OVERVALUATION AND STOCK PRICE CRASHES:

THE EFFECTS OF EARNINGS MANAGEMENT

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Abstract

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Prior literature has shown that managers have incentives to opportunistically and selectively withhold bad news from investors because of career concerns, compensation contracts, litigation risks, earnings targets, and empire building. In their 2006 paper, Jin and Myers develop the "Bad News Hoarding" theory which suggests that when managers conceal bad news for extended periods of time, negative information is likely to get stockpiled within the firm. When managers' incentives for hiding bad news collapse or when the accumulation of bad news reaches a critical threshold level, all of the hitherto undisclosed negative firm-specific shocks become public at once, resulting in an abrupt decline in stock prices.

Earnings management (EM) has been identified as the primary means employed by managers to conceal bad news. Earlier studies have shown separately that overvalued firms and firms characterized by high EM are associated with a greater risk of future stock price crash risk. In this thesis, I investigate the joint effect of extreme overvaluation and high EM on future stock price crash risk. It is shown that there is a robust positive relationship between extreme overvaluation accompanied by high EM and one-year ahead stock price crashes for a sample of U.S. public firms during the years 1995-2011.

This result is consistent with Jensen's (2004, 2005) argument that when a firm becomes extremely overvalued it sets up organizational forces and incentives that are likely to impair the value of the firm. However, I also find that extremely overvalued firms that are not accompanied by high EM as well as firms with high EM that are not extremely overvalued do not exhibit greater crash risk.

The results are robust to alternative proxies of crash risk and EM and hold after controlling for endogeneity. The effects are more pronounced in the post-SOX period and for firms that engage in real earnings management (REM), are small size, or have low analyst coverage. In addition, I find that accrual earnings management (AEM) is positively associated with future stock price crash risk in the early stages of overvaluation whereas REM is positively associated with future stock price crash risk in the late stages of overvaluation. Finally, I find that extreme overvaluation with high EM is negatively associated with future stock price jumps.

I interpret these results as suggesting that the incentives to conceal bad news through EM do not necessarily arise in all cases of overvaluation and that both extreme overvaluation and high EM should co-exist for the crash risk to increase. In this way, my results fine tune Jensen's conjecture regarding overvalued firms.

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Chapter 1

Introduction

1.1 Research Question and Motivation

Crash risk, defined as the risk of extreme negative stock returns, has received increasing attention from investors and academic researchers since the 1987 stock market crash. The recent stock market crash of 2008-2009 motivates researchers to do more work in the field of firm-level crash risk. Bad news is likely to be built up within the firm if managers are capable of withholding and accumulating negative information in the firm for an extended period. But managers can only successfully hide or accumulate a limited amount of bad news in the firm. The accumulation of bad news can lead to significant stock price crashes in the future when the fundamentals are finally revealed to the market.

In this thesis, I investigate the firm-level relation between extreme equity overvaluation accompanied by high earnings management and stock price crashes. I am motivated to write this thesis by three streams of literature, i.e., bad news hoarding theory, crash risk literature, and agency theory of overvaluation, that recently draw the attention of researchers in accounting and finance.

The first stream of literature finds that managers have a variety of incentives to opportunistically withhold or delay the disclosure of bad news, hoping that poor current performance can be "buried" in subsequent good performance. According to Graham, Harvey, and Rajgopal's (2005) survey, CFOs claim that they delay bad news disclosures in the hope that if the firms' performance improves before the required bad information release then they may never have to release that bad news. Kothari, Shu, and Wysocki (2009) find that career concerns can motivate managers to withhold bad news and gamble that future corporate events will camouflage the bad news. Ball (2001, 2009) argues that nonfinancial motives, such as empire building and maintaining the esteem of one's peers, also provide powerful incentives for managers to conceal bad news. However, if a sufficiently long run of bad firm-specific news is encountered, insiders have to release all the bad news at once, or the market will find out the truth, and all the bad news will come out at once. The accumulation of bad news will eventually lead to an abrupt extremely negative decline in stock price or a crash.

Built on the line of literature that managers strategically withhold bad news, Jin and Myers (2006) develop bad news hoarding theory. This theory suggests that lack of transparency enables managers to hide bad news from investors for extended periods of time. As a consequence, unfavorable information is likely to be built up within the firm. When managers' incentives for hiding bad news collapse or when the accumulation of bad news reaches a tipping point, all of the hitherto undisclosed bad information will be flooded to the market at once, resulting in an abrupt decline in stock prices, i.e., stock price crashes.

Bleck and Liu (2007) demonstrate that hoarding bad news for an extended period of time is not sustainable. The authors develop a model which predicts that opacity in financial statements hinders investors discriminating good projects from bad projects at an early stage. The poor performance of these projects can negatively impact the entire firm, causing an asset price crash.

The second stream of literature on firm-level crash risk is drawn from the bad news hoarding theory. Jin and Myers (2006) and Hutton, Marcus, and Tehranian (2009) find that opaque firms are more prone to stock price crashes. Kim, Li, and Zhang (2011a, 2011b) find evidence that tax avoidance and the sensitivity of a CFO's option portfolio value to stock price are both significantly and positively associated with future stock price crash risk. Francis, Hasan, and Li (2011) find proof that firms' prior real earnings management is positively associated with their stock price crash.

Jensen's (2004, 2005) agency theory of overvalued equity is the third stream of literature that motivates my research idea. Jensen (2004, 2005) argues that equity is overvalued when the stock price of a company exceeds its underlying value. According to Jensen (2004, 2005), overvalued equity means that the company will not be able to deliver, except by pure luck, the performance to justify its value. Managers like overvaluation because there are benefits to an overvalued stock, such as access to relatively low cost capital, favorable media coverage, rapid growth in personal wealth, and easy acquisition of another non-overvalued firm. The managers of overvalued firms not only resist market correction of overvalued stock prices, but also actually attempt to defend overvaluation in order to extract personal benefits from overvaluation. Jensen (2004, 2005) predicts that three main types of earnings management practices, i.e., accrual earnings management (AEM), real earnings management (REM), and non-GAAP violation, are likely to be undertaken by managers in order to meet the unrealistic performance goals, particularly in the short term.

My thesis focuses on EM which is the combined measure of AEM and REM because according to Jensen (2004, 2005), managers engage in both AEM and REM to sustain the overvalued equity. Consistent with Jensen's (2004, 2005) conjecture, I examine the link between extreme overvaluation accompanied by high EM and the likelihood of a firm's subsequent stock price crashes. Specifically, I predict that under the scenario of high EM, managers withhold negative news in the firm and with extreme overvaluation managers are likely to engage in all kinds of value destroying activities to maintain the extreme overvaluation. If at some point the true state of an extreme overvalued firm is revealed to the market, then I predict that such a firm will probably undergo a stock price plummet in the future.

This thesis conducts a simple test to show whether extreme equity overvaluation with high EM is associated with stock price crash risk. My empirical strategy involves the identification of proxies for stock price crashes, EM and overvaluation. Based on crash risk literature, I employ three measures of crash risk. CRASH is an indicator variable that equal to 1 if a firm incurs at least one extreme negative stock price plummet during the year. NCSKEW and DUVOL are continuous variables based on weekly returns. EM_IND is an indicator equal to 1 if the sum of AEM and REM measures is in the top quintile. Following Hutton, Marcus, and Tehranian (2009), AEM_SUM is the three-year moving sum of the absolute value of discretionary accruals. Following Francis, Hasan, and Li (2011), REM_SUM is the three-year moving sum of the absolute value of annual aggregate REM proxy. Consistent with finance and accounting literature, I estimate the intrinsic value of firms and firms that have top quintile of price to intrinsic value (P/V) ratio are classified as extremely overvalued firms. I create an interaction between extreme overvaluation and high EM and this interaction term is my main interest variable in the regression to predict stock price crashes. I also control for various firm characteristics that are shown to be associated with stock price crashes.

Briefly, my results, using a large sample of firms during 1995-2011, reveal the following. First, univariate tests show that, it is not EM per se, but it is extreme overvaluation with high EM that is associated with stock price crashes. Similarly, even if a firm is extremely overvalued but lacks high EM, the firm's crash risk will not increase.

Second, the multivariate results indicate that the combination of extreme overvaluation and high EM is positively associated with firms' future crash risk which is consistent with my hypothesis. The findings hold even after controlling for firm and year fixed-effects, investors' heterogeneity of Chen, Hong, and Stein

(2001), the measure of accruals quality used by Kim, Li, and Zhang (2011a), and other firm-specific factors that are known to be associated with crash risk. The above findings support Jensen's (2004, 2005) view that extreme overvaluation accompanied by high EM impairs firm value.

In order to partition the separate effects of AEM and REM, I test the interaction effect between extreme overvaluation and high AEM and the interaction effect between extreme overvaluation and high REM. The results show that REM dominates AEM, and extreme overvaluation with high REM is positively associated with a firm's crash risk. This finding is consistent with prior literature that REM has more serious consequences than AEM. AEM occurs when managers adjust revenue or expense accruals to alter financial reports. It has no direct effect on cash flows and is less likely to destroy long-term firm value. REM occurs when managers depart from normal operational practices and may have negative effects on future cash flow.

I also conduct a variety of sensitivity tests. First, I duplicate Hutton, Marcus, and Tehranian's (2009) results by showing that when logistic model is used, AEM is positively associated with stock price crash risk. But when I change the model to firm fixed-effects model which is a more appropriate model when the sample consists of panel data, I find that the coefficient of AEM is an insignificant predictor of crash risk.

Second, I retest my hypothesis by using an alternative measure of EM. Managers could plan out the extent of earnings management needed and “allocate” between AEM and REM. In this case, it is better to add AEM and REM first and then take the three-year moving sum. I find that the results still hold when using the alternative measure of EM.

Third, the Sarbanes-Oxley Act (SOX), enacted in 2002 substantially increased the oversight of financial statements. Presumably then, the act would also have increased the crash likelihood if managers still engage in high EM to maintain extreme equity overvaluation in the post-SOX period. The results show that the effect of extreme overvaluation and high EM on stock price crash risk is significant in the post-SOX period but is insignificant in the pre-SOX period.

Fourth, to test whether investors have limited attention and might not be able to tease out whether a managerial action is an EM activity or a normal course of operation, I examine the effect of extreme overvaluation with high EM on crash risk in small versus big firms. In small firms, investors’ attention is more severely limited than in large firms, suggesting that managers in small firms are more likely to withhold bad news. Consistent with my conjecture, I find that the effect of extreme overvaluation with high EM on crash risk is more pronounced in small firms than in big firms.

Fifth, the accumulation of bad news might be more prevalent in firms that have low analyst following. Therefore, crash risk should be higher when firms have higher information asymmetry proxied by low analyst coverage. I find that the impact of extreme overvaluation with high EM on crash risk is more prominent in low analyst coverage firms than in high analyst coverage firms.

Sixth, Badertscher (2011) finds that the duration of overvaluation affects managers' use of alternative earnings management. Specifically, he finds that managers engage in AEM in the early stages of overvaluation and switch to REM in order to sustain their overvalued equity. Consistent with Badertscher's (2011) finding, I find that in the first two years of overvaluation, managers are more likely to engage in AEM to maintain overvaluation and therefore increase crash risk. I also find that for firms that have been overvalued for more than three years, managers are more likely to do REM to maintain overvaluation and these firms incur higher crash risk.

Seventh, I employ a firm fixed-effects model and quartile regression to control for endogeneity issues. The results are robust after controlling for endogeneity. Finally, the results show that firms with extreme overvaluation and high EM are less likely to have stock price jumps.

Collectively, this thesis provides consistent evidence that extreme overvaluation with high EM is positively associated with stock price crashes. The effect is stronger in the post-SOX period, in small firms, and for firms with low analyst coverage. The effect is robust when using different measures of EM and crash risk and after controlling for endogeneity.

1.2 Contribution of the Thesis

Earnings management (EM) has been identified as the primary means employed by managers to conceal bad news. Earlier studies have shown separately that overvalued firms and firms characterized by high EM are associated with a greater risk of future stock price crash risk. In this thesis, I show the joint effect of extreme overvaluation and high EM is positively associated with future stock price crash. This thesis contributes to the extant literature and has empirical implications for practitioners.

First, my thesis adds to the overvaluation literature. Badertscher (2011) finds that overvaluation at early stages is positively associated with AEM but after firms have been overvalued for 3 years and beyond, overvaluation is positively associated with REM. When I duplicate his results, I find the similar relation between overvaluation and AEM/REM. However, overvaluation only explains about 8 percent of the total variance of EM based on the incremental R-squared. These results suggest that overvaluation per se is not a sufficient condition to cause EM and therefore is not a sufficient condition leading to crash risk.

In settings where overvaluation is not accompanied by managerial intervention to mask real performance, the efficient market hypothesis suggests that such overvaluation is more likely due to the failure of the intrinsic valuation model to fully incorporate all information than due to unrealistic market valuation of the firm. For example, overvaluation could be the result of a pattern of high earnings growth (Jensen, 2005) that has not been incorporated into the intrinsic valuation of the firm. The firm could be mispriced due to inherently diffuse information where both the managers and investors have near-symmetric but diffuse firm-specific information. A history of mergers and acquisitions (Tehranian, Travlos, and Waegelein, 1987; Moeller, Schlingemann, and Stulz,

2005) could also result in such information dispersion. My thesis extends Badertscher's (2011) finding by showing that AEM is positively associated with stock price crashes in the early stages of overvaluation and REM is positively associated with stock price crashes in the late stages of overvaluation.

Second, my thesis contributes to the EM literature. EM has become a widespread practice for U.S. corporations. Most studies in the literature focus on whether certain incentives facilitate managers to manipulate accruals and manage real activities of business, and there has been little evidence documenting the consequences of EM. This thesis extends prior literature by examining how current aggregate AEM and REM affect future extreme events, i.e., firms' crash risk and finds that extreme overvaluation accompanied by high EM increases firms' future crash risk.

Third, my thesis identified an additional factor that explains stock price crashes and negative return skewness. Because extreme returns are less likely to be caused by chance, Taleb (2007) argues that a good understanding of extreme outcomes can provide valuation insight into the true nature of the phenomena. Wang and Du (2012) show that overvalued firms have higher crash risk than otherwise identical but non-overvalued firms. However, Wang and Du (2012) use the abnormal market-to-book ratio to proxy for equity overvaluation. Market-to-book ratio is not a good proxy for overvaluation because it can also be used to proxy for growth (Lakonishok, Shleifer, and Vishny, 1994), monopoly power (Conine, 1983), or risk (Berk, 1995). Using a refined measure of overvaluation and interacting overvaluation with EM, I show that the combination of extreme overvaluation and high EM leads to crash risk.

Hutton, Marcus, and Tehranian (2009) find that firms' prior AEM is positively associated with their stock price crashes. However, their results are not robust after controlling for omitted firm fixed-effects. Francis, Hasan, and Li (2011) find that firms' prior REM is positively associated with their stock price crash. However, REM might be undertaken by managers of firms that are not overvalued for the purpose of providing more information to investors. For instance, Gunny (2010) finds that firms that meet earnings benchmarks using REM have better subsequent performance than those that do not. She argues that managers could undertake REM to achieve earnings targets, which in turn provides access to resources that allow the firm to perform better in the future or signal future firm value. Hence it is not obvious that REM per se could result in high crash risk. I find that only when managers engage in high REM to maintain overvaluation, firms' crash risk will be increased. The predictability of extreme overvaluation with high EM is incremental significantly above and beyond the measure of investor belief heterogeneity of Chen, Hong, and Stein (2001), the measure of accruals quality used by Kim, Li, and Zhang (2011a), and firm characteristics fund by prior studies to be associated with crash risk.

Furthermore, my thesis can help senior managers and board members better understand the consequences of engaging in revenue and expense manipulation to manage their reported earnings numbers. Besides, this thesis is also potentially useful for investment bankers, security analysts, and auditors who monitor companies because the results imply that collaborating with managers to inflate stock prices will destroy the long term value of the firm. This study is also potentially informative for regulators and standard-setters because the findings suggest that mangers' opportunistic behaviors may lead to stock price crashes.

1.3 Organization of the Thesis

The reminder of the thesis is organized as follows.

Chapter 2 presents a literature review. Section 2.1 reviews prior literature on managers' incentives to strategically withhold bad news. Section 2.2 provides a detailed discussion of crash risk and the related literature regarding the firm characteristics associated with crash risk. Section 2.3 reviews prior literature on the agency costs of overvalued equity. Section 2.4 reviews prior literature on incentives and consequences of EM.

Chapter 3 presents the specific research hypothesis regarding the relation between extreme overvaluation accompanied by high EM and crash risk.

Chapter 4 presents the research methodology in this thesis. Section 4.1 describes the measures of key variables. Section 4.2 describes the univariate and multivariate design for hypothesis testing.

Chapter 5 shows the empirical results. Section 5.1 discusses the sample selection procedure. Section 5.2 shows the descriptive statistics. Section 5.3 provides univariate test results. Section 5.4 provides multivariate test results. Section 5.5 reports the impact of AEM versus REM test results.

