Abnormally long audit report lags and future stock price crash risk: evidence from China

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Abstract

Purpose – Although a substantial body of literature investigates the determinants of audit report lag (ARL), scant empirical evidence exists on the consequences of ARL. The purpose of this paper is to examine the association between abnormally long ARL and future stock price crash risk.

Design/methodology/approach – This quantitative study employed a large scale (14,445 firm-year observations) of annual financials, audit and ownership information for the Chinese listed companies during 2002–2013 which were retrieved from the China Stock Market and Accounting Research database.

Findings – This study finds evidence that abnormally long ARL increases the risk of a future stock price crash. Furthermore, the study finds that this adverse consequence is more pronounced for firms with a poor internal control environment.

Practical implications – Recently literature started to explore the consequences of abnormal ARL such as going concern audit opinion and restatements in the subsequent periods. This paper reveals that abnormal ARL has consequences for investor wealth losses as well. This is relevant in China, where the ongoing economic growth has attracted, and will continue to attract, a growing body of domestic and international investors. Understanding what factors could expose investors to wealth losses is of paramount importance for allocating their scarce capital.

Originality/value – This study extends the scant literature on the consequences of ARL, and provides useful insights for the Chinese regulatory authorities when considering the appropriateness of the current filing deadline for listed firms.

Keywords China, Internal control, Stock price crash risk, Abnormally long audit report lags

Paper type Research paper

1. Introduction

This paper examines the association between abnormally long audit report lags (hereafter, abnormal ARL) and the future stock price crash in China. ARL is defined as the period between a company's fiscal year-end and the audit report date, and it is one of the few externally observable audit output variables that allow outsiders to gauge audit efficiency (Bamber *et al.*, 1993). As the audit report contains the auditor's opinion regarding the credibility of the financial statements, ARL has signaling potential.

Prior research on ARL indicates that following factors affect audit delays: audit and auditor attributes (e.g. auditor affiliation, auditor tenure, non-audit services, going concern opinions and auditor changes), firm-specific fundamental variables (e.g. the complexity of the audit, owing to client size, foreign operations or number of subsidiaries), client financial condition (existence of loss and/or distress risk) and organizational risk (e.g. leverage) (Abernathy *et al.*, 2017; Habib, Bhuiyan, Huang and Miah, 2019). Audit delays may delay earnings announcements, reduce earnings informativeness and generate lower market response to earnings (Whittred and Zimmer, 1980); hence investors prefer a shorter, as opposed to a longer, audit delay. However, recent studies suggest that longer report lags may actually evidence higher audit efforts and higher audit quality (Blankley *et al.*, 2014; Knechel and Payne, 2001; Knechel *et al.*, 2009; Tanyi *et al.*, 2010). Only excessively long ARL may signal a problem, as they could cause late filings (Bryant-Kutcher *et al.*, 2013). Therefore, instead of testing all ARL, both normal and abnormal, our study focuses on examining the capital market consequences of excessively long (thus abnormal) ARL.

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The extant literature defines crash risk as related to negative skewness in the distribution of returns for individual stocks (Callen and Fang, 2015; Chen *et al.*, 2001; Kim and Zhang, 2014). Crash risk captures extreme negative returns and, hence, has important implications for portfolio theories and for asset and option-pricing models. Conceptually, crash risk is based on the argument that managers have a tendency to withhold bad news for an extended period, allowing bad news to stockpile. This is done to maximize compensation, protect employment and minimize litigation concerns emanating from bad news disclosures (Kothari *et al.*, 2009). If managers successfully block the flow of negative information into the stock market, the distribution of stock returns should be asymmetric (Hutton *et al.*, 2009; Kothari *et al.*, 2009). When the accumulation of bad news passes a threshold, it is revealed to the market at once, leading to a large negative drop in stock price (Jin and Myers, 2006).

Hong and Stein (2003) developed a model that incorporates heterogeneity in investors' beliefs, one of the key drivers of a stock price crash. This model begins with the assumption that a group of investors (e.g. mutual funds) cannot short-sell stocks and thus can take long positions only. Such constraints inhibit the revelation of negative information known to the pessimistic investors in stock prices. However, if other previously optimistic investors exit the market, the former group of investors may become the marginal buyers. Arbitrageurs will perceive this as "additional bad news" on top of the exit of optimistic investors, if the marginal buyers (the group of pessimistic investors) fail to provide "buying support." The bad news previously hidden from the pessimistic investors will then surface. Ultimately, an accumulation of bad news is released at once when the market is falling, and results in a price crash. Prior literature has examined a number of firm-specific determinants[1] as increasing or decreasing crash risk, including financial reporting opacity (Hutton *et al.*, 2009; Francis *et al.*, 2016); CEO/CFO equity incentives (Kim *et al.*, 2011a); CEO age (Andreou *et al.*, 2017)[2]; and innovative/defensive business strategies (Habib and Hasan, 2017). We propose that abnormal ARL signals bad news hoarding and, thus increases investor uncertainty and subsequent price crash risk.

An abnormal ARL may often suggest the presence of prolonged period of auditor–client negotiations emanating from concerns about the client firms' earnings quality (Chan *et al.*, 2016). Managers often have incentives to hide bad news by manipulating reported financials, and this may subsequently increase price crash risk (Hutton *et al.*, 2009). External auditing plays a vital role by verifying the credibility of financial statements, and has the potential to ensure the timely disclosure of bad news, thus constraining price crash risk. Consistent with this view, Robin and Zhang (2015) found that industry specialist auditors reduce the price crash. Empirical research has also documented the negative association between non-audit tax services and stock price crash risk (Habib and Hasan, 2016). Furthermore, Feng *et al.* (2018) found that engagement auditor industry specialization reduces crash risk over and above the effects of auditor industry specialization. These studies implicitly assume that timely disclosures of audited financial statements reduce the heterogeneity of investor belief and, thus, the price crash.

In contrast, an abnormal ARL could signal auditor–client disagreements regarding upward or downward accounting adjustments. The grounded theory of interactions between auditor and client, as developed by Beattie *et al.* (2001, 2011), suggests that such interactions can lead to outcomes such as high/low quality of accounting, compliance/non-compliance with regulations and easy/difficult agreements. Moreover, the consequences of such interactions can directly impact the future accounting periods and fee negotiations, as well as the quality of the auditor–client relationship. Although the client and auditor may reach an agreement on some less critical accounting issues after a longer than usual negotiation, if the issues remain unresolved in the next period, the auditor may be unlikely to compromise owing to the increased audit risk.

In a recent study, Chan *et al.* (2016) revealed that Chinese firms with abnormal ARL receive going concern opinions and have their financial statements restated in future periods. We show that abnormal ARL has consequences for investor wealth losses as well. Retail investors tend to concentrate investments in a small number of firms (Barber and Odean, 2013), and stock price crashes of firms in their portfolios can be highly detrimental to their personal wealth. This is relevant in China, where the ongoing economic growth has attracted, and will continue to attract, a growing body of domestic and international investors[3]. Understanding what factors could expose them to wealth losses is of paramount importance for allocating their scarce capital.

