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THE DARK SIDE OF EARNINGS RESPONSE COEFFICIENT: THE ROLE OF ERC IN FUTURE STOCK CRASH RISK PREDICTION

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The Dark Side of Earnings Response Coefficient: the Role of ERC in Future Stock Crash Risk Prediction

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Abstract

This study tries to explain individual crash risk from the perspective of valuation theory. We find that a higher Earnings Response Coefficient (ERC) predicts a higher probability of price crash than a lower ERC. This finding can be explained by investors' misevaluation of earnings persistence and systematic risk of the firm, which is also related to the bad news hoarding hypothesis. If managers hold back the bad news, this would prevent the investors from correcting their valuation of the systematic risk, hence resulting in a higher ERC and higher crash risk. Consistent with prior literature on earnings opacity, we find that the valuation theory could explain the increasing crash risk, which is further supported by cross-sectional analyses.

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I. Introduction

There is a growing literature on Accounting and Finance that attempts to link firm characteristics to individual stock crash risk, which the stock crash risk is defined as an extremely positively skewed distribution of stock return. The theoretical framework of crash risk can be dated back to Jin and Myers (2006), which indicates that the information asymmetry between the firm management and investors results in stock price crash risk. This further leads to the formation of Bad News Hoarding hypothesis, i.e., managers engage in earnings management out of managerial equity incentive, as negative earnings surprises can result in costly equity and debt. When managers block the flow of negative information and release it at once to the stock market, the stock price would become extremely negative (Chen et al., 2001; Hutton et al., 2009; Kothari et al ,. 2009; Kim et al.2011a; Chang et al., 2016).

Although the bad news hoarding hypothesis gives an explanation of stock crash risk, tension still exists on to what extent that investors could decipher the accounting information. For example, Ak et al,. (2015) and Cheng and McNamar (2000) argue that the lesser weightage assigned to extreme earnings announcement in a poor information environment could itself reinforce the magnitude of future stock price crash risk. In other words, even though markets are efficient in valuing financial friction-related information conveyed in management's selected disclosures, the amount of bad news hoarded by managers and the level of default probability can hardly be appraised by the outsiders (Dye, 1985; Jung and Kwon, 1988; Dichev, 1998; Griffin and Lemmon, 2002; Campbell et al., 2008).

Hence, in this thesis, we want to bring in a valuation theory perspective into the explanation of determinants of stock crash risk. The intuition of this perspective is very simple: price of a stock could be written as the following

$$\text{Price} = \beta * (real\ Earnings + \text{Opacity}), \qquad (*)$$

where β is the price-earnings relationship indicator

The bad news hoarding literature could be related to the opacity variable while the price earnings relationship could be related to the beta in this equation. The stronger the relationship is, the more skewness the price could be, after controlling the opacity.

Following this argument, the magnitude of investors' reaction to earnings news, being correct or not, should also play a very important role in causing a potential stock price crash. First, we demonstrate that the earnings-return relationship indicators, such as the Earnings-Price ratio (EP ratio) and Earnings Response Coefficient (ERC), could predict future stock crash risk after controlling for bad news hoarding factors such as earnings opacity.

As a result, we find that a higher ERC or a lower EP ratio could lead to higher crash risk, and a lower EP ratio or higher ERC could Granger-cause future stock price crash. If the ERC of a particular stock is low, this means that investors have already fully anticipated the possible risk in the future market, or earnings could not provide more new information to the market,[1] and thus there should be a much slim chance for such stock suffering a price crash. However, if the ERC of a particular stock is high, and the EP ratio is low, the stock would react strongly to the earnings news, and if the earnings news is released at once, the market has a higher chance of experiencing crash risk.

After we build up a link between ERC and future crash risk, we would like to draw more connections from firm fundamental-related variables to the forecasting of future crash risk. There are some well-received determinants of ERC, such as CAPM beta (risk), capital structure (leverage), earnings persistence, accruals quality and growth opportunities (Collins and Kothari 1989), which should also have their linkage to the prediction of stock crash risk. In other words, if the difference in ERC could be the key reason for crash risk (other than the bad news hoarding hypothesis), there should be a salient difference in at least one of those indicators between the stock with crash risk and the others without crash risk.

One of the main factors that influences ERC and stock prices is sales and earnings growth. While finance literature on asset pricing has studied thoroughly how a firm's growth is priced in the market independent of other factors using a risk approach, accounting literature generally incorporates the growth component into the accrual and cash flows, taking in the informativeness of the mapping terms. For example, firms with sustained increases in earnings have a higher ERC than other firms; in contrast, a similar amount of earnings increase across firms need not signal similar information because an earnings

[1] A short-window earnings response coefficient is typically small in magnitude, indicating that before the earnings announcement, other information sources could have revealed the potential new information that might be carried by the earnings news. See Ball and Shivakumar (2006).

increase could emanate from different components of earnings (Barth et al., 1999). The growth pattern of a firm with increasing earnings from sustained growth in cash flow is different from that of the firms with sustained growth in accruals. Hence, we hypothesize that firms with a higher ERC and more cash flow-based earnings growth are less exposed to crash risk, while firms with a higher ERC but more accrual-based earnings growth are more exposed to crash risk.

Besides growth, earnings persistence also plays an important role in ERC determination. For instance, firms have a higher ERC may face crash risk due to the different informative and persistent components, such as more discretionary accruals vs. more cash flow, after controlling for earnings growth. This phenomenon could lead to the internal linkage between the valuation hypothesis and bad news hoarding hypothesis. The definitions of accrual opacity and operational cash flow opacity are also based on the fact that the persistence of different earnings components is different from the market evaluation. If the persistence of accruals is much longer than what the market has expected, it would make investors over-value the stock, and once the market realizes the fact, the stock would go back to its fundamental value and crash.

In additional to this theoretical argument, several measurements related to financial reporting quality are employed, and corporate disclosures are actually related to investors' valuation of the earnings figures issued by the management. For example, the measurement of earnings opacity, which is the sum of past three years' absolute value of discretionary accruals, and the positive relationship between crash risk and earnings opacity reflect the possibility that extreme earnings or extreme discretionary accruals were not correctly priced by the market, hence resulting in individual stock price crashes. Therefore, we conclude that the bad news hoarding hypothesis and valuation theory are all possible explanations for stock price crash risk, and they are two sides of the same coin.

Last but not the least, linkage between ERC and crash risk could explain the counter-intuitive explanatory power of other control variables, such as size, market to book ratio and non-linearity of earnings opacity used in Hutton et al. (2009) and Zhu (2016). Size is associated with greater crash risk in Hutton et al. (2009), which is counter-intuitive since larger-sized firms should have a better information environment (which makes it more difficult for management to hide bad news) and less default risk (which also makes it less possible to encounter a crash risk). But after including a variable of value relevance such as EP ratio into the regression, the coefficient sign of size flips compared to negative, which is consistent with the generally-accepted reason, and so does the sign of market to book ratio.

We make several contributions to the literature. Our primary contribution is introducing the valuation theory perspective into the explanation of determinants of crash risk. Using multiple identifications of stock price crash, we document a positive relationship between ERC and future crash risk. Second, what distinguishes our study from the vast prior literature in this area is that we try to find the components of accruals that are misevaluated by the market and would cause a potential crash risk. By re-decomposing firms' earnings, we find that firms experiencing a stock price crash have more severely overvalued discretionary accruals and growth-related accruals. Finally, our study complements prior research that examines the effect of firm-specific characteristics on future crash risk. Our study is related to the work by Hutton et al. (2009) which find earnings opacity to be a key determinant of crash risk. In contrast, we argue that valuation is a more dominant factor than earnings opacity, since the market is efficient given that all the information is available to investors, and management may have hoarded the bad news or do not know the existence of bad news.

The rest of the thesis is organized as follows. Section II discusses the related literature and hypothesis development. Section III presents the sample and data. Section IV describes the empirical results and Section V demonstrates some additional analyses. Section VI concludes the thesis.

II. Literature Review and Hypothesis Development

2.1 Crash Risk and its determinants

Scholars have renewed their interest in tail risk after the financial crisis in 2008. There is a growing literature on accounting and finance that attempts to find the underlying determinants of probability of price crashes for individual firms, which is represented by the extreme negative observation in the distribution of firm-level weekly returns (Hutton et al. 2009). Such determinants could be market-level indicators such as investor protection and disclosure requirement (Jin and Myers 2006), institutional indicators such as adoption of IFRS (Kim et al. 2013), firm characteristics indicators such as risk of operations (Chen et al. 2001), properties of investor beliefs (Cao et al. 2002; Hong and Stein 2003), and attributes of financial reporting (Hutton et al. 2009; Kim et al. 2011).

In general, there are two underlying mechanisms suggested in the literature that associate accruals with future price crashes. When managers seek to suppress or hoard bad news, they tend to make aggressive income-increasing accrual estimates, making firms with more hidden bad news among firms with high accruals compared to firms with low accruals. Therefore, when accumulated bad news crosses a tipping point, it is released all at once and results in a price crash (Jin and Myers 2006; Benmelech et al. 2010). Another mechanism is that, extreme negative accruals reflect severe performance deterioration due to financial distress and consequently high default risk (Ng 2005; Khan 2008). Firms with higher default risk are more likely to fail, leading to more price crashes for firms with low accruals relative to firms with high accruals.

There is ample evidence consistent with the bad news hoarding hypothesis. Hutton et al. (2009) show that more opaque firms experience more price crashes over the following year. Following the study of Hutton et al., Kim et al. (2011) show that the CFOs' option incentive ratio is positively associated with future price crashes. This finding suggests that a higher sensitivity of the option portfolio value to stock price increases creates a stronger incentive for CFOs to hide bad news, consistent with the prediction by Benmelech et al. (2010). Other predictors of price crashes include tax avoidance (Kim et al. 2011), internal control weakness (Kim et al. 2011), accounting conservatism (Kim and Zhang 2013), management forecast frequency (Hamm et al., 2012), and CEO over-confidence (Kim et al. 2013).

