PRICE EFFICIENCY, BUBBLES, CRASHES AND CRASH RISK: EVIDENCE FROM CHINESE STOCK MARKET

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Abstract

When there is bad news hoarding from managers, returns of stocks are no longer efficient. We hypothesize that a proxy for efficient returns predicts stock price bubbles, crashes and crash risk. We find evidence in support of our hypotheses. Lagged price efficiency significantly predicts bubbles, crashes and crash risk in multivariate linear regressions and logit regressions, as predicted by our hypotheses. We also find that the lagged probability of bubbles is only correlated with future returns. In contrast, the lagged probability of crashes is correlated with both future returns and fundamental values of stocks. This result validates our explanation for the formation of bubbles and crashes. Finally, the out-of-sample accuracy ratio of our bubble and the crash prediction model is higher than in previous studies. Our results provide alternative explanations of the mechanics of stock price bubbles and crashes and are helpful for academicians, investors and policymakers.

Keywords: Stock price crash risk, bubbles, crashes, price efficiency, bad news hoarding
JEL Classification: G32, P22, C53, C10

1. Introduction

Recently there have been many research papers about determinants of stock price crash risk, a measure of the tendency for actual crashes (Habib *et al*., 2018). On the other hand, some recent research papers have been about stock price bubbles (*e.g*., Greenwood *et al*., 2019). However, we have found few papers studying the stock price crash risk, stock price crashes and bubbles simultaneously. Papers studying determinants of stock price crash risk introduce a variable associated with increased information asymmetry due to managerial bad news hoarding before the crashes. As suggested by Jin and Meyers's (2006) early research work, that variable is considered one of the determinants of stock price crash risk. In this paper, we study the implication of managerial bad news hoarding, price delay and its effects on stock price bubbles, crashes and crash risk.

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The relationship between managerial bad news hoarding, inefficient stock prices, bubbles, crashes and crash risk is explained below. According to the efficient market hypothesis, stock returns are assumed to follow a random walk on an efficient market. The returns are random because the information they depend on follows a random walk. But if managers hoard negative information about the stock and release only positive information, the distribution of stock returns no longer remains random. Therefore, we can expect a delayed reaction in stock returns to bad news that carries information about the stock returns. As a result, the stock returns become inefficient. When stock returns are inefficient because of bad news hoarding, they are predictable, positively skewed and overvalued. Speculators observe this situation and try to take advantage of it. They have two options. Firstly, to trade against the mispricing, as an arbitrager, sell the stocks short of taking advantage of the overvaluation. The problem with this strategy can be short-selling constraints. Speculators are not sure about the timing of the price correction as all the market participants know about the inefficient stock returns and try to take advantage of positively skewed stock returns. Secondly, speculators can buy the overvalued equity to take advantage of predictable future stock return movements as the stock price bubble grows, and sell the stocks just before the bubble crashes. So in our settings, the stock price bubbles grow due to an interplay between managers, who set the stage for the bubble to grow, and speculators, who take advantage of positively skewed returns. Bubbles are thus related to a lagged increase in price inefficiency.

When price inefficiency decreases because of negative news about the stock, speculators get the signal to offload their long positions in the overvalued stock. After the release of negative news about the stock, only investors selling their stocks the earliest avoid loss. This kick starts rapid sales of the overvalued investments from all investors to avoid losses. So, crashes are related to a decrease in price inefficiency of an overvalued stock. Similarly, an increase in price inefficiency is also related to an increase in stock price crash risk, as the stocks are overvalued when the crash risk is high.

Our paper makes the following contributions to the literature. Firstly, our paper is one of very few to study the relationship between bad news hoarding by managers and price efficiency (Amairi *et al*., 2021). Secondly, we suggest and find evidence of new explanations for stock price bubbles and crashes. Our models rank bubbles and crashes with a greater out-of-sample accuracy ratio, between 0.78 and 0.85, than the previous research, (Jang and Kang, 2019). Thirdly, we find that stock price bubbles are purely speculative while crashes are correlated with the fundamental values of the stock. These results offer new insights into the nature of bubbles and crashes.

The rest of our paper is organized as follows. Section 2 presents a literature review in related fields. Section 3 presents hypotheses and a methodology to test them. Section 4 describes data and variables. Section 5 presents the results of our empirical tests and a discussion. Section 6 concludes.

2. Literature Review

Our research relates to various fields, including stock price bubbles and crashes, informational efficiency of firms, a small but emerging body of literature about return predictability in the presence of information asymmetry, and literature on mispricing and bubbles and crashes on the Chinese stock market.

2.1 Stock price crash risk, bubbles and crashes

Jang and Kang (2019) developed a measure of overpricing and the probability of stock price crashes. They jointly estimated the probability of stock price crashes and jackpots to avoid mixing probability of crashes with volatility. In contrast with the previous literature, they find that institutional investors prefer buying overvalued stocks and that investors who buy overvalued stocks are more profitable. Their evidence implies that sophisticated investors may not always trade against mispricing. Greenwood *et al*. (2019) show that industry-level bubbles convey some information about the probability of a crash. They find some attributes related to bubbles, which eventually help forecast crashes. Daniel *et al*. (2017) find that a high past return predicts future crashes for small groups of firms for which arbitrage is limited. Our paper is also related to the theoretical literature on bubbles that presents some models for rational speculation (Blanchard and Watson, 1982; Tirole, 1985).

