

# Earnings quality and crash risk in China: an integrated analysis

Earnings  
quality and  
crash risk in  
China

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## Abstract

**Purpose** – The authors provide a comprehensive empirical examination on the impact of earnings quality on stock price crash risk in China.

**Design/methodology/approach** – The authors acknowledge and distinguish two-dimensional proxies for earnings quality – accounting-based (earnings management degree) and market-based (earnings transparency) known in accounting and finance literature.

**Findings** – The authors find that both generally indicate that better earnings quality is associated with less crashes. However, extremely high earnings transparency interacted with insider trading profit can also actually exacerbate stock price crashes.

**Originality/value** – This study is the first to highlight the pertinence of accounting-based measures to proxy for earnings quality in a fast-growing emerging market environment such as China.

**Keywords** Stock price crash risk, Earnings quality, China

**Paper type** Research paper

## 1. Introduction

The stock market crash in China started on 12<sup>th</sup> June 2015 and lasted until early February 2016 and has caused its market capitalization to reduce by one-third in a short period of time. This has received tremendous amount of coverages from media and news around the world. Although it is unclear about the main cause of the crash, it has been largely agreed among all market participants that paying more careful attention to listed companies' fundamentals is one way to improve sustainability in the Chinese stock market going forward.

One of the primary pieces of information that investors can observe regarding a firm's prospect/fundamental is its earnings. Francis *et al.* (2004), for example, emphasize that investors

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pay more attention to earnings information than other indicators such as dividends, cash flow and others. Nevertheless, finance literature suggests that selective information disclosure by insiders can still lead to misleading earnings numbers and thus the stock price crash in time. [Hutton et al. \(2009\)](#), among others, show that US companies with poor financial disclosure tend to display lower information transparency (e.g. higher stock price synchronicity or  $R^2$ ). This, in turn, increases the probability of stock price crashes for them. In other words, the worse the earnings quality, the higher the stock price crash risk. Whether this phenomenon can be generalized to an emerging market such as China is an important empirical question. There are only few empirical studies examining stock price crash risk in China. The focus, however, has been on factors such as excess perks, social trust (region based), internal control and others (see, e.g. [Xu et al. \(2014\)](#); [Li et al. \(2017\)](#); and [Chen et al. \(2017\)](#)). To the best of our knowledge, there is no comprehensive study that formally examines the impact of earnings quality on stock price crash risk in China. We expect to find a negative relation between earnings quality and crash risk in China. As suggested by [Hutton et al. \(2009\)](#), managers from firms with poor earnings quality are more likely to hide firm-specific information (in particular, unfavorable information). When the information cannot be withheld anymore, the information will be released to the market all at once, causing the firms to face a higher probability of extreme outcomes.

Researchers acknowledge two main aspects in constructing the measures of earnings quality. The first one is “earnings management degree.” It verifies whether earnings are measured and disclosed in accordance with the provisions of the accounting guidelines. In other words, it directly addresses whether the reported earnings number is manipulated with subjective judgment by management. The other one is “earnings transparency.” This latter method is also called the value relevance level of earnings information as it observes the linkage between reported earnings information and stock returns. It also reflects investor’s trust in the earnings information announced to the public. Theoretically, both measures are important in reflecting the quality of a company’s earnings. However, whether these approaches/metrics are appropriate in predicting stock price crashes in an emerging financial market, such as China, remains an open question.

The impact of earnings quality on stock price crashes in China is particularly important to investigate. While the growing importance/potential of Chinese stocks in international portfolio context is evident, China’s trading environment still experiences problems as would any financial market in the immature stage. Deeper knowledge of the stock market price movement dynamics (especially around its extreme downturns) provides investors with protection that is more sustainable than relying on occasional interventions from the authority [1].

Studying all valid A-share listed sample companies in both Shanghai and Shenzhen (largely perceived as China’s Nasdaq) exchanges during the 2006–2013 period, we find that earnings quality decreases stock price crash risk in China. This finding is consistent for both earnings manipulation (estimation of earnings management degree through discretionary accruals as per the modified [Jones \(1991\)](#) model) and earnings transparency (explanatory power of earnings numbers on stock returns as per [Barth et al. \(2013\)](#) model) metrics. Specifically, our results uncover a positive relation between earnings management degree and crash risk and a negative relation between earnings transparency and crash risk.

While the aforementioned results appear to be largely consistent with previous studies in developed markets, we find that earnings transparency may not be a reliable indicator of earnings quality in the Chinese context [2]. Several studies point to the severity of agency problems among Chinese corporations. For example, [Xu et al. \(2014\)](#) show that perk (fringe benefits) consumptions among Chinese managers of state-owned enterprises (SOEs), in conjunction with earnings management, significantly increase stock price crash risk. [Cao et al. \(2016\)](#) find that lack of social trust is a determinant of crash risk in low social trust provinces in China: firms in provinces with lower social trust are more likely to hide bad news and thus experience higher crash risk. [Zhang and Nam \(2016\)](#) note that excessive information

transparency in China can actually lead to higher stock price crash risk. In other words, as an “indirect” earnings quality indicator from the information user’s perspective rather than the accounting data itself, high earnings transparency could also indicate the insufficiency of nonearnings information in the public. For example, it is possible that insiders, knowing that individual investors follow their released earnings numbers blindly, manipulate stock prices for their own personal benefits. This leads to a seemingly high earnings transparency that actually does not reflect the true prospects of a firm in a timely manner. Higher crash risk follows ultimately as a result. To explore this possibility, we investigate the impact of extreme earnings transparency on crash risks conditional on high insider trading profit. Our findings confirm this conjecture. Specifically, crash risk increases with extreme earnings transparency when interacted with the intensity of insiders’ profits.

Our research contributes to the existing literature in two ways. Firstly, despite China’s increasingly prominent role in the global stock markets, existing literature of stock price crash risk in Chinese stock market is sparse. We add to the existing literature by establishing the relation between earnings quality and crash risk in China. Secondly, our findings indicate that earnings management and earning transparency are not completely interchangeable in measuring earnings quality in an emerging market such as China. Contrary to the prior studies of developed markets, our results suggest that high earnings transparency is not necessarily associated with better earnings quality and lower crash risk. Extremely high earnings transparency can exacerbate the crash risk among Chinese firms. This is an important finding to future researchers as it indicates that caution should be exercised when measuring earnings quality by earnings transparency in the Chinese context.

The remainder of this paper is organized as follows: [Section 2](#) reviews related literature and develops our hypotheses. [Section 3](#) describes data and methodology, and [Section 4](#) presents empirical results. [Section 5](#) concludes.