Chapter 6 presents the additional tests results. Section 6.1 presents the results of duplicating Hutton, Marcus, and Tehranian (2009). Section 6.2 reports the alternative measure of EM results. Section 6.3 collaborates with Badertscher's (2011) results to show the effects of overvaluation duration on managers' EM choices and their impact on crash risk. Section 6.4 presents the impact of SOX on crash risk. Section 6.5 examines the effect of extreme overvaluation and high EM on crash risk in small firms versus in big firms. Section 6.6 compares the effects of extreme overvaluation and high EM on crash risk in low analyst coverage firms versus in high analyst coverage firms. Section 6.7 presents the quantile regression results. Section 6.8 demonstrates the relation between extreme overvaluation with high EM and stock price jumps.

Chapter 7 summarizes the major findings and concludes the entire thesis.

Chapter 2

Related Literature

2.1 Why Do Managers Strategically Conceal Bad News

The stock price crash literature is based on the bad news hoarding theory. The information asymmetry between managers and shareholders motivates self-interested managers to maximize their self-interests and sacrifice the long-term interests of shareholders. Beginning from Jin and Myers (2006), researchers find evidence consistent with the nature of agency problems motivating managers to strategically control the disclosure of bad news about the firm to the public.

The bad news hoarding theory stems from the fact that managers have a variety of motivations to strategically hide and accumulate bad news in the firm. Prior literature has found that financial motives are important reasons for managers to accumulate bad news in the firm. First, career concerns can incentivize managers to conceal bad news and gamble that future corporate events will allow them to "bury" the bad news. Second, compensation motivators, including gaining performance-based bonuses and avoiding a decline in the value of stocks, stock appreciation rights, and options, can also prompt managers to disguise negative news in the company. Third, litigation risks, such as avoiding debt covenant violations that could lead to restrictions on new investment, dividend payments, and further borrowing, or avoiding corporate bankruptcy and hiding other fraud can also be dominant reasons for managers to withhold bad news.

Basu (1997) claims that managers often possess valuable private information about firm operations and asset values and that if managerial compensation is linked to reported earnings performance, then they have incentives to hide any information that would adversely affect their compensation. Fischer and Verreechia (2000) demonstrate that when the market cannot perfectly adjust for managers' bias, managers have incentives to bias reporting. The information content of a manager's reporting falls as the private cost to the manager of biasing the report falls, and as the uncertainty about the manager's objective increases. Graham, Harvey, and Rajgopal (2005) conduct a comprehensive survey that asks CFOs to describe their choices related to their reported accounting numbers and voluntary disclosure. CFOs admit that they have the tendency to delay the disclosure of bad news more than good news. Survey results also indicate that managers are interested in meeting or beating earnings benchmarks primarily to influence stock prices to benefit the manager's career and reputation. Focusing on dividend changes and management earnings forecasts, Kothari, Shu and Wysocki's (2009) empirical evidence regarding stock price reactions suggests that, on average, managers delay the release of bad news to investors. Analogously, Hermalin and Weisbach (2012) also suggest that career concerns would induce managers to strategically bias disclosure if they are to be evaluated against such disclosure.

Different from the argument of withholding bad news to meet financial expectations, Ball (2001, 2009) argues that managers' nonfinancial motives are also powerful incentives for managers to withhold bad news. He points out that nonfinancial motivators, such as maintaining the esteem of one's peers or empire building, are more powerful than commonly believed, and sometimes are the main reason to conceal negative information. Collectively, prior literature has found that both financial and nonfinancial motives play important roles for managers to opportunistically withhold bad news in the firm.

2.2 How Do Bad News Hoarding Activities Cause Stock Price Crashes

Recent studies have investigated how stock price crashes could arise from managers' bad news hoarding behaviors. When the accumulation of bad news reaches a cutoff point at which the costs of continuing withholding bad news beyond managers' controllable range, a firm's probability of experiencing a sudden plummet of stock price increases. (Jin and Myers, 2006; Kim, Li, and Zhang, 2011a, 2011b; Kim and Zhang, 2012 etc.). I summarize the related literature into two groups, one group of literature finds evidence that some firm characteristics induce managers to disguise bad news and cause stock price crashes. The other group of literature provides evidence that good monitoring mechanisms or reporting properties constrain management's opportunistic activities and prevent stock price crashes.

2.2.1 Firm Characteristics that Have Positive Associations with Crash Risk

The motivation for bad news hoarding theory comes from the extreme stock price declines associated with recent financial crisis (2008-2009) and accounting scandals (e.g., WorldCom). Starting from Jin and Myers (2006) and Bleck and Liu (2007), researchers have been concerned that agency costs arising from managers' inside information could be related to stock price crash risk. A firm is called to have stock price crash risk if the firm has a tendency to experience a sudden drop in its stock price.

Opaque firms have higher crash risk. Hutton, Marcus, Tehranian (2009) further consider the empirical link between opacity and the distribution of stock returns. They develop a new measure of opacity for individual firms based on AEM, i.e., the prior three-year moving sum of the absolute value of discretionary accruals. More opaque firms have higher stock price crash risk because when news is particularly bad, managers minimize earnings partially to enable shifting of discretionary income to future periods and partially to reduce the inferred precision of the bad news. When managers release bad news at once, stock price crashes. Therefore, they hypothesize that when a firm's financial reports are more opaque, less firm-specific information is available to affect stock returns. Their findings support that opaque firms are more prone to stock price crashes, consistent with the prediction of Jin and Myers (2006).

Aggressiveness in tax avoidance increases crash risk. Kim, Li, and Zhang (2011a) argue that the perplexity and complexity of tax transactions, combined with the different treatments of tax planning transactions under financial and tax reporting, create tools for managers to manage earnings and withhold negative operating outcomes from outside investors under the pretense of minimizing corporate tax obligations. Accordingly, bad performance and negative information are likely to stockpile within the firm. When a threshold is crossed, an asset price crash occurs. They find evidence that tax avoidance is positively related to crash risk consistent with the bad news hoarding theory of stock price crashes.

Equity compensation motivates managers' short-termist behavior which leads to crash risk. Jensen and Meckling (1973) argue that interest conflict will arise between shareholders and managers if the ownership and management in corporations is separated. Jensen and Murphy (1990) suggest that in order to decrease the conflict between shareholders and managers, firms should increase the use of equity-based compensation. However, Bebchuk (2009) raises an issue that managers may engage in counterproductive behavior to inflate current stock prices to the detrimental of future firm value. Kim, Li, and Zhang (2011b) find evidence consistent with the prediction that managerial equity incentives, e.g., CFO option incentives, are positively related to future crash risk.

REM accelerates crash risk. Not only does AEM increase crash risk (Hutton, Marcus, Tehranian, 2009), but REM is also shown to be positively related to crash risk. Francis, Hasan, and Li (2011) argue that REM also affects the information quality of firms' financial statements, and REM deviates from business norms and has negative effects on future cash flow. Based on this argument, the authors hypothesize that firms with higher level of prior REM are more likely to experience stock price crashes. Their evidence provides support to their hypothesis.

Managers' voluntary earnings guidance is positively related to crash risk. Hamm, Li, and Ng (2012) examine the relationship between managers' voluntary earnings guidance and stock price crash risk. Their results show that there is a positive association between management guidance frequency and crash risk, which is consistent with the hypothesis that management uses guidance opportunistically to inflate stock prices via the withholding of bad news or by guiding investors' earnings expectations upward. They also find that the positive association is stronger for firms with lower litigation risk, lower percentage of dedicated institutional ownership, upward-biased forecasts, and higher executive stock ownership.

Mandatory IFRS adoption affects crash risk in different ways depending on the information environment. DeFond, Hung, Li, and Li (2011) examine how mandatory IFRS adoption in the European Union in 2005 affects crash risk. For industrial firms, the authors find evidence suggesting that crash risk decreases among these firms by decreasing information opaqueness and increasing transparency. For financial firms, the authors find evidence suggesting that crash risk increases among these firms by inducing greater earnings volatility and affording more opportunities for manipulation.

Overvalued firms tend to use more AEM and have higher stock price crash risk. Wang and Du (2012) classify a firm as overvalued if the firm's unexpected market-to-book ratio is positive. They suggest that positive abnormal market-to-book firms tend to use AEM (higher financial opacity) in order to conceal firm specific information from investors. They find evidence consistent with the agency cost of overvalued equity by Jensen (2005) that equity overvaluation affects a firm's AEM decision and increases subsequent stock price crash risk.

The deviation of voting rights (control) from cash flow rights (ownership) is positively associated with stock price crash risk. Hong, Kim, and Welker (2012) find a positive relation between the likelihood of stock price crash risk and the deviation of voting rights from cash flow rights at dual-class firms, which they call the ownership-control wedge. Their results show that as the control-wedge increases, stock price crash risk increases, suggesting that managers and controlling shareholders of high-wedge firms tend to hide negative information to a greater extent than those of low-wedge firms.

The presence of internal control material weaknesses increases stock price crash risk. Zhou, Kim, and Yeung (2013) argue that ineffective internal controls induce managerial opportunism in financial reporting and provide managers with greater ability and more opportunities to withhold unfavorable news for an extended period. Therefore, internal control weaknesses are likely to be positively associated with the likelihood of observing an abrupt decline in stock price or extreme, negative return outliers. They further argue and find evidence that when publically disclosed internal control weaknesses are subsequently remediated, stock price crash risk declines or disappears.

2.2.2 Firm Characteristics that Have Negative Associations with Crash Risk

The purpose of this line of literature is to investigate whether external environment and monitoring mechanism pre-empt bad news hoarding activities and reduce future stock price crash risk.

Audit-Client relationship deters crash risk. Callen and Fang (2012a) posit that it takes time for auditors to obtain a deeper understanding of a client's business. Thus auditors with longer tenure should be more effective at detecting and deterring bad news hoarding activities by the client which will reduce future stock price crash risk. They show evidence that one-year ahead stock price crashes is negatively associated with auditor tenure. Their finding supports that learning perspective helps monitoring, i.e., long audit-client relationship helps auditor develop client-specific knowledge and prevent managers' bad news hoarding behaviors and curb stock price crashes.

Religiosity at the country level hinders crash risk. Based on the view that religion acknowledges the overall importance of ethical behavior and rejects managerial manipulative behavior, Callen and Fang (2012b) argue that a more religious business environment reduces managerial bad news hoarding activities and decreases future stock price crash risk. Consistent with their argument that religion curbs bad news hoarding activities, the authors find robust empirical evidence that firms headquartered in countries with higher levels of religiosity exhibit significantly lower levels of future stock price crash risk.

Institutional investor stability curtails crash risk. Callen and Fang (2012c) test two opposing views in regard to institutional investors: monitoring view versus short-termism view. If institutional investors maintain their investment in the firm over a long-term, they are likely to benefit from monitoring manager's activities to maximize the long-term values. On the contrary, if institutional investors are short-term investors, they can induce managers' opportunistic behaviors because they have influential impact on managers' short term earnings goals. The authors find robust evidence that the relationship between institutional investor stability and one-year-ahead stock price crash risk is statistically negative. The evidence suggests that institutional investors curbs managers' bad news hoarding behaviors in the firm and reduce future stock price crash risk.

Conditional conservatism decreases crash risk. Watts (2003) and Kothari, Ramanna, and Skinner (2010) make an argument that conditional conservatism constrains managers' ability and motivations to postpone the disclosure of bad news and expedite the release of good news. Kim and Zhang (2012) also argue that the asymmetric verifiability requirement of conservative accounting policy compensates for managers' inclinations to withhold bad news and expedite good news realization in audited financial reporting. Furthermore, the timelier realization of losses than gains warns shareholders and the board of directors to recognize negative present value (NPV) projects earlier and compel managers to discontinue them. Therefore, conditional conservatism should curtail stock price crash risk. Kim and Zhang's (2012) results support that conditional conservatism in financial statements significantly reduces the probability of a firm to experience future stock price crashes.

Enhancing corporate governance mechanisms can help reduce crash risk. Andreou, Antoniou, Horton, and Louca (2012) investigate the relationship between the quality of firms' corporate governance systems and their stock price crashes. They conclude that effective corporate governance mechanisms oversee managers' behaviors and alleviate interest conflict between shareholders and managers. Therefore, strong corporate governance systems limit short-run price maximization and decrease stock price crashes. In their paper, they use four measures of corporate governance, i.e., CEO power and incentives, financial statement opacity, ownership structure, and board structure and processes. They find that crashes are positively related to institutional ownership and directors' stock ownership, highlighting that stock ownership encourages suboptimal practices. In addition, the opacity of financial reports is positively related to crashes, suggesting that suboptimal decision making occurs in more opaque environments. On the other hand, they find that the higher percentage of independent members on the audit committee, the lower the stock price crash risk, supporting that auditor independence increases the validity of financial statements.

2.3 What are the Agency Costs of Overvalued Equity

2.3.1 Definition of Equity Overvaluation and Agency Costs

Jensen (2004, 2005) posits that equity overvaluation occurs when a firm's stock price is higher than its underlying value. That is, the company will not be able to deliver the financial performance the market requires to justify that valuation. According to Jensen and Meckling (1976), agency costs arise when one entity, the principal, hires another entity, the agent, to act for him or her. They define agency costs as the sum of the contracting, monitoring, and bonding costs undertaken to reduce the costs due to conflicts of interest plus the "residual loss" that occurs because it is generally impossible to perfectly align the agents' interests with that of the principal. Jensen (2004, 2005) emphasizes that there are prohibitive agency costs associated with overvalued equity.

2.3.2 Why Do Managers Like Equity Overvaluation

According to prior literature, there are various reasons that managers like inflated stock prices. The first reason is target-based corporate compensation systems. Jensen (2004, 2005) argues that the fundamental problem of target-based corporate compensation systems is that these compensation systems train managers to forsake integrity and honesty in order to inflate stock prices. In these compensation systems, managers are paid for their performance relative to some targets. In order to achieve these targets, CEOs and CFOs engage in earnings surprise games with financial analysts and the financial market. Prior studies provide evidence that managers beat/meet various earnings benchmarks. For example, Degeorge, Patel, and Zeckhauser (1999) show that managers try to prevent reporting earnings that miss analysts' estimates. Brown (2001) shows that median earnings surprise has shifted rightward from small negative (miss analyst estimates by a small amount) to zero (meet analyst estimates exactly) to small positive (beat analyst estimates by a small amount) during 1984 to 1999. Matsumoto (2002) shows that managers engage in both AEM and expectations management to achieve non-negative earnings surprises. Burgstahler and Eames (2006) provide evidence that managers guide analysts' forecasts down to avoid negative earnings surprises.

The second reason is equity-based compensation for managers. Equity-based compensation could actually make the agency problems in the firm worse because it may exacerbate the interest conflict between current and future investors. (Bolton, Scheinkman, and Xiong, 2006). Consistent with the counterproductive effects of equity-based compensation, Efendi, Srivastava, and Swanson (2007) document that firms with CEOs who have large amounts of "in-the-money" options are much more likely to be involved in restatements. Moreover, Kim, Li, and Zhang (2011b) find that the CFOs' equity-compensation is significantly and positively related to the firm's future stock price crash risk.

Additional reasons that managers like overvalued equity include the following. First, it gives the firm access to below cost-of-capital funds (in both the debt and equity markets), and this can lead to lavish and wasteful internal spending. Second, it increases the wealth of managers and board members whose wealth are related to equity-based compensation (stocks, restricted stocks, unrestricted stocks, and options). Third, overvaluation may attract favorable media attention for managers and board members. Fourth, overvaluation makes hiring employees and managers much easier if overvalued firms offer stock options to employees. Fifth, overvaluation also gives cheap equity currency to use in acquisition of firms whose equity is not highly overvalued.

2.3.3 The Agency Costs of Extremely overvalued Equity

If a firm is extremely overvalued, it means except by pure luck, the firm cannot produce the performance required to justify that stock price. Managers know that the market will penalize the firm if true performance of the firm is revealed. In order to at least make it appear that the firm is delivering the performance to justify the price, managers hide the bad performance in the firm by manipulating the accounting numbers at the risk of destroying substantial shareholder value in the long run (Chi and Gupa, 2009; Badertscher, 2011).

In addition, managers may take excessive acquisitions (Shleifer and Vishny, 2003), accept negative NPV projects (Polk and Sapienza, 2004), or delay the start of projects (Graham, Harvey, and Rajgopal, 2005). Moelloer, Schlingemann, and Stulz (2005) document that in the three-day period surrounding the announcement of acquisitions during 1998-2001 acquiring firms lost a total of $240 billion. Jensen (2004, 2005) labels the above phenomenon as the agency costs of extremely overvalued equity because extreme overvaluation sets up organizational forces and incentives that are likely to harm the long term value of the firm.

However, costs associated with extremely overvalued equity are high: the market will eventually find out that the firm's overvaluation is sustained by EM and the stock price of the firm inevitably plummets or even crashes (Jensen, 2004, 2005). Enron is an extreme example that managers engage in earnings management to preserve the inflated stock price and eventually the firm collapses due to the agency costs of extreme equity overvaluation. At the time of Enron's peak market of $70 billion, the company was actually worth about $30 billion. Senior managers' effort to defend the $40 billion of excess valuation destroyed the $30 billion core value through accounting manipulations, hiding debt through off-balance sheet partnerships, and over hyping new ventures such as their broadband futures efforts. In doing this, Enron's managers accumulated negative information in the firm. Once the bad news reached the limit, it all came to the market at once. Had Enron's managers not continued to support the overvaluation, the company may still be alive and viable. In fact, many other companies, such as WorldCom, Xerox, Lucent, Vodaphone, Adelphia, Lernout and Hauspie Speech Products etc., are also involved in accounting scandals and frauds. One thing in common for these companies is that they all engaged in equity overvaluation game and could not bear the agency costs from the game.