The regulatory initiative for providing guidance on audit report dates in China commenced in 2003, when the Chinese Institute of Certified Public Accountants issued a detailed guideline specifying the factors that auditors should consider in deciding when to submit their audit reports. Some of these include the timing of completion of audit procedures, the resolution of outstanding issues and management's acknowledgment of its responsibility for the financial statements (CICPA, 2003). In 2007, the Auditing Regulation No. 1501 reinforced these principles, emphasizing that audit reports should be submitted only after obtaining sufficient and appropriate audit evidence to determine the audit opinion on the financial statements (CICPA, 2007). Article 66 of the Securities Law of the People's Republic of China (2014 Amendment) reconfirms that a listed company shall, within four months of the end of each fiscal year, submit an annual report to the securities regulatory authority and the stock exchange (Standing Committee of the National People's Congress, 2014). If companies fail to submit annual reports on or before the deadline, they are required to make relevant disclosures about the reasons for the delay, and to pay penalties. Importantly, the shares of the company can be suspended from trading by the relevant stock exchange until the annual report is released (Chan *et al.*, 2016).

Using a large sample of 14,448 firm-year observations from 2002 to 2013, we find robust evidence that abnormal ARL increases the one-year-ahead stock price crash risk. We then investigate whether the association between abnormal ARL and a price crash is moderated by the quality of the internal control (IC) environment of the client firms. Prior research shows that ineffective IC increases business risk, exacerbates agency problems and reduces contracting efficiency (Ashbaugh-Skaife *et al.*, 2008; Doyle *et al.*, 2007a, b). An ineffective IC environment provides opportunities for managers to conceal bad news, thus requiring auditors to spend considerable time in detecting and reporting accounting manipulation. Such a long delay increases investor uncertainty and thus, price crash risk. We find evidence in support of this prediction, i.e., the adverse consequences of abnormal ARL on price crash risk are primarily confined to firms with a poor IC environment.

We extend the scant literature on the consequences of the ARL. Blankley *et al.* (2014) and Chan *et al.* (2016) documented an increase in future restatements, and the probability of receiving a going concern opinion, for firms with an abnormally long audit reporting lag. Although these outcomes have adverse economic consequences for investors, these authors could not quantify the extent of such adverse consequences. We, on the other hand, examine crash risk: an outcome with direct economic consequences for investors, particularly for small retail investors. We also contribute to a growing body of stock price crash risk research in China that incorporates some unique Chinese institutional settings. Our study is expected to be useful to Chinese securities regulators in considering the appropriateness of the current filing deadline regulation. Our study also documents the significant moderating effect of a strong IC environment on attenuating the positive association between abnormal ARL and future stock price crash risk. The findings shed some light on the importance of IC in reducing the abnormal ARL-induced risk of stock price crash. This study highlights the importance of proper IC policies and disclosures for the Chinese regulatory authorities, and provides useful insights into corporate governance policies and practices in the Chinese listed companies.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature and develops the hypotheses. Section 3 explains research design issues. The following section provides our sample selection procedure and descriptive statistics. Section 5 explains the regression results. Section 6 concludes the paper.

2. Literature review and hypotheses development

ARL are defined as the number of days between the financial year-end and the date of the audit report (Ashton *et al.*, 1987). Timeliness is crucial to ensure the relevance and usefulness of financial information received by investors and stakeholders (FASB, 2010). The determinants of ARL can be categorized into: audit and auditor attributes, including auditor affiliation, auditor expertise, audit fees, non-audit services, going concern opinion, auditor tenure and auditor changes, audit busy season and IC weakness (ICW); corporate governance variables, for instance, audit committee and board characteristics, and ownership concentration; and firm-specific fundamental variables, such as the complexity of the audit due to client size, foreign operations or number of subsidiaries and client financial condition and organizational risk (Abernathy *et al.*, 2017; Habib, Bhuiyan, Huang and Miah, 2019; MohammadRezaei and Mohd-Saleh, 2018). Capital market research also documents a few determinants of ARL, including analyst coverage and analysts' cash flow forecasts (Fang *et al.*, 2014; Mao and Yu, 2015).

Despite a plethora of research on the determinants of ARL, limited studies exist on the consequences of abnormal ARL. Blankley *et al.* (2014) found that abnormal ARL is associated positively with subsequent financial restatements in the USA, and this is largely attributable to the time pressure on auditors to complete audit work within the regulatory timeframe. This is consistent with Bryant-Kutcher *et al.* (2013) and Lambert *et al.* (2011), who found that the acceleration of filing deadlines reduced earnings quality and increased subsequent accounting restatements, suggesting that the quick filing deadline may have impacted on the auditors' ability to detect material misstatements. In a distinctive institutional environment, Chan *et al.* (2016) found that Chinese firms with long ARL are more likely to receive going concern opinions and to have their financial statements restated in the future, compared to firms with short ARL. These studies suggest that abnormally long ARL is a warning signal, rather than an indication of good quality audit.

An abnormal ARL may often suggest the presence of prolonged auditor–client negotiations to settle significant disagreements between auditor and clients. Such disagreements often relate to poor quality earnings due to improper accounting treatments (Chan *et al.*, 2016). Crash risk literature theorizes that managers can conceal bad news by making financial statements more opaque (Hutton *et al.*, 2009). Since external auditors are responsible for verifying the credibility of financial statements, it is expected that auditors would detect and report such misstatements since these are attributes of audit quality (DeAngelo, 1981). It is also expected that they would do that in a timely manner so that investors can rely on auditor opinions for decision making.

However, detecting material misstatements requires auditors to expend considerable time and effort, which may delay release of the audit report. Regardless of whether the abnormal ARL is a result of incompetent auditors or a problematic client, the consequences of the prolonged interaction between client and auditor impact on future accounting quality directly (Beattie *et al.*, 2001, 2011). An excessively long delay implies that firms have a high possibility of receiving a non-standard audit opinion, or of having their financial statements restated in the next period, compared to firms with a short ARL (Chan *et al.*, 2016). Hence, an abnormal delay in releasing the audit report signals future accounting problems and increases investor uncertainty. Since the latter is a catalyst for a price crash (Hong and Stein, 2003), we posit that an abnormal ARL will increase the price crash. Furthermore, Carslaw and Kaplan (1991) suggested that, when firms incur losses, companies are likely to delay the announcement of losses by requesting that the auditor schedule the commencement of the audit later than usual. Often, this implies additional audit work and, consequentially, a long ARL, if auditors consider that the reported negative changes in earnings would increase the probability of financial failure. Reporting losses could also be associated with distress risk, which might prompt auditors to conduct more substantive testing to confirm that the company is a going concern. This, too, has the potential to increase heterogeneity in investor beliefs about the future prospects of the firm and may increase price crash risk. We develop the following hypothesis:

H1. Abnormal ARL increases the risk of a future price crash.