## 2. Literature review and hypothesis development

### 2.1 Two dimensions of earnings quality measures

Researchers in finance and accounting have classified earnings quality measures into two broad types of metrics, the degree of earnings management and earnings transparency. Earnings management measures are mainly based on the accrued total profit method designed to reflect the various accrued profit manipulation behaviors of listed companies. [Healy \(1985\)](#) first divides the accruals in the report into parts that can be manipulated and cannot be manipulated. Because the earnings are equal to the accrued items amount plus the cash flow of operating activities (CFO), the degree to which the measurable items are manipulated can reflect the quality of the reported earnings numbers. Expanding on this principle, [Jones \(1991\)](#) obtains nondiscretionary earnings by calculating the amount of earnings corresponding to the nondiscretionary items. [Dechow et al. \(1995\)](#) later consider the impact of accounts receivable on total sales when measuring nondiscretionary accruals and propose the famous modified Jones model.

Other literature argues that a better measure of earnings quality should state how reported earnings numbers are captured by investors in the stock market, which is known as the earnings transparency. [Barth \(2003\)](#) formally examines earnings transparency as the explanatory power of earnings to changes in the company’s economic value. [Francis et al. \(2004\)](#) construct a regression model with current earnings, current earnings changes and stock returns. The  $R^2$  from these regression models is used as a proxy for earnings transparency. The larger the  $R^2$  value obtained by the regression, the higher the earnings transparency (and thus better earnings quality). In a similar vein, [Barth et al. \(2013\)](#) develop a more rigorous and popular model using  $R^2$  from the regression of the earnings and stock returns as the explanatory power of earnings information to the company’s value (the extent of earnings transparency) while taking into account the industry effect.

## 2.2 Earnings quality and stock price crash risk

The undesirable stock price crash happens when the following characteristics appear for a certain stock. First, the stock price volatility is excess and unpredictable without supports from formal information regarding firms' fundamentals available in the public. Second, the probability of negative stock volatility is disproportionately greater than the probability of positive volatility (asymmetric tendency of losses in the investment). In the worst scenario, the risk of individual stock price crash may spread to the entire capital market (Hong and Stein, 2003) as observed in the midyear of 2015 for the Chinese stock market.

Regarding stock price crash risk metrics, Chen *et al.* (2001) employ Negative Coefficient of Skewness (NCSKEW) and Down-to-Up Volatility (DUVOL) as proxies of stock price collapse risk. Building on the work of Chen *et al.* (2001); Kim *et al.* (2011a, b); Kim *et al.* (2014); Kim and Zhang (2014) and Xu *et al.* (2014), improve the method by replacing  $R_{i,t}$  with  $W_{i,t}$  and calculating the values of NCSKEW and DUVOL. Hutton *et al.* (2009), on the other hand, define "Crash" as a binary variable. It is 1 if the stock encounters at least one stock crash in the year; and 0 otherwise. The definition of the stock price collapse week is defined as the stock-specific weekly yield ( $W_{i,t}$ ) of the week less than the mean value of the stock's specific weekly yield minus 3.09 times the standard deviation. In the normal distribution, 3.09 standard deviations are at the 0.1% boundary of the entire distribution, where the stock returns are extremely abnormal and the stock price collapse is likely to occur. Kim *et al.* (2011a, b) change the 3.09 standard deviation to 3.2 to obtain a more stringent stock price crash risk indicator.

In literature, earnings quality is one of the forefront factors proposed to explain the stock price crash risk [3]. Hutton *et al.* (2009) study the role of opaque financial reporting on information transparency (proxied by stock price synchronicity) and thus stock price crash risk. The results show that if a company reduces the transparency in its financial reporting, the company's related news dissemination efficiency will be low (e.g. higher  $R^2$ ). The lack of such price informativeness causes the stock price to be overestimated. Over time, this leads to higher probability of stock price crashes. Moreover, Kim *et al.* (2011b) and Benmelech *et al.* (2010) argue that CEOs have incentives to hide bad news for the company's long-term development. The rising stock prices may lead to excessive overinvestment and overvaluation, leading to subsequent stock price collapses. Studying a large sample of the US stocks from 1964 to 2007, Kim and Zhang (2016) arrive at the same conclusion that the company's accounting conservatism (e.g. less earnings manipulation) is negatively correlated with future stock price crash risks. The findings are more prominent for firms with more severe asymmetric information problem. Francis *et al.* (2016) find that earnings management significantly increases the risk of stock price collapse as it is a common means for insiders to maximize their self-interests. Using 2008 financial crisis as an exogenous shock to the overall trust in the capital market, Da Silva (2019) documents that precrisis earnings quality is an important determinant of abnormal crash risk.

Existing literature studying crash risk in China is limited. Xu *et al.* (2014) show that Chinese SOEs with higher excess perks are more prone to stock price crashes during the 2003–2010 period. Executives in such SOEs withhold bad news to enhance their ability to enjoy fringe benefits from the company. Focusing on five components of corporate internal control, Chen *et al.* (2017) provide empirical evidence based on listed stocks in both Shanghai and Shenzhen stock exchanges from 2007 to 2012. They find that poor internal control within Chinese listed firms leads to higher probability of crashes. Going beyond the firm-level characteristics/factors, Li and Cai (2016) document the desirable impact of religious environment intensity on crash risk. Specifically, among Chinese listed A-share companies during the 2003–2013 study period, firms that are registered in locations closer to religious activities sites (through Google Earth) experience less stock price crash. In the same vein, Li *et al.* (2017) report that Chinese firms that are headquartered in regions (provincial and city level) of high social trust experience less stock price crash. Also, this finding is stronger among firms with greater state ownership, weaker monitoring and higher risk taking.

Interestingly, all of the aforementioned studies use earnings quality as the underlying channel/mechanism through which their proposed explanatory variables could affect stock price crash risk. In other words, all of the aforementioned studies make an implicit assumption that lower earnings quality (exacerbated by agency issues within Chinese companies) increases stock price crash risk without formally establishing such relation.

Based on the earlier discussion, we propose the following hypotheses:

*H1.* Chinese firms with higher degree of earnings management are associated with higher stock crash risk

*H2.* Chinese firms with higher earnings transparency are associated with lower crash risk

### 3. Data and methodology

Our study covers all Chinese A-share listed companies in both Shanghai and Shenzhen stock exchanges from 2006 to 2013. Same as previous studies that examine stock price crash risk in China, we end our sample period before 2015 to avoid possible irrationalities that took place in the year of the systematic crash. The stock return data, company financial data and insider trading data are all retrieved from the CSMAR (China Stock Market and Accounting Research) database.

Our sample companies are selected following [Chen et al. \(2001\)](#); [Hutton et al. \(2009\)](#) and [Barth et al. \(2013\)](#). Final sample consists of 1,964 companies. Key variables are winsorized at 1% top and bottom.