Our paper is also related to growing literature on stock price crash risk. Li *et al*. (2019) used a sample of Chinese A-share firms and found that employee stock ownership plan announcement is significantly and negatively associated with crash risk. He *et al*. (2021) used a large sample of US firms and revealed a positive association between insider sales and future stock price crash risk. Furthermore, the positive relation of insider trades with crash risk is stronger for firms with high information opacity and weaker for financially constrained firms. Kim *et al.* (2016) document that firms managed by overconfident CEOs have higher crash risk because overconfident managers overestimate the returns. They continue projects with negative NPV. Balachandran *et al*. (2020) used a global sample of firms from 32 countries and revealed that enactment of merger and acquisition laws decreases the stock price crash risk. Wang *et al*. (2021) find that employee quality reduces the stock price crash risk. Chen *et al*. (2021) reveal that CEOs having early life disaster experience are more willing to accept risks associated with bad news hoarding, which, in turn, leads to stock price crash risk, suggesting a positive association between CEOs with early life disaster experience and crash risk. Cao *et al*. (2021) reveal a positive association between idiosyncratic volatility and crash risk. Cheng *et al*. (2021) show that retail attention raises the future stock price crash risk. Al Mamun *et al*. (2020) show that firms managed by powerful CEOs use fewer negative words in annual reports, issue less negative earning guidance, and have a higher probability of financial restatements, suggesting that powerful CEOs facilitate bad news hoarding, which, in turn, leads to a positive association between CEO power and stock price crash risk. Qayyum *et al*. (2020) document that board gender diversity lowers the stock price crash risk because females reduce unwelcome news hoarding. He *et al.* (2019) used a sample of US listed firms. They revealed that analyst coverage reduces the stock price crash risk, indicating the effective role of analysts as information intermediaries and monitors for firms.

2.2 Information transparency in firms

Our paper is also related to literature on informational efficiency of firms. Some of the latest articles relating to informational efficiency are mentioned here. Hesarzadeh and Rajabalizadeh (2019) examined the impact of corporate reporting readability on informational efficiency and found a positive and significant association between readability and informational efficiency. Moreover, their results show that this association is stronger for firms with higher information asymmetry. Ahn *et al*. (2014) document the association of noise traders with more informative prices. Entry of many noise traders leads informed investors to trade more aggressively and makes the price more informative. Boehmer *et al*. (2009) identified institutional trading as one channel through which efficiency improvements can arise. Cao *et al*. (2007) found that the short-sale constraint forces investors to be sidelined with negative views on asset payoff. This effect can reduce informational efficiency of market prices.

2.3 Return predictability with information asymmetry

Our paper belongs to a small body of literature which relates return predictability of stock prices with information asymmetry. The rationale is that the asset price is usually random if information incorporated in prices of stocks is also random. But due to information asymmetry or information hoarding, prices of stocks only reflect positive returns, and negative returns are not reflected. Therefore, the prices show only positive information and will be predictable using various correlation measures. Amairi *et al.* (2021) show that firms away from big cities have higher information asymmetry, and their returns are non-random, as shown by various variance ratio tests. Dyakova (2013) finds that returns on rural stocks are predictable and that predictability increases during crisis periods, arguing that information asymmetry increases the non-randomness of stock returns. Tourani *et al*. (2016) show that foreign IPOs have less information asymmetry than Chinese IPOs as measured by variances ratio tests.

3. Hypotheses and Methodology

Our first prediction is related to price inefficiency measures and stock price crash risk. According to our framework of the relationship between stock price inefficiency, bubbles and crashes, if the price inefficiency is high due to bad news hoarding, the prices will be overvalued. Jang and Kang (2019) state that stocks with high crash probability are overpriced. The greater the price inefficiency, the higher the probability of a crash related to over-valuation. We therefore test whether stock price crash risk will be high for stocks with a high level of price inefficiency. We use a proxy of stock price crash risk from the literature, *NCSKEW* or *DUVOL,* to test this prediction. These measures are popular in the literature for measuring stock price crash risk. We run the following regression model to test the above relationship.

$$CRASH\ RISK_{i,t} = \alpha_0 + \alpha_1 CRASH\ RISK_{i,t-1} + \alpha_2 PRICE\ DELAY_{i,t-1} + \\ + \sum \beta CONTROL VARIABLE_{i,\ t-1} + u_{i,t} \quad (1)$$

where *CRASH RISK* is measured by *NCSKEW* and *DUVOL*, and *PRICE DELAY* measures price inefficiency of stocks. Control variables include various firm-specific characteristics, including firm *SIZE*, *LEVERAGE*, *AGE*, *ROA* (return on assets), *EBITDA* (earnings before interest, taxes, depreciation and amortization), *SD* (standard deviation) of stock returns, and *SG* (sales growth) of the firm.

We next turn towards the relationship between stock price bubbles, crashes and price efficiency. A stock price bubble is positively correlated with price inefficiency in our framework. Due to bad news hoarding, a high level of price inefficiency gives speculators an incentive to capitalize on positively skewed returns and earn more returns. Therefore, the stock price bubble is positively correlated with lagged price delay in stock returns. We test this relationship using the following specification.

$$\log it\left(Bubble_{i,t}\right) = \alpha_0 + \alpha_1 Bubble_{i,t-1} + \alpha_2 PRICE\ DELAY_{i,t-1} + \\ + \sum \beta CONTROL VARIABLE_{i,\ t-1} + u_{i,t} \quad (2)$$

In Equation 2, *Bubble* is a binary variable that takes the value 1 if a particular firm-year marks a cumulative price appreciation of at least 100% during the last two years. In Equation 2, α_0, α_1, α_2 and β_i represent the intercept term, the coefficient of the lagged value of the *Bubble*, the *PRICE DELAY* variable and coefficients of the control variables, respectively.