We further propose that *H1* is more pronounced for firms with a poor IC environment. Ineffective IC increases business risk, exacerbates agency problems and reduces contracting efficiency (Ashbaugh-Skaife *et al.*, 2008; Doyle *et al.*, 2007a, b; Leventis *et al.*, 2013; Liu and Lu, 2007; Mitra *et al.*, 2013). Ashbaugh-Skaife *et al.* (2008) and Doyle *et al.* (2007a, b) documented that effective IC can eliminate potential accounting errors or accrual adjustments, both intentional and unintentional, and can minimize the chance of financial misstatement. Conversely, ineffective IC, proxied by ICW disclosure, has a negative and significant impact on earnings quality (Chan *et al.*, 2008; Lu *et al.*, 2011).

In a recent study, Chen *et al.* (2017) documented a negative and significant association between IC quality and the price crash using data from China. An effective IC environment, as proxied by information and communication sharing and monitoring, reduces the possibility of earnings manipulation, enhances the quality of corporate disclosure and, hence, reduces information asymmetry and increases information transparency. A strong IC environment sets the "tone of the top management" and the overall culture of control in a business entity (Ji *et al.*, 2017). A firm with a relatively weak IC environment may, on the other hand, delay producing the financial data required by auditors, especially when the top management intentionally tries to hide some information from them. Hence, misrepresentation by management makes auditors' work more time consuming and makes it harder to detect misstatements. A weak IC environment would allow the management to withhold such bad news for a relatively long period and, consequently, firm stock suffers more severe price drops when the bad news is released. Therefore, we propose that a weak IC environment exacerbates the propensity for bad news hoarding, and that this increases ARL and the risk of price crash:

H2. The association between abnormal ARL and price crash risk is more pronounced for firms with a weak IC environment.

3. Research design and sample selection

3.1 Stock price crash risk

In this study, two measures of firm-specific crash risk are used, consistent with Chen *et al.* (2001). These measures are based on the firm-specific weekly returns, estimated as the residuals from the market model. This ensures that our crash risk measures reflect firm-specific factors rather than broad market movements. Specifically, we estimate the following expanded market model regression:

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

where $r_{j,\tau}$ is the return of firm j in week τ, and $r_{m,\tau}$ is the value-weighted A-share market return in week t. The lead and lag terms for the market index return are included, to allow for non-synchronous trading (Dimson, 1979). The firm-specific weekly return for firm j in week τ ($W_{j,\tau}$) is calculated as the natural logarithm of one plus the residual return from Equation (1). In estimating Equation (1), each firm-year is required to have at least 26 weekly stock returns. Our first measure of crash risk is the negative conditional skewness of firm-specific weekly returns over the fiscal year (*SKEW*). *SKEW* is calculated by taking the negative of the third moment of firm-specific weekly returns for each year and normalizing it by the standard deviation of firm-specific weekly returns raised to the third power. Specifically, for each firm j in year τ, *SKEW* is calculated as follows:

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

Our second measure of crash risk is the down-to-up volatility measure (*DUVOL*) of the crash likelihood. For each firm j over a fiscal year period τ, firm-specific weekly returns are separated into two groups: "down" weeks when the returns are below the annual mean, and "up" weeks when the returns are above the annual mean. The standard deviation of firm-specific weekly returns is calculated separately for each of these two groups. *DUVOL* is the natural logarithm of the ratio of the standard deviation in the "down" weeks to the standard deviation in the "up" weeks:

$$DUVOL_{j,\tau} = \log\left\{\left[\left(n_u-1\right)\sum_{Down} w_{j,\tau}^{2}\right)\right] \Big/ \left[\left(n_d-1\right)\sum_{Up} w_{j,\tau}^{2}\right)\right]\right\}. \tag{3}$$

A higher value of *DUVOL* indicates greater crash risk. According to Chen *et al.* (2001), *DUVOL* does not involve third moments and, hence, is less likely to be overly influenced by extreme weekly returns.

3.2 Internal control measure

In China, there are two main IC quality indices, namely, the index constructed by the Internal Control Research Center of Xiamen University, and the index constructed by DIB Enterprise Risk Management Technology Co. Ltd In this research, the DIB IC index is adopted to measure the IC quality. The DIB index, annually published since 2008, is a composite index constructed on five dimensions of IC: IC strategies, operational efficiency, financial reporting quality, legal compliance and asset safety (DIB Internal Control and Risk Management Database, 2017). The IC deficiencies reported by listed companies are also incorporated into the index to improve its rigor (Li, Shu, Tang and Zheng, 2017; Li, Wang and Wang, 2017; Lin and Yu, 2015). It reflects the IC information based on the listed firm's IC disclosure reports, IC assessment reports and auditing/assurance reports (Li, 2015). The index ranges from 1 to 1,000, where a high value represents a strong IC environment.

3.3 Empirical model

The following regression specification is estimated in order to test the association between abnormal ARL and price crash risk:

$$\begin{aligned} CRASH_{j,t+1} = {} & \gamma_0+\gamma_1 CRASH_{j,t}+\gamma_2 ABN\_ARL_{j,t}+\gamma_3 TURN_{j,t} \\ & +\gamma_4 SDRET_{j,t}+\gamma_5 RET_{j,t}+\gamma_6 SIZE_{j,t}+\gamma_7 MB_{j,t}+\gamma_8 LEV_{j,t} \\ & +\gamma_9 ROA_{j,t}+\gamma_{10}\left|DAC_{j,t}\right|+\gamma_{11}\left|REM_{j,t}\right|+\gamma_{12} IOWN_{j,t} \\ & +\gamma_{13} ANALYST_{j,t}+\gamma_{14} BSIZE_{j,t}+\gamma_{15} BIND_{j,t}+\gamma_{16} DUAL_{j,t} \\ & +\gamma_{17} BIG4_{j,t}+\gamma_{18} TOP10_{j,t}+YEAR_{j,t}+INDUSTRY_{j,t}+\varepsilon_{j,t}, \end{aligned} \tag{4}$$

where *CRASH* risk is proxied by the *SKEW* and *DUVOL* measures following Equations (2) and (3). We operationalize abnormally long audit reporting delay (*ABN_ARL*) in two different ways. First, we create a dummy variable coded 1 for firm-year observations in the top 10 percent of the ARL (the number of calendar days from fiscal year-end to the date of the auditor's report) distribution (*ABN_ARL1*). This procedure follows Chan *et al.* (2016). Second, we take the difference between actual ARL and expected ARL based on the ARL determinants model, as explained in Table AII. A positive (negative) residual implies abnormally long (short) audit reporting delay (*ARL_2*).