However, Hutton et al., (2009) establish an association between the variables in financial reporting and crash risk. Since earnings management has been hypothesized to be a cause of stock crash, by using the sum of absolute discretionary accruals over the past three years as a proxy for the opacity of financial reporting, they find a positive relationship between the proxy and stock crash risk. This positive relationship has been interpreted as that both positive and negative discretionary accruals are associated with hidden bad news. However, this conclusion contradicts the conventional belief that firms with negative discretionary accruals are associated with less hidden bad news than those with positive ones (Dechow et al. 1995; Xie 2001)

One way of resolving the contradiction is through corporate failure. For example, firms with higher default risk are more likely to suddenly release extremely bad news (or good news), resulting in a price crash (or a price jump). But prior literature could not provide evidence for this reasoning using proxies like firm size and leverage. The positive relationship between firm size and future price crashes, presented by Hutton et al. (2009) and Kim et al. (2011), goes against the common believe that large firms have a lower bankruptcy probability than smaller firms (Campbell et al. 2008). On the other hand, studies also show a negative association between leverage and future price crashes, which is also contradictory to the conclusion that high leverage firms have a higher probability of failure than lower leverage firms (Campbell et al. 2008).

Another explanation offered by the literature addressing such contradiction is that, the investors may underprice high leverage firms compared to lower leverage firms, making it less likely to observe a price crash for those firms ex post. There are other price crash risk explanations in the literature, including difference of opinions (Hong and Stein 2003) and information blockage (Cao et al. 2002). Consistent with these explanations, Chen et al

(2001) document that share turnover (proxy for differences of opinion) and past stock return (proxy for information blockage) positively predict the likelihood of future price crashes, measured as the negative return skewness. On the other hand, market inefficiency could reinforce the likelihood and magnitude of price crashes. Ak et al. (2015) show that mean stock returns over the next 6 months are significantly lower for high crash risk portfolios than for low crash risk portfolios, which suggests that the market is inefficient in price crash predictions. In other words, investors fail to understand the signal such as earnings. When future news arrives, people start to understand the bad news, and in this case we should find stronger evidence of price crash predictability when the market fails to adjust for bad news hoarding.

2.2 Value-Relevance of ERC and EP Ratio

The return-earnings relationship has been the core of accounting research since various researchers want to prove that accounting information provided for investors has contributed to the formation of stock prices. The Earnings Response Coefficient (ERC) is theoretically defined as "a change in the price induced by a one-dollar change in current earnings" (Collins and Kothari 1989) and typically measured as a slope coefficient in a regression of stock returns on unexpected earnings (Markowitz 1952, 1959). And the studies on the ERC are more interested in the nature of information about reported earnings and how they are related to firm valuation.

The emphasis of ERC is mainly put on how a firm's stockholders evaluate its accounting information announcement so as to make informed decisions. Ball and Brown (1968) are the first to discuss the earnings-return relationship, and the topic has since become prominent. There are also influential papers, such as Easton and Zmijewski (1989) Collins and Kothari (1989) and Kormendi and Lip (1987), which prompt further research. Ohlson and Schroof (1992) confirm that if investors use information other than earnings and dividends, there is a reason to prefer one specification over the other. Eaton and Harris (1991) use a different method to examine earnings as an explanatory variable for return and confirm the relationship between the level of earnings (scaled by price) and stock returns at the beginning of the period. The main difference in this study is that it has incorporated both the level of and changes in earnings rather than only a change in earnings. Kothari (1992) and Kothari and Sloan (1992) also examine the strength of the relationship between price and earnings. Contrary to previous studies, they deflate earnings by the share price at the beginning of the year, including returns for three leading periods. They explore the price-earnings regression when prices lead earnings. While on the other hand, Collin et al. (1994) incorporate up to three years of future earnings in their returns-earnings regressions and find the levels of explained return association that are higher when compared to regressions that only use contemporaneous earnings.

Hayn (1995) notes that losses are very important when estimating return-earnings relation, because they are not expected to continue forever, as shareholders have a liquidation option. When loss observations are excluded, the association between returns and earnings becomes much stronger. This is supported by Finnish data collected by Martikainan et al. (1997). Following the methodology proposed by Kothari and Sloan (1992), Jindrichovska (2001) reports that one-leading-year returns are as important as contemporaneous returns in terms of their sensitivity to annual changes in earnings. Jarmalaite (2002) analyses the relationship between accounting data and stock price returns in the stock markets of some other countries on the basis of the methodology developed by the same paper.

To address this bad-fitting problem, various studies have tried to modify the specification issues (Lev 1989; Judge et al. 1985; Cornell and Landsman 1989; Cheng et al. 1992). The studies find that a non-linear relationship significantly increases the adjusted R^2 statistics and better addresses the issues of heteroscedasticity, residual non-normality, omitted variables, and random coefficient variations. An S-shaped relation between unexpected return and unexpected earnings is tested in Freeman and Tse (1992). This implies that the markets responding to unexpected earnings are convex for bad news and concave for good news. And They suggest that earnings persistence is one reason for such a relationship. Since the valuation theory suggests that analysts and investors should place greater emphasis on forecasting high-persistence earnings than low-persistence earnings. The explanatory power of unexpected earnings to unexpected return is diminishing with the absolute value of the unexpected earnings (Freeman and Tse 1992).

Earnings persistence and earnings management are the most frequently used measurement of earnings quality (Dchow and Dichew 2002). Growth firms that generate more revenue from increasing cash flows are more likely to have sustainable growth and higher quality of earnings (Porter 1980, 1985). In addition, cash flow is always thought to be more difficult to manage than accruals (Ertimure et al. 2003). And prior studies (Jones 1991; Bartove 1993; Dechow et al. 1995; Bens et al. 2003) have identified several specific approaches that dictate earnings management. Hence, we expect that firms with a higher ERC and more cash flow-based earnings growth are less exposed to crash risk, while firms with a higher ERC but more accrual-based earnings growth are more exposed to crash risk.

Barth et al. (1999) show that the ERC is higher for firms reporting sustained increases in earnings than for other firms, suggesting that the path of growth in earnings is value relevant. Their results are consistent with the argument that a string of earnings increases signal a firm's competitive advantage and a higher likelihood of future earnings growth (Eccles et al. 2001). Smoothly growing earnings can also signal hard-working managers since the discretion to smooth earnings can be used to induce managers to exert a higher level of effort relative to shirking (Demski 1998). While Barth et al. (1999) study sustained increases in earnings, they do not distinguish among the alternative sources of growth in earnings. Sustained increases in earnings can be achieved through different components of earnings, which can provide incremental information beyond what the overall growth pattern contains. Since earnings are net of revenues and costs, they consider two broad strategies to achieve sustained increases in earnings—a revenue increasing strategy and a cost reduction strategy.

2.3 Hypothesis Development

In this paper, we want to argue that beside the popular cause that explains crash risk, i.e., the bad news hoarding hypothesis and default risk hypothesis, Value Relevance Theory could also play an important role in predicting future crash risk. Huttion et al. (2009) have already shown that earnings opacity predicts future crash risk. Hence, we want to segregate the effect of bad news hoarding in our research and also find the potential link between the two explanations. That is, after controlling for earnings opacity, the Earnings Responsive Coefficient could also predict future crash risk. And the predictive power of earnings opacity could also contribute to model specification and measurement errors.

This leads us to develop the following hypothesis:

H_1: ERC is positively related to future crash risk in addition to accrual opacity.

Moreover, prior literature presents the 5 main factors that could influence the value of ERC: Beta, earnings persistence, earnings growth, risk, and the risk-free interest rate. We also want to see which of these factors have been misvalued by the market due to bad news hoarding or mispricing of risk. Given that ERC is positively related to earnings persistence and growth opportunities while negatively related to the risk-free interest rate and systematic risk of individual firms' Beta, its mapping impact could predict future crash risk.

H_2^a: High ERC Firms with a sustaining increase in both earnings and discretionary accruals face more crash risk;

H_2^b: High ERC Firms with more cash flow-based earnings growth are less exposed to crash risk.

H_3: Earnings Persistence is positively related to future crash risk, and earnings persistence has more serious misvaluation problems in the context of crash risk.

III. Sample Selection, Variable Definitions and Descriptive Statistics

3.1 Sample selection and Data

Our sample consists of firms listed on both the Compustat and CRSP (monthly) databases. From Compustat, we obtain net income before extraordinary items and discontinued operations, operating cash flows, for which we adjust the accrual portion of extraordinary items and discontinued operations, total assets, sales revenue, changes in accounts receivable listed on the Statement of Cash Flows, and gross property, plant, and equipment. From CRSP, we obtain sufficient return data to calculate buy-and-hold stock returns for the 12-month period ending three months after the end of fiscal year t+1.[2] We also merge our data set with I/B/E/S analysts' forecasts of one-year ahead earnings. Also, we require a minimum of 10 firms per 2-digit SIC group when estimating abnormal and normal accruals in any particular year. We then impose the following selection criteria. First, we exclude firm-years with non-positive total assets and non-positive sales. Second, we require firms to be incorporated in the U.S. Third, stock prices at the fiscal year end should be at least equal to one U.S. dollar. Also, following Kim et al. (2011a, 2011b), we require that each firm should have at least 26 weekly returns for each year.[3] Further, we exclude financial institutions with SIC codes ranging from 6000 to 6799. Finally, firm-years with missing data for variables used in our empirical models described below are excluded in the empirical analysis. After applying these selection criteria, the sample size comprises 154,039 firm-year observations between 1988 and 2016. The time period starts in 1988 due to data availability of cash flow from operations from cash flow statements.

We measure total accruals (ACC) as the difference between income (before extraordinary

[2] As in Sloan (1996), if a firm delists during this period, we use available returns including their delisting return. If the delisting return is missing and the firm delists due to liquidation or an enforcement action, we assume a delisting return of –100%.