Similarly, in our theoretical framework, stock price crash represents the release of bad news hoarded by managers. A stock price crash occurs when managers release bad news about the firm, and thus the overvalued prices fall to their normal levels. Therefore, the relationship between the stock price crash and the price inefficiency should be negative. To test the above relationship, we estimate the following logit model equation.

$$\log it(CRASH_{i,t}) = \alpha_0 + \alpha_1 CRASH_{i,t-1} + \alpha_2 PRICE\,DELAY_{i,t-1} + \\ + \sum \beta CONTROL\,VARIABLE_{i,\,t-1} + u_{i,t} \tag{3}$$

In Equation 3, α_0, α_1 and β_i represent the coefficients of intercept term, lagged *CRASH*, the *PRICE DELAY* variable and the vector of coefficients of the control variables. *CRASH* is a dummy variable that takes the value 1 if the stock price falls by at least 70% during the last year. The control variable remains the same as in Equation 1.

Finally, we want to know the nature of bubbles and crashes. Specifically, we want to know whether bubbles and crashes are based purely on speculation or are correlated with fundamental values. The earlier explanation of stock price bubbles is speculative and need not have any connection with the fundamental values of a firm's stocks. On the other hand, the crashes can correlate with information about the future fundamental values of the firms' stocks besides being correlated with future returns. To explore the nature of bubbles and crashes, we need to have some estimates of future returns and fundamental values. We obtain these two variables by decomposition of the M/B (market-to-book ratio) variable using methods suggested by Rhodes *et al*. (2005). The decomposition produces factors that include *LNMV* (log of market value) and *FVAL* (fundamental value). After that, we regress the *LNMV* and *FVAL* on lagged probabilities of bubbles and crashes (calculated from the logit model) and control variables used in Equations 1–3.

4. Data and Variable Description

We use data from the Chinese stock market. This is because of the considerable literature on stock price crash risk on Chinese stock markets. This means that there exist plenty of opportunities to observe managerial bad news hoarding in this sample. For the sample period, we choose the period from 2000 to 2021. The total number of firms in our data is 3,528 during the sample period. All data, including stock returns, firm-specific variables, and corporate governance variables, are obtained from the CSMAR database. A description of variables used in the study is given below. Our data are unbalanced panel data consisting of firm-year observations. Descriptive statistics about the frequency of the different variables are given in Table 1.

NCSKEW

We follow Chen *et al*. (2001), Hutton *et al*. (2009) and Kim *et al*. (2011a; 2011b) and define *NCSKEW* (negative of skewness). We use the following mathematical expression to measure *NCSKEW*.

$$NCSKEW_{j,\tau} = -\frac{\left[n(n-1)^{3/2}\sum w_{j,\tau}^{3}\right]}{(n-1)(n-2)\left(\sum w^{2}{}_{j,\tau}\right)^{3/2}} \tag{4}$$

where $w_{j,t}$ is calculated using the following regression.

$$r_{j,\tau} = \alpha_j + \beta_{1j} r_{m,t-2} + \beta_{2j} r_{m,t-1} + \beta_{3j} r_{m,t} + \beta_{4j} r_{m,t+1} + \beta_{5j} r_{m,t+2} + \varepsilon_{jt} \tag{5}$$

$$w_{j,\tau} = \ln\left(1+\varepsilon_{j,\tau}\right) \tag{6}$$

where $r_{m,t}$ is the market return in the period t.

DUVOL

Our second measure is down-to-up volatility (*DUVOL*). For the firm j over the fiscal year t, weekly returns are split into "up" and "down" weeks. Up weeks have "returns higher than the annual mean", and down weeks have "returns below than annual mean". The standard deviation of firm-specific weekly returns is calculated for both groups separately. *DUVOL* is calculated as:

$$DUVOL_{J,\tau} = \log\left\{\frac{(n_u - 1)\sum_{Down} w_{j,\tau}^{2}}{(n_d - 1)\sum_{Up} w^{2}{}_{j,\tau}}\right\} \tag{7}$$

4.1 Price efficiency

To capture the effect of bad news hoarding on price efficiency, we use the variable price delay, a standard proxy for price efficiency in the literature (Vo, 2019). *PRICE DELAY* is an inverse measure of stock price efficiency. We compute *PRICE DELAY* using yearly stock returns. The reason for using yearly return is to capture the effect of bad news hoarding in the long run. There is ample empirical evidence (*e.g*., Greenwood *et al*., 2019) that shows that stocks remain overvalued for several years or bubbles grow over several years. The use of yearly stock returns is thus justified. One problem with using yearly returns is the small sample size. To minimize the effect of small sample size on the correctness of the estimates, we modify the formula to measure the price delay and reduce the number of parameters to be estimated by keeping lagged stock returns only. We use the following equations to measure the variable price delay.

$$r_{i,n} = \alpha_i + \beta_i r_{m,n} + \sum_{1}^{4} \delta_{i,k} r_{i,n-k} \tag{8}$$

$$r_{i,n} = \alpha_i + \beta_i r_{m,n} + \delta_i r_i \tag{9}$$

$$PRICE\ DELAY = 1 - \frac{R^2(9)}{R^2(8)} \tag{10}$$

In Equations 8–10, $r_{i,n}$ is the current period stock return, $r_{m,n}$ and $r_{i,n-k}$ represent the market return and k period lagged stock returns, respectively. The terms α, β, δ represent the regression coefficients of the constant term, market return and stock return, respectively. R^2 (Equation 8) and R^2 (Equation 9) represent the R^2 terms from Equations 8 and 9 respectively. We measure the price delay using weekly and yearly stock prices in Equation (10). The advantage of using price delay based on yearly prices is theoretically intuitive. The long periods during which the prices crash or jump coincide with corresponding price delays. The disadvantage of using this measure is that there is no time variation in the price delay based on yearly prices. The only variation in the model is from cross-sectional variation. That means that firms with massive yearly price delays are more likely to form bubbles in the following year than firms with fewer price delays. To check the robustness of our results, we include the price delays measured with both weekly and yearly stock prices. The *PRICE DELAY* measured with weekly prices for a particular year shows cross-sectional and time variation.