Inclusion of the control variables in Equation (4) follows prior literature on the determinants of crash risk (Hutton *et al.*, 2009; Kim *et al.*, 2011a, b). Stock market indicators include share turnover (*TURN*), standard deviation of firm-specific weekly returns (*SDRET*) and mean returns (*RET*). *TURN* is calculated as the average monthly share turnover for the current fiscal year period minus the average monthly share turnover for the previous fiscal year period, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month. *SDRET* and *RET* are the standard deviation and the average of the firm-specific weekly returns over the fiscal year period, respectively. Firm-specific control variables include: firm size (*SIZE*) measured as the natural logarithm of total assets, market-to-book (*MB*) ratio proxying for growth opportunities, leverage (*LEV*) calculated as the total long-term debt scaled by total assets, profitability ratio (*ROA*) calculated as net income divided by total assets and there are two earnings quality proxies: the absolute value of discretionary accruals (|*DAC*|) and the absolute value of real earnings management (|*REM*|). We also include a set of corporate governance variables including institutional ownership (*IOWN*), analyst following (*ANALYST*), board size (*BSIZE*), board independence (*BIND*), CEO duality (*DUAL*) and two auditor categories, *BIG4* and *TOP10*. Detailed definitions of the variables are listed in Table AII.

The independent variables, including the control variables, are calculated using data from the preceding year, as is consistent with the crash risk literature. We cluster the standard errors by firms in order to control for potential heteroskedasticity and autocorrelation problems, and to provide robust standard error estimation with reliable *t*-statistics.

4. Sample selection and descriptive statistics

We retrieve annual financials, audit and ownership information from the China Stock Market and Accounting Research (CSMAR) database. Our sample period spans from 2002 to 2013. We started from 2002 because some of the control variables used in the regression model had a better coverage from 2002 and onwards. We began with an initial sample of 15,799 firm-year observations with non-missing crash risk measures and crash risk-related control variables. We then removed 926 firm-year observations pertaining to finance industries. A further 300 firm-year observations were dropped because of missing ARL data. Finally, missing corporate governance data reduced the final sample size to 14,445 firm-year observations. For IC analysis, our sample size reduced to 8,193 firm-year observations, since the pertinent data only became available from 2008 onwards. Panel A in Table I explains the sample selection procedure.

The industry distribution of sample companies is presented in Panel B of Table I, and reveals that the machinery, equipment and instrument industry accounts for 17 percent of the total sample observations, followed by the petroleum, chemical and rubber (11.67 percent), and the metal and non-metal industries (9.34 percent).

Panel A of Table II presents descriptive statistics for the variables used in the regression variables. The mean (median) values of $SKEW_{t+1}$ are −0.05 (−0.03). The corresponding values for $DUVOL_{t+1}$ are 0.0049 (−0.01). The mean *ARL* is 86 days with a standard deviation of 24 days. The large standard deviation indicates that there is wide variation among companies with respect to the timeliness of audit reporting. Sample companies, on

Panel A: sample selection procedure	
Description	Observations
Client years in CSMAR over 2002–2013	15,799
Minus	
Observations in financial sections	(926)
Observations with missing audit report lag data	(300)
Observations with missing corporate governance data	(128)
Final sample	14,445

Panel B: industry distribution		
Industry	Observations	Percentage
A: farming, forestry, animal husbandry and fishery	312	2.16
B: mining and quarrying	326	2.26
C0: food and beverage	689	4.77
C1: textile, clothing, fur	644	4.46
C3: papermaking, printing	293	2.03
C4: petroleum, chemical, rubber, plastic	1,686	11.67
C5: electronic	667	4.62
C6: metal, non-metal	1,349	9.34
C7: Machinery, Equipment, Instrument	2,458	17.01
C8: medicine, biologic products	999	6.91
C9: other manufacturing	96	0.66
D: production and supply of power, gas and water	665	4.60
E: construction	308	2.13
F: transportation, storage	621	4.30
G: information technology industry	928	6.44
H: wholesale and retail trades	1,020	7.06
K: social services	484	3.35
L: transmitting, culture industry	43	0.30
M: integrated	857	5.93
Total	14,445	100.00

Notes: A, agriculture; B, mining; C, manufacturing; D, electricity, gas and water; E, building and construction; F, transportation and logistics; G, information technology; H, wholesale and retail trades; K, social service; L, culture and media; M, conglomerate. Industry category is based on "guidance on the industry category of listed companies" issued by the China Securities Regulatory Commission (CSRC)

Table I.
Sample selection and industry distribution

average, have moderately good IC environments (an average score of 684.2 out of a possible 1,000)[4]. The average change in monthly trading volume (as a percentage of shares outstanding) (*TURN*) is 0.02. The average firm in our sample has a firm-specific weekly return (*RET*) of 0.38 percent and a weekly return volatility (*SDRET*) of 0.06. Sample firms are large (with an average total asset of CNY 2.7bn, which is equivalent to $397.37m) and have growth opportunities (a mean *MB* ratio of 3.10), but are low-leveraged (mean *LEV* of 0.09). Absolute *DAC* is 7 percent and absolute *REM* is 10 percent of lagged total assets. Institutional owners own 27 percent of total outstanding shares and a firm is, on average, followed by six analysts. In total, 41 percent of the firm-year observations are audited by large (Big4 and Top10) audit firms. Average board size is 9, with 35 percent of the board members being independent directors.

Correlations among the variables are presented in Panel B. Both of the crash measures are positively and significantly correlated with *ABN_ARL1* and *ABN_ARL2* (correlation coefficients of 0.03 and 0.04 for both the crash measures). Our correlation analysis provides preliminary evidence that abnormal audit reporting delay increases the risk of a future-period stock price crash. *ABN_ARL1* is correlated with return volatility positively (correlation of 0.09 with *SDRET*) and is also correlated with earnings management proxies positively (correlation coefficients of 0.06 and 0.03 for |*DAC*| and |*REM*| measures).

Table II. Descriptive statistics and correlation analysis

Panel A: descriptive statistics

Variable	*n*	Mean	SD	1st qrt	Median	3rd qrt
$SKEW_{t+1}$	14,445	−0.05	0.85	−0.59	−0.03	0.49
$DUVOL_{t+1}$	14,445	0.0049	0.73	−0.48	−0.01	0.47
$SKEW_t$	14,445	−0.02	0.87	−0.57	−0.01	0.54
$DUVOL_t$	14,445	0.03	0.75	−0.47	0.01	0.51
ARL_t	14,445	86.14	24.35	73.00	87.00	106.00
ABN_ARL2_t	13,595	0.00	22.87	−12.72	1.70	17.20
$ICINDEX_t$	8,193	684.2	100.41	651.89	691.33	724.23
$TURN_t$	14,445	0.02	0.19	−0.06	0.01	0.10
$SDRET_t$	14,445	0.06	0.02	0.05	0.06	0.07
RET_t	14,445	0.0038	0.01	0.00	0.00	0.01
$SIZE_t$	14,445	21.74	1.16	20.98	21.66	22.42
MB_t	14,445	3.10	3.22	1.36	2.11	3.73
LEV_t	14,445	0.09	0.11	0.01	0.04	0.13
ROA_t	14,445	0.041	0.083	0.007	0.034	0.08
$\lvert DAC\rvert_t$	14,445	0.07	0.06	0.02	0.05	0.09
$\lvert REM\rvert_t$	14,445	0.10	0.11	0.03	0.06	0.12
$IOWN_t$	14,445	0.27	0.25	0.03	0.21	0.47
$ANALYST_t$	14,445	1.08	1.18	0.00	0.69	2.08
$BSIZE_t$	14,445	9.30	1.97	9.00	9.00	10.00
$BIND_t$	14,445	0.35	0.06	0.33	0.33	0.38
$DUAL_t$	14,445	0.13	0.34	0.00	0.00	0.00
$BIG4_t$	14,445	0.07	0.25	0.00	0.00	0.00
$TOP10_t$	14,445	0.34	0.47	0.00	0.00	1.00