#### 3.1 Earnings management measure

We draw on the relevant literature as discussed in the previous section and select “the modified Jones model” to estimate the discretionary accruals to measure the company’s earnings management degree. The following regression is conducted in each industry to estimate the relevant regression coefficients  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ :

$$\frac{TA_{i,t}}{A_{i,t-1}} = \alpha_0 + \beta_1 \left( \frac{1}{A_{i,t-1}} \right) + \beta_2 \left( \frac{\Delta REV_{i,t}}{A_{i,t-1}} \right) + \beta_3 \left( \frac{PPE_{i,t}}{A_{i,t-1}} \right) + \varepsilon_{i,t-1} \quad (1)$$

$TA_{i,t}$  is the total accrued profit of the company  $i$  in year  $t$ , which is the difference between the net profit after tax and the cash flow from operating activities;  $\Delta REV_{i,t}$  is the difference of the operating income between the year  $t$  and year  $t-1$  of company  $i$ ;  $PPE_{i,t}$  is the total fixed assets of the company in year  $t$ ;  $A_{i,t-1}$  is the total assets of the company  $i$  in year  $t$ .

Once the regression coefficients ( $\beta_1$ ,  $\beta_2$ ,  $\beta_3$ ) are obtained from the aforementioned regression model (1), we then calculate the company’s discretionary accruals ( $DA_{i,t}$ ) using the following model (2). Notice that  $\beta_1(1/A_{i,t-1}) + \beta_2(\Delta REV_{i,t} - \Delta REC_{i,t}/A_{i,t-1}) + \beta_3(PPE_{i,t}/A_{i,t-1})$  is the modified Jones model following [Hutton et al. \(2009\)](#) and [Dechow et al. \(1995\)](#), which represents nondiscretionary accruals. The inclusion of  $\Delta REC_{i,t}$  is the modification of Jones model.  $\Delta REC_{i,t}$  is the company’s accounts receivable changes between year  $t$  and  $t-1$ . Discretionary accruals can be obtained by subtracting the nondiscretionary accruals from total accruals.

$$DA_{i,t} = \frac{TA_{i,t}}{A_{i,t-1}} - \left( \beta_1 \left( \frac{1}{A_{i,t-1}} \right) + \beta_2 \left( \frac{\Delta REV_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}} \right) + \beta_3 \left( \frac{PPE_{i,t}}{A_{i,t-1}} \right) \right) \quad (2)$$

Following [Huttlon et al. \(2009\)](#), the sum of three lag periods absolute discretionary accruals is finally used to measure the degree of accrued earnings management.

$$AM_{Accrual_{i,t}} = |DA_{i,t}| + |DA_{i,t-1}| + |DA_{i,t-2}| \quad (3)$$

According to the aforementioned, the greater the  $AM_{Accrual}$ , the more likely the company is engaged in earnings management activities (e.g. the lower the earnings quality).

### 3.2 Earnings transparency measure

To measure earnings transparency, we employ the comprehensive approach introduced by [Barth et al. \(2013\)](#) to test our hypothesis. In a nutshell, the measure quantifies the explanatory power of current earnings (and the change of current earnings) on the observed stock returns for a certain firm in a certain year while taking into account the influences of the industry.

It is a two-step method. The first step is to regress the annual stock return of a company in a particular industry on price-scaled annual earnings (and price-scaled change in earnings) as stated in the following equation. In doing so, we have to firstly classify all the sample companies according to the industry (17 of them according to the CSRC (China Securities Regulatory Commission) industry classification in CSMAR database) and construct the industry portfolio. The idea here is to capture the commonality of accounting applications in the industry and thus reflect the heterogeneity between different industries.

The regression is carried out on yearly basis. The adjusted  $R^2$  (one number for each industry each year) estimates obtained from such regressions serve as the transparency measure of the industry earnings, namely  $ETRANS_{i,j,t}$ .

$$RETURN_{i,j,t} = \alpha_0^1 + \alpha_1^1 \left( \frac{E_{i,j,t}}{P_{i,j,t-1}} \right) + \alpha_2^1 \left( \frac{\Delta E_{i,j,t}}{P_{i,j,t-1}} \right) + \varepsilon_{i,j,t} \quad (4)$$

$RETURN_{i,j,t}$  is the annualized rate of return of the industry  $j$  company  $i$  (annualized rate of return calculated from the weekly return data of year  $t$ )

$E_{i,j,t}$  is the net profit of the industry  $j$  company  $i$  after deducting nonrecurring profit and loss (we use the operating profit data in the income statement)

$\Delta E_{i,j,t}$  is the net profit change after deducting nonrecurring gains and losses in industry  $j$  company  $i$ , using  $t$  year operating profit minus  $t-1$  year operating profit

$P_{i,j,t}$  is the year-end market value in year  $t-1$  in industry  $j$  (the market value at the beginning of year  $t$ )

$\varepsilon_{i,j,t}$  is the return residual of the industry  $j$  in year  $t$

The second step is to account for the degree of earnings transparency beyond the industry influence. Based on the “residuals” obtained from the first regression (4), the companies in each industry are sorted from smallest to largest in each year. The quartile cutoffs of the residuals are calculated and used as the benchmark to divide sample companies in each year into four groups [4]. We then combine the top 25% of each industry in the year to construct a combined “portfolio.” Finally, adjusted  $R^2$  from the regression of (5) is  $ETRANS_{i,p,t}$ . It represents the earnings transparency level based on the “portfolio” rankings free of the industry effect.

$$RETURN_{i,p,t} = \alpha_0^1 + \alpha_1^1 \left( \frac{E_{i,p,t}}{P_{i,p,t-1}} \right) + \alpha_2^1 \left( \frac{\Delta E_{i,p,t}}{P_{i,p,t-1}} \right) + \varepsilon_{i,p,t} \quad (5)$$

$RETURN_{i,p,t}$  is the annualized rate of return of the *portfolio*  $p$  company  $i$  (annualized rate of return calculated from the weekly return data of year  $t$ )

$E_{i,p,t}$  is the net profit of the *portfolio*  $p$  company  $i$  after deducting nonrecurring profit and loss (We use the operating profit data in the income statement)

$\Delta E_{i,p,t}$  is the net profit change after deducting nonrecurring gains and losses in *portfolio p* company *i*, using *t* year operating profit minus *t*–1 year operating profit

$P_{i,p,t}$  is the year-end market value in year *t*–1 in *portfolio p* (the market value at the beginning of the year *t*)

$\varepsilon_{i,p,t}$  is the return residual of the *portfolio p* in year *t*

The second step is performed to capture the explanatory power of earnings numbers on stock returns outside the industry influence. As argued by Barth *et al.* (2013), since each combination of stocks in each “portfolio” covers all industries, it effectively eliminates the influence of the industry. Therefore, changes in  $R^2$  cannot be attributed to changes in industry, but instead reflect differences in explanatory power induced by certain characteristics of a firm in the portfolio it belongs to.