2.4 Incentives and Consequences of EM

2.4.1 Definition of EM

EM can be categorized in to types: AEM and REM. AEM involves the use of accounting discretion to "obscure" or "mask" true economic performance (Dechow and Skinner, 2000). AEM tends to misrepresent the underlying operations of the firm in the books, but does not generally involve altering operations themselves. REM occurs when managers undertake real economic actions to alter reported earnings (Schipper, 1989), and it departs from normal operational practices (Roychowdhury, 2006). When managers engage in AEM or REM to conceal bad news in the firm, the financial statements in the firm do not reflect the true economic situation of the firm and are more opaque.

2.4.2 Why Do Managers Engage in EM

Existing evidence indicate the use of both AEM and REM mechanisms to avoid negative earnings surprises or achieve other earnings benchmarks. For example, Burgstahler and Dichev (1997) provide evidence that managers manipulate accruals, i.e., cash flow from operations and changes in working capital, to avoid earnings decreases and losses. Guidry, Leone, and Rock (1999) find that managers use AEM to maximize short term bonus compensation. Roychowdhury (2006) finds evidence consistent with managers engaging in REM to avoid reporting annual losses. Cohen, Dey, and Lys (2008) provide evidence that firms utilize REM in order to meet or beat prior year's earnings numbers, consensus analysts' forecasts, and avoiding losses in the post-SOX period. Cohen, Mashruwala, and Zach (2010) find managers reduce advertising spending to avoid losses and earnings decreases.

2.4.3 What Are the Consequences of EM

Prior literature also examines the consequences of using AEM and REM. For example, Chan, Jegadeesh, and Sougiannis (2004) find that for a $1 increase of current accruals, the impact on aggregate future earnings is $-0.046 and $-0.096 in the next one and three years respectively. Teoh, Wong, and Rao (1998) find that firms have unusual positive accruals and positive earnings in initial public offering (IPO) years. But after IPO years, firms experience unusual negative accruals and bad long-term earnings. Cohen and Zarowin (2010) show that seasoned equity offering (SEOs) firms engage in REM in SEO and performance declines in the post-SEO period. Chi and Gupta (2009) find that income-increasing AEM is negatively related to future abnormal stock returns and operating performance. However, not all EM has a negative impact on firms' future performance. For example, Gunny (2010) demonstrates that REM is positively associated with firms' future operating performance if they just meet earnings benchmarks. Therefore, whether EM has positive or negative impacts on future performance is not definitive.

Chapter 3

Hypothesis Development

Stock price crash literature shows that managers are able to strategically withhold bad news or negative information of the firm through opaque financial statements. (Jin and Myers, 2006; Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang, 2011a, 2011b). Using a two-period model, I show in Figure 1 the stock price change procedure based on the upcoming news and different managers' actions. In this model, I assume that the stock price at the beginning of period one is S_0 and in period one, managers can opportunistically disclose or hide the information to the market. However, in period two managers cannot hide the information anymore and all the hitherto concealed information is released to the market at once.

In period one, either there occurs bad news or good news. When bad news happens, if managers disclose it, then stock price in period one will drop to S_1 (S_1<S_0) and the firm has been correctly priced. In period two, when managers disclose bad news, the stock price will decrease further (S_2<$S_1 < S_0$). The stock price decreases progressively each time when there is some bad news released to the market. If in period two, managers disclose some good news, then the stock price will increase to S_2 ($S_2 \cong S_0$>S_1).

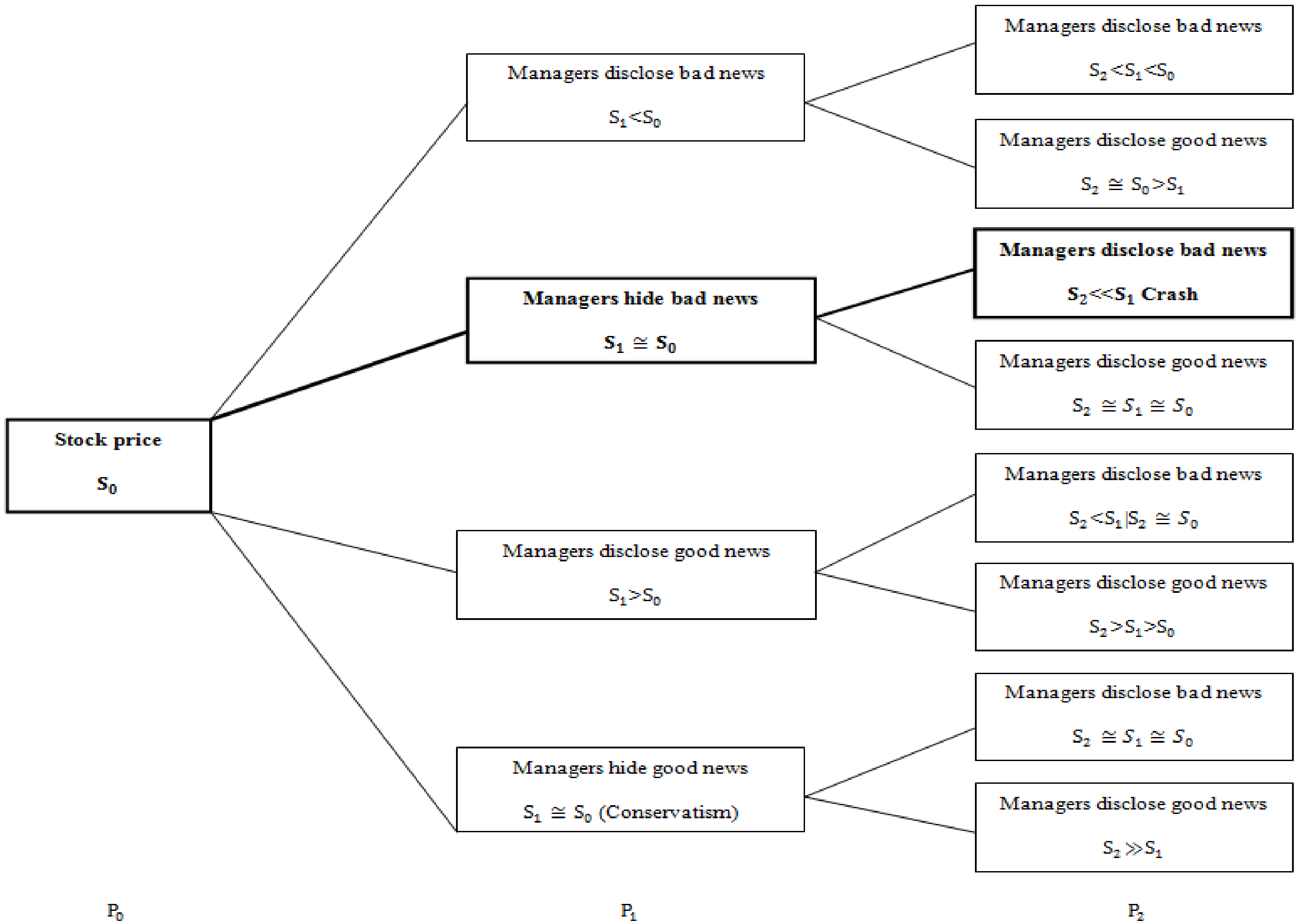

Figure 1 Two-period Stock Price Change Model

Suppose in period one there occurs bad news but managers hide bad news. Then the stock price during period one will approximate the stock price at the beginning of period one ($S_1 \cong S_0$). When in period two, as managers disclose bad news, the accumulation of the negative information for multiple periods of time will cause a sudden price plummet or stock price crash ($S_2 << S_1$). If however, managers disclose good news in period two, the effects of good news in period two and the effects of bad news in period one cancel out, then the stock price approximately equals to the stock price in the previous periods ($S_2 \cong S_1 \cong S_0$).

In period one, good news may occur. Manager can release good news, then the stock price in period one will increase to S_1 ($S_1 > S_0$). Then in period two, if managers disclose bad news, the stock price will drop to approximately the stock price at the beginning of period one ($S_2 < S_1 | S_2 \cong S_0$). If in period two, good news is disclosed, the stock price will increase further to S_2 ($S_2 > S_1 > S_0$).

If in period one, good news occurs and managers withhold good news, the stock price in period one will remain about the same as the stock price at the beginning of period one ($S_1 \cong S_0$). If in period two managers disclose bad news, the effect of good news in period one offsets the effects of bad news in period two, and the stock price in period two still approximates the stock price in the previous period ($S_2 \cong S_1 \cong S_0$). If managers disclose good news in period two, the release of the accumulated good news will increase the probability that the firm experiences a stock price jump ($S_2 >> S_1$).

In this thesis, I conjecture that earnings management is the most common method for managers to conceal bad news in the firms in period one of my model. AEM and REM are useful tools for managers to hide negative information in the firm to manage earnings. AEM occurs when managers use accounting estimates and judgments to affect accruals, which is known as accrual-based earnings management. REM occurs when managers take real economic transactions such as reducing research and development (R&D) and advertising expenditures to improve earnings performance, which is known as real activities based earnings management.

A firm's stock price can be overvalued for various reasons.[1] Although the factors that cause equity overvaluation are beyond the scope of this thesis, I conjecture that extreme overvaluation accompanied by high EM increases firms' stock price crash risk. This conjecture is consistent with Jensen's (2004, 2005) argument that extreme overvaluation motivates managers to engage in various value destroying activities. Furthermore, managers can hide and accumulate bad news in the firms by engaging in high EM. Based on the above discussion, I build the following testable hypothesis between extreme overvaluation accompanied by high EM and future stock price crash risk.

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[1] For example, overvaluation can be managerial reporting or actions induced (managers engage in AEM or REM). In addition, overvaluation can be investor-based without managers' actions. Kahneman and Tversky (1982) point out that an individual tends to overweight recent information and underweight prior data. For example, glamour stocks are overvalued by investors without managers' engagement.

Hypothesis: Firms with extreme equity overvaluation accompanied by high EM are more likely to experience stock price crashes than firms without both extreme overvaluation and high EM.

Chapter 4

Research Design

4.1 Measurement of Major Variables

4.1.1 Measurement of Firm-specific Crash Risk

In this thesis, I follow previous literature and use three proxies of stock price crash risk. The first proxy is an indicator which equal to 1 if a firm has at least one crash week in the whole fiscal year. Crash week is labeled for a firm in a fiscal year if the weekly abnormal return is 3.2×(standard deviation) lower than the average firm-specific abnormal weekly return in that fiscal year (Hutton, Marcus, and Tehranian, 2009; Kim, Li, and Zhang 2011a, 2011b).[2] To calculate the firm-specific abnormal weekly returns for each firm and year, denoted as W, I run the following expanded index regression model:

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{i,t-1} + \beta_{3,j} r_{m,t} + \beta_{4,j} r_{i,t} + \beta_{5,j} r_{m,t+1} + \beta_{6,j} r_{i,t+1} + \varepsilon_{j,t} \quad (1)$$

Where:

$r_{j,t}$= the return on stock j in week t (CRSP RET).

$r_{m,t}$= the market index weighted by value from CRSP in week t. (CRSP VWRETD)

[2] In a normal distribution, the probability of a 3.2 standard deviation below mean corresponds to 0.1%.

$r_{i,t}$ = the Fama and French value-weighted industry index in week t (weekly stock returns are weighted by market capitalization for 48 Fama-French industries).

I include two week prior and two week post industry and market returns in Model (1) to account for microstructure noise, consistent with Dimson (1979). The firm-specific weekly return equals to natural log of the residual in model (1) plus one, i.e., $W_{j,t} = \ln(1 + \varepsilon_{j,t})$. My first measure of stock price crash risk is an indicator CRASH which equal to 1 if a firm-year incur at least one crash week in the whole fiscal year, and zero otherwise.

Following Chen, Hong, and Stein (2001) and Kim, Li, and Zhang (2011a, 2011b), the negative conditional return skewness (NCSKEW) is used as the second measure of stock price crash risk. NCSKEW is the normalization of the third moment of weekly return with respect to standard deviation of weekly return.

$$\mathrm{NCSKEW}_{j,t} = -[n(n-1)^{3/2} \sum W_{j,t}^{3}]/[(n-1)(n-2)(\sum W_{j,t}^{3})^{3/2}]$$

The down-to-up volatility (DUVOL) is used as the third measure of stock price crashes, consistent with Chen, Hong, and Stein (2001) and Kim, Li, and Zhang (2011b). In order to calculate DUVOL, I first separate all the weeks into “down” weeks if firm-specific abnormal weekly returns are lower than the annual average return and “up” weeks if the firm-specific abnormal weekly returns are higher than the annual average return. DUVOL is the logarithm of the standard deviation on the down weeks minus the logarithm of the standard deviation on the up weeks.

$$\mathrm{DUVOL}_{j,t} = \log\left\{(n_u - 1)\sum_{\mathrm{DOWN}} W_{j,t}^2 \Big/ (n_d - 1)\sum_{\mathrm{UP}} W_{j,t}^2\right\}$$

Where n_u is the number of up weeks and n_d is the number of down weeks. Again, the higher value of this measure corresponds to a more left skewed distribution, which indicates the higher incidence of stock price crashes.

4.1.2 Measurement of Overvaluation

I use the Edwards-Bell-Ohlson (EBO) model valuation technique to estimate a firm's intrinsic value (V) and then calculate the P/V ratio. As Jensen (2005) points out "Equity is overvalued when a firm's stock price is higher than its underlying value". That is, overvaluation happens when the ratio of stock price to underlying intrinsic value exceeds 1.

Edwards and Bell (1961), Ohlson (1990, 1995), Lehman (1993), and Feltham and Ohlson (1995) show the theoretical development of the EBO residual income valuation method. Empirically, I estimate the EBO model as described by Frankel and Lee (1998) and Badertscher (2011) as follows:

$$V_t = B_t + \frac{(\mathrm{FROE}_t - r_e)}{(1 + r_e)} B_t + \frac{(\mathrm{FROE}_{t+1} - r_e)}{(1 + r_e)^2} B_{t+1} + \frac{(\mathrm{FROE}_{t+2} - r_e)}{(1 + r_e)^2 r_e} B_{t+2}$$

EBO model consists of ex ante observations on the right-hand side. In order to estimate V_t, I need to derive future book values (B_t, B_{t+1}, and B_{t+2}) and future return of equities (FROE_t, FROE_{t+1}, and FROE_{t+2}). I employ a sequential procedure (See Appendix B for calculate procedures) and use I/B/E/S consensus earnings-per-share (EPS) forecasts[3] to derive these future variables. I also use Fama and French (1997) four-factor risk model to calculate the industry-based cost of equity capital, r_e.[4] Following Dong, Hirshleifer, Richardson, and Teoh (2006), any estimate of the discount rate that is outside the range of 3-30 percent is winsorized to lie at the border of the range.

In order to measure the degree of overvaluation and identify extremely overvalued firms, I form annual portfolios on June 1 by ranking firms based on the P/V ratio. Also, price (P) is measured at the beginning of June. Jensen (2005) emphasizes high overvaluation problems arise "not when there are small overvaluation, but when there are extreme overvaluation, say by 100 or 1,000%." Therefore firms in the highest quintile rank of P/V indicate extremely overvalued firms. $\mathrm{OVER\_IND}_{jt}$ is an indicator variable which equals 1 if the firm has been in the top quintile of P/V in year t, and 0 otherwise (Badertscher, 2011).[5]

4.1.3 Measurement of AEM, REM, and EM

4.1.3.1 Measurement of AEM

Following Hutton, Marcus, and Tehranian (2009), I employ the modified Jones model (Dechow, Sloan, and Sweeney, 1995) to estimate a proxy for AEM. Specifically, I first estimate the following cross-sectional Jones model (1991) for

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[3] I use the I/B/E/S mean (also called consensus) forecast from the May statistical period of year t to ensure that forecasted earnings correspond to the correct fiscal year. This mean estimate is determined from analyst forecasts on file with I/B/E/S as of the Thursday after the third Friday of May.

[4] Fama and French (1997) four-factor model: $R_i - R_f = a_i + b_i(R_m - R_f) + s_i SMB + h_i HML + u_i UMD + e_i$. The data source is Fama-French Factors Monthly. R_f is FF r_f, $R_m - R_f$ is FF mktrf, SMB is smb, HML is FF hml, UMD is FF umd. Industry return is calculated by 60 month time-series rolling regression for Fama and French 48 industries.

[5] In my sample, the eightieth percentile of the P/V ratio is 2.047.

each Fama and French 48-industry classification in each fiscal year from 1995 to 2011 with at least 20 observations in a given year:

$$\frac{ACCR_{jt}}{TA_{jt-1}} = \alpha \frac{1}{TA_{jt-1}} + \beta_1 \frac{\Delta SALE_{jt}}{TA_{jt-1}} + \beta_2 \frac{PPE_{jt}}{TA_{jt-1}} + \varepsilon_{jt} \qquad (2)$$

Where:

$ACCR_{jt}$= total accruals for firm j or income before extraordinary items (Compustat IBC) minus operating cash flow from operating activities adjusted for extraordinary items and discontinued operations (Compustat OANCF minus XIDOC).

TA_{jt-1}= the total assets (Compustat AT) for firm j at the beginning of the year.

$\Delta SALE_{jt}$= the change in sales (Compustat SALE) for firm j.

PPE_{jt}= gross property, plant and equipment (Compustat PPEGT) for firm j in Fama and French 48 industry.