Panel B: correlation analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) $SKEW_{t+1}$	–									
(2) $DUVOL_{t+1}$	*0.92*	–								
(3) ABN_ARL1_t	*0.03*	*0.04*	–							
(4) ABN_ARL2_t	*0.03*	*0.04*	*0.40*	–						
(5) $TURN_t$	*0.10*	*0.11*	−0.01	0.01	–					
(6) $SDRET_t$	*0.06*	*0.09*	*0.09*	*0.03*	*0.28*	–				
(7) RET_t	0.02	*0.04*	0.02	0.00	*0.59*	*0.39*	–			

(*continued*)

Table II.

(8) $SIZE_t$	*–0.13*	*–0.13*	*–0.03*	0.00	*0.04*	*0.03*	*0.27*	–		
(9) MB_t	*–0.06*	*–0.07*	*0.04*	0.00	*0.11*	*0.28*	*0.38*	*0.20*	–	
(10) LEV_t	–0.01	0.00	0.02	0.00	*–0.03*	*–0.04*	–0.02	*0.17*	*–0.09*	–
(11) ROA	*–0.12*	*–0.14*	*–0.15*	–0.06	–0.01	*–0.08*	*0.17*	*0.43*	*0.11*	*–0.08*
(12) $\lvert DAC\rvert_t$	–0.01	–0.02	*0.06*	–0.01	–0.01	*0.12*	*0.05*	*–0.03*	*0.10*	*–0.03*
(13) $\lvert REM\rvert_t$	0.00	–0.01	*0.03*	–0.02	–0.01	*0.09*	*0.04*	–0.01	*0.11*	*–0.09*
(14) $IOWN_t$	*–0.11*	*–0.12*	–0.02	0.00	*–0.11*	*–0.05*	*0.08*	*0.61*	*0.17*	*0.11*
(15) $ANALYST_t$	*–0.06*	*–0.08*	*–0.08*	0.00	*–0.03*	0.00	*0.09*	*0.69*	*0.09*	*0.10*
(16) $BSIZE_t$	0.01	0.00	*–0.04*	0.00	0.00	*–0.09*	*–0.03*	*0.14*	*–0.10*	*0.11*
(17) $BIND_t$	–0.01	0.00	*0.07*	0.00	0.00	*0.11*	*0.08*	*0.19*	*0.09*	*0.04*
(18) $DUAL_t$	–0.01	–0.01	0.02	0.00	0.01	*0.04*	*0.04*	0.02	*0.08*	*–0.07*
(19) $BIG4_t$	0.01	0.01	*–0.03*	0.00	–0.01	*–0.07*	*–0.03*	*0.28*	*–0.08*	*0.09*
(20) $TOP10_t$	*–0.06*	*–0.06*	0.00	0.00	*–0.09*	*–0.10*	*–0.04*	*0.30*	0.01	*0.05*

Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) $SKEW_{t+1}$										
(2) $DUVOL_{t+1}$										
(3) ABN_ARL1_t										
(4) ABN_ARL2_t										
(5) $TURN_t$										
(6) $SDRET_t$										
(7) RET_t										
(8) $SIZE_t$										
(9) MB_t										
(10) LEV_t										
(11) ROA	–									
(12) $\lvert DAC\rvert_t$	*–0.03*	–								
(13) $\lvert REM\rvert_t$	*0.03*	*0.41*	–							
(14) $IOWN_t$	*0.29*	–0.02	*0.04*	–						
(15) $ANALYST_t$	*0.45*	*–0.04*	0.02	*0.60*	–					
(16) $BSIZE_t$	*0.04*	*–0.06*	*–0.06*	*0.03*	*0.11*	–				
(17) $BIND_t$	*0.03*	0.02	*0.03*	*0.20*	*0.16*	*–0.30*	–			
(18) $DUAL_t$	–0.01	*0.03*	*0.03*	*0.03*	*0.05*	*–0.12*	*0.11*	–		
(19) $BIG4_t$	*0.08*	*–0.04*	–0.02	*0.12*	*0.18*	*0.13*	0.02	*–0.04*	–	
(20) $TOP10_t$	*0.07*	*–0.05*	–0.01	*0.27*	*0.25*	*0.04*	*0.10*	*0.04*	*0.38*	–

Notes: See Table AI for variable definitions. Italicized faced correlations are significant at $p < 0.001$

5. Results

5.1 Abnormal ARL and crash risk

Table III presents the regression results of stock price crash risk on abnormal ARL. The dependent variable *CRASH* is proxied by the *SKEW* and *DUVOL* measures, respectively. The coefficients for *ABN_ARL1* are 0.098 and 0.091, both significant at $p < 0.001$ for the $SKEW_{t+1}$ and $DUVOL_{t+1}$ measures, respectively, in the OLS model) (Columns (1) and (2)). Columns (3) and (4) use *ABN_ARL2* (residuals from the expected ARL model) as the ARL proxy and, again, reveal positive and significant coefficients (the coefficients are 0.001, significant at $p < 0.001$ for both the *SKEW* and *DUVOL* measures). This supports *H1*, revealing that subsequent period price crash risk increases with an increase in current-period ARL. In terms of economic significance, the reported coefficient estimates of 0.001 on *ABN_ARL2* in Columns (3) and (4) imply a 2.29 percent increase in $SKEW_{t+1}$ and $DUVOL_{t+1}$, respectively.