Finally, the earnings transparency degree of each firm in each year,  $ETRANS_{i,t}$ , is calculated from the combination of the aforementioned two steps.

$$ETRANS_{i,t} = ETRANS_{i,p,t} + ETRANS_{i,j,t} \quad (6)$$

$ETRANS_{i,t}$  is the earnings transparency of company *i* in year *t*

$ETRANS_{i,j,t}$  is the earning transparency of industry *j* in year *t*

$ETRANS_{i,p,t}$  is earnings transparency of portfolio *p* (exclude industry effect)

### 3.3 Stock price crash risk measure

Three proxies of stock price crash risk are prominent in financial research (see, e.g. Jin and Myers, 2006; Hutton *et al.*, 2009; Kim *et al.*, 2011a, b, among others). They are the negative return skewness coefficient (NCSKEW) measure, DUVOL measure and a binary CRASH likelihood measure. Among the three, NCSKEW and DUVOL are closer in their construction. In this study, we use NCSKEW and CRASH as the primary measures of crash risk and DUVOL for robustness check.

We first carry out the following regression:

$$r_{i,d} = \alpha + \beta_1 r_{j,d-1} + \beta_2 r_{m,d-1} + \beta_3 r_{i,d} + \beta_4 r_{m,d} + \beta_5 r_{j,d+1} + \beta_6 r_{m,d+1} + \varepsilon_{i,d} \quad (7)$$

$r_{i,d}$  is the weekly return of the company *i* in the week *d* without considering the cash dividend reinvestment;  $r_{m,d}$  is the weekly market return in week *d* without considering the cash dividend reinvestment;  $r_{j,d}$  is the value-weighted return of industry *j* that company *i* belongs to in week *d*. The residual  $\varepsilon_{i,d}$  is the degree to which the company’s stock return deviates from the market weekly yield, indicating that the weekly stock return cannot be explained by the fluctuation of the market weekly yield. We set  $R_{i,d} = \ln(1 + \varepsilon_{i,d})$ .

Based on aforementioned “return” metrics, we construct the following three indicators of stock price crash risk on the “firm-year” basis:

- (1) CRASH (Hutton *et al.* (2009); Kim *et al.* (2011a, b))

The crash week is identified when  $R_{i,d}$  is lower than  $R_{i,d}$  subtracted by 3.2 times the standard deviation of the *t*-year average  $R_{i,d}$ . For the company *i* in year *t*, if there is at least one crash week, then  $CRASH_{i,t}$  is 1, 0 otherwise.

- (2) NCSKEW (Chen *et al.* (2011))

$$NCSKEW_{i,t} = \left( -n(n-1)^{\frac{3}{2}} \sum R_{i,d}^3 \right) / \left( (n-1)(n-2) \left( \sum R_{i,d}^2 \right)^{\frac{3}{2}} \right) \quad (8)$$

where *n* is the number of trading weeks for company *i* in year *t*. The skewness coefficient reflects the symmetry of the parameters. The larger the NCSKEW, the higher the degree of

negative bias coefficient of the company's stock return, which means that the risk of stock price collapse is higher.

(3) DUVOL (Chen *et al.* (2011))

$$DUVOL_{i,t} = \log \left\{ \left( (n_{up} - 1) \sum_{down} R_{i,d}^2 \right) / \left( (n_{down} - 1) \sum_{up} R_{i,d}^2 \right) \right\} \quad (9)$$

With this procedure, we divide the weekly yield of the stock during year  $t$  into two groups: higher than average yield (up weeks) and lower than average yield (down weeks).  $n_{up}$  ( $n_{down}$ ) is the number of weeks of "up" weeks ("down" weeks) group. DUVOL [5] is the annual stock volatility. The larger the DUVOL, the higher the volatility, the higher the stock crash risk.

### 3.4 Control variables

We control for variables that are known in the literature as determinants of stock price crash risk (see, e.g. Chen *et al.* (2001); Hutton *et al.* (2009); Kim *et al.* (2011a, b); Xu *et al.* (2014), among others). For the main control variables, previous research shows that there is a strong positive correlation between detrended stock turnover (DTURN), market volatility (SIGMA), market return (RETURN), stock price crash risk (NCSKEW) and the company's stock price crash risk in the coming year. DTURN controls for the heterogeneity of investors. Specifically, it is the monthly average turnover rate in the year  $t$  minus the monthly average turnover rate in year  $t-1$ . SIGMA is the standard deviation of the firm's weekly specific rate of return while RETURN is the firm specific buy-and-hold return over the fiscal year period.

In addition, we also control for the "more generic" firm-specific characteristics, including company size (SIZE), market-to-book ratio (MB), financial leverage (LEV) and return to asset (ROA). SIZE is the natural logarithm of the total assets in the year  $t$ ; MB is the sum of the market value of the outstanding shares plus the book value of the nontradable shares divided by the book value of the equity; LEV is the ratio of assets to liabilities; ROA is the ratio of the profit before interest and taxes to the total assets at the beginning of the year.

Another important variable used in our study to scrutinize the relation between stock price crash risk and earnings transparency further is "insider trading profit." It considers the impact amount, frequency and number of insider transactions and thus proxies for the extent of private benefit enjoyed by insiders of a particular firm. Following the methodology of Skaife *et al.* (2013), we use a combination of the following three indicators to quantify insider trading.

$$INSI_{RETURN_{i,t}} = \frac{\sum_{j=1}^n \text{Max} \{ (\text{ABRET}_{i,t,j} * \text{VALUE}_{\text{bought } i,t,j} - \text{ABRET}_{i,t,j} * \text{VALUE}_{\text{sold } i,t,j}), 0 \}}{MV_{i,t-1}} \quad (10)$$

$\text{ABRET}_{i,t,j}$  is the one-year-hold excess return rate for the insider transaction in week  $t$ .  $n$  represents the number of weeks after the transaction. This paper uses the one-year trading window period (47 weeks).  $\text{VALUE}_{\text{bought } i,t,j}$  and  $\text{VALUE}_{\text{sold } i,t,j}$  are the insider buy amount and the insider sales amount, respectively.  $MV_{i,t-1}$  is the market value of company  $i$  at the beginning of year  $t$ .

### 3.5 Regression model

To test whether there is a relation between earnings quality and stock price crash risk in China, we employ the following multivariate regression to test our hypotheses. We use CRASH and NCSKEW as the main dependent variables for crash risk but also use DUVOL for robustness check.

$$\begin{aligned} & \text{CRASH}_{i,t+1} \text{ or} \\ & \text{NCSKEW}_{i,t+1} = \beta_0 + \beta_1 \text{ETRANS}_{i,t} + \beta_2 \text{AM}_{\text{Accrual}_{i,t}} + \beta_3 \text{INSI}_{\text{RETURN}_{i,t}} + \beta_4 \text{MB}_{i,t} \\ & \quad + \beta_5 \text{SIGMA}_{i,t} + \beta_6 \text{LEV}_{i,t} + \beta_7 \text{ROA}_{i,t} + \beta_8 \text{SIZE}_{i,t} + \beta_9 \text{DTURN}_{i,t} \\ & \quad + \beta_{10} \text{RETURN}_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (11)$$

Based on our hypotheses, we expect  $\beta_1$  to be negative and  $\beta_2$  to be positive.