[3] A sample year is viewed as the 12-month period ending three months after the fiscal year end.

items and discontinued operations) and operating cash flows required under SFAS No. 95. We present results for two abnormal accrual measures. The first is based on the cross-sectional Jones (1991) model modified by Dechow et al. (1995). This model is estimated annually within 2-digit SIC code groups.

$$\frac{ACC_t}{ATA_t} = \beta_1 \frac{1}{ATA_t} + \beta_2 \frac{(\Delta REV_t - \Delta REC_t)}{ATA_t} + \beta_3 \frac{PPE_t}{ATA_t} + e_t \tag{1}$$

where

ACC_t is total accruals in year t;

ATA_t is average total assets in year t;

ΔREV_t is the change in sales revenue in year t;

ΔREC_t is the change in accounts receivable in year t; and

PPE_t is gross property, plant, and equipment at the end of year t.

The residuals (e_t) from this model are a measure of discretionary accruals (*DAC*), while the fitted values are considered nondiscretionary accruals (*NDAC*).

Follow the definition of Hutton et al. (2009), the measure of opacity in financial reports is the three-year moving sum of the absolute value of annual discretionary accruals:

$$OPACITY_t = abs(DAC_{t-1}) + abs(DAC_{t-2}) + abs(DAC_{t-3}) \tag{2}$$

The measurement of opacity is a proxy for earnings management, since the idea behind this measure is that firms with consistently large absolute values of discretionary accruals are more likely to have managed reported earnings. Large positive abnormal accruals following negative abnormal accruals would result in a high level of earnings management (Dechow, Sloan and Sweeney 1996). Hutton et al. (2009) employ this measure to capture the multi-year effects of earnings management and the moving sum is more likely to reflect an underlying policy of the firm to manage earnings.

3.2 Measurement of Stock Crash Risk Indicator

3.2.1 CRASH as the measurement of firm-specific crash risk

For our empirical tests, we use three measures of stock crash risk, which is the negative skewness in return distribution. Our first measure of stock crash risk is CRASH (Jin and Myers 2006). The reasoning is stated as follows: the lack of transparency concerning firm performance enables managers to capture a portion of cash flow in the process of absorbing part of the variation in firm-specific performance. This would increase the R^2 of the unexpected earnings and unexpected return regression. If there is temporary bad performance, the managers are willing to hide the bad news in fear of losing their jobs. But, if the bad performance is persistent, they would not be able to hide the bad news anymore and all of the unobserved negative firm-specific shocks become public at once, resulting in a crash.

As defined in Hutton et al. (2009) and Kim et al. (2011), one of the crash measurements is CRASH, which is the likelihood of stock price crash for each firm in each year, i.e. the firm-specific weekly return in a given fiscal year where one or more weeks have experienced a firm-specific weekly return which is more than 3.09 standard deviations below the mean firm-specific weekly return over the entire year. The following table reports the frequency of crash in our sample.

[Insert Table 1 here]

[Insert Graph 1 here]

Table 1 highlights the frequency of crash across the sample years. The frequency of crash is significantly higher in the second half of the sample period than in the first half. This might be attributed to the implementation of Sarbances-Oxley Act, suggesting that earnings management has decreased or that firms can hide less information in the new regulatory environment (Hutton et al. 2009).

3.2.2 NCSKEW as the measurement of firm-specific crash risk

As indicated in Chen et al. (2001) and Kim et al. (2011), another measure of crash likelihood is the negative conditional return skewness. It is the negative of the third moment of firm-specific weekly return during the same fiscal year, divided by the standard deviation of firm-specific weekly returns raised to the third power. NCSKEW is calculated as follows:

$$NSKEW = -\left[n(n-1)^{3/2}\sum w_{j,\tau}^{3}\right] / \left[(n-1)(n-2)\left(\sum w_{j,\tau}^{2}\right)^{3/2}\right]$$

(3)

3.2.3 DUVOL as the measurement of firm-specific crash risk

The measure of crash risk is the down-to-up volatility measure of the crash likelihood. For each firm j over fiscal year t. firm-specific weekly returns are separated into two groups: down weeks when the returns are below the annual mean, and p weeks when the returns are above the annual mean. The standard deviation of firm-specific weekly returns is calculated separately for each of these two groups. DUVOL is calculated as follows:

$$DUVOL_{j,\tau} = \log\{(n_u - 1)\sum_{Down} w^2{}_{j,\tau}/(n_d - 1)\sum_{Up} w^2{}_{j,\tau}\}.$$

(4)

3.3 Measurement of ERC and E/P ratio

To investigate the ability of Earnings Response Coefficient and E/P ratio in forecasting the future crash risk, we follow prior studies (Barth et al. 1999; Ohlson 1995) that relate stock prices to earnings and book value. Although our focus is on ERC, Ohlson (1995) points out that one implication of his valuation model is that a higher weight on earnings corresponds to a lower weight to book value. And there are also studies (Burgstahler and Dichev 1997; Collins et al. 1998; Cheng and Zhang 2002) finding that the relative weight on book value is negatively associated with the weight on earnings level.

$CAR_t = a + b\ UX + \varepsilon_{it}$, (5)

where CAR is the measure of risk-adjusted return for security I cumulated over period t, UX is a measure of unexpected earnings (with appropriate scales), and e is a random disturbance term assumed to be distributed with $N(0,\sigma^2)$. And the slope coefficient b is called the earnings response coefficient (ERC).

More specifically, by following a variation model of Ohlson (1995), the return model is presented as follows:

$Ret_{it} = b_0 + b_1\Delta E_{it}/P_{it-1}*D^{\Delta E+} + b_2\Delta E_{it}/P_{it-1} * D^{\Delta E-} + c_1\ \Delta BV_{it}/P_{it-1}*D^{\Delta E+} + b_1\Delta E_{it}/P_{it-1} * D^{\Delta E-} + \varepsilon_{it}$, (6)

where Ret_{it} is the compounded stock return form the fourth month of fiscal year t to the third month after the year end, and $D^{\Delta E+}$ and $D^{\Delta E-}$ are dummy variables for positive and negative changes in earnings, respectively.

We use both the CAR model and the return model because together they provide a complementary set of results (Barth et al. 2001; Gu 2005). While valuation takes a measurement perspective, the return models can also be justified from an information perspective. If ΔE is considered as a proxy for earnings surprises, then the return models use the traditional long-window earnings-returns relations to measure the informativeness of earnings.

We further break down the earnings into operating cash flow and accruals. A common perception in the contemporary accounting research is that managers opportunistically manipulate accruals so that extreme accruals tend to reflect greater earnings management (Warfield et al. 1995; Becker et al. 1998; Bartov et al. 2000; Richardson et al. 2001). So it is reasonable that a careful investor fails to understand the signal such as earnings. When future news arrives, people start to understand the bad news and in this case we should find stronger evidence of price crash predictability when the market fails to adjust for bad news hoarding. And this would be further discussed in the later sections.

3.4 Descriptive Statistics and Correlation Matrix

[insert table 2 here]

Table 2 provides descriptive statistics of firm-years on the 154,039 firm-year observations over the period 1988-2016 used in the sample. In Panel A, variables related to fundamentals of firms such as earnings (and their decomposed items) and book to market values are reported. And Panel B reports the regression results for return-earnings relationship. Panel C of Table 1 provides the mean values of earnings components, which are average assets for the deciles of earnings. Not surprisingly, the various measures have fat left tails. And kurtosis, crash risk probability and skewness are all positively correlated.

[insert table 3 here]

In table 3 we report the mean value of opacity, squared opacity and crash risk proxies such as CRASH, NCSKEW and DUVOL grouped by ERC rank. We find that as the ERC rank increases, CRASH, NCSKEW and DUVOL also increase, indicating a positive relation between crash risk proxies and ERC rank.

IV. Mathematical Analyses

In this section, regression analysis is employed to examine the relationship between E/P ratio, ERC and crash risk. In the previous section, we have mentioned our intention, i.e. bringing in the valuation theory into the explanation of future crash risk.

4.1 EP ratio in Explaining Crash Risk

The EP ratio is calculated by dividing the earnings per share by the firm’s current market price, which is used by the investment community to capture risk and growth of a stock. They reasonably assess a firm’s value using a benchmark method especially when a firm’s value is not observable (Boatsman and Baskin 1982; Lechlair 1990). The EP ratio is the annual earnings of a security per share at a given time divided into its price per share. In other words, it is the inverse of the Price-Earnings Ratio, which is a way to determine stock valuation or the fair value of a stock in a perfect market. It is also a measure of expected growth, since it is also a measure indicating the rate at which investors will capitalize a firm’s expected earnings in the coming period. If EP is low, it warns of an over-priced stock, of which the price is much higher than its actual growth potential, so these stocks are more liable to individual stock price crash risk. On the other hand, if EP is high, it signals that the stock is undervalued and hence exposed to lesser crash risk.

Even though the EP ratio is not totally neutral, which is heavily dependent on the firm’s peers, its prediction power is not weakened by the characteristics of certain industries. In addition, including the EP ratio into the regression which has been done by Hutton et al. (2009) could solicit the impact of financial report opacity other than the misvaluation of earnings numbers. Since in accounting literature, there are different ways of decomposing earnings and each earnings component would have different persistence.

[Insert table 4 here]

Table 4 presents logit analysis supporting the link between EP ratio and crash risk. Each firm-year is assigned zero if the firm experiences no crash during the fiscal year and one if the firm experiences at least one week during the fiscal year in which the stock price crashes. In the light of replicating the regression done by Hutton et al. (2009), other variables are the same as those in their regression, with an additional variable, EP ratio. The marginal impact of the explanatory variable is found in the second column of the table.

In contrast to Hutton et al. (2009), we realize that once the valuation factor, i.e. the EP ratio has been included into the logit regression function, the explanatory power of earnings opacity will disappear, even though the predicted sign is still consistent with the prior regression. In other words, the valuation of the earnings news given measured by the EP ratio has significant explanatory power of crash risk, which reinforces our hypothesis of valuation theory. The negative, significant coefficient indicates that the higher the EP ratio, the lower the crash risk. A higher EP ratio indicates that the stock is undervalued compared to the majority of stocks, and this kind of stocks have lower crash risk since the stocks are already undervalued according to the efficient market hypothesis. Another explanation could be that if the stock price has incorporated more earnings news, the chance that the individual stock encounters a crash risk is lesser. This would further make us to concentrate on the valuation theory explanation of crash risk.