The discretionary accruals (DA_{jt}) are calculated based on estimated coefficients from model (2) (Dechow, Sloan, and Sweeney, 1995).

$$DA_{jt} = \frac{ACCR_{jt}}{TA_{jt-1}} - \widehat{\alpha} \frac{1}{TA_{jt-1}} - \widehat{\beta}_1 \frac{\Delta SALE_{jt} - \Delta REC_{jt}}{TA_{jt-1}} - \widehat{\beta}_2 \frac{PPE_{jt}}{TA_{jt-1}} \qquad (3)$$

Where:

ΔREC_{jt}= the change in accounts receivable (Compustat RECT) and $\widehat{\alpha}$, $\widehat{\beta}_1$, and $\widehat{\beta}_2$ are the estimated coefficients from model (2).

The variable AEM_SUM_{jt} is the moving sum of the absolute value of discretionary accruals over the last three year.

$$AEM\_SUM_{jt}=|DA_{jt-1}|+|DA_{jt-2}|+|DA_{jt-3}|$$

AEM_IND_{jt} is an indicator equal to 1 if the moving sum of the absolute value of discretionary accruals over the last three years (AEM_SUM) is in the top quintile and 0 otherwise.

4.1.3.2 Measurement of REM

Following Roychowdhury (2006), Cohen and Zarowin (2010), and Zang (2012), I develop my proxies for REM. Specifically, I first estimate the following cross-sectional regressions for each Fama and French 48 industry with at least 20 observations in a given year.

$$\frac{CFO_{jt}}{TA_{jt-1}} = \alpha_0 + \alpha_1 \frac{1}{TA_{jt-1}} + \alpha_2 \frac{SALE_{jt}}{TA_{jt-1}} + \alpha_3 \frac{\Delta SALE_{jt}}{TA_{jt-1}} + \varepsilon_{jt} \qquad (4)$$

Where:

CFO_{jt} = operating cash flow from operating activities adjusted for extraordinary items and discontinued operations (Compustat OANCF minus XIDOC).

TA_{jt-1}= the total assets (Compustat AT) for firm j at the beginning of the year.

$SALE_{jt}$= total sales (Compustat SALE) for firm j.

$\Delta SALE_{jt}$=the change in sales (Compustat SALE) for firm j.

$$\frac{PROD_{jt}}{TA_{jt-1}} = \alpha_0 \frac{1}{TA_{jt-1}} + \alpha_1 \frac{SALE_{jt}}{TA_{jt-1}} + \alpha_2 \frac{\Delta SALE_{jt}}{TA_{jt-1}} + \alpha_3 \frac{\Delta SALE_{jt-1}}{TA_{jt-1}} + \varepsilon_{jt} \qquad (5)$$

Where:

$PROD_{jt}$=the sum of cost of goods sold (Compustat COGS) and the change in inventories (Compustat INVT). $PROD_{jt}=COGS_{jt} + (INVT_{jt} - INVT_{jt-1})$.

TA_{jt-1}= the total assets (Compustat AT) for firm j at the beginning of the year.

$SALE_{jt}$= total sales (Compustat SALE) for firm j.

$\Delta SALE_{jt}$= the change in sales (Compustat SALE) for firm j.

$\Delta SALE_{jt-1}$= the change in sales (Compustat SALE) for firm j.

$$\frac{DISX_{jt}}{TA_{jt-1}} = \alpha_0 \frac{1}{TA_{jt-1}} + \alpha_1 \frac{SALE_{jt-1}}{TA_{jt-1}} + \varepsilon_{jt} \qquad (6)$$

Where:

$DISX_{jt}$= the discretionary expenditures for firm j, defined as the sum of advertising expenses (Compustat XAD), R&D expenses (Compustat XRD), and SG&A expenses (Compustat XSGA).

The residuals from models (4)-(6) are used to measure unusual cash flow from operations (R_CFO), unusual production costs (R_PROD) and unusual discretionary expenses (R_DISX) respectively. In order to capture the total effects of REM, I aggregate the three individual measures to compute an overall measure of REM activities. REM activities cause unusually lower cash flow from operations and unusually lower discretionary expenses. Therefore, consistent with Cohen and Zarowin (2010) and Zang (2012), I multiply unusual cash flows from operations (R_CFO) and unusual discretionary expenses (R_DISX) by negative one such that they have a positive relation with REM. The sum of standardized

R_CFO, R_PROD, and R_DISX is REM_PROXY, which is the REM measure.[6] Following Francis, Hasan, and Li (2011), I take the sum for the absolute value of the estimated REM_PROXY in the prior three years as the proxy for REM.[7]

$$\mathrm{REM\_SUM}_{jt}=|\mathrm{REM\_PROXY}_{jt-1}|+|\mathrm{REM\_PROXY}_{jt-2}|+|\mathrm{REM\_PROXY}_{jt-3}|$$

$\mathrm{REM\_IND}_{jt}$ is an indicator equal to 1 if the firm's prior three-year moving sum of REM measure (REM_SUM) is in the top quintile and 0 otherwise.

4.1.3.3 Measurement of EM

In order to capture the overall level of EM, I add the measures for AEM and REM.

$$\mathrm{EM}_{jt}=\mathrm{AEM\_SUM}_{jt}+\mathrm{REM\_SUM}_{jt}$$

$$=\sum_{t-3}^{t-1}|\mathrm{DA}_{jt}|+\sum_{t-3}^{t-1}|\mathrm{REM\_PROXY}_{jt}|$$

I classify high EM firms as those firms that are in the top quintile of EM measure. $\mathrm{EM\_IND}_{jt}$ is an indicator that equals 1 if the firm's prior three-year moving sum of AEM measure and REM measure is in the top quintile, and 0 otherwise.

4.2 Hypothesis Testing

Both univariate and multivariate tests are employed to examine the hypothesis formulated in Chapter 3.

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[6] The method of standardizing the individual REM measures and then adding them is consistent with Cohen, Dey, and Lys (2008).

[7] Francis, Hasan, and Li (2011) suggest two reasons to take the absolute value of REM proxies. First, REM may reverse in time. Sales manipulation by lenient credit terms in one period will lead to increase in abnormal cash flow in the future when customers pay their credit purchases. Overproduction in current period will be balanced by decreasing in production in later period since the total quantity is constrained by the total sales. The cutting of R&D and advertising expenses will be made up in the future periods. Second, REM may be used to smooth earnings (Matsuura, 2008).

4.2.1 Univariate Tests of Hypothesis

To obtain an overview of the relation among EM, overvaluation, and crash risk, I conduct univariate analysis. For this purpose, I first sort my sample observations into two EM groups (whether the firm has high EM or not) and two overvaluation groups (whether the firm has been extremely overvalued or not) in year t-1. These two-way sorts result in a 2×2 grid of firms for all observations. Then, for each cell of firms in each 2×2 grid, I calculate the average value of crash risk in year t.

Table 1 Univariate Hypothesis Testing Framework

		Extreme overvaluation (OVER_IND)	
		1	0
High EM (EM_IND)	1	Cell 1	Cell 2
	0	Cell 3	Cell 4

I employ the univariate tests to assess the crash risk difference among different portfolios. To be consistent with my hypothesis, the crash risk for extreme overvaluation accompanied by high managerial EM (Cell 1) should be higher than the crash risk with high EM but not extremely overvalued (Cell 2) and the crash risk with extreme equity overvaluation but without high EM (Cell 3).In addition, the crash risk for non-overvaluation and non EM (Cell 4) should be the lowest among all cells.

4.2.2 Multivariate Tests of Hypothesis

The multivariate model to test the hypothesis is:

$$\mathrm{CRASH\ MEASURE}_{jt} = \alpha_0 + \alpha_1 \mathrm{OVER\_IND}_{jt-1} + \alpha_2 \mathrm{EM\_IND}_{jt-1}$$

$$+\alpha_3 \mathrm{OVER\_IND}_{jt-1} \times \mathrm{EM\_IND}_{jt-1} + \alpha_4 \mathrm{DTURN}_{jt-1} + \alpha_5 \mathrm{NCSKEW}_{jt-1}$$
$$+\alpha_6 \mathrm{SIGMA}_{jt-1} + \alpha_7 \mathrm{WRET}_{jt-1} + \alpha_8 \mathrm{LSIZE}_{jt-1} + \alpha_9 \mathrm{MB}_{jt-1} + \alpha_{10} \mathrm{LEV}_{jt-1}$$
$$+\alpha_{11} \mathrm{ROA}_{jt-1} + \alpha_{12} \mathrm{AQ}_{jt-1} + \sum_{t=1}^{T-1} \mathrm{YEAR}_t + \varepsilon_{jt} \quad (7)$$

I predict that extremely overvalued firms accompanied by high managerial EM are more likely to experience stock price crashes compared to extremely overvalued firms that lack high EM and firms with high EM but without extreme overvaluation. In other words, in the regression, I expect the interaction term between extreme overvaluation and high EM to be positively related to crash risk but the main effects of extreme overvaluation and high EM to be unrelated to predict crash risk. Therefore, in the regression test, I expect $\widehat{\alpha}_3$ to be significantly positive but $\widehat{\alpha}_1$ and $\widehat{\alpha}_2$ to be insignificant.

Following Kim, Li, and Zhang (2011a, 2011b), the dependent variables in multiple regressions are measured in year t, while the independent variables are measured in year t-1. A set of other control variables are also considered and included in the regression based on prior research (Chen, Hong, and Stein 2001; Hutton, Marcus, and Tehranian 2009; and Kim, Li, and Zhang, 2011a, 2011b).[8] The definitions of the variables included in the multivariable model are as following:

Stock price crash measures($\mathrm{CRASH\ MEASURE}_{jt}$): firm j specific crash risk measures: CRASH_{jt}, NCSKEW_{jt} or DUVOL_{jt}.

[8] I do not include $\mathrm{AEM\_SUM}_{jt-1}$ as an independent variable because it is part of the EM measure. Including $\mathrm{AEM\_SUM}_{jt-1}$ will create multicollinearity issue.

Overvaluation proxy ($\mathrm{OVER\_IND}_{jt-1}$): an indicator equal to 1 if firm j is in the top quintile of P/V ratio and thus deemed to be overvalued, and 0 otherwise.

High EM proxy ($\mathrm{EM\_IND}_{jt-1}$): an indicator equal to 1 if the firm's prior three-year moving sum of AEM measure and REM measure is in the top quintile of aggregate EM measure, and 0 otherwise.

Detrended stock trading volume (DTURN_{jt-1}): the average monthly share turnover for the last fiscal year minus the average monthly share turnover for the year before the last fiscal year. The total monthly trading volume ((CRSP VOL)) divided by the total monthly number of shares outstanding (CRSP SHROUT) is monthly share turnover. Chen, Hong, and Stein (2001) show that there is a positive relationship between high turnovers and future crash risk. Therefore I expect a positive relation between detrended stock trading volume and the crash risk measures.

Negative skewness (NCSKEW_{jt-1}): negative skewness for firm j. To capture the potential persistence of the third moment of stock returns, I include the one year lag of NCSKEW. Chen, Hong, and Stein (2001) show that high return skewness in year t-1 is likely to have high crash risk in year t as well. Therefore, I predict a positive relation between negative skewness and crash risk measures.

Stock return volatility (SIGMA_{jt-1}): the standard deviation of firm-specific abnormal weekly returns ($\mathrm{W}_{j,t}$ from model (1)). Chen, Hong, and Stein (2001) find that firms with high stock return volatility increase stock price crashes. I expect a positive relation between crash risk measures and stock return volatility.

Firm-specific abnormal weekly returns ($\mathrm{WRET}_{\mathrm{jt-1}}$): 100 times of the previous fiscal year's average firm-specific abnormal weekly returns ($\mathrm{W}_{\mathrm{j,t}}$ from model (1)). Chen, Hong, and Stein (2001) find that higher past returns is positively associated with future stock price crashes. I expect a positive relation between abnormal weekly returns and the crash risk measures.

Firm size ($\mathrm{LSIZE}_{\mathrm{jt-1}}$): natural logarithm of market value (shares outstanding (CRSP SHROUT) times price (CRSP PRC) adjusted for stock splits) in June, used to control for the size effect. Because there is no particular theory related to whether big firms or small firms are more likely to incur crash. I follow Kim and Zhang (2012) and do not predict the sign of the relation between crash risk and firm size.

Market-to-book ratio ($\mathrm{MB}_{\mathrm{jt-1}}$): the market capitalization of shareholders' equity (Compustat PRCC_F*CSHO) divided by the book value of shareholders' equity (Compustat CEQ). Hutton, Marcus, and Tehranian (2009) document that a high MB ratio is positively associated with future crash risk. Therefore, I expect a positive relation between crash risk and MB ratio.

Financial leverage ($\mathrm{LEV}_{\mathrm{jt-1}}$): leverage ratio, calculated as short-term debt (Compustat DLC) plus long-term debt (Compustat DLTT, scaled by total assets (Compustat AT). Following Kim and Zhang (2012), I do not predict the sign of the relation between crash risk and firms' financial leverage.

Return on assets (ROA_{jt-1}): net income before extraordinary items (Compustat IB) divided by total assets (Compustat AT) at the beginning of the year, used to control for a possible contemporaneous relation between profitability and crash risk. Hutton, Marcus, and Tehranian (2009) find a negative relation between ROA and crash risk, but Kim, Li, and Zhang (2011b) find a positive relation between ROA and crash risk. Therefore, I do not have a prediction on the relation between ROA and crash risk.

Accruals quality (AQ_{jt-1}): the standard deviation of the firm-level residuals from the Dechow and Dichew (2002) model during the previous 5 years and multiplied by -1.[9] Kim, Li, and Zhang (2011a) find that lower accrual quality is more crash-prone. Therefore, I expect a negative relation between AQ and crash risk.

Control for year effects ($YEAR_t$): equal to 1 for year t, and 0 for other years. The subscript t equals 1, 2⋯or T-1, where T represents the number of unique years in the sample period. Year indicators are included to account for year fix effects.[10]

To control for firm-level fixed effects in my regressions, I use firm fixed-effects model.[11] By controlling for firm-fixed effects, I address the concern that

[9] See Appendix C for calculation details of AQ.

[10] Even though I use market and industry adjusted (firm-specific) returns to construct the crash risk measure, it is still necessary to control for year fixed effects. Table 4 shows that the firm-specific crash risks are significantly higher during the pre-crisis period (2002, 2004-2008) than during other periods.

[11] An alternative to firm fixed-effects model is Least Square Dummy Variable model (LSDV) which is OLS estimation with explicit firm indicator variables. That approach generates the same coefficient estimates, but it is computationally intensive, infeasible for models with thousands of

my results may be driven by some unobserved firm-level characteristics that affect both firms' incentives to engage in EM and inflate firms' valuation.

firms (as is the case in my test), and it also generates higher adjusted R^2. So my reported adjusted R^2s are more conservative.

Chapter 5

Empirical Results

5.1 Sample Selection

The sample is drawn from the intersection of data from Compustat Fundamentals Annual, daily Center for Research in Security Prices (CRSP), and summary I/B/E/S for the period 1995-2011.[12] Table 2, Panel A summarizes the sample selection process to collect testable observations. I start from Compustat Fundamentals Annual (101,460 firm-years and 13,249 firms). Because firms in regulated industries likely have different characteristics from non-regulated industries, I exclude 18,205 firm-years (1,762 firms) in financial service (SIC codes 6000-6999) and utilities (SIC codes 4900-4999). The sample is therefore restricted to all non-regulated firms with available data. Next, consistent with Frankel and Lee (1998) and Badertscher (2011), I further restrict firms with fiscal year-ends between June and December inclusively by dropping 12,103 firm-years (1,350 firms). This constrain ensures that I/B/E/S forecasts issued in May correspond to the correct fiscal year. Consistent with Kim, Li, and Zhang (2011a), I also eliminate 7,953 firm-years (849 firms) with missing total asset and book value. I further delete 2,997 firm-years (158 firms) with non-positive book values

[12] I use 1994-2012 data to calculate a firm's accruals quality because there is a one year lead and one year lag cash flow from operations (CFO) as shown in Appendix C.

because ROEs for these firms cannot be interpreted in economic terms. In addition, I exclude share price that is lower than $1 as of the beginning of June (2,994 firm-years and 193 firms) since these firms have poor liquidity. Furthermore, 18,113 firm-years (3,166 firms) with insufficient financial data to calculate control variables are removed from the sample. Moreover, 3,743 firm-years (444 firms) with incomplete financial data to calculate EM measures are dropped from the sample. I further remove 12,215 firm-years (1,193 firms) with missing one-year-ahead or two-year-ahead analysts' consensus forecasts from I/B/E/S to calculate overvaluation proxy. I eliminate 15 firm-years (1 firm) with insufficient data to calculate crash proxies. Finally, I delete 1,447 firms (2,072 firm years) with less than 3 years data during the sample period. This criterion ensures that I can employ a firm fixed-effects model which demeans the variables. The final sample consists of 21,050 firm-year observations (2,686 firms) for the sample period during 1995-2011.

Table 2, Panel B illustrates that the sample includes 42 of the 48 Fama and French industry definitions. It also shows that the number of firm-year observations with stock price crashes varies significantly across industries.