#### 4. Empirical results

We start the empirical section by reporting the summary statistics of all variables mentioned in Section 3 in our sample after data screening in Table 1. Overall, the reasonably close proximity of mean and median numbers across variables suggests that our sample data does not have serious abnormality problem.

Table 2 reports the extent of stock price crash risk observed in our sample. We show both the annual crash probability and the average NCSKEW broken down in calendar years. During our sample period between 2006 and 2013, stock price crash probability is the highest in 2010 and the lowest in 2008. The average yearly NCSKEW and the average crash probability follow the same pattern over the years, indicating that these two indicators are reasonably consistent.

Variable	Number of observations	Mean	S.D.	Min	0.250	Mdn	0.750	Max
NCSKEW <sub>i,t+1</sub>	11,030	-0.240	0.790	-2.610	-0.680	-0.050	0.140	1.830
CRASH	11,030	0.0900	0.290	0	0	0	0	1
ETRANS	11,030	0.300	0.240	-0.170	0.130	0.250	0.410	1.120
AM <sub>Accrual</sub>	11,030	-1.450	0.690	-3.240	-1.890	-1.440	-1	0.390
NCSKEW <sub>i,t</sub>	11,030	-0.190	0.790	-2.440	-0.650	-0.040	0.200	1.950
MB	11,030	3.550	3.780	-5.240	1.590	2.560	4.280	25.94
SIGMA	11,030	0.050	0.020	0.020	0.040	0.050	0.060	0.100
LEV	11,030	52.99	22.83	7.520	37.46	53.04	67	147.9
ROA	11,030	3.600	6.850	-25.12	1.040	3.210	6.360	25.17
RETURN	11,030	-0.070	0.280	-0.750	-0.250	-0.080	0.100	0.680
DTURN	11,030	-9.710	354.2	-918.5	-211.2	-8.230	204.6	882.6
SIZE	11,030	15	1.330	12.07	14.10	14.86	15.74	19.42
INSI <sub>RETURN</sub>	11,030	0.140	0.840	0	0	0	0	6.970

**Table 1.**  
Descriptive statistics

Year	No of companies	No of companies crashed	No of companies not crashed	Crash %	Average NCSKEW
2006	1,133	80	1,053	7.1%	-0.1485
2007	1,191	104	1,087	8.7%	-0.1080
2008	1,200	83	1,117	6.9%	-0.3719
2009	1,289	107	1,182	8.3%	-0.2806
2010	1,399	191	1,208	13.7%	-0.0530
2011	1,469	163	1,306	11.1%	-0.2246
2012	1,570	119	1,451	7.6%	-0.3232
2013	1,779	164	1,615	9.2%	-0.3176

**Table 2.**  
Summary of crashed companies

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#### 4.1 Earnings management degree and crash risk in China

We run the regression equation mentioned in Section 3.5 to formally test Hypothesis 1 that higher earnings management degree is associated with higher stock price crash risk in China. As a preliminary test, correlation analysis is presented in Table 3. Overall, the table shows no serious multicollinearity in the regression model [6].

Table 4 reports the OLS regression results of the impact of earnings management degree ( $AM_{Accrual,i,t}$ ) on the stock price crash risk. Column (1) is the result of mixed regression with NCSKEW as the dependent variable while column (2) is the result of mixed regression with CRASH as the dependent variable. Supporting Hypothesis 1, the coefficient of  $AM_{Accrual,i,t}$  is significantly positive at the levels of 1 and 5% for NCSKEW and CRASH, respectively. The higher the degree of earnings management, the greater the crash risk, consistent with the findings documented in Hutton *et al.* (2009). Our results are also robust with the inclusion of the year fixed effect [7].

#### 4.2 Earnings transparency and crash risk in China

Unlike earnings management measure, earnings transparency has never been linked in any way to stock price crash risk in China so far, perhaps due to its complexity. We start this section by describing the dynamics of earnings transparency estimated using our sample. Figure 1 shows the eight-year average adjusted  $R^2$  generated by industry when calculating  $ETRANS_{i,j,t}$ . It indicates variations of the average  $ETRANS_{i,j,t}$  measures across industries. The industries with top overall earnings transparency are scientific research and technical service, health and social work and real estate. Industries with lowest earnings transparency are leasing and business services, electric heating gas and water production and supply.

Figure 2(a) shows the trend of annual average earnings transparency by its components over time. The overall earnings transparency is maintained at 15–20% level. Specifically, the overall earnings transparency in 2008 and 2011 is above average. By depicting Figure 2(b) (Shanghai Composite Index from 2006 to 2014), it is observable that the two years of significant increase in earnings transparency occurred mainly after the two bull markets in 2007 and 2010.

Finally, Table 5 provides the regression results on the impact of earnings transparency on stock price crash risk. Hypothesis 2 predicts that higher transparency leads to lower risk in stock price crash. The reported results are largely consistent with such prediction. Regression coefficients reported in columns (1) and (2) present mixed results for all industries and all years. Regression coefficients in columns (3) and (4) show the results while including the year fixed effect. The hypothesized negative coefficients of  $ETRANS_{i,t}$  are observable and statistically significant across all four models. If the year fixed effect is considered, one unit change in  $ETRANS_{i,t}$  is associated with lower stock price crash risk of  $-0.721$  (in terms of negative skewness) and  $-0.0381$  (in terms of probability of at least one week crash during the year), respectively.

#### 4.3 A closer look on the impact of earnings transparency on crash risk

The empirical design of earnings transparency suggests that the higher the explanatory power of earnings variation on stock return variation, the higher is the earnings quality. But it is also possible that too much reliance on reported earning numbers could indicate lack of other nonearnings-based information available to stock investors. In such scenario, the insiders of the company with higher agency issues would be even more motivated to send false signals to the stock market through misleading earnings numbers (and thus lower earnings quality). This phenomenon can be quite crucial in an inefficient market with large amount of insider trading such as China.