BUBBLE

BUBBLE is a binary variable which takes the value 1 if the cumulative stock returns for the firm were at least 100% during the last two years, and 0 otherwise. We follow Greenwood *et al.* (2019) in choosing a threshold for the bubble period and cumulative returns.

CRASH

CRASH is a binary variable that takes the value 1 if the firm's stock returns were at most −70% during the last year, and 0 otherwise. We follow Jang and Kang (2019) in choosing the threshold for the crash. An alternative way of defining the *BUBBLE* and *CRASH* events in the literature is using risk-adjusted abnormal returns of stocks (Habib *et al.*, 2018). This approach usually uses weekly data and ascertains a value of 0 or 1 for a particular stock week based on whether the abnormal returns in that week are 3.09 standard deviation above or below the mean returns in measuring *BUBBLE* or *CRASH* variable. Since we carry out our analysis yearly, we adopt the standard methodology for computing *BUBBLE* and *CRASH* yearly (Greenwood *et al.*, 2019; Jang and Kang, 2019).

4.2 Control variables

LNTA is the natural logarithm of total assets in the year *t*. *EBITDA* are earnings before interest, taxes, depreciation and amortization. *ROA* is the ratio of net income to total assets. *BETA* represents the sensitivity of stock returns with market risk premium in the CAPM model. *AGE* measures the number of years since the firm's listing on the stock market. *LEVERAGE* measures total long-term debt divided by total assets. It measures the standard deviation of the firm's yearly stock returns. *SD* measures the standard deviation of the firm's yearly stock returns. *SG* represents the firm's sales growth and is obtained after subtracting the sales revenue for the previous fiscal year from that of the current fiscal year and then dividing the result by the sales revenue for the previous fiscal year. *LNTOBINSQ* is the company's total market value (equity market value + liabilities market value) divided by total book value (equity book value + liabilities book value). *SYNC* is a measure of stock synchronicity. It is measured as

$$SYNC = \log\left[R^2 / \left(1 - R^2\right) \right] \tag{11}$$

where R^2 is the r-squared of the CAPM model estimated using weekly return data. *IDIO RISK* is defined as the standard deviation of the error term in (a2). *INST PRC* (Institutional ownership) is the percentage of shares held by institutional investors to the total shares outstanding at the end of the previous year. It is a measure of type 2 agency cost. *SNR MGT PRC* (Senior manager share ownership) is the percentage value of the senior managers' holdings to the total shares outstanding at the end of the previous year. *ASSET TURN* is the asset turnover ratio of the firm. It is a measure of type 1 agency cost.

5. Empirical Results

We first present the descriptive statistics of the variables used in this study. A detailed definition of the variables used in the study is presented in the previous section. Table 1 presents various descriptive statistics of the variables such as the mean, median, standard deviation, standard error of mean, minimum and maximum. The results in Table 1 suggest that the variables are well behaved.

Table 1 presents the descriptive statistics of the main variables used in the paper. All the variables used in the table are defined in Section 4. Crash risk is measured by negative conditional skewness (*NCSKEW*) and down-to-up volatility (*DUVOL*). The average crash risk is −0.166 for negative conditional skewness and −0.055 for down-to-up volatility. *M/B* is the rate of return calculated by the market-to-book ratio decomposition. *FVAL* is a measure of the stock's fundamental value computed by the decomposition of the *M/B* ratio.

Table 1: Summary statistics

	N	SD	Mean	SE	p50	range	min	max
NCSKEW	43,666	0.761	−0.159	0.005	−0.133	11.418	−4.561	6.850
DUVOL	43,629	0.281	−0.046	0.002	−0.049	5.392	−1.798	3.585
MB	31,928	1.093	22.262	0.007	22.116	10.115	18.643	28.754
FVAL	28,301	1.044	22.296	0.008	22.192	9.473	18.994	28.460
PROB CRASH	15,283	0.066	0.022	0.001	0.003	0.911	0	0.911
PROB BUBBLE YRET	13,928	0.316	0.287	0.003	0.164	1	0	1
PRICE DELAY	15,399	0.264	0.476	0.002	0.490	1	0	1
YPRICE DELAY	27,301	0.262	0.428	0.003	0.415	1	0	1
LNTA	32,002	1.314	21.451	0.008	21.338	18.808	10.845	29.650
LNTOBINSQ	26,193	1.178	3.766	0.009	3.634	13.703	−1.691	12.005
EBITDA	28,362	1,115.827	−7.665	7.368	0.148		−168,950.991	178.822
ROA	29,283	14.168	−0.080	0.093	0.031	2,153.801	−2,145.999	7.697
BETA	31,983	0.392	1.057	0.002	1.055	26.382	−16.232	10.145
SD	29,347	0.027	0.067	0.001	0.063	0.081	0.038	0.114
SG	27,392	6.266	0.397	0.044	0.140	472.819	−0.986	471.825
AGE	29,027	0.673	1.966	0.005	2.089	3.188	0.010	3.188
DIR	29,384	2.065	9.248	0.015	9.008	16.008	3.008	19.008
INDDIR PRCTG	33,209	9.443	33.060	0.057	33.333	35.003	15.003	50.003
INST PRC	18,273	0.152	0.134	0.002	0.084	1.770	0.010	1.770
ASSET TURN	36,292	0.585	0.639	0.004	0.515	36.156	−0.123	36.028
SNR MGT PRC	29,174	0.154	0.062	0.002	0.005	0.896	0.005	0.896

Source: CSMAR database

PROB CRASH is the probability of a crash where the crash is measured in yearly stock returns. Similarly, *PROB BUBBLE* are probabilities of *BUBBLE* when measured in terms of yearly stock returns. *LNTOBINSQ* is the logarithm of the *TOBINSQ* variable. *EBITDA* is the earnings before interest, taxes, depreciation and amortization. *ROA* is the return on assets. *BETA* measures the sensitivity of the stock returns with the market risk premium. *SD* and *SG* measure the firm's standard deviation of returns and sales growth. *AGE* measures the number of years since the listing of the stock. *DIR* is the number of directors on the board, and *INDDIR PRCTG* is the percentage of independent directors on the board. *ASSET TURN* measures the asset turnover ratio of the firm. *SNR MGT PRC* is the percentage share owned by the firm's senior management. *SOE* is a binary variable indicating whether the firm is state-owned or not.