Table 2 Sample Description

Panel A: Sample selection

	No. of firm years	No. of firms
Initial sample in the COMPUSTAT from 1995–2011	101,460	13,249
Excluding firm fiscal years:		
Financial services (SIC 6000-6999) and utilities (SIC 4900-4999)	(18,205)	(1,762)
Fiscal year-ends between January and May	(12,103)	(1,350)
Missing total assets and book value	(7,953)	(849)
Non-positive total assets and book value	(2,997)	(158)
Share price lower than $1	(2,994)	(193)
With insufficient data to calculate control variables	(18,113)	(3,166)
With insufficient financial data to calculate RM proxies	(3,743)	(444)
With insufficient financial data to calculate overvaluation	(12,215)	(1,193)
With insufficient financial data to calculate crash proxies	(15)	(1)
With less than 3 years data during the sample period	(2,072)	(1,447)
Final sample	21,050	2,686

Table 2—*Continued*

Panel B: Fama and French industries

Industry	No. of Firm Year	No. of Crash	Percentage of firms with stock price crash	Industry	No. of Firm Year	No. of Crash	Percentage of firms with stock price crash
Agriculture	2	1	50.000	Electrical Equipment	369	70	18.970
Food Products	397	62	15.617	Automobiles and Trucks	413	60	14.528
Candy & Soda	1	0	0.000	Aircraft	12	3	25.000
Beer & Liquor	3	1	33.333	Shipbuilding, Railroad Equipment	4	1	25.000
Recreation	157	31	19.745	Defense	3	0	0.000
Entertainment	355	63	17.746	Petroleum and Natural Gas	1119	120	10.724
Printing and Publishing	229	33	14.410	Communication	502	76	15.139
Consumer Goods	423	76	17.967	Personal Services	334	86	25.749
Apparel	345	76	22.029	Business Services	2974	616	20.713
Healthcare	567	122	21.517	Computers	1082	246	22.736
Medical Equipment	941	207	21.998	Electronic Equipment	1745	322	18.453
Pharmaceutical Products	1416	339	23.941	Measuring and Control Equipment	741	147	19.838
Chemicals	623	99	15.891	Business Supplies	336	51	15.179
Rubber and Plastic Products	189	35	18.519	Shipping Containers	3	0	0.000
Textiles	112	21	18.750	Transportation	793	110	13.871
Construction Materials	504	89	17.659	Wholesale	862	159	18.445
Construction	271	49	18.081	Retail	831	181	21.781
Steel Works Etc	464	74	15.948	Restaurants, Hotels, Motels	496	81	16.331
Fabricated Products	44	9	20.455	Others	218	37	16.972
Machinery	1170	168	14.359	Overall	21,050	3,921	18.627

Table 3 shows the statistics for annual observations and the crash percentage of firms in a fiscal year. Panel A of Table 3 shows the statistics in the Compustat universe. Panel B of Table 3 shows the statistics in my final sample. Comparing these two panels, I find that the crash percentage in my final sample is slightly higher than those in the Compustat universe. On average, 18.6 percent of firm-year observations in my sample incur stock price risk in a year compared to 15.8 percent in Compustat universe. The yearly crash pattern is consistent with the finding of Zhou, Kim, and Yeung (2013).

Table 3 Stock Price Crashes in the Sample

Panel A: All observations in COMPUSTAT			
Year	Number Of Firms	Number Of Firms With Crash	Percent Of Firms With Crash
1995	7,174	794	0.111
1996	7,424	922	0.124
1997	7,507	883	0.118
1998	7,250	1,022	0.141
1999	6,945	869	0.125
2000	6,704	1,016	0.152
2001	6,404	1,086	0.170
2002	5,698	1,109	0.195
2003	5,405	837	0.155
2004	5,382	1,001	0.186
2005	5,381	1,017	0.189
2006	5,313	983	0.185
2007	5,424	1,059	0.195
2008	5,022	985	0.196
2009	4,721	698	0.148
2010	4,585	808	0.176
2011	4,029	741	0.184
Overall	100,368	15,830	0.158

Table 3—*Continued*

Panel B: Final Sample			
Year	Number Of Firms	Number Of Firms With Crash	Percent Of Firms With Crash
1995	1,013	121	0.119
1996	1,158	199	0.172
1997	1,306	183	0.140
1998	1,361	223	0.164
1999	1,371	190	0.139
2000	1,331	257	0.193
2001	1,255	219	0.175
2002	1,160	268	0.231
2003	1,316	241	0.183
2004	1,317	308	0.234
2005	1,338	326	0.244
2006	1,313	297	0.226
2007	1,267	265	0.209
2008	1,231	276	0.224
2009	1,180	180	0.153
2010	1,076	173	0.161
2011	1,057	195	0.184
Overall	21,050	3,921	0.186

5.2 Descriptive statistics

Table 4 presents the descriptive statistics for the variables used in my multivariate analyses. Detailed definitions of all variables are provided in Chapter 4 and in Appendix A, Appendix B, and Appendix C. All continuous variables are winsorized at 1 and 99 percentile.[13] Table 4 shows that the CRASH mean value is 0.186. This suggests that on average the probability of a firm to experience an unconditional crash event during a year is 18.6 percent. Here, the mean CRASH is higher than that reported by Kim, Li, and Zhang (2011a) (16.1 percent) and Kim

[13] I do not winsorize leverage because firms could have zero or high debt ratio. It is a firm's strategy.

and Zhang (2012) (12 percent). However, it should be noted that my sample period is more recent and covers the financial crisis of 2008. The mean value of NCSKEW is 0.001, which is also higher than that reported by Kim, Li, and Zhang (2011a) (-0.079) and Kim and Zhang (2012) (-0.229), suggesting that firms in my thesis are, on average, more crash-prone than those in these two studies. In fact, the distributions of all crash risk measures, including CRASH, NCSKEW, and DUVOL are similar to those reported by Hong, Kim, and Welker (2012). I classify a firm as overvalued when its P/V ratio is in the top quintile, and the P/V ratio is 2.047 at eightieth percentile. The distributions of other variables are also largely consistent with those reported in prior studies.

Table 5 presents the Pearson/Spearman correlation matrix for all variables used in my regression analysis. The three measures for crash risk, CRASH, NCSKEW, and DUVOL, are all significantly positively correlated with each other, with CRASH and NCSKEW having a ratio of 0.600, CRASH and DUVOL having a ratio of 0.548 and NCSKEW and DUVOL having a ratio of 0.982 using the Pearson correlations measures, suggesting that they capture the same underlying construct. I find that the correlation between high overvaluation and crash risk is positive and significant, which supports Jensen's (2004, 2005) conjecture that overvalued firms are more likely to experience stock price crashes. I also observe a positive correlation between EM and future crash risk, which is consistent with the finding of Hutton, Marcus, and Tehranian (2009) and Francis,

Table 4 Descriptive Statistics

Variable	N	Mean	Std.Dev.	Minimum	20%	Median	80%	Maximum
Crash proxies								
$CRASH_{jt}$	21,050	0.186	0.389	0.000	0.000	0.000	0.000	1.000
$NCSKEW_{jt}$	21,050	0.001	0.814	-5.302	-0.543	-0.055	0.493	5.384
$DUVOL_{jt}$	21,050	-0.020	0.362	-1.697	-0.311	-0.036	0.263	1.745
Earnings Management Proxies								
EM_SUM_{jt-1}	21,050	1.527	1.264	0.116	0.560	1.147	2.246	7.493
AEM_SUM_{jt-1}	21,050	0.215	0.192	0.022	0.083	0.158	0.302	1.148
REM_SUM_{jt-1}	21,050	1.312	1.203	0.094	0.397	0.936	1.990	6.345
Overvaluation Proxy								
P/V_{jt-1}	21,050	1.698	1.885	0.114	0.719	1.314	2.047	14.538
Control Variables								
$DTURN_{jt-1}$	21,050	0.007	0.142	-0.491	-0.059	0.003	0.072	0.557
$NCSKEW_{jt-1}$	21,050	0.010	0.742	-1.759	-0.529	-0.052	0.486	2.606
$SIGMA_{jt-1}$	21,050	0.055	0.028	0.015	0.032	0.050	0.076	0.146
$WRET_{jt-1}$	21,050	-0.186	0.192	-1.040	-0.281	-0.121	-0.049	-0.010
$LSIZE_{jt-1}$	21,050	6.495	1.696	3.172	5.011	6.358	7.859	11.253
MB_{jt-1}	21,050	2.914	2.365	0.449	1.321	2.233	3.894	14.629
LEV_{jt-1}	21,050	0.186	0.173	0.000	0.002	0.160	0.335	0.929
ROA_{jt-1}	21,050	0.040	0.131	-0.526	-0.004	0.058	0.118	0.335
AQ_{jt-1}	21,050	-0.066	0.066	-0.401	-0.092	-0.044	-0.023	-0.006

Variables are defined in Appendix A.

Table 5 Correlation Matrix for Major Variables

Variables		A	B	C	D	E	F	G	H	I	J	K	L	M	N
$CRASH_{jt}$	A		0.635***	0.576***	0.032***	0.023***	0.013*	0.027***	-0.002	0.014**	0.027***	0.041***	-0.032***	0.032***	-0.029***
$NCSKEW_{jt}$	B	0.600***		0.954***	0.020***	0.031***	0.028***	0.022***	-0.027***	0.033***	0.089***	0.054***	-0.027***	0.075***	0.002
$DUVOL_{jt}$	C	0.548***	0.982***		0.012*	0.030***	0.029***	0.020***	-0.045***	0.049***	0.106***	0.051***	-0.025***	0.089***	0.015**
EM_IND_{jt-1}	D	0.032***	0.01	0.007		0.053***	0.006	0.018***	0.166***	-0.154***	-0.072***	0.203***	-0.179***	-0.038***	-0.184***
$OVER\_IND_{jt-1}$	E	0.023***	0.027***	0.027***	0.053***		0.020***	0.023***	-0.078***	0.076***	0.129***	0.094***	-0.034***	0.101***	0.011
$DTURN_{jt-1}$	F	0.013*	0.027***	0.027***	-0.001	0.020***		0.039***	0.082***	-0.085***	0.051***	0.072***	0.015**	0.074***	0.013*
$NCSKEW_{jt-1}$	G	0.022***	0.020***	0.018***	0.012*	0.022***	0.045***		0.091***	-0.066***	0.092***	0.058***	-0.025***	0.025***	-0.007
$SIGMA_{jt-1}$	H	0.01	-0.035***	-0.040***	0.163***	-0.079***	0.043***	0.044***		-0.966***	-0.466***	0.072***	-0.107***	-0.368***	-0.323***
$WRET_{jt-1}$	I	-0.01	0.035***	0.040***	-0.163***	0.079***	-0.043***	-0.033***	-1.000***		0.384***	-0.084***	0.090***	0.376***	0.300***
$LSIZE_{jt-1}$	J	0.035***	0.110***	0.112***	-0.074***	0.128***	0.083***	0.112***	-0.518***	0.520***		0.313***	0.073***	0.264***	0.164***
MB_{jt-1}	K	0.052***	0.069***	0.066***	0.175***	0.123***	0.083***	0.072***	-0.013*	0.014**	0.383***		-0.063***	0.071***	-0.130***
LEV_{jt-1}	L	-0.032***	-0.018***	-0.017**	-0.197***	-0.029***	0.028***	-0.019***	-0.167***	0.167***	0.122***	-0.150***		-0.061***	0.176***
ROA_{jt-1}	M	0.045***	0.101***	0.103***	0.035***	0.160***	0.099***	0.039***	-0.299***	0.300***	0.300***	0.351***	-0.155***		0.286***
AQ_{jt-1}	N	-0.035***	0.015**	0.018***	-0.178***	0.018***	0.027***	0.001	-0.401***	0.401***	0.222***	-0.090***	0.260***	0.191***	

Correlations are computed based on 21,050 firm-years in the sample period 1995-2011.
The Spearman (Pearson) correlations are above (below) the diagonal.
Variables are defined in Appendix A.
One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

Hasan, and Li (2011) that EM firms have higher crash risk. The Spearman correlations among these variables are similar. However, caution should be taken not to draw any conclusions from the univariate correlation relation, because other confounding factors can potentially drive the relation between a predictor and crash risk association.

5.3 Univariate Tests of Hypothesis

Panel A of Table 6 shows that the crash risk decreases monotonically from the portfolio of extreme overvaluation and high EM to the portfolio of non-overvaluation and non-EM. Panel B of Table 6 shows that future crash probability is statistically higher for the portfolio with extreme overvaluation and high EM than for both the portfolio of extreme overvaluation but without high EM and the portfolio of high EM but without extreme overvaluation. The results are consistent with my hypothesis that high EM accompanied by extreme overvaluation increases firms' future crash risk. The results of using CRASH, NCSKEW, and DUVOL are qualitatively similar.

Table 6 Portfolio Analysis of Stock Price Crash Risk

Panel A: Crash Risk in Different Portfolio				
Portfolios		crash %	Avg_NCSKEW	Avg_DUVOL
Over & EM	(n=1,019)	0.253	0.136	0.030
Over & Not EM	(n=3,186)	0.189	0.024	-0.007
Not Over & EM	(n=3,186)	0.197	0.001	-0.025
Not Over & Not EM	(n=13,659)	0.178	-0.015	-0.026
Overall	(n=21,050)	0.186	0.001	-0.020

Table 6—*Continued*

Panel B: Statistic Tests for Cash Risk Difference in Different Portfolios			
Hypotheses	Crash %	Avg_NCSKEW	Avg_DUVOL
H0: Over & EM =Over& Not EM H1: Over &EM≠Over& Not EM	z-statistic=3.80 Two-tailed P-value<0.001	t-statistic=3.63 Two-tailed P-value<0.001	t-statistic=2.78 Two-tailed P-value=0.005
H0: Over & EM =Not Over& EM H1: Over &EM≠Not Over& EM	z-statistic=3.61 Two-tailed P-value<0.001	t-statistic=4.22 Two-tailed P-value<0.001	t-statistic=4.03 Two-tailed P-value<0.001

Variables are defined in Appendix A.

5.4 Multivariate Tests of Hypothesis

My hypothesis predicts that extreme overvaluation with high EM is positively related to future stock price crash risk because it facilitates managerial bad news hoarding and rent diversion. Table 7 presents the firm fixed-effects model analysis for hypothesis testing.[14] The three columns represent the regression results with each of the three proxies for crash risk as the dependent variable. When CRASH is the dependent variable, firm fixed-effects logistic regression is used. When NCSKEW and DUVOL are the dependent variables, firm fixed-effects multivariate regression is used. Consistent with Kim and Zhang (2012), all regressions in the multivariate tests also include year indicators to control for year fixed effects.

[14] The Breusch and Pagan Lagrangian multiplier test tests the following hypothesis:
H_0: $Cov(\alpha_i, \varepsilon_{it})=0$
H_1: $Cov(\alpha_i, \varepsilon_{it})\neq 0$
χ^2=8.35 and p=0.002, therefore, I reject H_0 that the unobserved firm heterogeneity is uncorrelated with residuals and I should use random-effects or firm-fixed effects model rather than OLS model.
The Hausman test tests the following hypothesis:
H_0: $Cov(x_{it}, \alpha_i)=0$
H_1: $Cov(x_{it}, \alpha_i)\neq 0$
Where α_i is unobserved firm heterogeneity which is constant from time to time but is different from firm to firm. χ^2=2,815.69 and p=0.000, therefore, I reject H_0 that the unobserved firm heterogeneity is uncorrelated with predictors and I should use firm fixed-effects model.

Consistent with my hypothesis across all columns, I find the coefficients for the interaction term between extreme overvaluation and high EM are significantly positive ($p<0.05$ in column (1), $p<0.01$ in column (2) and (3)), suggesting extreme overvaluation with high EM in year t-1 increases crash risk in year t even after controlling for other determinants of crash risk. This finding suggests that high EM provides self-interested managers in extremely overvalued firms with opportunities, methods, and masks to hide negative information, which when accumulated to a tipping point leads to an increase in crash risk.

Table 7 Overvaluation and Stock Price Crash Risk: The Impact of EM

Variables	CRASH (1)	NCSKEW (2)	DUVOL (3)
$\mathrm{OVER\_IND}_{jt-1}$	-0.062	-0.001	-0.002
	(-1.011)	(-0.068)	(-0.240)
$\mathrm{EM\_IND}_{jt-1}$	-0.029	-0.006	-0.006
	(-0.376)	(-0.235)	(-0.554)
$\mathrm{OVER\_IND}_{jt-1} \times \mathrm{EM\_IND}_{jt-1}$	**0.268****	**0.112*****	**0.046*****
	(2.316)	**(2.699)**	**(2.608)**
DTURN_{jt-1}	0.204	0.110***	0.049***
	(1.574)	(2.652)	(2.795)
NCSKEW_{jt-1}	-0.220***	-0.130***	-0.057***
	(-8.466)	(-15.335)	(-15.462)
SIGMA_{jt-1}	1.803	2.260*	1.315**
	(0.440)	(1.844)	(2.471)
WRET_{jt-1}	0.979*	0.390**	0.219***
	(1.908)	(2.552)	(3.319)
LSIZE_{jt-1}	0.372***	0.156***	0.068***
	(8.689)	(11.906)	(11.876)

Table 7—*Continued*

MB_{jt-1}	-0.006	-0.004	-0.002
	(-0.485)	(-0.929)	(-0.846)
LEV_{jt-1}	0.060	-0.022	-0.022
	(0.282)	(-0.317)	(-0.716)
ROA_{jt-1}	1.074***	0.477***	0.237***
	(4.724)	(6.193)	(7.498)
AQ_{jt-1}	0.010	0.131	0.066
	(0.023)	(0.890)	(1.062)
Intercept		-1.053***	-0.496***
		(-11.792)	(-12.789)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
No. of observations	21,050	21,050	21,050
Pseudo-R2 (R Square)	0.033	0.045	0.050

Variables are defined in Appendix A. The z-statistics (t-statistics) reported in parentheses are computed using standard errors corrected for serial correlation and heteroskedasticity. One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

To assess the economic significance of my test results, using the coefficients in CRASH model (column 1), I compute the marginal effect of the interaction term, that is, the change in CRASH probability arising from the change to extreme overvaluation and high EM, holding all other independent variables at their mean values. The marginal effect of the interaction between extreme overvaluation and high EM is 3.4%. This is economically significant, given that the average unconditional probability of a crash in my sample is 18.6 percentage points, as reported in Table 4. In addition, firms' NCSKEW increases by 0.112 and DUVOL increases by 0.046 compared to firms without extreme overvaluation or little EM, holding all other independent variables fixed. Given that the average unconditional NCSKEW and DUVOL in my sample are 0.001

and -0.020 respectively reported in Table 4, the results are economically significant.