4.2 Return-Earnings Relationship and Crash Risk

4.2.1 ERC and Crash Risk

The reasons for investors' misevaluation of earnings have been carefully examined by prior literature. On explanation is that as the market anticipates the reversal of abnormal working capital accruals, the reported magnitude of earnings surprises that contain abnormal accruals will differ from the underlying magnitude that is priced by the market. Hence, the ERC should be lower when discretionary accruals exaggerate the magnitude of earnings surprise, and vice versa (Defond and Park 2001). In other words, for stocks which are believed that earnings are heavily managed through discretionary accruals (termed as abnormal accruals in the paper), it is rational for investors not to react to the earnings surprise and it would eventually result in a stock crash if the information sent by the managers through earnings is constantly ignored. Hence, we expect that ERC should be low prior to the stock crash and high after the crash.

According to the valuation theory, the extreme earnings news may not necessarily be priced by the investors. This brought us to the theory of Earnings Response Coefficient. If the market does not react to earnings numbers, the ERC should be low. The difference in market response could be due to the differences in CAPM beta, capital structure, earnings persistence, accruals quality, growth opportunities and informativeness of the price. In other words, if the difference in ERC could be the key reason for crash risk (rather than the bad news hoarding hypothesis), there should be a salient difference in at least one of those indicators between the stocks with crash risk and the others without crash risk. On the other hand, the measurement of accrual opacity in Hutton et al. (2009) is also related to the quality of accruals and it is proven in the paper that quality of accruals, which influence the ERC, would have an impact on crash risk. The stock crash risk can be explained by using the valuation theory since the extreme earnings prior to the crash have not been incorporated into the stock price, and once the market realizes the mistake, it would lead to a crash or a jump depending on the nature of extreme earnings. In this case, if an individual stock experiences a crash, the ERC should be lower prior to the crash if the earnings are very extreme.

The coefficients on EP ratio in the previous table suggest that when the EP ratio is higher, the crash risk is lower. The EP ratio is a contemptuous measurement while we also want to know how the change in the earnings-return relationship affects the crash risk. To avoid scaling measurement errors, we use the rank of ERC instead of the absolute value of ERC since some of the firms would have a negative value due to negative return or negative earnings.

[Insert table 5 here]

Table 5 presents logit analysis supporting the link among one-year lagged rank of ERC, two-year lagged rank of ERC and crash risk. Similar to the pervious section, we did a replication of Hutton et al. (2009) with the addition of one-year lagged ERC rank and two-year lagged ERC rank. Lagged terms are included into the regression to see whether the crash risk would be influenced by the past earnings-return relationship and whether past relationship would also help us to predict future crash risk. Similar to the previous section, not surprisingly, opacity and its squared term lose their predictive power once the rank of ERC and its lagged term are included.

To summarize, the impact of ERC rank and EP ratio on crash risk is statistically highly significant and consistent with the valuation theory prediction. However, the quantitative or economic scale of the variable is worthy of discussion. Unlike the EP ratio, the ERC reflects investors' reaction (unexpected returns) to the unexpected earnings news, while the EP ratio is a more rough proxy for the price and earnings at the end of the fiscal year. Here, we find that the EP ratio is more significant than ERC, because the price factor in the EP ratio is more related to price of the stock, and price is a direct base factor of crash risk. ERC is a regression coefficient of unexpected earnings and unexpected return, which is a relatively distant factor in determining crash risk.

4.2.2 Granger's Causality Test

Granger's (1980) causality test uses an inferential approach without direct reference to the background of accounting theory; it is more explicit about temporal dynamics in terms of the incremental predictability of one variable conditional on another. In other words, we would test whether a higher ERC rank (and lower lagged ERC rank) would Granger-cause individual stock crash risk at time t+l; that is, we test whether predictions of crash risk based on its own past values *and* on the past values of ERC rank are better than predictions of crash risk based only on its own past values. Mathematically, a higher ERC at time t Granger-causing higher crash risk at time t+1 implies that:

Prob (Higher Crash Risk t+1| all information dated t and earlier) ≠ Prob (Higher Crash Risk t+1| all information dated t and earlier omitting information about X).

We use the Ordinary Least Squares (OLS) method and show that the rank of ERC and lagged ERC rank predict crash risk in the following period, but lagged crash risk could not be predicted by the rank of ERC. The result further reflects how investors' evaluation of accounting earnings has an impact on crash risk, which is not a simple Logit regression. Here crash risk is not proxied by using the definition of a dummy variable, rather a continuous variable is used that measures the negative skewness of the distribution, NCSKEW.

[Insert table 6 there]

Table 6 Panel A presents OLS analysis supporting the link between the ERC rank and crash risk proxy, NCSKEW. The coefficient of lagged ERC rank is positively significant, indicating that a higher ERC rank at time t could increase the probability of crash risk (increasing NCSKEW). Analogous to the previous Logit regression, a one-year lagged ERC rank could positively predict the future crash risk, estimated as a dummy variable. These two regressions have served as a robustness test of each other which solicits the relationship between the rank of ERC and crash risk.

On the other hand, in Panel B, when the dependent variable changes to ERC rank while explanatory variables are replaced by lagged crash risk, the correlation coefficient of lagged crash risk becomes insignificant. Even though economically, the sign of the coefficient is still positive in line with the prior regression; the insignificant coefficient indicates that the lagged crash risk has no explanatory power of future ERC rank. To summarize, a positive shift of one-year lagged ERC rank could Granger-cause an increase in crash risk or the negative skewness of return distribution (NCSKEW), while an increase in one-year lagged crash risk (NCSKEW) has no predictive power in the present ERC rank changes. It is not surprising but worth noting that the signs of coefficients of other fundamental explanatory variables are consistent with the crash- ERC rank relationship using both Logit and OLS regressions. First, the EP ratio in both models has a positive correlation coefficient, reconfirming that EP ratio has a positive impact on forecasting future crash risk. In other words, after controlling for other fundamentals, those firms with overpriced earnings in the previous year would be more vulnerable to crash risk in the following year.

To summarize, the one-year past ERC rank is significantly positively related to NCSKEW, a crash risk indicator, but the ERC rank could not be predicted by the one-year lagged crash risk indicator, lag_NCSKEW. This proves that the higher ERC rank would Granger-cause higher crash risk in the future.

4.2.3 Size as a special explanatory variable

As mentioned in the previous section, firm size is the other factor affecting ERC, earnings announcements and unexpected return around the earnings announcement time in medium and small-sized companies, but this relationship is not found among large companies. ERC also increases by more disclosure made by large companies, so in the long term, ERC increases by size. Other studies show that companies with more persistence in their earnings and revenues have higher earnings quality and a higher ERC as well. These companies encounter less earnings management and their book value response coefficients are less.

Consistent with Hutton et al. (2009) and Kim et al. (2011a, 2011b), the coefficient sign of size and future crash is positive, which contradicts the observation that larger firms have a lower bankruptcy probability than smaller firms (Campbell et al. 2008). This conclusion is opposite to the well-perceived knowledge that firms with higher default risk are more likely to suddenly release extremely bad news, leading to a stock crash, because they have a more extreme outcome as a going concern. This doubtful result is also pointed out by Zhu (2016), while his perspective is more concerned with the decomposition of earnings. However, the factor of size become insignificant in our Logit regression once the EP ratio is included. This would further indicate that the market in the long run should be efficient so that such default risk should be priced in a year's time. In addition, the mysterious sign of explanatory variables such as size and Market-to-Book has flipped after changing the proxy of crash risk from a dummy variable to a continuous variable. This fact is more consistent with the explanation given in Hutton et al. (2009), putting the definition of a crash as a cause of such artifact sign of coefficient. In other words, large firms have lower standard deviations of returns than smaller ones. Therefore, the absolute magnitude of a return needed to qualify as a crash is smaller for larger firms; hence, the size has a positive contribution to crash risk according to the dummy variable definition.

4.3 The Effects of Firm Growth and Model Specification Choices of Accruals

4.3.1 The effect of Firm Growth on Crash Risk

Prior literature (e.g., Collins and Kothari 1989) has studied the relationship between accounting earnings and stock return. It is well-received in the academia that growth opportunities, earnings persistence, firm size, interest rate, financial leverage, capital market risk and financial disclosure are some common factors that would have impact on the earnings-return relation. In general, accounting earnings affect investment decisions, and earnings growth is a signal for good firm performance. The effects of risk (Charitou et al. 2001), interest rate, earnings growth (Ghosh et al. 2005), earnings persistence (Ghosh et al. 2005) and firm size (Freeman 1985; Chaney and Jeter 1992) on ERC have been studied before. The results of this study show that ERC has a reverse relationship with the interest rate and a company's risk. Also the results show a positive relationship between ERC and earnings growth and earnings persistence as well. Moreover, this study implies that the large companies probably have more opportunities for growth; therefore, they have higher earnings and also a higher ERC.

Collins and Kothari (1989) mention that earnings persistence, risk and growth are the cross-sectional variation while the risk-free interest rate is temporal variation. In the context of our analysis, the risk-free interest rate could be taken as given due to the fact that it is known to the whole market and to the cost of re-adjusting investors' leverage during a year's time; thus the influencing power of interest rates over ERC should be negligible. In short, a higher ERC could imply higher growth rates, higher persistence, higher financial report disclosure and larger size.

We hence emphasize the role of growth in ERC. It is because growth is not only related to the value of ERC but also to the pricing of stocks directly. This has been carefully studied in the finance and asset pricing literature (Jegadeesh and Titman 1993; Zhang 2006; Dong et al. 2006), which indicates that investors would generally underreact to growth firms due to uncertainty in the future. In other worlds, greater sales growth in the future would lead to greater uncertainty about the impact of news on stock value, leading to higher expected returns following the release of future news than the returns of stocks with lesser growth opportunities.