Table 2 regresses the price delay measures, weekly and yearly, on different firm-specific corporate governance and information asymmetry measures (*e.g.*, *SYNC, IDIO RISK, ASSET TURN* and *SNR MGT PRC*). This analysis aims to uncover underlying determinants of price delay measures and thus price inefficiency. Overall, the results confirm that our measures of price efficiency are related to different information asymmetry and corporate governance variables. Generally, higher information asymmetry is related to higher and significant price delays in stock returns. This is evident as a positive significant coefficient of the idiosyncratic risk variable and a negative and significant coefficient of the firm age variable. Idiosyncratic risk increases under information asymmetry while firm age decreases under information asymmetry.

In Table 3, we present the regression results of the two measures of crash risk on the weekly and yearly price delay. All four models include year-fixed effects and industry-fixed effects. Year-fixed effects control yearly variation in dependent variables that are fixed for a particular year. For example, reforms in a particular year could affect the crash risk in all the firms. An example was share reforms on the Chinese stock market in 2006. Industry-fixed effects control the different independent variables related to different industries. In all the models in Table 3 and subsequent tables, the standard errors are robust to heteroscedasticity. We find consistent and enormously significant results in all the models confirming that stock price crash risk is significantly and positively related to the lagged values of weekly and yearly price delay variables. This is according to our prediction. This is interpreted as a positive relationship between stock price crash risk and price delay.

We further predicted that bubbles and crashes should be positively and negatively related to the lagged values of the weekly and yearly price delay variables. Our results in Tables 4 and 5 reveal exactly the predicted relationship. The lagged values of the weekly and yearly price delay variables are positively related to the bubbles in Table 4 while negatively related to crashes. There is a difference when we use weekly versus yearly price delay variables. The coefficients of the yearly price delay variables are robust to the use of the industry and year dummy, while the coefficients of the weekly price delay are only robust to the use of the industry dummy. When we use the year dummy, the results are not significant. This is perhaps because the time variation in the price delay measure in firms on an aggregate level covaries with the year dummy. This can be due to the particular years when corporate governance reforms were introduced on the Chinese stock market, which affected the news hoarding by managers. Suppose reforms change the managers' news hoarding behaviour. In that case, the year dummy in the model will reduce the time variation in the price delay measure, and the coefficient of the time delay measure will become insignificant.

Table 2: Determinants of price delay measures

	(1)	(2)	(3)	(4)
	PRICE DELAY	***PRICE DELAY***	***YPRICE DELAY***	***YPRICE DELAY***
$SYNC_{t-1}$	−0.132*** (−13.70)	−0.0095 (−1.12)	−0.0984** (−2.10)	−0.0017** (−2.54)
$IDIO\ RISK_{t-1}$	1.184** (2.00)	0.551*** (3.24)	0.00265 (0.07)	0.0858 (0.92)
DIR_{t-1}	−0.0005 (−0.17)	0.0057* (1.81)	−0.0006 (−0.38)	−0.0015 (−0.91)
$INDDIR_{t-1}$	−0.0565 (−0.67)	−0.0056 (−0.65)	0.0109** (2.47)	0.0055 (1.21)
$SEPERATION_{t-1}$	0.0446 (0.85)	−0.0197 (−0.04)	−0.0535*** (−2.62)	−0.0792*** (−3.65)
$ASSET\ TURNOVER_{t-1}$	−0.0271*** (−3.60)	0.00344 (0.37)	0.00296 (1.09)	0.0146*** (3.21)
$SNR\ MGT\ PRC_{t-1}$	0.475** (2.32)	0.0158 (0.09)	0.0096 (0.00)	0.00267 (0.01)
$INST\ PRC_{t-1}$	−0.0481* (−1.77)	0.0033 (0.13)	0.0757*** (6.69)	0.0624*** (5.15)
TA_{t-1}	– –	−0.0216*** (−6.22)	– –	0.0145*** (8.31)
$LEVERAGE_{t-1}$	– –	0.0599*** (4.31)	– –	−0.0223*** (−2.62)
$TOBINSQ_{t-1}$	– –	0.0155*** (3.84)	– –	0.0053*** (2.73)
$EBITDA_{t-1}$	– –	0.0100 (1.43)	– –	−0.0321 (−0.09)
ROA_{t-1}	– –	0.117* (1.79)	– –	0.0634** (2.39)
AGE_{t-1}	– –	−0.0173** (−2.10)	– –	−0.0319*** (−5.47)
SD_{t-1}	– –	0.788** (2.07)	– –	0.0500 (0.30)
SG_{t-1}	– –	0.0547 (1.52)	– –	−0.0350 (−0.25)
$BETA_{t-1}$	– –	−0.0952*** (−5.65)	– –	−0.0179** (−2.45)
CONSTANT	0.474*** (11.11)	0.636*** (7.47)	0.145*** (15.90)	−0.0582 (−1.35)
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Hausman *p*-value	0.000***	0.000***	0.000***	0.000***
N	12,746	12,823	11,863	10,937
adj. R^2	0.062	0.241	0.018	0.051

Note: The values in the parentheses are *t*-statistics. Asterisks are assigned as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: CSMAR database

Table 2 presents the regression results of price efficiency variables on various information asymmetry, corporate governance and control variables. In models 1 and 2, the dependent variable is *PRICE DELAY*, calculated from weekly returns. In models 3 and 4, the dependent variable is *YPRICE DELAY*, calculated from yearly stock returns.