Among the control variables, the coefficient on average returns (*RET*) is positive, and that on return volatility (*SDRET*) is negative, suggesting that firms with better stock

Table III. Abnormal audit report lag and stock price crash risk

Variables	(1) *ABN_ARL1* *TOP10% = = 1* *OLS* $SKEW_{t+1}$	(2) *ABN_ARL1* *TOP10% = = 1* *OLS* $DUVOL_{t+1}$	(3) *ABN_ARL2* *Residual model* *OLS* $SKEW_{t+1}$	(4) *ABN_ARL2* *Residual model* *OLS* $DUVOL_{t+1}$
$SKEW_t$	−0.043*** (−5.26)	–	−0.047*** (−5.54)	–
$DUVOL_t$	–	−0.064*** (−8.19)	–	−0.069*** (−8.35)
ABN_ARL_t	0.098*** (4.33)	0.091*** (4.92)	0.001*** (3.71)	0.001*** (4.90)
$TURN_t$	0.783*** (14.43)	0.751*** (16.62)	0.793*** (13.72)	0.758*** (15.79)
$SDRET_t$	−5.502*** (−9.76)	−5.747*** (−11.99)	−5.368*** (−8.94)	−5.645*** (−11.05)
RET_t	11.398*** (8.98)	11.744*** (10.65)	10.892*** (8.21)	11.675*** (10.13)
$SIZE_t$	−0.139*** (−12.76)	−0.133*** (−14.26)	−0.136*** (−11.76)	−0.130*** (−13.23)
MB_t	−0.016*** (−5.14)	−0.020*** (−7.54)	−0.015*** (−4.56)	−0.020*** (−7.08)
LEV_t	0.180** (2.47)	0.169*** (2.81)	0.173** (2.31)	0.149** (2.42)
ROA_t	−0.091* (−1.92)	−0.068 (−1.47)	−0.266** (−2.30)	−0.238** (−2.52)
$\lvert DAC \rvert_t$	−0.232* (−1.93)	−0.267*** (−2.67)	−0.217* (−1.75)	−0.269*** (−2.59)
$\lvert REM \rvert_t$	0.098 (1.42)	0.035 (0.62)	0.100 (1.36)	0.033 (0.57)
$IOWN_t$	−0.049 (−1.22)	−0.048 (−1.41)	−0.074* (−1.75)	−0.056 (−1.57)
$ANALYST_t$	0.053*** (5.98)	0.024*** (3.24)	0.061*** (6.37)	0.030*** (3.83)
$BSIZE_t$	0.004 (1.12)	0.004 (1.18)	0.004 (0.94)	0.003 (1.01)
$BIND_t$	0.029 (0.22)	0.070 (0.64)	0.039 (0.27)	0.083 (0.74)
$DUAL_t$	−0.027 (−1.32)	−0.016 (−1.02)	−0.016 (−0.72)	−0.006 (−0.38)
$BIG4_t$	0.158*** (4.79)	0.156*** (5.60)	0.144*** ((4.26)	0.138*** (4.87)
$TOP10_t$	−0.020 (−1.14)	−0.009 (−0.67)	−0.020 (−1.11)	−0.011 (−0.72)
Constant	2.974*** (12.65)	2.902*** (14.37)	2.921*** (11.83)	2.834*** (13.52)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Firm	No	No	No	No
Observations	14,445	14,445	13,595	13,595
Adjusted R^2	0.09	0.14	0.09	0.14

Notes: Columns (1) and (2) present regression results of stock price crash risk on abnormally long ARL, whereby the latter is proxied by a dummy variable coded 1 if the firms-year observations are in the top 10 percent of the ARL distribution and 0 otherwise. Columns (3) and (4) results are based on abnormal ARL measured as the residual from the determinants of ARL model as tabulated in Table AII. Number of firm-year observations in Columns (3) and (4) are smaller than the original sample of 14,445 because of missing audit fees observations. Robust *t*-statistics in parentheses. Other variable definitions are in Table AI. *,**,***Statistically significant at the 10, 5 and 1 percent levels, respectively (two-tailed test) and accounting performance and lower volatility are more likely to experience crashes. Trading volume (*TURN*) increases crash risk, consistent with findings in Chen *et al.* (2001). We find that the firm size (*SIZE*) variable is negative and significant, as is firm profitability proxied by *ROA*. Earnings management proxied by |*DAC*| is associated with crash proxies negatively, a finding that is counter-intuitive. One of the reasons could be the way accruals are defined. Hutton *et al.* (2009) used a three-year moving average of accruals as their earnings management proxy while, like most other studies, we use abnormal accruals calculated annually using a cross-sectional regression analysis (Kothari *et al.*, 2005) (since the use of a moving average reduces our sample size substantially). The coefficients on *ANALYST* are positive and significant across all the regression specifications. The coefficient on institutional ownership (*OWN*) is significantly negative suggesting that crash risk decreases for firms with more institutional shareholdings (An and Zhang, 2013; Callen and Fang, 2013).

Taken together, our findings provide robust evidence that current-period abnormal ARL increases the risk of a future stock price crash.

5.2 Endogeneity tests

Our analysis so far suggests a positive association between ARL and future price crash risk. However, the sign, magnitude and statistical significance of these estimates may be biased if our regression estimates suffer from omitted variables, reverse causality or model misspecification problems (Woolridge, 2002). We perform a number of tests to alleviate such concerns. First, we perform fixed effects regression to control for the effects of time-invariant unobservable factors, and document results that are consistent with the OLS results in Table III (e.g. the coefficient on *ABN_ARL* is 0.07 ($p < 0.01$) and 0.063 ($p < 0.01$) for *SKEW* and *DUVOL* measures, respectively) (Columns (1) and (2) in Panel A of Table IV).

Second, we control for additional determinants of price crash risk to alleviate the omitted variable bias. A growing body of research on the price crash in China has identified a number of unique determinants of the price crash, including political connections (Lee and Wang, 2017; Li and Chan, 2016; Luo *et al.*, 2016); political events (Piotroski *et al.*, 2015); IC quality (Chen *et al.*, 2017); analyst coverage and analyst herding (Xu, Chan, Jiang and Yi, 2013; Xu, Jiang, Chan and Yi, 2013; Xu *et al.*, 2017); director and officer liability insurance (Yuan *et al.*, 2016); split share reform (Sun *et al.*, 2017); social trust (Cao *et al.*, 2016; Li, Shu, Tang and Zheng, 2017; Li, Wang and Wang, 2017); excess perks (Xu *et al.*, 2014); and corporate donations (Zhang *et al.*, 2016). Failure to control for some of these determinants in our main regression model may bias our reported results. Therefore, we include SOE vs non-SOE status (*SOE*); large controlling shareholding (*LARGE_OWN*); corporate donations (*DONAT*); communist party membership (*CPC*); excess parks (*PERK_EXC*); and two other provincial governance variables, namely, *LEGAL* (legal enforcement of property rights) and *CAP* (the access to stock market financing in a region) as some additional independent variables. Reported results in Columns (5)–(8) in Panel A of Table IV are consistent with our baseline results, in that the coefficients on both *ABN_ARL1* and *ABN_ARL2* are positive and significant across both crash measures. For example, the coefficients on *ABN_ARL2* are 0.001 (significant at $p < 0.01$) and 0.001 (significant at $p < 0.01$) for the $SKEW_{t+1}$ and $DUVOL_{t+1}$ measures, respectively, in Columns (7) and (8). Of the additional determinants, the coefficients on *PERK_EXC* are positive and significant across three of the four specifications, whilst those on *DONAT* are positive and significant in two of the four specifications. Taken together, our main findings are robust to controlling for additional determinants of crash risk in China.