We hence decompose the ERC and segregate the impact of Growth by doing a regression that

$$ERC_{it+1} = a + b\ Growth_t + e_{it} \quad (7)$$

And

[insert table 7 here]

From the above regression, we find that both the component that could be explained by growth and the residual have explanatory power for future crash risk. However, the growth component of ERC has more significant power of predicting future crash risk than the residual component of ERC. This further implies that investors' misvaluation of earnings could come from both the growth component and the other components of earnings. According to Ohlson's clean surplus model, companies with both earnings and revenue growth in comparison to those with just earnings growth have higher earnings quality, a higher ERC and higher earnings persistency. In the following section, we want to evaluate how investors misevaluate different components of the accruals.

4.3.2 Correlation among lagged terms of Discretionary Accruals between High and Low Crash Risk Groups

Another explanation of misevaluation is the mistakes committed by investors in estimating the persistence of earnings components. Xie (2001) find that investors keep on over-pricing discretionary persistence or implications of discretionary accruals for one-year ahead earnings. This is consistent with the conclusion of Subramanyam (1996) and Sloan (1996), which demonstrate that the market overprices accruals and largely abnormal accruals which stem from managerial discretion. [4] This conclusion brings our notice to discretionary accruals, and we test whether abnormal discretionary accruals would lead to a potential increase in crash risk. First, we present the difference between the values of discretionary accruals for consecutive three years in line with Hutton et al. (2009), which take the sum of absolute values of discretionary accruals for past three years as earnings opacity. From Table 8, we see that for those firms experiencing crash risk, their discretionary accruals in the past three years are highly positively correlated, while for those firms without crash risk, they are much less correlated. Since investors over-value the discretionary accruals, the past two years' discretionary accruals of firms with crash risk are highly positively correlated, unlike those with lower crash risk. The definitions of discretionary accruals and other variables can be found in section 3.3. More importantly,

[4] In this paper, discretionary accruals and abnormal accruals are interchangeable terms. Even though in Jones (1991) the term is "discretionary accruals" while abnormal accruals are used as a proxy for managerial discretion (Subramanyam 1996; Erickson and Wang 1999), the residuals of Jone's (1991) model represent not only managerial discretion but also unusual nondiscretionary accruals and unintentional misstatement. But such difference does not make a difference in our study.

we also want to test whether the over-valuation of discretionary accruals for high crash risk firms is much severer than that for lower crash risk firms.

[insert table 8 here]

From Table 8, we see that for those firms which experienced a crash at year t, there is a higher positive correlation among their past three years' discretionary accruals, while for those firms which did not experience a crash at year t, there is a much less significant correlation, and the sign of the correlation is different as well. So we could conclude that the earnings pattern of firms with crash risk should be much different from that of firms with lesser crash risk.

4.3.3 Mishkin Test for Mispricing of Different Earnings Components

To find a precise misvaluation component, the Mishkin test is conducted in our paper, which is a test used in macro econometrics testing for market efficiency. But it has be adapted by Xie (2001) to do a statistical comparison between the forecasting coefficient of abnormal accruals and the valuation coefficient of abnormal accruals. In short, if the valuation coefficient is significantly smaller (larger) than the forecasting coefficient, it signals an underpricing (overpricing) of abnormal accruals (Xie 2001; Fairfield et al. 2003). Now the market efficiency demands for the model two constraints $\gamma_1=\gamma_1^*$, $\gamma_2=\gamma_2^*$ and $\gamma_3=\gamma_3^*$, which requires that the market anticipates rationally the impact of current accruals and cash flow on future earnings. As the different earnings persistence implies that $\gamma_2=\gamma_2^*$ and $\gamma_3=\gamma_3^*$, γ_2 and γ_3 may be equal if investors are not able to distinguish between cash flow and accruals components of earnings (Sloan 1996). Xie (2001) initially uses nonlinear Generalized Least Squares Estimations, but it is proven that such process is asymptotically equal to OLS (Dechow et al. 2011). The first stage imposes the estimation of the equations without constraints on coefficients, while in the second stage, equations are estimated with rational pricing constraints. The estimation of 2 SLS is a technique used for over-identified systems done in 2 stages (Brooks 2008). In addition, the market efficiency test is done by using likelihood ratio statistics, distributed asymptotically with Chi-square. The likelihood ratio statistics compare the values of the restricted and unrestricted cases, and consequently it will show whether the data are more likely under a model than under another. So the null hypothesis is that the market rationally prices one or more earnings components regarding the forecasting of future earnings. In addition, we separate our sample according to whether the firm has experienced a crash in the given fiscal year, trying to see whether there is a significant difference in the terms and magnitude of misvaluation between the firms with and those without crash risk.

Following the procedures mentioned in Xie (2001) and using the modified Jones model to decompose the accruals, the results are presented in the following system:

$$EARN_{t+1}= \gamma_0+\gamma_1 NDA_t+\gamma_2 DA_t+ \gamma_3 OCF_t+ \nu_{t+1}$$

(10)

Size-adjusted abnormal returns $_{t+1}$ =

$\beta \quad (Earnings_{t+1}-\gamma_0-\gamma_1{}^{*} NDA_t-\gamma_2{}^{*} DA_t - \gamma_3{}^{*}OCF_t) + \varepsilon_{t+1}$,

(11)

where: $EARN_t$= Income before extraordinary items deflated by beginning total assets in year t

OCF_t= Operating Net Cash Flow deflated by beginning total assets in year t

$ACCR_t$= total accruals = $EARN_t$-OCF_t

NDA_t = residual values of the Jones model estimated in cross section for each two-digit SIC code and year combination

DA_t = predicted values of the Jones model estimated in cross section for each two-digit SIC code and year combination

Test Statistic is defined as:

$F=2n \log(SSR^c/SSR^u)$ follows $\chi^2(q)$,

(12)

where q is the number of constraints imposed by market efficiency

n is the number of observations

SSR^c is the sum of squared residuals from the constrained weighted system

SSR^u is the sum of squared residuals from the unconstrained weighted system

[Insert table 9 here]

Table 9 Panel A reports the coefficient estimates for equations (8) and (9) obtained in the first stage, with the segregation of firms experiencing a crash at year t and firms without a crash at year t. For OCF, $\gamma_1<\gamma_1^*$, the forecasting coefficient is greater than the valuation coefficient, indicating that the market underpricess OCF relative to its predictive power to one-year ahead earnings. To test the significance for such difference, the second stage test is done after imposing $\gamma_1=\gamma_1^*$, which means that the pricing of earnings components is rational. The likelihood ratio reported in Panel B is significant at the 1% level, suggesting that the underpricing of OCF is statistically significant.

Similarly, the valuation coefficients the market assigns to NDA and DA are larger than their forecasting counterparts, and all these differences are significant given the p value. This indicates that the market overvaluess both discretionary and non-discretionary accruals. However, the overvaluation of discretionary accruals is more severe than that of non-discretionary accruals, since the likelihood ratio rejects the null hypothesis (Rational Pricing Model) more for DA than for NDA. In addition, the likelihood ratio statistic rejects the hypothesis that the market rationally prices all three earnings components.

Panel B presents the likelihood ratio statistics that reject the rational pricing model (null hypothesis) of DA and NDA. We could observe that firms with crash risk have a higher likelihood ratio in the three factors of earnings than those without crash risk. This means that the crash risk group has more severe mispricing problems compared to the non-crash risk group, implying the valuation theory perspective of stock crash risk.

4.3.4 Replication of Logit Regression and Mishkin Test Using Dechow and Dichev (2002) Decomposition of Accruals

On the other hand, we want to employ the same test for another way of decomposition of accruals. Following Dechow and Dichev (2002), the accruals could be written as:

$ACC_t = \alpha_0 + \alpha_1 SGR_t + \alpha_2 EMPGR_t + \alpha_3 OCF_{t-1} + \alpha_4 OCF_t + \alpha_5 OCF_{t+1} + \varepsilon_t$,

where SGR is the growth rate of sales

EMPGR is the growth rate of employment,

CF is the cash flow

$EARN_{t+1} = \gamma'_0 + \gamma'_1$ Good Accruals $_t + \gamma'_2$ Accruals Estimation Errors $_t + \gamma'_3$ Cash Flow $_t + \nu'_{t+1}$ (13)

Abnormal returns $_{t+1} = \beta'$ (Earnings$_{t+1} - \gamma'_0 - \gamma'^{*}_1$ Good Accruals$_t - \gamma'^{*}_2$ Accruals Estimation Errors $_t$ – γ'^{*}_3Cash Flow$_t$)+ ε_{t+1} , (14)

where: $EARN_t$= Income before extraordinary items deflated by beginning total assets in year t

OCF_t= Operating Net Cash Flow deflated by beginning total assets in year t

$ACCR_t$= total accruals = $EARN_t - OCF_t$

We would like to know whether this decomposition of accruals could be properly priced by the market by employing the same procedure of Mishkin Test.

[insert table 10 here]

Table 10 Panel A reports the coefficient estimates for equations (13) and (14) obtained in the first stage, with the segregation of firms experiencing a crash at year t and firms without a crash at year t. For OCF, $\gamma_1 < \gamma_1^*$, the forecasting coefficient is greater than the valuation coefficient, indicating that the market underprices OCF relative to its predictive power to one-year ahead earnings. To test the significance for such difference, the second stage test is done after imposing $\gamma_1 = \gamma_1^*$, which means that the pricing of earnings components is rational. The likelihood ratio reported in Panel B is significant at the 1% level, suggesting that the underpricing of OCF is statistically significant.

Similarly, the valuation coefficients the market assigns to NDA and DA are larger than their forecasting counterparts, and all these differences are significant given the p value. This indicates that the market overvalues both discretionary and non-discretionary accruals. However, the overvaluation of discretionary accruals is more severe than that of non-discretionary accruals, since the likelihood ratio rejects the null hypothesis (Rational Pricing Model) more for DA than for NDA. In addition, the likelihood ratio statistic rejects the hypothesis that the market rationally prices all three earnings components.

Panel B presents that the likelihood ratio statistics reject the rational pricing model (null hypothesis) of DA and NDA. We could observe that, firms with crash risk have a higher likelihood ratio in the three factors of earnings than those without crash risk. This means that the crash risk group has more severe mispricing problems compared to the non-crash risk group, implying the valuation theory perspective of stock crash risk.