More importantly, I find that firms with extremely overvalued stock prices but no evidence of high EM, given by the OVER_IND variable, and firms engaged in high EM but with stock prices that are not extremely overvalued, given by the EM_IND variable, do not show any significant association with firm-specific future crash risk. Jointly, these results imply that stock price overvaluation and earnings management are individually necessary but only jointly sufficient for increased future crash risk.

Overall, the estimated coefficients of the control variables are generally consistent with the findings of prior studies.[15] First, I find the sign of detrended stock trading volume (DTURN) is significantly positive across two of the three models, consistent with Chen, Hong, and Stein (2001). Second, I find the lag of NCSKEW is significantly negative across all three models which is consistent with Kim and Zhang's (2012, Table 7) results. Third, I find that the sign of the coefficients of past return volatility (SIGMA) is significantly positive across two of the three models consistent with Chen, Hong, and Stein (2001) and Kim, Li, and Zhang (2011a, 2011b). Fourth, I find that the coefficients of the past stock return (WRET) are significantly positive across all the models, which is consistent

[15] To make sure that the results are not driven by multicollinearity problems, I checked Variance Inflation Factor (VIF) among the predictors. Only SIGMA (VIF 21) and WRET (VIF 17) have VIF higher than 10. If I remove either one of SIGMA or WRET, the VIFs for all predictors are smaller than 10. Consistent with Kim, Li, and Zhang (2011a, 2011b), the regression results include both SIGMA and WRET. All the regression results remain qualitatively the same if I remove one of the two.

with Harvey and Siddique's (2000) "stochastic bubble theory" that stocks with high past returns are more likely to experience crashes. The coefficients of lagged firm size are significantly positive. Chen, Hong, and Stein (2001), Hutton, Marcus, and Tehranian (2009), and Kim, Li, and Zhang (2011a, 2011b) also report a significantly positive coefficient for LSIZE, suggesting that large firms are more crash-prone. The coefficient on past ROA is significantly positive in all three models consistent with and Kim, Li, and Zhang (2011b). Finally, I find the coefficients of lagged market-to-book (MB), lagged leverage (LEV), and lagged accruals quality (AQ) are all insignificant.

Overall, the findings in Table 7 show the likelihood of future price crashes is significantly higher for firms with the ability to engage in high EM to preserve their extreme stock overvaluation. The relation is robust to different measures of crash risk. This result holds after controlling for firm and year fixed effects, the measure of investor heterogeneity of Chen, Hong, and Stein (2001), the measure of accruals quality used by Kim, Li, and Zhang (2011a) and other firm characteristics shown to have association with crash risk. The above results should be informative to managers and the board of directors about using excessive EM to opportunistically engage in behaviors such as concealing bad operating performance to meet/beat targets or analysts' forecasts and to maximize private gains in the case of extreme overvaluation.

5.5 Partition of AEM and REM

In my hypothesis testing, I examine the relation between extreme overvaluation with high overall EM and the crash risk. Next, I further examine how AEM and REM play separate roles in earnings management. For this purpose, I partition the EM measurement into AEM and REM separately. Specifically, AEM_IND captures AEM activities and is an indicator equal to 1 if the moving sum of the absolute value of discretionary accruals over the last three years (AEM_SUM) is in the top quintile and 0 otherwise. Similarly, REM_IND captures REM activities and is an indicator equal to 1 if the firm's prior three years' moving sum of REM measure (REM_SUM) is in the top quintile and 0 otherwise. In order to test the separate effects of AEM and REM, I create the interaction terms between overvaluation and AEM_IND (REM_IND) and run the following model:

$$\mathrm{CRASH\ MEASURE}_{jt} = \alpha_0 + \alpha_1 \mathrm{OVER}_{\mathrm{IND}_{jt-1}} + \alpha_2 \mathrm{AEM}_{\mathrm{IND}_{jt-1}} + \alpha_3 \mathrm{OVER\_IND}_{jt-1} \times \mathrm{AEM\_IND}_{jt-1} + \alpha_4 \mathrm{REM\_IND}_{jt-1} + \alpha_5 \mathrm{OVER\_IND}_{jt-1} \times \mathrm{REM\_IND}_{jt-1} + \alpha_6 \mathrm{DTURN}_{jt-1} + \alpha_7 \mathrm{NCSKEW}_{jt-1} + \alpha_8 \mathrm{SIGMA}_{jt-1} + \alpha_9 \mathrm{WRET}_{jt-1} + \alpha_{10} \mathrm{LSIZE}_{jt-1} + \alpha_{11} \mathrm{MB}_{jt-1} + \alpha_{12} \mathrm{LEV}_{jt-1} + \alpha_{13} \mathrm{ROA}_{jt-1} + \alpha_{14} \mathrm{AQ}_{jt-1} + \sum_{t=1}^{T-1} \mathrm{YEAR}_t + \varepsilon_{jt} \qquad (8)$$

Table 8 reports the results of partitioning the effects of AEM and REM. I find that the coefficient for the interaction term between extreme overvaluation and high REM is significantly positive across all three columns but the coefficient for the interaction term between extreme overvaluation and high AEM is insignificant in all three models. This suggests that when managers engage in high REM to preserve extreme overvaluation the negative influence is higher than when managers engage in high AEM to sustain extreme overvaluation. This is consistent with prior literature that REM is more costly than AEM because REM is not economically optimal and has more serious impacts on firms' future performance.

Table 8 Overvaluation and Stock Price Crash Risk: The Impact of AEM and REM

Variables	CRASH (1)	NCSKEW (2)	DUVOL (3)
$OVER\_IND_{jt-1}$	-0.029	-0.002	-0.002
	(-0.458)	(-0.116)	(-0.186)
AEM_IND_{jt-1}	0.019	-0.005	-0.002
	(0.290)	(-0.265)	(-0.210)
$OVER\_IND_{jt-1} \times AEM\_IND_{jt-1}$	-0.102	0.018	-0.001
	(-0.817)	(0.474)	(-0.073)
REM_IND_{jt-1}	-0.026	-0.004	-0.004
	(-0.333)	(-0.149)	(-0.335)
$OVER\_IND_{jt-1} \times REM\_IND_{jt-1}$	**0.229***	**0.102*****	**0.046*****
	(1.952)	**(2.742)**	**(2.768)**
$DTURN_{jt-1}$	0.205	0.110***	0.049***
	(1.579)	(2.714)	(2.732)
$NCSKEW_{jt-1}$	-0.219***	-0.130***	-0.057***
	(-8.449)	(-15.826)	(-15.584)
$SIGMA_{jt-1}$	1.858	2.274*	1.323**
	(0.453)	(1.900)	(2.490)
$WRET_{jt-1}$	0.987*	0.391***	0.220***
	(1.922)	(2.665)	(3.376)
$LSIZE_{jt-1}$	0.372***	0.157***	0.068***
	(8.679)	(12.870)	(12.532)
MB_{jt-1}	-0.007	-0.004	-0.002
	(-0.486)	(-1.054)	(-0.941)
LEV_{jt-1}	0.061	-0.022	-0.021
	(0.284)	(-0.340)	(-0.740)

Table 8—*Continued*

ROA_{jt-1}	1.082***	0.474***	0.236***
	(4.748)	(7.024)	(7.869)
AQ_{jt-1}	0.009	0.123	0.062
	(0.018)	(0.859)	(0.978)
Intercept		-1.055***	-0.497***
		(-12.288)	(-13.045)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
No. of observations	21,050	21,050	21,050
Pseudo-R2 (R Square)	0.033	0.045	0.050

Variables are defined in Appendix A. The z-statistics (t-statistics) reported in parentheses are computed using standard errors corrected for serial correlation and heteroskedasticity. One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

Chapter 6

Additional Analysis

6.1 Duplication of Hutton, Marcus, and Tehranian (2009)

Hutton, Marcus, and Tehranian (2009) find that opaque firms (proxied by AEM) are more prone to stock price crashes.[16] The question is whether AEM per se is sufficient to cause firms' crash risk. To address this question, I duplicate Table 7 of Hutton, Marcus, and Tehranian (2009) using my sample. Table 9 reports the duplication results. It shows that when logistic regression is employed (column (1)), AEM is significantly and positively associated with future crash indicator (CRASH) at a decreasing rate (coefficient of $\mathrm{OPAQUE}_{\mathrm{jt-1}}$>0, coefficient of $\mathrm{OPAQUE}_{\mathrm{jt-1}}^{2}$<0).

However, a firm fixed-effects model instead of logistic model will be the more appropriate model to use when the sample consists of panel data. Wooldridge (2002) points out that for panel data, it is important to control the firm fixed-effects, which vary from firm to firm but are invariant from time to time. A firm fixed-effects model eliminates the unobserved time-invariant firm characteristics by a within-transformation that demeans each variable for each firm (Wooldridge 2002). Failure to control for firm fixed-effects might bias the

[16] Opaque in Hutton, Marcus, and Tehranian's (2009) paper is calculated the same way as I calculate AEM_SUM.

independent variable coefficients upward because the effects of omitted variable will be picked up by the included variables. When I include firm fixed-effects in the logistic model (column (3)), the effect of AEM has been attenuated and losses its significance. The results provide support for my speculation that AEM is not a sufficient condition causing firms' crash risk.[17]

Table 9 Using Opacity to Predict Crash Risk

Variables	OLS		Firm Fixed-effects
	(1)	(2)	(3)
OPAQUE_{t-1}	**0.901*** **	**0.979*** **	**0.286**
	(3.478)	**(3.754)**	**(0.809)**
OPAQUE^2_{t-1}	-0.747***	-0.796***	-0.459
	(-2.799)	(-2.965)	(-1.331)
ROA_{t-1}	0.498***	0.698***	1.257***
	(3.438)	(4.684)	(5.655)
LSIZE_{t-1}	0.031***	0.007	0.335***
	(2.612)	(0.595)	(8.114)
MB_{t-1}	0.028***	0.032***	-0.009
	(3.608)	(4.083)	(-0.685)
LEV_{t-1}	-0.403***	-0.292***	-0.003
	(-3.772)	(-2.714)	(-0.016)
Intercept	-1.841***	-2.252***	
	(-20.148)	(-17.523)	
Year fixed effects	No	Yes	Yes
Firm fixed effects	No	No	Yes
No. of observations	21,050	21,043	21,021
Pseudo-R2 (R Square)	0.004	0.013	0.024

Variables are defined in Appendix A.
Z-statistics (t-statistics) are reported in parentheses.
One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

[17] The untabulated results of using NCSKEW and DUVOL as crash proxies are qualitatively similar to the results of using CRASH.

6.2 Alternative Measure of EM

In the main hypothesis testing, I assume that managers simultaneously are engaging in AEM and REM without an overall plan. Hence the EM activity is captured by EM=$\sum_{t-3}^{t-1}|\mathrm{AEM}|$+$\sum_{t-3}^{t-1}|\mathrm{REM}|$. Another possibility is that managers plan out the extent of EM needed and "allocate" between AEM and REM. In this case, EM is better captured by EM=$\sum_{t-3}^{t-1}|\mathrm{AEM}+\mathrm{REM}|$. I create a new dummy variable EM_IND that equal to 1 if the alternative measure of EM is in the top quintile. Using the new EM measure, I retest my hypothesis and Table 10 presents the results.

Table 10 Overvaluation and Stock Price Crash Risk: Alternative Measure of EM

Variables	CRASH (1)	NCSKEW (2)	DUVOL (3)
$\mathrm{OVER\_IND}_{jt-1}$	0.009	0.005	-0.000
	(1.133)	(0.283)	(-0.011)
$\mathrm{EM\_IND}_{jt-1}$	0.008	-0.014	-0.002
	(1.023)	(-0.539)	(-0.146)
$\mathrm{OVER\_IND}_{jt-1} \times \mathrm{EM\_IND}_{jt-1}$	**0.026***	**0.086****	**0.038****
	(1.605)	**(2.032)**	**(2.166)**
DTURN_{jt-1}	0.011	0.110***	0.049***
	(0.587)	(2.646)	(2.779)
NCSKEW_{jt-1}	0.007*	-0.130***	-0.057***
	(1.814)	(-15.322)	(-15.463)
SIGMA_{jt-1}	3.165***	2.299*	1.323**
	(7.200)	(1.875)	(2.488)
WRET_{jt-1}	0.405***	0.394**	0.220***
	(7.031)	(2.576)	(3.336)
LSIZE_{jt-1}	0.006***	0.156***	0.068***
	(2.826)	(11.912)	(11.913)
MB_{jt-1}	0.004***	-0.004	-0.002
	(2.963)	(-0.903)	(-0.914)

Table 10—*Continued*

LEV_{jt-1}	-0.031*	-0.025	-0.021
	(-1.939)	(-0.356)	(-0.693)
ROA_{jt-1}	0.101***	0.479***	0.237***
	(4.335)	(6.213)	(7.506)
AQ_{jt-1}	-0.070	0.120	0.065
	(-1.524)	(0.827)	(1.057)
Intercept		-1.054***	-0.498***
		(-11.746)	(-12.783)
Year fixed effects	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes
No. of observations	21,050	21,050	21,050
Pseudo-R2 (R Square)	0.016	0.045	0.050

Variables are defined in Appendix A. The z-statistics (t-statistics) reported in parentheses are computed using standard errors corrected for serial correlation and heteroskedasticity. One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

I find from Table 10 that coefficient for the interaction term between extreme overvaluation and the alternative high EM measure remains statistically significant but the coefficients for extreme overvaluation or high EM alone are still insignificant. The results for control variables are similar to the results in Table 7. Table 10 provides further evidence that when managers allocate between AEM and REM according to their overall EM plan to sustain equity overvaluation, the crash risk will be increased.

6.3 Duration of Extreme Overvaluation and the Choice of AEM versus REM

Badertscher (2011) examines how the duration of overvaluation affects management's use of alternative EM mechanisms. He finds that overvalued firms initially engage in AEM but at some point run out of AEM choices and switch to REM. If the duration of overvaluation forces managers to switch from AEM to REM, as suggested by Badertscher (2011), then one would predict that managers will likely engage in AEM at the early stages of extreme overvaluation but resort to REM for sustained extreme overvaluation. In order to test the relation between managers' EM choices and crash risk at different stages of overvaluation, I examine the relation between AEM or REM and crash risk for firms having been in the top quintile of P/V for consecutive years. OVER (i) is a subsample including firms that have been extremely overvalued for i consecutive years ($i \leq 5$).

Following Badertscher (2011), I use one year discretionary accruals to measure AEM activities and one year aggregate REM_PROXY to measure REM activities. In Table 11, I find that for firms that have been extreme overvalued for one to two consecutive years (column (1), (2), (4), (5), (7), and (8)), the coefficients on discretionary accruals are positive and significant to predict crash risk. Consistent with Badertscher (2011), the coefficients on REM_PROXY are statistically significant in predicting crash risk for firms that have been extreme overvalued for three consecutive years (column (3), (6), and (9)), suggesting firms resort to REM in their later stages of extreme overvaluation.