Table 3: Relationship between crash risk and *PRICE DELAY*

	(1)	(2)	(3)	(4)
	NCSKEW	***NCSKEW***	***DUVOL***	***DUVOL***
$NCSKEW_{t-1}$	0.0597^{***} (7.26)	0.0465^{***} (4.89)	– –	– –
$DUVOL_{t-1}$	– –	– –	0.0414^{***} (4.80)	0.0282^{***} (2.81)
$PRICE\ DELAY_{t-1}$	0.0331^{***} (3.20)	0.0339^{***} (3.96)	0.0792^{***} (6.35)	0.0825^{***} (6.52)
$LNTA_{t-1}$	-0.0430^{***} (−10.49)	-0.0404^{***} (−8.69)	-0.0223^{***} (−11.50)	-0.0207^{***} (−9.37)
LEV_{t-1}	−0.00184 (−0.12)	−0.00695 (−0.63)	−0.00145 (−0.26)	−0.00348 (−0.93)
$LNTOBINSQ_{t-1}$	0.0213^{***} (4.90)	0.0193^{***} (4.07)	0.0118^{***} (5.89)	0.0113^{***} (5.15)
$LNEBITDA_{t-1}$	0.0314^{***} (5.46)	0.0287^{***} (4.60)	0.0124^{***} (4.68)	0.0105^{***} (3.62)
$LNAGE_{t-1}$	-0.0905^{***} (−12.44)	−0.207*** (−15.07)	-0.0461^{***} (−13.79)	-0.0987^{***} (−15.23)
SD_{t-1}	0.560^{**} (2.58)	0.252 (1.00)	0.168 (1.64)	0.0301 (0.25)
SG_{t-1}	0.0020^{***} (6.01)	0.0017^{***} (5.57)	0.0007^{***} (4.93)	0.0006^{***} (5.10)
$BETA_{t-1}$	-0.146^{***} (−10.72)	-0.0940^{***} (−4.50)	-0.0657^{***} (−9.71)	-0.0445^{***} (−4.93)
CONSTANT	1.008^{***} (10.33)	1.177^{***} (10.69)	0.541^{***} (11.84)	0.610^{***} (11.81)
Industry FE	YES	YES	YES	YES
Hausman *p*-value	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
N	15,006	11,318	15,006	11,318
Adj. R^2	0.051	0.060	0.054	0.061

Note: The values in the parentheses are *t*-statistics, while the asterisks represent the different levels of *p*-values as $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Source: CSMAR database

Table 3 presents the effect of stock correlation indices and mispricing on the crash risk. The dependent variable in models 1–3 is *NCSKEW*, a standard stock price crash risk variable in the literature. The dependent variable in models 4–6, *DUVOL*, is another standard stock price crash risk variable in the literature. The exact calculation of the dependent variables in models 1–6 is given in Section 4.

Table 4: Forecasting *BUBBLES* and *CRASHES*

	(1)	(2)	(3)	(4)
	BUBBLE	***BUBBLE***	***CRASH***	***CRASH***
$BUBBLE_{t-1}$	0.1252^{**} (2.23)	0.1098^{*} (1.82)	– –	– –
$CRASH_{t-1}$	– –	– –	0.0512^{**} (2.19)	0.2174^{*} (1.89)
$PRICE\_DELAY_{t-1}$	0.330^{***} (3.52)	0.237^{***} (2.97)	-1.946^{***} (−3.45)	-1.756^{***} (−4.36)
$LNTA_{t-1}$	– –	-0.354^{***} (−13.54)	– –	0.463^{***} (10.30)
LEV_{t-1}	– –	−0.0410 (−0.35)	– –	-0.558^{***} (−2.69)
$LNTOBINSQ_{t-1}$	– –	-0.597^{***} (−15.31)	– –	0.492^{***} (11.19)
$LNEBITDA_{t-1}$	– –	-0.238^{***} (−6.15)	– –	0.306^{***} (5.27)
$LNAGE_{t-1}$	– –	-0.561^{***} (−8.13)	– –	-0.758^{***} (−5.93)
ROA_{t-1}	– –	-4.960^{***} (−3.38)	– –	1.844^{*} (1.88)
SD_{t-1}	– –	30.88^{***} (23.76)	– –	69.05^{***} (28.17)
SG_{t-1}	– –	−0.00315 (−0.94)	– –	0.0048^{**} (2.12)
$BETA_{t-1}$	– –	-0.752^{***} (−7.50)	– –	-1.090^{***} (−4.58)
CONSTANT	10.63^{***} (11.82)	8.984^{***} (13.32)	-11.31^{***} (−8.55)	-6.35^{***} (−15.00)
Industry FE	YES	YES	YES	YES
Hausman *p*-value	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
N	9,998	10,194	11,198	11,318
Pseudo R^2	0.062	0.101	0.261	0.279

Note: The values in the parentheses are *t*-statistics. The coefficients are assigned asterisks as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Source: CSMAR database

Table 4 presents the logit model results to forecast *BUBBLES* and *CRASHES*. The *BUBBLE* in models 3 and 4 is calculated from the firm's yearly stock returns. To classify as a bubble, a firm must have at least 100 per cent cumulative returns in the last two years. *BUBBLE* is a binary variable and takes the values of 1 and zero if the firm-year is classified as a bubble and otherwise, respectively. *CRASH* is also a binary variable with a value of 1 if the stock returns in the last year are at most 70%. The independent variable is the lagged price delay variable, *PRICE DELAY*, calculated using yearly returns. Other control variables involved in models 1 to 4 are defined in Section 4.