The marginal response of stock prices to unexpected earnings declines as the absolute magnitude of unexpected earnings increases (Freeman and Tse 1992). For extreme negative earnings, the stock price may underreact to the extreme earnings announcement. In addition, this would lead to an overvaluation of stocks due to both under-reaction to current earnings news (under-valuation of cash flow components) and anchoring of too much attention on previous earnings announcement last year (over-valuation of accruals, especially for non-discretionary components). For firms with extreme earnings information, their marginal earnings-return curve is more curved than that of firms with normal earnings announcements. Hence, we first want to see whether there is a correlation among the extreme earnings announcements, cash flow, discretionary accruals and non-discretionary accruals.

V. Additional Analysis

5.1 Earnings and Sales after Crash Risk

The existing literature has emphasized the determinants of individual stock crash risk, but the results of crash risk are not under careful analysis. If the investors ignore the earnings information that has been passed to the market through the extreme earnings, and once it is realized, it would lead to a crash risk. We want to investigate whether a crash risk is associated with succeeding negative earnings or negative return, or whether it would bring a red flag to the market, so that the price becomes more informative after the crash risk. Better information can bring the future forwards into current returns, and the measurement of Future ERC framework could shed light on it. The stock crash risk could be associated with the current earnings and earnings characteristics, such as income smoothing and earnings quality (Tucker and Zarowin 2006). Other studies have also documented a higher FERC for firms with higher earnings quality, such as audit quality (Lee et al. 2007) and financial statement comparability (Choi et al. 2014).

If the valuation hypothesis holds, investors underreact to the extreme earnings news in the past, and the noisiness of the stock price should be relatively high before the crash. While after the crash risk, the investors should be more aware of the earnings news, given the information environment of the stock; the investors should pay more attention to the earnings, hence lesser noise in the price, or an increase in informativeness of the stock, and individual future ERC should have increased. We hence investigate the long-term return-earnings relationship and noisiness of prices after the stock crash.

[Insert table 11 here]

VI. Conclusion

This study examines the relation between Earnings Response Coefficient (ERC) and stock price crash risk. Given the importance of earnings to the market, investors may have misevaluated different components of earnings, such as accrual persistence, growth opportunities, etc. With a higher ERC, investors may have misvalued the persistence of earnings and growth opportunities, while they do not realize the firm's idiosyncratic risk. Thus, we predict that the future stock price crash risk increases with a higher ERC. Moreover, after controlling for the growth rate of individual firms, we still find that ERC is positively related to future crash risk, which reinforces the different channels that cause crash risk other than the traditional hypothesis, such as bad news hoarding and default risk.

Using a sample of U.S. public firms from 1988 through 2017, we show that a higher ERC leads to an increase in future crash risk. The impact of ERC is above and beyond the prevailing bad news hoarding hypothesis. These results hold after controlling for earnings growth, and other determinants of extreme stock prices declines. These results are also robust to a battery of sensitivity analyses. In addition, we find that the future ERC increases after the firm experienced a crash, indicating that the stock price becomes more informative after the crash. Moreover, we find that the association between accrual opacity and crash risk is more due to the identification and decomposition of accruals, bringing us more attention to the effect of model specification choices and firm growth on testing crash risk. Together, our results indicate that a higher ERC leads to higher crash risk, which is the dark side of ERC. Our study provides the first evidence of a severe consequence of a higher ERC, in contrast to accruals opacity, in the equity market.

Appendix

Appendix A: Variable definitions

Variable	Definition
1. Dependent Variables	
CRASH	An indicator variable that takes the value of 1 for a firm-year that experiences one or more firm-specific weekly returns

	falling 3.09 standard deviations below the mean firm-specific weekly returns over the fiscal year t, with 3.09 chosen to generate frequencies of 0.1% in the normal distribution during the fiscal year t, and zero otherwise.
NCSKEW	The negative skewness of firm-specific weekly returns over the fiscal year period. It is equal to the negative of the third moment of firm-specific weekly returns during a fiscal year, weighted by the standard deviation of firm-specific weekly returns raised to the third power.
DUVOL	The natural logarithm of the standard deviation ratio of down weeks to that of up weeks

2. Test Variables

ERC	The slope coefficient of the regression $CAR_{it} = a + b\,UX_{it} + \varepsilon_{it}$
ERC_RANK	The standardized rank of *ERC* by year over all the firms in the sample
EP ratio	The annual earnings of a stock per share at a given year divided into its price per share. It is the inverse of the price-earnings ratio (P/E ratio).

EP ratio_RANK	The standardized rank of *EP ratio* by year over all the firms in the sample

3. Control Variables

OPACITY	The prior three years' moving sum of the absolute values of discretionary accruals, where discretionary accruals are estimated from the modified Jones model (denoted *OPAQUE* in Hutton et al. (2009))
OPACITY_sq	The performance-adjusted *ACCOPQ* estimated by controlling for current firm performance, measured by net income scaled by total assets
DTURN	The average monthly share turnover in the current fiscal year minus the average monthly share turnover in the last fiscal year, where monthly share turnover equals the monthly trading volume divided by the total number of shares outstanding during that month
SIGMA	Standard deviation of firm-specific weekly returns over the fiscal year
RET	The mean of firm-specific weekly returns over the fiscal year, multiplied by 100

SIZE	Log of market value of equity
MB	Market value of equity divided by book value of equity
LEV	Total long-term debts divided by total assets
ROA	Income before extraordinary items divided by lagged total assets

4. Earnings Partitioning Variables and Growth Variables

OCF	Operating Cash Flow of firm i in year t.
TA	Total Assets of firm i in year t
Sales	Sales of firm i in year t
PPE	Property, Plant and equipment for firm i in year t
ACC	Total Accruals of firm i in year t, measured by earnings minus cash flow
DAC	Discretionary Accruals of firm i in year t, calculated using the modified Jones model (Dechow et al. 1995), estimated by the following cross-sectional regression equation using firms in each Fama and French industry for each fiscal year between 1988 and 2017:

$ACC_{it}/TA_{it-1} = \alpha_0/\ TA_{it-1} + \beta 1{*}\Delta Sales_{it}/TA_{it-1} + \beta 2{*}PPE_{it}/TA_{it-1} + \varepsilon_{it}$

$DAC_{it} = ACC_{it}/TA_{it-1} – (\alpha_0/\ TA_{it-1} + \beta 1{*}\Delta Sales_{it} - \Delta receivables\ _{it}/TA_{it-1} + \beta 2{*}PPE_{it}/TA_{it-1})$

NDAC Non-Discretionary Accruals of firm i in year t, calculated using the modified Jones model (Dechow et al. 1995), estimated by the following cross-sectional regression equation using firms in each Fama French industry for each fiscal year between 1988 and 2017

$ACC_{it}/TA_{it-1} = \alpha_0/\ TA_{it-1} + \beta 1{*}\Delta Sales_{it}/TA_{it-1} + \beta 2{*}PPE_{it}/TA_{it-1} + \varepsilon_{it}$

$VDAC_{it} = \alpha_0/\ TA_{it-1} + \beta 1{*}\Delta Sales_{it} - \Delta receivables\ _{it}/TA_{it-1} + \beta 2{*}PPE_{it}/TA_{it-1}$

GROWTH

5. Other Variables

ANN_RET	The buy-and-hold returns for the 12-month period starting three months after fiscal year end of year t-1
CAR	
TIME	The number of years since 1992
DOWN	The number of crash weeks during the fiscal year, where crash week is defined as firm-specific weekly returns falling 3.09 standard deviations below the mean firm-specific weekly returns over the fiscal year
COUNT	The number of crash weeks during the fiscal year minus the number of jump weeks during the fiscal year
OCF_RESTATE	An indicator variable that takes the value of 1 for a firm-year that experiences one or more OCF restatement, and zero otherwise.
JUMP	An indicator variable that takes the value of 1 for a firm-year that experiences one or more firm-specific weekly returns rising 3.09 standard deviations above the mean firm-specific weekly returns over the fiscal year t
LRETR	The long-run cash effective tax rate, measured following Kim, Li, and Zhang (2011b) as the sum of income tax paid over the

	previous five years divided by the sum of a firm's pre-tax income less special items
CSCORE	Conditional conservatism, measured following Khan and Watts (2009)
OPT_INC	The incentive ratio of CFO option holdings, measured following Kim et al. (2005a) as *ONEPCT_OPT/ (ONEPCT_OPT* + *SALARY* + *BONUS),* where *ONEPCT_OPT* is the dollar change in the value of CFO option holdings resulting from a one percent increase in the firm's stock price
STK_INC	The incentive ratio of CFO stock holdings, measured following Kim et al. (2005a) as *ONEPCT_STK/(ONEPCT_STK* + *SALARY* + *BONUS),* where *ONEPCT_STK* is the dollar change in the value of CFO stock holdings resulting from a one percent increase in the firm's stock price
BONUS	CFO bonus divided by salary
SP1500	An indicator variable that takes the value of 1 for a firm that is in the S&P 1500 index, and zero otherwise

Tables and Graphs:

Table 1: Crash Frequency

Table 1 reports the frequency of firm-specific crashes for 151,765 firm-years in the sample period 1988-2017. Crashes and jumps are defined based on residuals from an expanded index model regression with market returns as explanatory variables. Weekly firm-specific residual returns that are 3.09 standard derivations below the mean for the firm-year are categorized as crashes.

Crashes in the firm-year	Number of observations	Percentage of Sample
0	128232	82.3
1	23532	16.5
2	368	0.45
3	1	0
Total	151,765	

Graph 1: Mean weekly return to market index and percentage of crashes in the sample observations

The graph represents adjusted magnitudes of weekly returns and percentage of crash risk in the year-wise sample. Blue bars represent the mean cross-sectional weekly returns of the market index, while red bars represent the percentage of firms in the year which experience a crash.