	NCSKEW <sub><i>t,t+1</i></sub>	CRASH <sub><i>t,t+1</i></sub>	ETRANS <sub><i>t</i></sub>	AM <sub>Accrual,<i>t,t</i></sub>	NCSKEW <sub><i>t,t</i></sub>	MB <sub><i>t,t</i></sub>	SIGMA <sub><i>t,t</i></sub>	LEV <sub><i>t,t</i></sub>	ROA <sub><i>t,t</i></sub>	RETURN <sub><i>t,t</i></sub>	DTURN <sub><i>t,t</i></sub>	SIZE <sub><i>t,t</i></sub>
CRASH <sub><i>t,t+1</i></sub>	0.380***	1										
ETRANS <sub><i>t,t</i></sub>	-0.048***	-0.040***	1									
AM <sub>Accrual,<i>t,t</i></sub>	0.041***	0.022**	0.016	1								
NCSKEW <sub><i>t,t</i></sub>	-0.021**	-0.007	0.127***	0.031***	1							
MB <sub><i>t,t</i></sub>	0.098***	0.028***	-0.075***	0.099***	-0.080***	1						
SIGMA <sub><i>t,t</i></sub>	0.073***	-0.042***	0.005	0.115***	-0.147***	0.288***	1					
LEV <sub><i>t,t</i></sub>	0.016*	0.016*	-0.014	0.169***	0.046***	-0.03***	0.088***	1				
ROA <sub><i>t,t</i></sub>	-0.018*	0.003	0.009	-0.023**	0.006	0.058***	-0.012	-0.09***	1			
RETURN <sub><i>t,t</i></sub>	0.103***	0.024***	-0.073***	-0.019*	-0.530***	0.132***	0.175***	-0.04***	0.018*	1		
DTURN <sub><i>t,t</i></sub>	0.026***	-0.021**	-0.179***	-0.017*	-0.100***	0.110***	0.305***	-0.011	-0.010	0.040***	1	
SIZE <sub><i>t,t</i></sub>	-0.011	0.027***	0.026***	0.067***	0.018*	0.307***	-0.385***	0.212***	0.031***	0.092***	-0.043***	1
INSI <sub>RETURN,<i>t,t</i></sub>	0.033***	0	-0.017*	-0.011	-0.047***	0.034***	0.021**	-0.09***	0.005	0.01	0.002	-0.07***

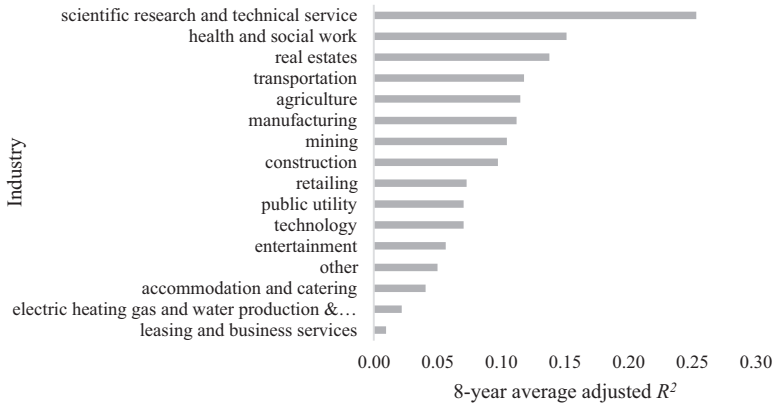
Note(s): The data listed in the table is the Pearson correlation coefficient. \*\*\*, \*\*, and \* indicate the significance level of 1, 5 and 10%, respectively

Table 3.  
Correlation of variables

Variables	(1) NCSKEW <sub><i>i,t+1</i></sub>	(2) CRASH <sub><i>i,t+1</i></sub>	(3) NCSKEW <sub><i>i,t+1</i></sub>	(4) CRASH <sub><i>i,t+1</i></sub>
AM <sub>Accrual <i>i,t</i></sub>	0.0337*** (0.011)	0.0097** (0.004)	0.0354*** (0.011)	0.0098** (0.004)
NCSKEW <sub><i>i,t</i></sub> /RASH <sub><i>i,t</i></sub>	0.0525*** (0.011)	0.0008 (0.004)	0.0498*** (0.011)	0.0001 (0.004)
MB <sub><i>i,t</i></sub>	0.0167*** (0.002)	0.0033*** (0.001)	0.0139*** (0.002)	0.0026*** (0.001)
SIGMA <sub><i>i,t</i></sub>	1.890*** (0.535)	-0.932*** (0.198)	2.476*** (0.632)	-1.077*** (0.234)
LEV <sub><i>i,t</i></sub> (10 <sup>-3</sup> )	0.0003 (0.350)	0.0002 (0.129)	0.0001 (0.349)	0.0002* (0.129)
ROA <sub><i>i,t</i></sub> (10 <sup>-3</sup> ) (10 <sup>-3</sup> )	-0.29** (0.113)	0.0021 (0.042)	-0.30*** (0.112)	0.0023 (0.042)
RETURN <sub><i>i,t</i></sub>	0.317*** (0.032)	0.0297** (0.012)	0.353*** (0.033)	0.0244** (0.012)
DTURN <sub><i>i,t</i></sub> (10 <sup>-4</sup> ) (10 <sup>-4</sup> )	0.157 (0.216)	-0.0745 (0.080)	-0.468 (0.302)	0.0704 (0.112)
SIZE <sub><i>i,t</i></sub>	0.0139** (0.007)	0.0031 (0.002)	0.0172** (0.007)	0.0019 (0.002)
Year dummy	No	No	Yes	Yes
Constant	-0.532*** (0.113)	0.0828** (0.042)	-0.779*** (0.121)	0.103** (0.045)
Observations	11,030	11,030	11,030	11,030
R-squared	0.024	0.006	0.039	0.009

**Note(s):** Standard errors in parentheses; \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

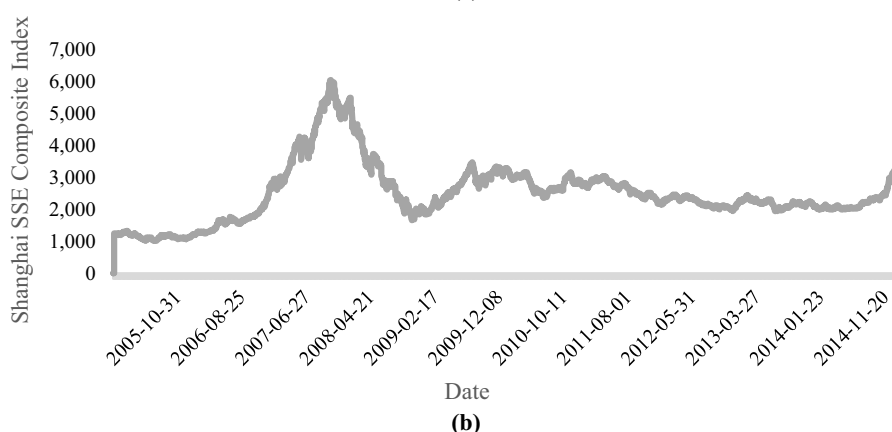
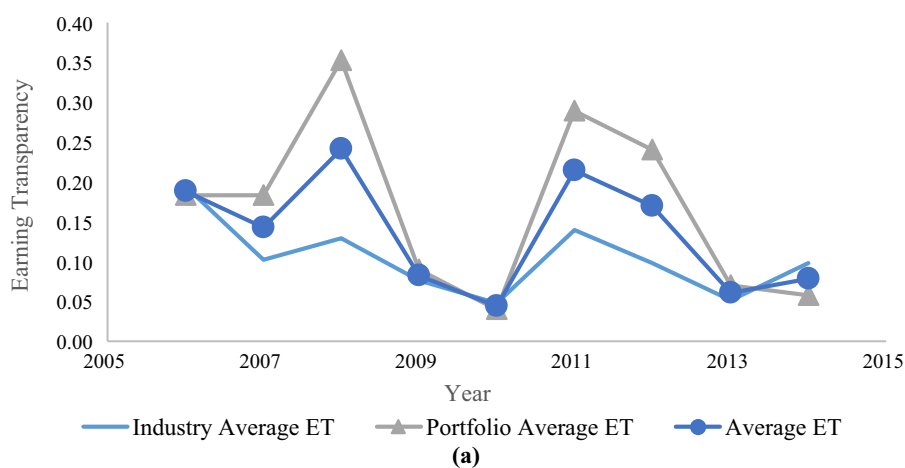
**Table 4.** Regression result of AM and NCSKEW/CRASH