Table 5: Nature of *BUBBLES* and *CRASHES*

	(1)	(2)	(3)	(4)
	MV	***FVAL***	***MV***	***FVAL***
PROB BUBBLE$_{t-1}$	0.0316^{***} (3.36)	0.0744 (1.12)	– –	– –
PROB CRASH$_{t-1}$	– –	– –	-0.690^{***} (−2.93)	-0.405^{***} (−2.59)
LNTA$_{t-1}$	0.836^{***} (131.31)	0.772^{***} (147.98)	0.819^{***} (127.06)	0.767^{***} (152.27)
LNTOBINSQ$_{t-1}$	0.0666^{***} (7.01)	−0.00135 (−0.21)	0.0486^{***} (6.07)	-0.0226^{***} (−3.02)
EBITDA$_{t-1}$	−0.000781 (−0.13)	−0.00263 (−0.37)	0.00936 (1.15)	0.00507^{**} (2.48)
ROA$_{t-1}$	2.539^{***} (6.17)	2.119^{***} (7.31)	1.581^{***} (4.47)	1.004^{***} (2.84)
BETA$_{t-1}$	-0.167^{***} (−6.40)	-0.0594^{***} (−2.86)	-0.250^{***} (−5.24)	-0.148^{***} (−4.13)
SD$_{t-1}$	5.514^{***} (8.94)	2.079^{***} (4.26)	5.839^{***} (7.97)	2.602^{***} (4.41)
SG$_{t-1}$	0.0004 (0.73)	−0.0004 (−0.66)	0.0034 (1.16)	0.0011 (0.49)
LNAGE$_{t-1}$	0.0781^{***} (2.78)	−0.0285 (−1.29)	0.0559^{**} (2.06)	-0.0585^{***} (−2.71)
CONSTANT	3.374^{***} (17.91)	5.232^{***} (35.11)	4.242^{***} (22.80)	5.801^{***} (38.73)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Hausman *p*-value	0.000^{***}	0.000^{***}	0.000^{***}	0.000^{***}
N	10,702	10,546	10,092	11,931
adj. R^2	0.867	0.906	0.867	0.908

Note: The values in the parentheses are *t*-statistics. The asterisks are assigned to the coefficients according to their *p*-values as * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: CSMAR database

We then move towards testing H_{4A} and H_{4B}. In Table 5, we regress the *LNMV* and *FVAL* (speculative and fundamental value components of the mispricing) on the lagged probabilities of bubbles and crashes, calculated from generalized logit models, along with control variables and year and industry dummies. We find exciting results from these regressions. On average, the lagged probability of a bubble is positively correlated with speculative future price movements but not with the firms' future fundamental values. In contrast, the crashes carry information about the future returns and the firms' fundamental values, as evident by their significant correlation with *LNMV* and *FVAL*. These results verify our explanation of the mechanics of bubbles and crashes that bubbles start with the opportunity of speculation about future returns. In contrast, crashes occur because of the elimination of future speculative returns and the release of negative news about the firm.

Table 5 presents the regression of *MV* (market values) and *FVAL* (fundamental values) on the probability of bubbles and the probability of crashes. *MV* and *FVAL* are calculated by decomposition of the *M/B* ratio according to Rhodes *et al*. (2005). Models 1 and 2 present the regression results of *MV* and *FVAL* on the probability of a bubble. Models 3 and 4 present the regression results of *MV* and *FVAL* on the probability of a crash.

Table 6 presents the accuracy ratio for out-of-sample forecasting using Equations 2 and 3. Columns 2 and 3 present accuracy ratios for crash and bubble models.

Table 6: Accuracy ratios

YEAR	*CRASH*	*BUBBLE*
2007	0.80	0.74
2008	0.81	0.75
2009	0.79	0.75
2010	0.84	0.78
2011	0.82	0.79
2012	0.81	0.81
2013	0.80	0.80

Source: CSMAR database

Table 6 calculates the out-of-sample accuracy ratio (Vassalou and Xing, 2004) of our models for predicting *BUBBLES* and *CRASHES*. The accuracy ratio captures how correctly our models assigns probabilities of crashes and bubbles to out-of-sample firms. We first fit the forecast model on a yearly expanding window starting from 2001–2007 and ending in 2001–2013. From the fitted model, we assign the probabilities to the data excluded from the window and check the accuracy of our assigned probabilities. The accuracy ratio is a measure of checking the accuracy of that assigned probability. The calculated out-of-sample accuracy ratio for the *CRASH* prediction models is 0.8–0.84, while the out-of-sample accuracy ratio for the *BUBBLE* prediction models is in the range of 0.74–0.81, which is much higher than reported by existing research (Jang and Kang, 2019).

5.1 Robustness tests

To check whether the results obtained in this paper are sensitive to the choice of variables, we decided to conduct robustness tests by changing the independent variable in the study. One of the implications of bad news hoarding is that the stock returns become highly autocorrelated in the presence of bad news. Based on this prediction, we calculate the yearly autocorrelation of the stock returns from weekly returns. We use the absolute value of the yearly autocorrelation as the independent variable. Overall our results from this new independent variable are similar in sign and are significant at a 10% confidence level.

Table 7 presents the robustness test for forecasting crash risk with absolute autocorrelation (AAC_{t-1}).

Table 8 presents the robustness test for forecasting *BUBBLES* and *CRASHES* with absolute autocorrelation (AAC_{t-1}) in the logit model.

Tables 7 and 8 present a robustness test of forecasting crash risk and bubbles and crashes with an absolute value of the autocorrelation of returns. Looking at the results in Tables 7 and 8, it is clear that when we replace the independent variable *PRICE DELAY* with *AAC*, the sign of the coefficients remains and the significance of the coefficients is retained. Our results are robust to the choice of the proxy measuring stock price inefficiency. We repeat our tests on different sub-samples, before and after GFC, according to the period in unreported results. Still, our results remain of the same sign and statistically significant in different subsamples.