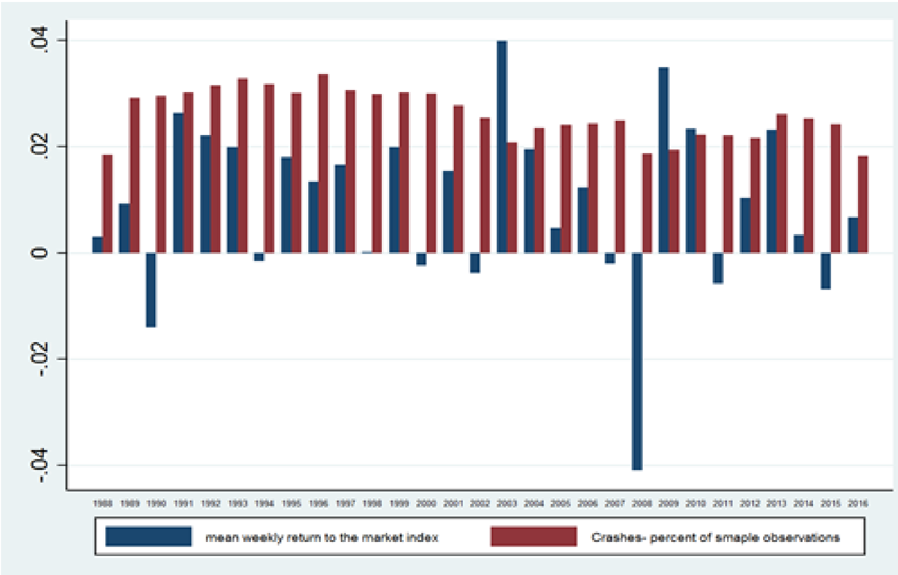
.04
.02
0
-.02
-.04
1988 1989 1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
mean weekly return to the market index
Crashes- percent of smaple observations

Table 2: Descriptive Statistics and Key variables of control

The following table covers 154,029 firm-years in the sample period 1988-2016. Panel A gives the basic descriptive statistics of them. Panel B presents the correlation tables among the key variables of interest. Panel C displays the mean value of selected values for deciles based on Earnings magnitude

Panel A. Descriptive Statistics

Variable	Q1	Mean	Median	Q3	Standard deviation
Return(RET)	0.183	0.617	24.89	-0.95	0.617
Net income (NI)	0.053	0.096	0.659	-0.788	0.096
Operating cash flow (OCF)	0.088	0.12	0.853	-0.786	0.121
Nondiscretionary accruals (NDAC）	-0.031	0.076	0.64	-0.693	0.076
Discretionary accruals (DAC）	-0.004	0.108	0.774	-0.813	0.108
Market Value	61.2	3,157.8	258.0	1,191.5	13,465.5
Opaque	0.102	0.243	0.174	0.302	0.251
StdDev[ln(1+residual)]	0.036	0.058	0.052	0.074	0.043
Kurtosis	0.152	1.672	0.878	2.146	2.730
Skewness	-0.277	0.113	0.134	0.523	0.776
ROE	-0.006	-0.011	0.087	0.155	0.426
Market-to-book	1.321	3.077	2.028	3.453	3.434
Leverage	0.308	0.475	0.484	0.634	0.213
Var (Industry Index)	0.0004	0.0010	0.0007	0.0012	0.0010

Panel B: Correlation matrix among key variables of interest —Pearson (Spearman) Correlations Above (Below) the Diagonal

Variable	NI	CF	ACC	DAC	NDAC
NI		0.52	0.46	0.43	0.16
CF	0.5		-0.52	-0.43	-0.28
ACC	0.33	-0.55		0.88	0.46
DAC	0.26	-0.46	0.82		-0.02
NDAC	0.18	-0.28	0.47	-0.03	

Panel C: Mean Values of Selected Characteristics for Deciles based on Earnings

Earnings	Low	2	3	4	5	6	7	8	9	High
NDAC	-0.22	-0.12	-0.09	-0.07	-0.05	-0.03	-0.02	0.01	0.05	0.15
DAC	-0.14	-0.14	-0.12	-0.11	-0.1	0.08	0.07	0.12	0.15	0.26
OCF	-0.09	-0.04	-0.02	-0.01	0.12	0.14	0.16	0.19	0.33	0.63
CRASH	0.145	0.145	0.163	0.168	0.173	0.182	0.181	0.179	0.171	0.170
OPACITY	0.146	0.127	0.118	0.123	0.137	0.151	0.172	0.205	0.241	0.299
Skewness	-0.092	-0.069	-0.006	0.003	0.006	0.031	0.021	0.019	-0.023	-0.028

Table 3: Mean value opacity, squared opacity and crash risk grouped by ERC rank

The table provides the mean value of crash risk proxies, CRASH, NCSKEW and DUVOL and mean value of earnings opacity and earnings opacity squared terms defined in Hutton et al. (2009). The definitions of all these variables could be found in Appendix A. Observations use year-wise ERC rank among all the sample firms.

Rank_ERC_20	OPACITY	$OPACITY^2$	NCSKEW	DUVOL	CRASH
1	0.112	0.031	-0.052	-0.011	0.142
2	0.113	0.030	-0.033	-0.039	0.152
3	0.111	0.030	-0.089	-0.029	0.152
4	0.113	0.027	-0.049	-0.012	0.161
5	0.119	0.026	-0.013	-0.000	0.163
6	0.117	0.025	-0.001	0.001	0.161
7	0.119	0.025	0.006	0.004	0.164
8	0.129	0.029	0.001	0.001	0.172
9	0.135	0.031	0.016	0.006	0.173
10	0.128	0.032	0.030	0.001	0.172
11	0.144	0.034	0.034	0.012	0.171
12	0.158	0.041	0.026	0.010	0.172
13	0.145	0.043	0.021	0.006	0.174
14	0.131	0.032	0.019	0.007	0.177
15	0.135	0.059	0.017	0.010	0.178
16	0.132	0.072	0.021	0.014	0.178
17	0.127	0.087	0.012	0.007	0.179

18	0.145	0.091	0.033	0.009	0.178
19	0.167	0.107	0.017	0.027	0.179
20	0.132	0.159	0.040	0.049	0.179
Total	0.144	0.053	-0.008	0.003	0.169

Table 4. Logit regression of Crash Risk on earnings opacity and EP ratio

In this table, Logit regression is used to explain crash risk. The dependent variable CRASH is an indicator variable equal to one if within its fiscal year a firm experiences one or more firm-specific weekly returns falling 3.09 or more standard deviations below the mean firm-specific weekly return for its fiscal year, and zero otherwise.

CRASH	Coef.	Marginal effect dy/dx	Std. Err.	z	P>z
OPACITY	0.2331	0.0302	0.965841	0.24	0.809
$OPACITY^2$	-0.3613	-0.0467	1.513977	-0.24	0.811
EP $ratio_{t-1}$	-0.7399	-0.0958	0.029935	-4.47	0.000
$SIZE_{t-1}$	0.0438	0.0058	0.020346	1.25	0.211
MB_{t-1}	-4.3E-05	-0.0005	0.002245	-0.02	0.985
LEV_{t-1}	-0.3251	-0.0421	0.255841	-1.27	0.204
ROA_{t-1}	0.0524	0.0069	0.133341	0.39	0.694
cons	-1.8891	-	0.175622	-10.76	0

Table 5: Logit Regression of Crash risk on ERC and lagged ERC.

In this table, Logit regression is used to explain crash risk. The dependent variable CRASH is an indicator variable equal to one if within its fiscal year a firm experiences one or more firm-specific weekly returns falling 3.09 or more standard deviations below the mean firm-specific weekly return for its fiscal year, and zero otherwise. Besides the control variables which appear in Hutton et al. (2009), one-year and two-year lagged ERC ranks have been included in the regression.

crash	Coef.	Std. Err.	z	P>z
$Rank\_ERC_{t-1}$	.00004	.00002	2.55	0.011
$Rank\_ERC_{t-2}$	-0.4180	0.2135	-2.63	0.009
OPACITY	0.4201	0.1597	0.54	0.592
$OPACITY^2$	-0.5954	0.2245	-0.80	0.425
MB_{t-1}	-0.00006	0.0001	-0.65	0.518
LEV_{t-1}	-0.0236	0.0369	-0.64	0.522
$SIZE_{t-1}$	0.0351	0.0039	8.89	0.000
ROA_{t-1}	-0.0165	0.0179	-0.92	0.360
cons	-1.7907	0.0349	-51.24	0.000

Table 6: OLS regression on rank ERC, EP ratio and other control variables (Granger Causality Test)

In this table, Ordinary Least Squares (OLS) regression is used to explain crash risk. The dependent variable NCSKEW is the negative skewness of firm-specific weekly returns over the fiscal year period. It is equal to the negative of the third moment of firm-specific weekly returns during a fiscal year, weighted by the standard deviation of firm-specific weekly returns raised to the third power. Definitions of other variables could be found in Appendix A.

Panel A:

NCSKEW	Coef.	Std. Err.	t	P>t
ERC_rank_{t-1}	0.925	1.229	7.52	0.000
EP $ratio_{t-1}$	-0.812	1.663	-4.88	0.000
$SIZE_{t-1}$	-0.659	1.953	-33.75	0.000
MB_{t-1}	-0.124	0.029	-4.26	0.000
LEV_{t-1}	0.179	3.17	5.66	0.000
ROA_{t-1}	-0.452	1.705	-2.65	0.008
_cons	3.289	1.202	273.61	0.000

Panel B:

ERC_rank	Coef.	Std. Err.	t	P>t
$NCSKEW_{t-1}$	9.75E-07	1.31E-06	0.75	0.456
EP $ratio_{t-1}$	0.217	0.831	2.61	0.009
$SIZE_{t-1}$	0.029	0.098	29.26	0
MB_{t-1}	0.0092	0.00145	0.07	0.946
LEV_{t-1}	0.001489	0.001765	0.84	0.399

ROA_{t-1}	0.022203	0.008591	2.58	0.01
_cons	-0.17183	0.007302	-23.53	0

Table 7: The impact of growth of ERC and crash risk

In this table, Ordinary Least Squares (OLS) regression is used to explain crash risk. The dependent variable NCSKEW is the negative skewness of firm-specific weekly returns over the fiscal year period. It is equal to the negative of the third moment of firm-specific weekly returns during a fiscal year, weighted by the standard deviation of firm-specific weekly returns raised to the third power. ERC Growth Component is the OLS estimation of one-year lagged sales growth in explaining the ERC of time t. Similarly, ERC residual is the OLS estimated residual of the parts of ERC that could not be predicted by one-year lagged sales growth. Definitions of other variables could be found in Appendix A.