**Figure 1.** Sample industry average earnings transparency

In 2006, China promulgated relevant laws and regulations, allowing insiders to buy and sell stocks of their own companies under certain conditions. Figure 3 shows that China's insider trading behavior has increased over the years. The number of insider transactions started from 497 in 2006 and increased to 8,987 in 2014. Trading approaches range from auction bidding transactions (accounting for 64%) to secondary market trading (accounting for 21%) as shown in Figures 3(a) and (b). All these findings point to the ever-present insiders and their exploitive behaviors in China. The more their trading activities, the more likely their reported earnings numbers to mislead investors (and subsequent crashes that could follow). Numbers reported in Table 3 support this conjecture. The variable, insider trading profit (INSI<sub>RETURN</sub>) is positively related to NCSKEW<sub>*t+1*</sub> at 1% significance level, indicating that if insiders generate positive trading profit in year *t*, then the stock crash risk would increase in year *t+1*.

As discussed previously, high earnings transparency may not necessarily indicate better earnings quality, especially in the case of extreme reliance on reported earnings numbers (which could come from opportunistic insiders having learned that investors rely on their released earnings numbers only). While we show in the previous section that earnings transparency reduces stock price crash risk in general, it may not be the case when the transparency measure shows extreme numbers. This is especially true in the presence of insider trading.

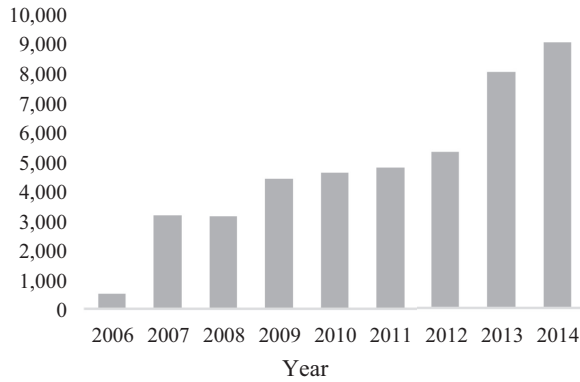


**Figure 2.**  
 (a) Overall earnings transparency level by year (b) SSE (000001) trend from 2006 to 2014

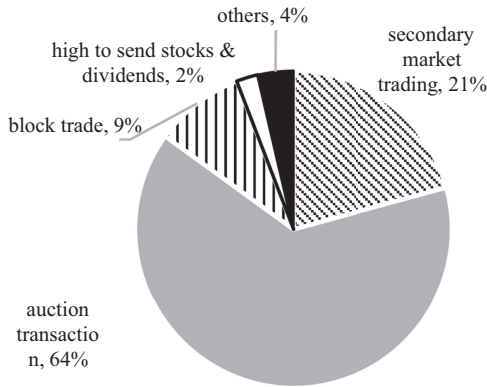
To investigate the aforementioned point, we calculate the crash probability for the four earnings transparency levels based on CRASH variable we created from the previous section. Such crash probability is calculated as the total number of crashed companies between 2006 and 2013 divided by the total number of listed companies in a particular earnings transparency level. As seen in Figure 4(a), the earnings transparency is steadily decreasing as the earnings transparency levels increase. However, if we look closer into the high transparency group alone and further divide this high transparency group into another four levels, the opposite pattern emerges. As reported in Figure 4(b), the crash probability generally increases as the earnings transparency increases.

To formally confirm the aforementioned, we rerun the regression presented in Table 5 but limit our sample to the high earnings transparency group (top 25%) only. The results suggest no significant relation between earnings transparency and stock price crash risk in this subsample [8]. In other words, an extremely high earnings transparency does not guarantee lower crash risk. The high earnings transparency might, on the contrary, indicate the insufficiency of nonearnings information, which in turn leads to higher crash risk.

As explained earlier, the disappearing effect of earnings transparency in reducing stock price crash risk should be more pronounced in the presence of agency issues among insiders.



(a)



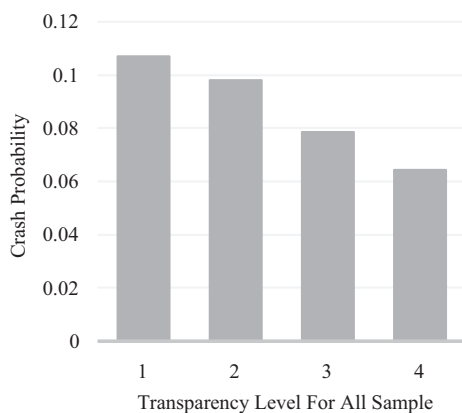
(b)

**Figure 3.**  
(a) Number of insider transactions  
(b) Approaches for insider trading

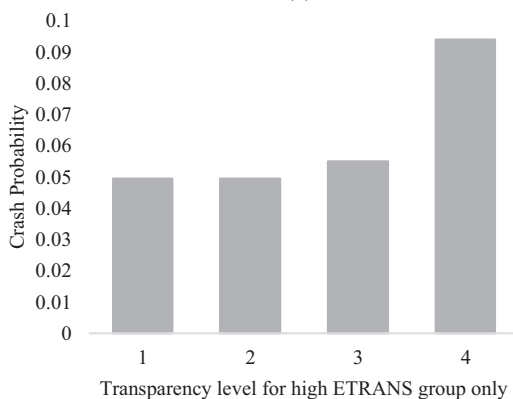
Variables	(1) NCSKEW <sub>i,t+1</sub>	(2) CRASH <sub>i,t+1</sub>	(3) NCSKEW <sub>i,t+1</sub>	(4) CRASH <sub>i,t+1</sub>
ETRANS <sub>i,t</sub>	-0.130*** (0.031)	-0.0447*** (0.012)	-0.0721** (0.036)	-0.0381*** (0.013)
NCSKEW <sub>i,t</sub>	0.0577*** (0.011)	0.0025 (0.004)	0.0521*** (0.011)	0.0009 (0.004)
MB <sub>i,t</sub> (10 <sup>-2</sup> )	0.0165*** (0.214)	0.0032*** (0.079)	0.0144*** (0.222)	0.0028*** (0.082)
SIGMA <sub>i,t</sub>	2.196*** (0.536)	-0.833*** (0.198)	2.663*** (0.630)	-1.022*** (0.233)
LEV <sub>i,t</sub> (10 <sup>-2</sup> ) (10 <sup>-3</sup> )	0.0415 (0.345)	0.0246* (0.127)	0.0263 (0.345)	0.0260** (0.128)
ROA <sub>i,t</sub> (10 <sup>-2</sup> ) (10 <sup>-3</sup> )	-0.0290** (0.113)	0.0003 (0.042)	-0.0306*** (0.112)	0.0001 (0.042)
RETURN <sub>i,t</sub>	0.314*** (0.032)	0.0288** (0.012)	0.349*** (0.033)	0.0224* (0.012)
DTURN <sub>i,t</sub> (10 <sup>-3</sup> ) (10 <sup>-3</sup> )	-0.0039 (0.022)	-0.014* (0.008)	-0.0504* (0.030)	0.0059 (0.011)
SIZE <sub>i,t</sub>	0.0129* (0.007)	0.0028 (0.002)	0.0166** (0.007)	0.0018 (0.003)
Year dummy	No	No	Yes	Yes
Constant	-0.547*** (0.112)	0.0807* (0.041)	-0.805*** (0.121)	0.104** (0.045)
Observations	11,030	11,030	11,030	11,030
R-squared	0.025	0.006	0.038	0.010