Table 11 Duration of Extreme Overvaluation and the Choice of AEM versus REM

Variables	CRASH			NCSKEW			DUVOL		
	OVER(1) (1)	OVER(2) (2)	OVER(3) (3)	OVER(1) (4)	OVER(2) (5)	OVER(3) (6)	OVER(1) (7)	OVER(2) (8)	OVER(3) (9)
DA_{jt-1}	**2.324****	**3.113***	0.924	**1.056*****	**1.410*****	1.300	**0.390****	**0.586*****	0.580
	(2.058)	**(1.808)**	(0.329)	**(2.959)**	**(2.775)**	(1.450)	**(2.495)**	**(2.670)**	(1.500)
REM_PROXY_{jt-1}	0.033	0.342	**1.091****	0.093	0.157	**0.348****	0.034	0.071	**0.144****
	(0.131)	(1.162)	**(2.039)**	(1.143)	(1.556)	**(2.090)**	(0.960)	(1.631)	**(2.004)**
$DTURN_{jt-1}$	0.449	1.465*	2.016	0.066	0.375	0.432	0.009	0.111	0.115
	(1.245)	(1.719)	(1.459)	(0.543)	(1.481)	(0.990)	(0.165)	(1.021)	(0.611)
$NCSKEW_{jt-1}$	-0.262***	-0.498***	-0.525***	-0.140***	-0.241***	-0.260***	-0.060***	-0.098***	-0.109***
	(-3.917)	(-4.262)	(-2.955)	(-6.238)	(-6.253)	(-4.489)	(-6.148)	(-5.909)	(-4.389)
$SIGMA_{jt-1}$	9.046	8.308	62.424	6.865**	18.418***	24.679**	3.733***	6.792**	9.905*
	(0.957)	(0.461)	(1.452)	(2.199)	(2.995)	(2.050)	(2.728)	(2.559)	(1.909)
$WRET_{jt-1}$	1.188	0.620	10.896	0.717	2.937***	3.372	0.427**	1.031**	1.333
	(0.897)	(0.218)	(1.236)	(1.573)	(2.881)	(1.410)	(2.135)	(2.344)	(1.294)
$LSIZE_{jt-1}$	0.460***	0.499**	0.888**	0.099***	0.117**	0.081	0.045***	0.058**	0.033
	(4.897)	(2.338)	(2.184)	(3.653)	(1.980)	(0.762)	(3.783)	(2.285)	(0.721)
MB_{jt-1}	-0.028	-0.004	0.054	-0.004	0.006	0.001	-0.003	-0.001	-0.008
	(-0.920)	(-0.073)	(0.591)	(-0.421)	(0.331)	(0.023)	(-0.701)	(-0.093)	(-0.655)
LEV_{jt-1}	0.464	1.166	-3.149	0.134	0.491	-0.739	0.054	0.204	-0.286
	(0.848)	(1.100)	(-1.513)	(0.729)	(1.333)	(-1.199)	(0.667)	(1.285)	(-1.076)
ROA_{jt-1}	-1.002	-0.027	-6.412	-0.147	-0.173	-1.488	0.055	0.134	-0.186
	(-1.462)	(-0.015)	(-1.262)	(-0.635)	(-0.304)	(-1.243)	(0.543)	(0.547)	(-0.360)
AQ_{jt-1}	-2.147*	-3.808	-0.758	-0.033	0.575	1.928**	0.042	0.225	0.745*
	(-1.836)	(-1.533)	(-0.213)	(-0.083)	(0.836)	(2.008)	(0.245)	(0.759)	(1.801)
Intercept				-0.911***	-1.395***	-1.018	-0.446***	-0.660***	-0.436
				(-4.086)	(-2.956)	(-1.186)	(-4.567)	(-3.238)	(-1.178)

Table 11—*Continued*

Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	4,205	1,581	753	4,205	1,581	753	4,205	1,581	753
Pseudo-R2 (R Square)	0.011	0.013	0.023	0.016	0.019	0.021	0.017	0.017	0.018

Column OVER(i) contains subsample firm-years that have been overvalued for i consecutive years. Variables are defined in Appendix A. The z-statistics (t-statistics) reported in parentheses are computed using standard errors corrected for serial correlation and heteroskedasticity. One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

Overall, Table 11 supports Badertscher's (2011) finding that the duration of overvaluation affects managers' EM choices and suggests that the combination of the duration of extreme overvaluation and high EM choices are positively associated with stock price crash risk.

6.4 Sarbanes-Oxley Act and Crash risk

Congress passed SOX in 2002 in response to a number of highly publicized accounting scandals in 2001. As a result of SOX, CEOs and CFOs must individually certify the accuracy of financial statements. SOX improved the composition and function of audit committee and the board of directors. SOX also increased the independence of the outside auditors who report directly to the auditor committee. Outside auditors are restricted on limited nonaudit-related work and are subject to mandatory audit partner rotation. In addition, company's auditors are required to issue an annual report on the effectiveness of internal controls (SOX section 404). By imposing harsher penalties for fraudulent financial activity, requiring more oversight, and dealing with potential conflicts of interests, SOX aims to restore the integrity of financial statements. Therefore, the penalties for managers using high EM to preserve extreme overvaluation are presumably higher in the post-SOX period than in the pre-SOX period.

I test this hypothesis by partitioning the sample to pre- SOX (1995-2001) and post- SOX (2003–2011) and repeating Table 7. The year 2002 is excluded to avoid confounding issues. Table 12 presents the results for the subsample tests in the pre-SOX and post-SOX periods. For all three measures of crash risk, I find the coefficients are positive and significant for the interaction term between the top quintile of overvaluation and top quintile of EM only in the period following SOX (column (2), (4), and (6)). Giving SOX increases the oversight for financial statements, the results is not surprising.

Table 12 Overvaluation and Stock Price Crash Risk: The Impact of SOX

Variables	CRASH		NCSKEW		DUVOL	
	Pre-SOX (1)	POST-SOX (2)	Pre-SOX (3)	POST-SOX (4)	Pre-SOX (5)	POST-SOX (6)
$OVER\_IND_{jt-1}$	0.003	-0.017	0.044	-0.042	0.024*	-0.021*
	(0.232)	(-1.296)	(1.620)	(-1.425)	(1.915)	(-1.656)
EM_IND_{jt-1}	0.013	-0.021	0.016	-0.058	0.008	-0.027
	(0.575)	(-1.072)	(0.345)	(-1.386)	(0.386)	(-1.483)
$OVER\_IND_{jt-1} \times EM\_IND_{jt-1}$	**0.030**	**0.066****	**0.031**	**0.161****	**0.015**	**0.068****
	(0.986)	**(2.396)**	**(0.530)**	**(2.544)**	**(0.561)**	**(2.556)**
$DTURN_{jt-1}$	0.022	0.002	-0.025	0.074	-0.010	0.036
	(0.634)	(0.086)	(-0.371)	(1.285)	(-0.348)	(1.459)
$NCSKEW_{jt-1}$	-0.064***	-0.048***	-0.210***	-0.173***	-0.093***	-0.076***
	(-9.025)	(-8.397)	(-16.244)	(-14.771)	(-15.960)	(-15.018)
$SIGMA_{jt-1}$	-0.468	-0.653	0.281	0.274	0.048	0.985
	(-0.459)	(-0.727)	(0.139)	(0.140)	(0.053)	(1.172)
$WRET_{jt-1}$	0.122	-0.009	0.096	0.111	0.033	0.167
	(1.033)	(-0.082)	(0.391)	(0.422)	(0.303)	(1.514)
$LSIZE_{jt-1}$	0.081***	0.083***	0.223***	0.261***	0.099***	0.116***
	(6.938)	(7.744)	(8.880)	(10.256)	(8.942)	(10.771)
MB_{jt-1}	0.000	-0.003	-0.010	-0.007	-0.004	-0.004
	(0.130)	(-0.851)	(-1.445)	(-0.750)	(-1.336)	(-1.229)
LEV_{jt-1}	-0.064	0.093*	-0.093	0.125	-0.056	0.052
	(-1.185)	(1.714)	(-0.827)	(0.972)	(-1.102)	(0.941)
ROA_{jt-1}	0.145**	0.202***	0.625***	0.390***	0.290***	0.205***
	(2.488)	(3.867)	(4.898)	(3.027)	(5.057)	(3.936)
AQ_{jt-1}	0.186	-0.080	0.487	0.141	0.213	0.082
	(1.088)	(-0.816)	(1.505)	(0.646)	(1.454)	(0.900)
Intercept			-1.373***	-1.652***	-0.637***	-0.776***
			(-8.858)	(-9.182)	(-9.279)	(-10.125)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	8,795	11,095	8,795	11,095	8,795	11,095
Pseudo-R2 (R Square)	0.044	0.044	0.071	0.055	0.070	0.061

The pre-SOX period is from 1995-2001 and the post-SOX period is from 2003-2011. Variables are defined in Appendix A. The z-statistics (t-statistics) reported in parentheses are computed using standard errors corrected for serial correlation and heteroskedasticity. One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

6.5 The Impact of Firm Size

If investors have limited attention and therefore are not able to tease out whether managers use high EM to sustain extreme equity overvaluation, the positive relation between extreme overvaluation with high EM and crash risk should be attenuated in firms with higher information transparency. I follow the past literature by using firm size to gauge the investors' attention.

Table 13 splits the sample into two subsamples based on the median number of total assets and estimates the regression model separately for each sub-sample. Table 13 shows that the coefficients on OVER_IND×EM_IND are positive for both below median and above median firm size, but significant only for below median firm size in all three crash risk specifications (column (1), (3), and (5)). The findings in Table 13 show that the impact of extreme overvaluation with high EM on stock price crash risk is more pronounced for firms with small size.

Table 13 Overvaluation and Stock Price Crash Risk: The Impact of Firm Size

Variables	CRASH		NCSKEW		DUVOL	
	Size		Size		Size	
	Small (1)	Big (2)	Small (3)	Big (4)	Small (5)	Big (6)
$OVER\_IND_{jt-1}$	-0.042	-0.029	0.035	-0.003	0.014	-0.004
	(-0.437)	(-0.350)	(1.121)	(-0.126)	(1.035)	(-0.322)
EM_IND_{jt-1}	-0.105	0.026	-0.051	0.078*	-0.024	0.026
	(-1.033)	(0.192)	(-1.427)	(1.649)	(-1.568)	(1.273)
$OVER\_IND_{jt-1} \times EM\_IND_{jt-1}$	**0.385****	**0.136**	**0.142****	**0.044**	**0.053****	**0.028**
	(2.376)	**(0.743)**	**(2.297)**	**(0.750)**	**(2.017)**	**(1.071)**
$DTURN_{jt-1}$	0.295*	0.065	0.184***	0.005	0.071***	0.016
	(1.721)	(0.298)	(3.483)	(0.078)	(3.156)	(0.555)

Table 13—*Continued*

$NCSKEW_{jt-1}$	-0.210***	-0.189***	-0.148***	-0.107***	-0.064***	-0.048***
	(-5.905)	(-4.956)	(-12.290)	(-8.808)	(-12.182)	(-9.012)
$SIGMA_{jt-1}$	-9.559	4.908	-2.753	2.773	-0.545	1.313
	(-1.603)	(0.728)	(-1.555)	(1.485)	(-0.699)	(1.583)
$WRET_{jt-1}$	-0.605	2.516**	-0.270	0.719***	-0.035	0.340***
	(-0.854)	(2.511)	(-1.288)	(2.692)	(-0.388)	(2.873)
MB_{jt-1}	0.074***	0.021	0.031***	0.003	0.013***	0.002
	(4.452)	(1.142)	(5.354)	(0.534)	(5.370)	(0.882)
LEV_{jt-1}	-0.156	-0.101	-0.308***	-0.051	-0.156***	-0.027
	(-0.517)	(-0.310)	(-2.941)	(-0.471)	(-3.554)	(-0.570)
ROA_{jt-1}	1.679***	1.815***	0.721***	0.645***	0.334***	0.325***
	(6.250)	(3.816)	(7.891)	(4.300)	(8.781)	(5.337)
AQ_{jt-1}	0.216	-0.166	0.196	0.179	0.074	0.152
	(0.377)	(-0.194)	(1.019)	(0.730)	(0.928)	(1.433)
Intercept			-0.122	-0.149**	-0.119***	-0.085***
			(-1.525)	(-2.375)	(-3.371)	(-2.929)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	10,520	10,530	10,520	10,530	10,520	10,530
Pseudo-R2 (R Square)	0.045	0.026	0.060	0.031	0.066	0.035

Small firms are firms that below median of total assets and big firms are firms that above median of total assets. Variables are defined in Appendix A. The z-statistics (t-statistics) reported in parentheses are computed using standard errors corrected for serial correlation and heteroskedasticity. One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

6.6 The Impact of Analyst Coverage

If the positive relation between extreme overvaluation with high EM and future crash risk is due to EM facilitating opportunistic managerial behaviors, such as bad news hoarding, one can expect the strength of the relation to be attenuated for firms with effective external monitoring. Financial analysts play an important role as information intermediators between insider managers and outsider investors. Ball (2001) argues that analysts monitor managerial disclosure behavior. Lang, Lins, and Miller (2003) provide evidence that analysts' information monitoring reduces information asymmetry between insiders and outsiders. Yu (2008) finds that firms with high analyst coverage engage less in opportunistic EM. The above findings suggest that information asymmetry is higher for firms with low analyst coverage. Therefore, I expect managers are more capable of withholding bad news when analyst coverage is low and the impact of using high EM to maintain extreme overvaluation on stock price crash risk is more pronounced for firms with low analyst coverage.

Table 14 splits the sample into two subsamples based on the median number of analysts. I find that the coefficients on the interaction term between extreme overvaluation and high EM are positive for both subsamples, but significant only for firms with a below median (low) analyst coverage (column (1), (3), and (5)). The findings in Table 14 are consistent with the expectations that external scrutiny curbs managerial opportunistic behaviors and decreases stock price crash risk.

Table 14 Overvaluation and Stock Price Crash Risk: The Impact of Analyst Coverage

Variables	CRASH		NCSKEW		DUVOL	
	Analyst Coverage		Analyst Coverage		Analyst Coverage	
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
$OVER\_IND_{jt-1}$	-0.131	-0.020	-0.003	0.007	-0.001	0.003
	(-1.341)	(-0.232)	(-0.112)	(0.273)	(-0.114)	(0.233)
EM_IND_{jt-1}	-0.172	0.101	-0.041	0.042	-0.013	0.007
	(-1.460)	(0.829)	(-1.021)	(0.963)	(-0.786)	(0.398)
$OVER\_IND_{jt-1} \times EM\_IND_{jt-1}$	**0.339***	**0.166**	**0.140****	**0.044**	**0.050***	**0.021**
	(1.836)	**(1.009)**	**(2.277)**	**(0.711)**	**(1.905)**	**(0.833)**
$DTURN_{jt-1}$	0.289	0.133	0.107*	0.098	0.061**	0.033
	(1.385)	(0.735)	(1.899)	(1.628)	(2.448)	(1.323)

Table 14—*Continued*

$NCSKEW_{jt-1}$	-0.290***	-0.244***	-0.161***	-0.154***	-0.071***	-0.066***
	(-7.613)	(-6.354)	(-12.986)	(-11.785)	(-13.005)	(-12.023)
$SIGMA_{jt-1}$	2.840	0.418	1.955	1.642	1.223	0.939
	(0.458)	(0.068)	(1.156)	(0.811)	(1.621)	(1.100)
$WRET_{jt-1}$	0.991	0.993	0.272	0.392	0.167*	0.216*
	(1.286)	(1.274)	(1.353)	(1.434)	(1.837)	(1.948)
$LSIZE_{jt-1}$	0.362***	0.456***	0.158***	0.181***	0.069***	0.080***
	(5.094)	(6.704)	(7.424)	(8.924)	(7.477)	(8.831)
MB_{jt-1}	0.027	-0.039**	0.009	-0.014**	0.004	-0.006**
	(1.164)	(-2.101)	(1.128)	(-2.370)	(1.042)	(-2.171)
LEV_{jt-1}	0.265	-0.079	-0.028	-0.043	-0.016	-0.023
	(0.774)	(-0.246)	(-0.270)	(-0.385)	(-0.358)	(-0.479)
ROA_{jt-1}	1.147***	1.347***	0.494***	0.528***	0.235***	0.255***
	(3.259)	(3.804)	(4.549)	(4.255)	(5.004)	(5.215)
AQ_{jt-1}	0.265	0.057	0.362	-0.020	0.152	0.013
	(0.377)	(0.080)	(1.586)	(-0.096)	(1.527)	(0.149)
Intercept			-1.032***	-1.229***	-0.507***	-0.571***
			(-8.496)	(-7.797)	(-9.518)	(-8.228)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	10,561	10,473	10,561	10,473	10,561	10,473
Pseudo-R2 (R Square)	0.050	0.034	0.062	0.050	0.068	0.052

Low analyst coverage firms are firms with below median of analyst coverage and high analyst coverage firms are firms with above median of analyst coverage. Variables are defined in Appendix A. The z-statistics (t-statistics) reported in parentheses are computed using standard errors corrected for serial correlation and heteroskedasticity. One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

6.7 Quantile Regression

It is possible that unobserved factors affect both crash risk and the combination of extreme overvaluation and high EM. In order to address the "hidden bias" arising from unobserved variables that simultaneously affect assignment to treatment and the outcome variable, I use the quantile regression procedure (Koenker and Basset, 1978; Yasar, Nelson, and Rejesus, 2006). This methodology involves the estimation of conditional quantiles, rather than estimation of coefficients at a single measure of central tendency. I evaluate the relative effects of overvaluation, EM and other variables at different points of the conditional output distribution. Table 15 shows the results of quantile regression.[18] The regression estimates for crash risk quantiles 0.1, 0.25. 0.5, 0.75 and 0.9 show positive and significant estimates for the interaction term for firms in the top quintile of overvaluation and EM in all estimates except 0.25 (0.1) quantile in NCSKEW (DUVOL). The results are similar to the firm fixed-effects regression in Table 7 supporting the evidence of higher conditional future crash risk only for the extremely overvalued firms engaging in high EM across the entire distribution of the dependent variables especially on the upper right tail.

[18] The regression is estimated only for NCSKEW and DUVOL since quantile regression is based on conditional distribution of the output variable. Hence the methodology does not apply CRASH, an indicator output variable.