Table 7: Forecasting crash risk with AAC_{t-1}

	(1)	(2)
	NCSKEW	***DUVOL***
$NCSKEW_{t-1}$	0.0614*** (7.41)	– –
$DUVOL_{t-1}$	– –	0.0414*** (4.69)
AAC_{t-1}	0.0743* (1.80)	0.0231* (1.88)
$LNTA_{t-1}$	−0.0293*** (−7.12)	−0.0156*** (−8.07)
LEV_{t-1}	−0.0101 (−1.10)	−0.00524 (−1.90)
$LNTOBINSQ_{t-1}$	0.00786 (1.79)	0.00487* (2.39)
$LNEBITDA_{t-1}$	0.0255*** (4.55)	0.00879*** (3.41)
$LNAGE_{t-1}$	0.00207*** (4.24)	0.000661*** (3.94)
SD_{t-1}	0.409 (1.32)	0.503** (3.07)
SG_{t-1}	−0.0593*** (−8.28)	−0.0308*** (−9.35)
$BETA_{t-1}$	−0.0551*** (−4.42)	−0.0353*** (−5.20)
CONSTANT	−0.469*** (−4.77)	−0.0952* (−2.06)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Hausman p-value	0.000***	0.000***
N	15,111	15,111

Notes: *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: CSMAR database

Table 8: Forecasting *BUBBLE* and *CRASH* with AAC_{t-1}

	(1)	(2)
	BUBBLE	***CRASH***
$BUBBLE_{t-1}$	0.764*** (9.62)	– –
$CRASH_{t-1}$	– –	0.474* (1.66)
AAC_{t-1}	0.409*** (4.05)	–1.622** (–2.58)
$LNTA_{t-1}$	–0.103*** (–3.79)	0.448*** (7.85)
LEV_{t-1}	–0.0507* (–2.15)	0.0210 (0.64)
$LNTOBINSQ_{t-1}$	–0.116*** (–3.88)	0.389*** (8.56)
$LNEBITDA_{t-1}$	0.0350 (0.92)	0.395*** (5.31)
$LNAGE_{t-1}$	0.00156 (0.69)	0.00725* (2.54)
SD_{t-1}	32.82*** (14.82)	71.11*** (20.57)
SG_{t-1}	–0.224*** (–4.99)	–0.0820 (–0.83)
$BETA_{t-1}$	–0.389*** (–3.58)	–0.758* (–2.34)
CONSTANT	0.201 (0.30)	–18.93*** (–14.00)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Hausman p-value	0.000***	0.000***
N	15,107	14,882

Notes: *t*-statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: CSMAR database

5.2 Discussion

We argue for and provide evidence of a new variable, *PRICE DELAY* (price inefficiencies), that can predict stock price bubbles and crashes. Our argument (that stock price bubbles are created because of managers' signals about bad news hoarding, which investors detect from stock price inefficiencies and stock price crashes, and are the result of the release of that bad news) is different from earlier literature. Although earlier literature has explained speculation as one of the reasons for stock price bubbles (Hong *et al*., 2006), stock price inefficiency as one of the causes behind that is new to the literature. So, our study advances the determinants of stock price bubbles to price delays (stock price inefficiencies). Our results suggest that price inefficiencies lead to bubbles and subsequent crashes. The evidence presented in our article starts an entirely new debate on the consequences of departure from the efficient market hypothesis. The results presented here for the regression and logit models have robust standard errors. We also incorporate time and industry-fixed effects in various models.

Our sample is from Chinese listed firms. This sample is unique for studying the research questions raised in this paper. Stock prices in China have been inefficient due to Chinese firms' unique corporate governance characteristics. Therefore, Chinese stock markets have undergone reforms to eliminate this lack of inefficiency problem. So, in the Chinese sample, we have cross-sectional and time-series variation in the stock price efficiency (proxied by price delay and correlation variables). Therefore, the implications of stock price inefficiency can be studied best in our sample. However, the research has shown that despite differences between the Chinese economy and advanced western economies, the economic behaviour of Chinese investors is rational. Furthermore, the results of this paper should be generalizable to other economies as well. Still, there is a need to perform these tests on data from other economies, especially the US.

The results in Table 4 use future market values and firms' fundamental values to check whether the bubbles are speculative. The calculation of the fundamental value of a firm is very tricky. However, we use a market-based estimate of the fundamental value from Rhodes *et al*. (2005). It would be better if future studies could use some other methods of calculating the firm's fundamental value to see if the results are robust to changes in fundamental value calculation. Our results are obtained after controlling for the variables suggested by the literature, eliminating the doubt of missing variable bias in our results.

6. Conclusion

We conducted many different tests of predicting the stock price crash risk, bubbles and crashes in Chinese listed firms. Our results are different from earlier research. For example, our suggested predictors predict stock price bubbles and crashes with a higher out-of-sample accuracy ratio than previous research. We use the fact that firms' crashes and high crash risk situations are preceded by unusually high information asymmetry because of the managerial bad news hoarding. We study the implications of this bad news hoarding for firms' price efficiency and thus for the stock price bubbles, crashes and crash risk. We suggest a different mechanism for the propagation of an asset price bubble and the occurrence of stock price crashes, which is consistent with our evidence. Specifically, we suggest that before the onset of a bubble, there are signs of diminishing price efficiency in firms' stock returns due to managers' bad news hoarding. This proves to be breeding ground for speculators who exploit the speculation opportunity, knowing that there is minimal price efficiency among stock returns. These new insights about bubbles and crashes have implications for academicians, policymakers and investors. Looking at the statistical properties of returns, it is easy to predict future crashes, bubbles and levels of crash risk with a higher probability. This will help portfolio investors make better portfolio decisions. However, there are limitations under which our results should be interpreted. We use Chinese stock market data to carry out our analysis. There is a need to perform the tests on other stock markets to see if our results hold there.

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