**Note(s):** Standard errors in parentheses; \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

**Table 5.**  
Regression result of  
ETRANS and  
NCSKEW/CRASH



(a)



(b)

**Figure 4.**  
(a) Crash prob. for all  
ETRANS level (b)  
Crash prob. for high  
ETRANS group

To verify this point, we employ  $INSI_{RETURN_{i,t}}$  variable to capture the managerial incentive. According to the agency theory, to maximize the personal profits, management (insiders) could benefit from its information advantage through adjusting its disclosure strategy. As disclosure of nonearnings information is optional, managers could selectively disclose it to shareholders. Insider trading is an effective indicator of manager's personal profit from this information advantage. Therefore, we set a dummy variable  $Top\_ETRANS$  for top 10% ETRANS stocks and introduce  $INSI_{RETURN_{i,t}}$  variable to capture the potential abnormal profit from the transaction and a dummy variable  $Top\_ETRANS*INSI_{RETURN_{i,t}}$  to identify the stocks of both high ETRANS and high insider trading profit. We then perform regression analysis to investigate the impact of extremely high earnings transparency interacted with high insider trading profit on crash risk. If our prediction is correct, we expect to see the positive regression coefficient of this interaction variable.

Reported results in Table 6 are in line with our expectations. The  $Top\_ETRANS$  group still shows significant negative relation with NCSKEW and CRASH at 1 and 5% significance levels, respectively. However, the  $INSI_{RETURN_{i,t}}$  is positively related to NCSKEW at 1% level of significance. Meanwhile, the interaction variable of  $Top\_ETRANS$  and  $INSI_{RETURN_{i,t}}$  is positively related to NCSKEW at 5% level of significance. In other words, when the agency

Variables	(1) NCSKEW <sub><i>i,t+1</i></sub>	(2) CRASH <sub><i>i,t+1</i></sub>
Top_ETRANS	-0.0665*** (0.026)	-0.0200** (0.009)
Top_ETRANS*INSI <sub>RETURN<sub><i>i,t</i></sub></sub>	0.0443** (0.035)	0.0156 (0.013)
INSI <sub>RETURN<sub><i>i,t</i></sub></sub>	0.0278*** (0.009)	-0.0004 (0.003)
NCSKEW <sub><i>i,t</i></sub>	0.0553*** (0.011)	0.0016 (0.004)
MB <sub><i>i,t</i></sub>	0.0171*** (0.002)	0.0034*** (0.001)
SIGMA <sub><i>i,t</i></sub>	2.079*** (0.536)	-0.872*** (0.198)
LEV <sub><i>i,t</i></sub> (10 <sup>-3</sup> )	0.0005 (0.345)	0.0003** (0.127)
ROA <sub><i>i,t</i></sub> (10 <sup>-3</sup> ) (10 <sup>-3</sup> )	-0.293*** (0.113)	0.0013 (0.042)
RETURN <sub><i>i,t</i></sub>	0.318*** (0.032)	0.0301** (0.012)
DTURN <sub><i>i,t</i></sub> (10 <sup>-3</sup> ) (10 <sup>-3</sup> )	0.0055 (0.022)	-0.0105 (0.008)
SIZE <sub><i>i,t</i></sub>	0.0130* (0.007)	0.0029 (0.002)
Constant	-0.580*** (0.112)	0.0696* (0.041)
Observations	11,030	11,030
R-squared	0.024	0.006

**Table 6.**  
Regression result of  
top\_ERANS\*INSI and  
NCSKEW/CRASH

**Note(s):** Standard errors in parentheses; \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

problem is severe, the high earnings transparency could actually indicate the absence of nonearnings information, which ultimately results in crash risk.

## 5. Conclusions

Using a sample of listed Chinese stocks during the 2006–2013 period, we show that earnings quality is strongly associated with stock price crash risk as hypothesized in finance literature. Confirming the implicit assumption made by previous studies, we provide empirical evidence that earnings management significantly increases the crash risk in China, whereas earnings transparency (not studied in Chinese context before) reduces the crash risk. However, with the strong presence of agency issues and active insider trading activities in China, we raise a concern that the negative relation between earnings transparency and crash risk may be spurious and may require further investigation. We argue that extreme transparency (measured by the extent of explanatory power of earnings numbers on stock return) may facilitate insiders to conceal bad news and thus increase the likelihood of stock price crash over time. Our further empirical test supports this conjecture.

Our study implies that the two metrics for earnings quality: earnings management degree and earnings transparency are not completely interchangeable. Different from earnings management degree (which is measured using accounting data), earnings transparency is an indirect earnings quality indicator from the information user's perspective. We need to be cautious when using it as an explanatory variable of stock price crash risk (or even a metric of earnings quality for other empirical purposes) in an emerging market such as China.

## Notes

1. Trading halts during Chinese stock market crashes in 2015 are believed to spread fear and panic among Chinese individual investors even further.
2. There has been no study relating earnings transparency to stock price crash risk in China.
3. Other categories of determinants of crash risk including factors related to managerial incentives and characteristics, capital market transactions, corporate governance mechanisms and informal institutional mechanisms. See a review of literature in [Habib et al. \(2018\)](#).
4. Our empirical investigations show that dividing portfolios outside the choice of four leads to less efficient estimations.

5. For brevity, we do not report the results of DUVOL. They are available upon request.
6. We calculate Variance Inflation Factor (VIF) to confirm that multicollinearity is not too harmful in our regression models.
7. All results in our study are largely robust to the inclusion of “industry” fixed effect.
8. For brevity, the regression results are not reported here but are available upon request.

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