Jones (1991) model.
AILLIQ is the Amihud (2002) illiquidity measure that is equal to the mean for month m of the daily ratio of absolute return to the dollar volume of a firm in the month m.
NCSKEW is the negative weekly skewness (third moment, over a 52-week window) of the previous year (lagged 12 months), that is given by the following formula: $\boldsymbol{NCSKEW_{i,t}} = \frac{-\left[n(n-1)^{\frac{3}{2}}\sum W_{i,t}^{3}\right]}{(n-1)(n-2)\left(\sum W_{i,t}^{3}\right)^{\frac{3}{2}}}$

APPENDIX II

Table 24: Credit Ratings based on Standard & Poor's

This table shows how the letter ratings of Standard & Poor's are transformed into numbers in order to create the credit rating variable, *CR*.

SD/D	0
C	1
CC	2
CCC-	3
CCC	4
CCC+	5
B-	6
B	7
B+	8
BB-	9
BB	10
BB+	11
BBB-	12
BBB	13
BBB+	14
A-	15
A	16
A+	17
AA-	18
AA	19
AA+	20
AAA	21