NCSKEW	Coef.	Std. Err.	t	P>t
ERC Growth Component $_{t-1}$	0.0155	2.98E-03	5.19	0
EP ratio$_{t-1}$	0.002675	0.000839	3.19	0.001
SIZE$_{t-1}$	0.032528	0.00106	30.68	0
MB$_{t-1}$	-9.87E-06	1.68E-05	-0.59	0.557
LEV$_{t-1}$	0.023855	0.011552	2.06	0.039
ROA$_{t-1}$	-0.00817	0.004221	-1.93	0.053
_cons	-0.19194	0.006718	-28.57	0

NCSKEW	Coef.	Std. Err.	t	P>t
ERC Growth Residual $_{t-1}$	6.08E-06	4.21E-06	2.45	0.008
EP ratio$_{t-1}$	0.002146	0.000837	2.57	0.01
SIZE$_{t-1}$	0.031124	0.001028	30.29	0
MB$_{t-1}$	2.37E-06	1.49E-05	0.16	0.874
LEV$_{t-1}$	0.029374	0.009813	2.99	0.003
ROA$_{t-1}$	0.001775	0.001763	1.01	0.314

_cons	-0.18732	0.006378	-29.37	0

Table 8: Correlation among current year, year before and two years before discretionary accruals

In this table, correlations are computed for the sample period 1988-2017. The left panel of the table contains firm-year observations which encountered a crash while the right panel of the table contains firm-year observations which did not encounter a crash. Pearson correlations are above the diagonal and spearman correlations below the diagonal. See Appendix A for variable definitions.

	CRASH=1				CRASH=0		
	DAC_{t-3}	DAC_{t-2}	DAC_{t-1}		DAC_{t-3}	DAC_{t-2}	DAC_{t-1}
DAC_{t-3}		0.569***	0.675***	DAC_{t-3}		-0.090	0.029
DAC_{t-2}	0.827***		0.754***	DAC_{t-2}	-0.124*		-0.096
DAC_{t-1}	0.632***	0.846***		DAC_{t-1}	0.035	-0.043	

Table 9: Mishkin Test for Different Components of Accruals, Decomposed Using Method by Modified Jones Model

This table present the Mishkin test for rational pricing by the market of different components of earnings, i.e., operational cash flow, non-discretionary accruals and discretionary accruals. In panel A, two OLS regressions have been run separately,

Forecasting Model: Earnings $_{t+1}$= γ_0+γ_1NDA $_t$+γ_2 DA$_t$+ γ3 OCF$_t$+ ν_{t+1}
(10)

Valuation Model: Abnormal Returns $_{t+1}$= β (Earnings$_{t+1}$-γ0-γ1* NDA$_t$-γ2* DA$_t$ – γ3*OCF$_t$) + ε_{t+1}
(11)

Panel B is to test whether the two models are of the same specification. The likelihood ratio is reported in Panel B for different null hypotheses.

Panel A: Market pricing of earnings components with respect to their implications for one-year ahead earnings

Forecasting Coefficients			**Valuation Coefficient**		
Parameter	**Estimation**	**Asy Std Error**	**Parameter**	**Estimation**	**Asy Std Error**
Group 1: High Crash Risk					
γ1 OCF	0.45	0.004	γ1 OCF	0.39	0.005
γ2 NDA	0.38	0.007	γ2 NDA	0.42	0.002
γ3 DA	0.64	0.005	γ3 DA	0.76	0.003
Group 2: Low Crash Risk					
γ1 OCF	0.56	0.013	γ1 OCF	0.51	0.009
γ2 NDA	0.46	0.024	γ2 NDA	0.54	0.031
γ3 DA	0.54	0.018	γ3 DA	0.58	0.026

Panel B: Test of Rational Pricing of Earnings Components

Group 1: Lower crash risk

Null Hypotheses	likelihood ratio statistic	P-value
OCF: γ_1=γ_1*	23.11	0.0000
DA: γ_2=γ_2*	11.21	0.0000

NDA: $\gamma_3=\gamma_3^*$	47.23	0.0000
DA,NDA: $\gamma_2=\gamma_3$ and $\gamma_2^*=\gamma_3^*$	177.28	0.0000
OCF,DA and NDA $\gamma_1=\gamma_1^*$, $\gamma_2=\gamma_2^*$ and $\gamma_3=\gamma_3^*$	221.32	0.0000

Group 2: Higher crash risk

Null Hypotheses	likelihood ratio statistic	P-value
OCF: $\gamma_1=\gamma_1^*$	34.11	0.0000
DA: $\gamma_2=\gamma_2^*$	32.21	0.0000
NDA: $\gamma_3=\gamma_3^*$	47.23	0.0000
DA,NDA: $\gamma_2=\gamma_3$ and $\gamma_2^*=\gamma_3^*$	147.28	0.0000
OCF,DA and NDA $\gamma_1=\gamma_1^*$, $\gamma_2=\gamma_2^*$ and $\gamma_3=\gamma_3^*$	421.32	0.0000

Table 10: Mishkin Test for Different Components of Accruals, Decomposed Using Method by Dechow and Dichev (2002)

This table present the Mishkin test for rational pricing by the market of different components of earnings, i.e., operational cash flow, non-discretionary accruals and discretionary accruals. In panel A, two OLS regressions have been run separately,

Forecasting Model: Earnings t+1= γ’0+γ’1 Good Accruals t+γ’2 Accruals Estimation Errors t+ γ’3 Cash Flow t+ ν’t+1
(10)

Valuation Model: Abnormal returns t+1= β’ (Earningst+1-γ’0-γ’1* Good Accrualst-γ’2* Accruals Estimation Errors t – γ’3*Cash Flowt)+ εt+1
(11)

Panel B is to test whether the two models are of the same specification. The likelihood ratio is reported in Panel B for different null hypotheses.

Panel A: Market pricing of earnings components with respect to their implications for one-year ahead earnings

Forecasting Coefficients			Valuation Coefficient		
Parameter	**Estimation**	**Asy Std Error**	**Parameter**	**Estimation**	**Asy Std Error**
Group 1: High Crash Risk					
γ_1 OCF	0.65	0.012	γ_1*OCF	0.53	0.013
γ_2 Sales Growth	0.28	0.007	γ_2* Sales Growth	0.32	0.024
γ_3Empy Growth	0.15	0.008	γ_3*Empy Growth	0.19	0.018
γ_4 Error term	0.57	0.005	γ_4* Error term	0.79	0.062

Group 2: Low Crash Risk

γ_1 OCF	0.49	0.013	γ_1*OCF	0.41	0.009
γ_2 Sales Growth	0.22	0.024	γ_2* Sales Growth	0.27	0.031
γ_3Empy Growth	0.13	0.014	γ_3*Empy Growth	0.15	0.026
γ_4 Error term	0.41	0.022	γ_4* Error term	0.47	0.083

Panel B: Test of Rational Pricing of Earnings Components

Group 1: Lower crash risk

Null Hypotheses	likelihood ratio statistic	P-value
OCF: $\gamma_1=\gamma_1^*$	23.11	0.0000
Sales Growth: $\gamma_2=\gamma_2^*$	11.21	0.0000
Empy Growth: $\gamma_3=\gamma_3^*$	47.23	0.0000
Sale Growth & Empy Growth: $\gamma_2=\gamma_3$ and $\gamma_2^*=\gamma_3^*$	177.28	0.0000
OCF, Sale Growth & Empy Growth $\gamma_1=\gamma_1^*$, $\gamma_2=\gamma_2^*$ and $\gamma_3=\gamma_3^*$	221.32	0.0000

Group 2: Higher crash risk

Null Hypotheses	likelihood ratio statistic	P-value
OCF: $\gamma_1=\gamma_1$*	34.11	0.0000
Sales Growth: $\gamma_2=\gamma_2$*	32.21	0.0000
Empy Growth: $\gamma_3=\gamma_3$*	47.23	0.0000
Sale Growth & Empy Growth: $\gamma_2=\gamma_3$ and γ_2*$=\gamma_3$*	147.28	0.0000
OCF, Sale Growth & Empy Growth $\gamma_1=\gamma_1$*, $\gamma_2=\gamma_2$* and $\gamma_3=\gamma_3$*	421.32	0.0000

Table 11 Sales and Earnings after Stock Crash Risk

The table presents the impact of stock crash risk on prediction of negative sales and negative earnings in the future. Two different OLS regressions are conducted where subsamples of negative sales and negative earnings are taken from the whole sample. Crash is a dummy variable, as defined in Appendix A. Definitions of other control variables could also be found in Appendix A.

Panel A: Negative Sales

Negative $Sales_t$	Coef.	Std. Err.	z	P>z
$CRASH_{t-1}$	0.1653	0.0733	3.25	0.000
$Earnings_{t-1}$	-0.0003	0.0014	-2.2	0.028
$SIZE_{t-1}$	-0.0755	0.0141	-5.33	0.000
MB_{t-1}	-0.0008	0.0001	-0.45	0.654
LEV_{t-1}	0.0322	0.0408	0.79	0.430

ROA_{t-1}	-0.0597	0.0194	-3.07	0.002
_cons	-2.9232	0.0721	-40.57	0.000

Panel B: Negative Earnings

Negative $Earnings_t$	Coef.	Std. Err.	z	P>z
$CRASH_{t-1}$	0.1472	0.0334	3.41	0.000
$SALES_{t-1}$	-0.0034	0.0013	-2.26	0.024
$SIZE_{t-1}$	-0.0781	0.0142	-5.48	0.000
MB_{t-1}	-0.0008	0.00010	-0.43	0.666
LEV_{t-1}	0.0312	0.0399	0.78	0.434
ROA_{t-1}	-0.0781	0.0222	-3.51	0.000
_cons	-2.8796	0.0694	-41.47	0.000

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