Third, we perform a propensity-matching test to mitigate the selection problem arising from observables. Matching on firm characteristics (covariates) is ideal when the number of characteristics over which the treated and control groups differ is limited. Rosenbaum and

Table IV.
Endogeneity tests

Panel A: firm fixed effects regression with additional variables included to alleviate omitted variable concerns

	Firm fixed effects regression				Omitted variable test			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ABN_ARL1	*ABN_ARL1*	*ABN_ARL2*	*ABN_ARL2*	*ABN_ARL1*	*ABN_ARL1*	*ABN_ARL2*	*ABN_ARL2*
	TOP10% = = 1	*TOP10% = = 1*	*Residual model*	*Residual model*	*TOP10% = = 1*	*TOP10% = = 1*	*Residual model*	*Residual model*
	FFE	*FFE*	*FFE*	*FFE*	*FFE*	*FFE*	*FFE*	*FFE*
Variables	$SKEW_{t+1}$	$DUVOL_{t+1}$	$SKEW_{t+1}$	$DUVOL_{t+1}$	$SKEW_{t+1}$	$DUVOL_{t+1}$	$SKEW_{t+1}$	$DUVOL_{t+1}$
$SKEW_t$	−0.137*** (−16.47)	–	−0.143*** (−16.23)	–	−0.148*** (−15.47)	–	−0.156*** (−15.25)	–
$DUVOL_t$	–	−0.148*** (−18.19)	–	−0.154*** (−17.69)	–	−0.159*** (−17.10)	–	−0.166*** (−16.54)
ABN_ARL_t	0.070*** (2.78)	0.063*** (3.05)	0.001*** (3.60)	0.001*** (4.35)	0.061** (2.14)	0.056** (2.42)	0.001*** (3.02)	0.001*** (3.58)
$TURN_t$	0.668*** (12.41)	0.652*** (14.51)	0.679*** (11.73)	0.661*** (13.73)	0.653*** (11.43)	0.644*** (13.47)	0.670*** (10.97)	0.658*** (12.91)
$SDRET_t$	−3.020*** (−4.62)	−3.852*** (−6.95)	−3.004*** (−4.39)	−3.861*** (−6.67)	−3.806*** (−5.28)	−4.753*** (−7.76)	−3.822*** (−5.13)	−4.808*** (−7.63)
RET_t	18.598*** (13.37)	19.346*** (15.92)	17.614*** (12.16)	18.986*** (15.01)	20.618*** (13.79)	21.140*** (15.96)	19.304*** (12.38)	20.592*** (14.88)
$SIZE_t$	−0.366*** (−15.38)	−0.375*** (−18.41)	−0.354*** (−13.88)	−0.359*** (−16.57)	−0.357*** (−12.78)	−0.369*** (−15.51)	−0.357*** (−12.51)	−0.365*** (−14.93)
MB_t	−0.020*** (−4.68)	−0.022*** (−5.95)	−0.018*** (−4.09)	−0.022*** (−5.56)	−0.021*** (−5.05)	−0.023*** (−6.06)	−0.021*** (−4.64)	−0.023*** (−5.86)
LEV_t	0.151 (1.35)	0.133 (1.44)	0.139 (1.17)	0.092 (0.93)	0.164 (1.31)	0.141 (1.36)	0.130 (0.99)	0.090 (0.80)
ROA	−0.055* (−1.71)	−0.029 (−0.95)	−0.148 (−1.62)	−0.121* (−1.71)	−0.157* (−1.73)	−0.137* (−1.89)	−0.138 (−1.47)	−0.120 (−1.64)
$\lvert DAC\rvert_t$	−0.264** (−1.97)	−0.291*** (−2.64)	−0.257* (−1.82)	−0.295** (−2.53)	−0.305** (−2.08)	−0.313*** (−2.60)	−0.298* (−1.91)	−0.320** (−2.51)
$\lvert REM\rvert_t$	0.033 (0.41)	−0.013 (−0.20)	0.032 (0.38)	−0.027 (−0.39)	0.095 (1.08)	0.042 (0.59)	0.093 (1.00)	0.029 (0.39)
$IOWN_t$	−0.250*** (−4.38)	−0.230*** (−4.68)	−0.262*** (−4.37)	−0.231*** (−4.46)	−0.328*** (−5.11)	−0.315*** (−5.76)	−0.334*** (−4.93)	−0.315*** (−5.45)
$ANALYST_t$	0.095*** (7.11)	0.075*** (6.60)	0.101*** (7.26)	0.080*** (6.67)	0.082*** (5.62)	0.065*** (5.17)	0.088*** (5.75)	0.070*** (5.30)
$BSIZE_t$	0.015** (1.96)	0.015** (2.29)	0.016** (2.01)	0.015** (2.34)	0.014 (1.51)	0.015** (1.99)	0.016* (1.73)	0.017** (2.17)
$BIND_t$	−0.017 (−0.09)	0.099 (0.61)	0.099 (0.48)	0.198 (1.16)	−0.077 (−0.32)	0.002 (0.01)	0.082 (0.32)	0.113 (0.52)
$DUAL_t$	−0.031 (−0.87)	−0.013 (−0.47)	−0.023 (−0.61)	−0.008 (−0.29)	−0.031 (−0.79)	−0.014 (−0.44)	−0.017 (−0.41)	−0.003 (−0.10)
$BIG4_t$	0.156*** (2.77)	0.151*** (3.01)	0.164*** (2.78)	0.148*** (2.81)	0.167*** (2.63)	0.160*** (2.81)	0.177*** (2.70)	0.159*** (2.69)
$TOP10_t$	−0.006 (−0.22)	0.008 (0.38)	−0.016 (−0.57)	0.001 (0.03)	−0.013 (−0.45)	−0.006 (−0.25)	−0.022 (−0.74)	−0.014 (−0.55)
LARGE_OWN	–	–	–	–	0.029 (0.21)	0.130 (1.08)	0.036 (0.25)	0.134 (1.11)
SOE	–	–	–	–	0.049 (1.00)	0.062 (1.55)	0.032 (0.64)	0.051 (1.25)
LEGAL	–	–	–	–	−0.002 (−1.12)	−0.001 (−0.97)	−0.001 (−0.57)	−0.001 (−0.47)
CAP	–	–	–	–	2.141 (0.22)	2.031 (0.23)	8.801 (0.92)	6.899 (0.78)
PERK_EXC	–	–	–	–	0.871** (2.12)	0.804** (2.10)	0.659* (1.71)	0.600 (1.63)
DONAT	–	–	–	–	0.000* (1.95)	0.000 (1.41)	0.000* (1.83)	0.000 (1.23)
CPC	–	–	–	–	0.028 (0.56)	0.025 (0.59)	0.064 (1.46)	0.043 (1.09)
Constant	7.600*** (15.12)	7.826*** (18.14)	7.333*** (13.67)	7.487*** (16.40)	7.514*** (12.89)	7.745*** (15.48)	7.430*** (12.49)	7.597*** (14.86)

(continued)