Table 15 Overvaluation and Stock Price Crash Risk: Quantile Regression

Variables	NCSKEW					DUVOL				
	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
$OVER\_IND_{jt-1}$	-0.017	-0.012	-0.017	0.015	-0.010	-0.005	-0.010	-0.010	-0.000	-0.003
	(-0.679)	(-0.783)	(-1.035)	(0.776)	(-0.294)	(-0.392)	(-1.129)	(-1.215)	(-0.041)	(-0.256)
EM_IND_{jt-1}	-0.045*	-0.000	-0.003	-0.011	-0.033	-0.000	-0.005	-0.000	0.001	-0.020
	(-1.701)	(-0.011)	(-0.149)	(-0.528)	(-0.889)	(-0.015)	(-0.519)	(-0.002)	(0.134)	(-1.378)
$OVER\_IND_{jt-1} \times EM\_IND_{jt-1}$	**0.110****	**0.041**	**0.068****	**0.117*****	**0.192*****	**0.035**	**0.034***	**0.040****	**0.045****	**0.084*****
	(2.069)	**(1.310)**	**(2.023)**	**(2.874)**	**(2.764)**	**(1.375)**	**(1.947)**	**(2.287)**	**(2.164)**	**(3.050)**
$DTURN_{jt-1}$	0.059	0.104***	0.090**	0.036	0.190**	0.029	0.053**	0.055***	0.037	0.053
	(0.900)	(2.704)	(2.188)	(0.724)	(2.189)	(0.950)	(2.486)	(2.618)	(1.476)	(1.607)
$NCSKEW_{jt-1}$	-0.005	-0.007	-0.003	0.014	0.006	-0.001	-0.005	-0.003	0.004	-0.001
	(-0.412)	(-0.966)	(-0.434)	(1.423)	(0.368)	(-0.246)	(-1.166)	(-0.791)	(0.810)	(-0.101)
$SIGMA_{jt-1}$	5.254***	3.453***	3.786***	6.196***	12.761***	1.875***	2.153***	2.094***	3.002***	3.526***
	(3.660)	(4.020)	(4.041)	(5.410)	(6.343)	(2.808)	(4.504)	(4.356)	(5.193)	(4.469)
$WRET_{jt-1}$	0.600***	0.427***	0.510***	0.787***	1.660***	0.213**	0.277***	0.297***	0.379***	0.483***
	(3.183)	(3.805)	(4.151)	(5.203)	(6.340)	(2.440)	(4.439)	(4.712)	(4.969)	(4.651)
$LSIZE_{jt-1}$	0.072***	0.053***	0.041***	0.030***	0.038***	0.027***	0.025***	0.023***	0.019***	0.018***
	(10.013)	(12.029)	(8.708)	(5.413)	(4.043)	(8.069)	(10.160)	(9.659)	(6.973)	(5.040)
MB_{jt-1}	-0.007*	-0.004	-0.002	0.010***	0.008	-0.003	-0.001	-0.000	0.003	0.004*
	(-1.663)	(-1.591)	(-0.664)	(2.876)	(1.325)	(-1.544)	(-0.845)	(-0.255)	(1.595)	(1.709)
LEV_{jt-1}	-0.048	-0.063**	-0.089***	-0.076*	0.064	-0.009	-0.034*	-0.064***	-0.053**	0.008
	(-0.867)	(-1.963)	(-2.580)	(-1.835)	(0.839)	(-0.343)	(-1.868)	(-3.638)	(-2.517)	(0.268)
ROA_{jt-1}	0.463***	0.382***	0.272***	0.423***	0.658***	0.228***	0.185***	0.162***	0.211***	0.237***
	(6.159)	(8.428)	(5.470)	(6.967)	(6.087)	(6.391)	(7.345)	(6.342)	(6.833)	(5.569)

Table 15—*Continued*

AQ_{jt-1}	-0.143	-0.031	0.014	-0.063	-0.156	-0.020	0.033	0.007	0.032	-0.045
	(-0.934)	(-0.341)	(0.143)	(-0.535)	(-0.768)	(-0.272)	(0.662)	(0.147)	(0.531)	(-0.568)
Intercept	-1.366***	-0.892***	-0.474***	-0.177***	-0.101	-0.681***	-0.491***	-0.275***	-0.098***	0.050
	(-16.291)	(-17.655)	(-8.738)	(-2.703)	(-0.326)	(-17.290)	(-17.479)	(-9.857)	(-2.962)	(0.409)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of observations	21,050	21,050	21,050	21,050	21,050	21,050	21,050	21,050	21,050	21,050
Pseudo-R2	0.028	0.022	0.015	0.016	0.023	0.026	0.025	0.019	0.018	0.028

Variables are defined in Appendix A. The t-statistics reported in parentheses are robust to autocorrelation and heteroscedasticity. One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

6.8 Future Stock Price Jumps

My previous analyses indicate that extreme overvaluation with high EM predicts crashes. These results immediately raise another question: does extreme overvaluation with high EM predict fat tails generally or only one-sided exposure to crashes? I predict that there should be a negative association between extreme overvaluation with high EM and stock price jumps, because it is unlikely that managers use high EM to hide good news when the firm has been extremely overvalued.

Following Hutton, Marcus, and Tehranian (2009), I define JUMP as an indicator equal to 1 if a firm experiences at least one jump week in a fiscal year. The jump week are those weeks that firm-specific abnormal weekly returns are 3.2 standard deviations above the average firm-specific weekly abnormal returns for the entire fiscal year. I repeat the firm fixed-effects logistic regression analysis for jump probabilities. Table 16 supports my prediction that extreme overvaluation with high EM is statistically and negatively associated with the occurrence of stock price jumps. Using the coefficients estimation, I compute the marginal effect of OVER_IND × EM_IND, that is, the change in JUMP (the probability of a jump) arising from extreme overvaluation and high EM, holding all other independent variables at their mean values. The marginal effect of OVER_IND × EM_IND is about -0.037, suggesting that changing to high overvaluation and high EM results in a 3.7 percent point decrease in the probability of a jump. This is economically significant, given that the average unconditional probability of a jump in my sample is 16.69 percent points.

Table 16 Overvaluation and Stock Price Jump: The Impact of EM

Variables	JUMP
$\mathrm{OVER\_IND}_{jt-1}$	-0.029
	(-0.448)
$\mathrm{EM\_IND}_{jt-1}$	0.066
	(0.790)
$\mathrm{OVER\_IND}_{jt-1} \times \mathrm{EM\_IND}_{jt-1}$	**-0.273****
	(-2.063)
DTURN_{jt-1}	-0.219
	(-1.552)
NCSKEW_{jt-1}	0.226***
	(8.363)
SIGMA_{jt-1}	-8.582**
	(-2.100)
WRET_{jt-1}	-0.664
	(-1.341)
LSIZE_{jt-1}	-0.215***
	(-5.058)
MB_{jt-1}	-0.009
	(-0.611)
LEV_{jt-1}	0.529**
	(2.387)
ROA_{jt-1}	-1.113***
	(-4.900)
AQ_{jt-1}	-0.312
	(-0.673)
Year fixed effects	Yes
Firm fixed effects	Yes
No. of observations	21,050
Pseudo-R2	0.027

Variables are defined in Appendix A. The z-statistics (t-statistics) reported in parentheses are computed using standard errors corrected for serial correlation and heteroskedasticity. One to three stars are used to indicate significant level at 10%, 5%, and 1% respectively.

Chapter 7

Summary and Conclusions

This thesis discusses potential theoretical explanations for why firms experience stock price crashes and explores the relation between firms' extreme equity overvaluation with high EM and stock price crashes. EM has been identified as the primary means employed by managers to conceal bad news. Earlier studies have shown separately that overvalued firms and firms characterized by high EM are associated with a greater risk of future stock price crash risk. In this thesis, I investigate the joint effect of extreme overvaluation and high EM on future stock price crash risk.

In the thesis I find that there is a robust positive relationship between extreme overvaluation accompanied by high EM and one-year ahead stock price crashes for a sample of U.S. public firms during the years 1995-2011. In contrast, I find that neither high EM nor extreme overvaluation alone is associated with future crash risk. The results are robust to alternative proxies of crash risk and EM, and hold after controlling for endogeneity. The findings are more pronounced in the post-SOX period and for firms that engage in REM, are small size, or have low analyst coverage. In addition, I show that the duration of overvaluation affects managers' EM choices. Finally, I show that extreme overvaluation with high EM is negatively associated with stock price jumps.

My results are, overall, consistent with EM promotes managerial opportunistic behavior (Hutton, Marcus, and Tehranian, 2009; Francis, Hasan, and Li, 2011). EM creates tools for managers to manufacture earnings and conceal negative operating outcomes. Accordingly, bad performance and negative information are likely to stockpile within the firm, until an asset price crash occurs when a threshold is crossed. However, my thesis complements previous research by showing that although EM activities could be utilized by managers to conceal managers' opportunistic behavior. These activities will not increase firms' future crash risk if they are not accompanied by extreme overvaluation. I interpret these results as suggesting that the incentives to conceal bad news through EM do not necessarily arise in all cases of overvaluation and that both extreme overvaluation and high EM should co-exist for the crash risk to increase. In this way, my results fine tune Jensen's conjecture regarding overvalued firms.

In the context of the crash risk literature, my thesis provides further support to Jin and Myers (2006) and Bleck and Liu's (2007) bad news hoarding theory and identifies an additional determinant of stock price crash risk. Given the recent stock market collapse, investors, researchers, and regulators have paid increasing attention to the causes and consequences of extreme negative return outcomes or crashes. My thesis can be seen as a test of the consequences of high

EM and the agency cost of extremely overvalued equity argument of Jensen (2004, 2005).

The findings of the thesis have implications for various market participants and provide avenues for future academic research. My thesis may help managers and the board of directors become cautious about overvaluation and EM because extreme overvaluation accompanied by high EM likely lead to stock price crashes. For regulators, increasing scrutiny and further constraining EM would potentially decrease the stock market's unstable factors. Researchers interested in determining why firms are likely to experience stock price crashes should consider the impact that high EM and extreme overvaluation play in management's opportunistic behaviors. Finally, future research could examine the different reasons that might cause firms to become extremely overvalued, and the relation between different types of overvaluation and stock price crashes.

Appendix A

Variable Definitions

$\mathrm{AEM\_IND}_{jt-1}$= an indicator equal to 1 if the moving sum of the absolute value of discretionary accruals over the last three years (AEM_SUM) is in the top quintile and 0 otherwise.

$\mathrm{AEM\_SUM}_{jt-1}$= the moving sum of the absolute value of discretionary accruals over the last three years.

AQ_{jt-1}= the standard deviation of the firm-level residuals from the Dechow and Dichew (2002) model during the previous 5 years and multiplied by -1. See Appendix C for details.

CRASH_{jt} = an indicator variable that equals 1 if a firm experience one or more crash events in a year, and zero otherwise.

DA_{jt-1}= discretionary accruals calculated from Modified Jones model (1995) for firm j.

DTURN_{jt-1}= the average monthly share turnover for the last fiscal year minus the average monthly share turnover for the year before the last fiscal year. The total monthly trading volume ((CRSP VOL)) divided by the total monthly number of shares outstanding (CRSP SHROUT) is monthly share turnover.

DUVOL_{jt}= the down-to-up volatility measure of crash likelihood.

EM_{jt-1}= the EM proxy, equals to the sum of AEM_SUM and REM_SUM. In the alternative measure, it is equal to the absolute value of the sum of discretionary accruals and REM_PROXY in prior three years.

$\mathrm{EM\_IND}_{jt-1}$= an indicator equal to 1 if the firm's prior three-year moving sum of AEM measure and REM measure is in the top quintile, and 0 otherwise.

JUMP_{jt}= an indicator equal to 1 if a firm experience one or more jump events, and zero otherwise.

LEV_{jt-1}= leverage ratio, calculated as short-term debt (Compustat DLC) plus long-term debt (Compustat DLTT), scaled by total assets (Compustat AT).

LSIZE_{jt-1} = nature logarithm of market value (shares outstanding (CRSP SHROUT) times price (CRSP PRC) adjusted for stock splits) in June.

MB_{jt-1} = the market capitalization of shareholders' equity (Compustat PRCC_F*CSHO) divided by the book value of shareholders' equity (Compustat CEQ).

NCSKEW_{jt}= the negative conditional return skewness.

$\mathrm{OVER\_IND}_{jt-1}$= an indicator equal to 1 if firm j is in the top quintile of P/V ratio and thus deemed to be overvalued, and 0 otherwise.

$\mathrm{OVER(i)}_{jt-1}$= an indicator equal to 1 if the firm has been in the top quintile of P/V for consecutive years, and 0 otherwise. For every firm-year, only one OVER (i) indicator variable can be equal to 1.

$\mathrm{REM\_IND}_{jt-1}$= an indicator equal to 1 if the firm's prior three-year moving sum of REM measure (REM_SUM) is in the top quintile, and 0 otherwise.

$\mathrm{REM\_SUM}_{jt-1}$ = the moving sum for the absolute value of the estimated REM_PROXY over the prior three years.

ROA_{jt-1}= net income before extraordinary items (Compustat IB) divided by total assets (Compustat AT) at the beginning of the year.

$SIGMA_{jt-1}$= the standard deviation of firm-specific abnormal weekly returns ($W_{j,t}$ from model (1)).

$WRET_{jt-1}$= 100 times of the previous fiscal year's average firm-specific abnormal weekly returns ($W_{j,t}$from model (1)).

$YEAR_t$= 1 for year t, and 0 for other years. The subscript t equals 1, 2⋯or T-1, where T represents the number of unique years in the sample period.

Appendix B

Procedures to Derive Future Book Values and ROEs

Following Frankel and Lee (1998), I use the following three-step approach to calculate three future book values (B_t, B_{t+1}, and B_{t+2}) and three future ROEs ($FROE_t$, $FROE_{t+1}$, and $FROE_{t+2}$) to implement the EBO formula.[19]

Step 1: Estimating B_t and $FROE_t$. All sample firms cannot have missing values of one-year-ahead I/B/E/S consensus (mean) EPS forecast (FY1). Consensus (mean) forecast (I/B/E/S MEANEST) in year t divided by the average book value per share (Compustat BKVLPS) in year t-1 is $FROE_t$.[20] Using $FROE_t$ and the dividend payout ratio (k), I then derive the ending book value in year t.[21]

$$FROE_t = FY1/[(B_{t-1} + B_{t-2})/2]$$

$$B_t = B_{t-1}[1 + FROE_t(1 - k)]$$

$$K = \frac{D_t}{NI_t}$$

Where D_t and NI_t are the common stock dividends (Compustat DVC) and net income before extraordinary items available for common stock (Compustat IBCOM) for period t respectively. Following Frankel and Lee (1998), Lee, Myers, and Swaminathan (1999), Dong, Hirshleifer, Richardson, and Teoh (2006), if k<0 (due to negative NI), I divide dividends by (0.06×total assets) (Compustat AT) to derive an estimate of the payout ratio. In other words, I assume that earnings are on average 6 percent of total assets. I also delete all

[19] Consistent with Frankel and Lee (1998), I exclude firms with ROEs or FROEs are greater than 100%.

[20] To avoid an abnormally low book value to inflate forecasted ROEs, I use the annual average of book values.

[21]Consistent with Frankel and Lee (1998), I exclude firms with dividend payout ratios that are greater than 100%.

observations for which the computed k is higher than one (Dong, Hirshleifer, Richardson, and Teoh, 2006).

Step 2: Estimating B_{t+1} and $FROE_{t+1}$. All sample firms cannot have missing values of two-year-ahead I/B/E/S consensus (mean) EPS forecast (FY2). I estimate B_{t+1} and $FROE_{t+1}$ analogously as in step 1:

$$FROE_{t+1}=FY2/[(B_t+B_{t-1})/2]$$

$$B_{t+1} = B_t[1 + FROE_{t+1}(1 - k)]$$

Step 3: Estimating B_{t+2} and $FROE_{t+2}$. I compute B_{t+2} and $FROE_{t+2}$ as follows if a long-term growth estimate (I/B/E/S LTG) is available:

$$FROE_{t+2}=[FY2(1+Ltg)]/ [(B_{t+1}+B_t)/2]$$

$$B_{t+2}=B_{t+1}[1+FROE_{t+2}(1-k)]$$

If LTG is not available, then I use $FROE_{t+1}$ to proxy for $FROE_{t+2}$.

Appendix C

Procedures for Estimating AQ

Following Kim, Li, and Zhang (2011b), I employ Dechow and Dichev (2002) model to estimate accrual quality. I first estimate the following cross-sectional regressions for each Fama and French 48 industry with at least 20 observations in a given year from 1995-2011.

$$\frac{ACCR_{jt}}{TA_{jt}} = \alpha_0 + \alpha_1 \frac{CFO_{jt-1}}{TA_{jt}} + \alpha_2 \frac{CFO_{jt}}{TA_{jt}} + \alpha_3 \frac{CFO_{jt+1}}{TA_{jt}} + \varepsilon_{jt} \quad (C.1)$$

Where $ACCR_{jt}$=total accruals for firm j during year t. It is the income before extraordinary items (Compustat IBC) minus operating cash flow from operating activities adjusted for extraordinary items and discontinued operations (Compustat OANCF minus XIDOC).

TA_{jt}=average total assets from firm j in year t (Compustat AT).

CFO_{jt}=the operating cash flows from operations adjusted for extraordinary items and discontinued operations (Compustat OANCF minus XIDOC) for firm j in year t.

Then AQ is computed as the standard deviation of the firm-level residuals from the Dechow and Dichev (2002) model during the previous 5 years and multiplied by -1.

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