Industry	No	No	No	No	No	No	No	No
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,445	14,445	13,595	13,595	11,896	11,896	11,193	11,193
Adjusted R^2	0.12	0.18	0.12	0.18	0.13	0.19	0.13	0.19

Panel B: propensity-matching analysis

B.1: covariates matching

Variable	Treated	Controls	Difference	*t*-statistic
$SIZE_t$	21.65	21.66	−0.01	−0.28
MB_t	3.52	3.65	−0.13	−0.80
LEV_t	0.09	0.09	0.00	0.52
ROA_t	0.01	0.03	−0.02	−2.63*
$\lvert DAC\rvert_t$	0.08	0.08	0.00	−0.75
$\lvert REM\rvert_t$	0.11	0.11	−0.01	−1.39
$IOWN_t$	0.25	0.26	−0.01	−1.00
$ANALYST_t$	0.77	0.79	−0.02	−0.45
$BSIZE_t$	9.06	9.04	0.02	0.28
$BIND_t$	0.36	0.37	0.00	−1.06
$DUAL_t$	0.15	0.18	−0.03	−1.96**
$BIG4_t$	0.04	0.04	0.00	0.24
$TOP10_t$	0.34	0.33	0.01	0.40

B.2: PSM regression results

	(1)	(2)	(3)	(4)
	ABN_ARL1	*ABN_ARL1*	*ABN_ARL1*	*ABN_ARL1*
	TOP10% = = 1	*TOP10% = = 1*	*TOP10% = = 1*	*TOP10% = = 1*
	NN	*NN*	*ATE*	*ATE*
Variables	$SKEW_{t+1}$	$DUVOL_{t+1}$	$SKEW_{t+1}$	$DUVOL_{t+1}$
$SKEW_t$	−0.064*** (−3.23)	–	0.004 (0.12)	–
$DUVOL_t$	–	−0.065*** (−3.41)		0.005 (0.16)
ABN_ARL_t	0.051* (1.73)	0.055** (2.07)	0.066* (1.86)	0.080*** (2.66)
$TURN_t$	0.683*** (5.42)	0.639*** (5.96)	0.862*** (4.78)	0.816*** (5.18)
$SDRET_t$	−5.239*** (−4.21)	−5.696*** (−5.41)	−4.080** (−2.04)	−4.712*** (−2.69)
RET_t	19.300*** (7.16)	18.444*** (7.97)	11.733*** (3.31)	10.903*** (3.25)
$SIZE_t$	−0.162*** (−6.46)	−0.138*** (−6.55)	−0.169*** (−4.44)	−0.142*** (−4.14)

(*continued*)

Table IV.

MB_t	−0.007 (−1.35)	−0.011*** (−2.61)	−0.023*** (−2.85)	−0.026*** (−3.89)
LEV_t	0.294* (1.87)	0.259** (1.98)	0.212 (0.88)	0.080 (0.39)
ROA_t	−0.144 (−1.15)	−0.148 (−1.49)	−0.051 (−0.89)	−0.084 (−1.58)
$\lvert DAC\rvert_t$	−0.146 (−0.55)	−0.231 (−1.03)	0.088 (0.22)	0.044 (0.12)
$\lvert REM\rvert_t$	0.152 (0.93)	0.082 (0.66)	0.458* (1.91)	0.326 (1.49)
$IOWN_t$	−0.182* (−1.95)	−0.092 (−1.19)	−0.333** (−2.25)	−0.202 (−1.48)
$ANALYST_t$	0.070*** (3.49)	0.045*** (2.65)	0.103*** (3.15)	0.069** (2.49)
$BSIZE_t$	0.021** (2.27)	0.017** (2.10)	0.037*** (2.90)	0.026** (2.22)
$BIND_t$	−0.206 (−0.69)	−0.008 (−0.03)	0.101 (0.18)	0.488 (0.97)
$DUAL_t$	−0.051 (−1.11)	−0.016 (−0.42)	−0.074 (−0.96)	−0.059 (−0.90)
$BIG4_t$	0.202*** (2.68)	0.140** (2.06)	0.263** (2.16)	0.165 (1.47)
$TOP10_t$	−0.001 (−0.03)	0.001 (0.02)	−0.004 (−0.07)	−0.009 (−0.17)
Constant	3.314*** (6.00)	2.925*** (6.27)	3.035*** (3.68)	2.670*** (3.57)
Industry	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	2,898	2,898	2,799	2,799
Adjusted R^2	0.11	0.16	0.15	0.18

Notes: Robust t-statistics in parentheses. Variable definitions are in Table AI. *,**,***Statistically significant at the 10, 5 and 1 levels, respectively (two-tailed test)

Table IV.

Rubin (1983) proposed matching, by a function of covariates, the probability of an individual selection into the treatment group. We use the nearest neighbor (*NN*) and average treatment effects (*ATE*) to perform the PSM model. Proper implementation of PSM requires the treatment and the control group to be similar across a number of firm characteristics, excluding the main variable on which they are expected to differ. Therefore, we first document the covariate matching, based on the calculated propensity score (Armstrong *et al.*, 2010). We report the results in Panel B.1 of Table IV. The reported *t*-statistics in the last column indicate that the matching algorithm was relatively successful in achieving balance for most covariates. In particular, 11 of the 13 *t*-tests are not statistically significant. Panel B.2 of Table IV shows the PSM regression results, using the *NN* technique in Columns (1) and (2) and the *ATE* technique in Columns (3) and (4). We find results that are generally consistent with the main results. For example, the coefficients on *ABN_ARL1* are positive and significant across all four specifications with coefficients ranging from 0.051 ($p < 0.10$) in Column (1) to 0.80 ($p < 0.01$) in Column (4). Overall, we conclude that our primary results are robust to control for endogeneity.

5.3 Internal control (IC) environment, abnormal ARL and crash risk

As discussed in Section 2, the strength of an IC environment plays a significant role in smoothing out the auditor–client negotiation, in that auditors consider management representations for firms with strong IC environments as being more reliable than those for firms with poor IC environments. In 2008, the Chinese regulatory authorities issued the Basic Standard of Enterprise Internal Control (often referred to as China SOX in the literature) (MOF, 2008), and the additional three IC guidelines were published in 2010. Chen *et al.* (2017) focused on the strength of IC in Chinese listed firms, and found a significant negative association between the quality of IC and crash risk.

To test the prediction that the association between abnormal ARL and price crash risk varies based on the quality of the IC environment, we run Equation (4) for firms with a strong IC environment (IC score greater than, or equal to, the median value) vs firms with a weak IC environment (IC score smaller than the median value) groups separately, using the IC index data developed by DIB Enterprise Risk Management Technology Co. Ltd Results are reported in Table V. As is evident from the results, the coefficients on both the abnormal ARL measures are positive and significant for the weak IC sub-sample only. For example, the coefficient on *ABN_ARL1* is 0.088 (t-statistics = 2.33, significant at $p < 0.01$) for the $SKEW_{t+1}$ measure (Column (2)). The corresponding coefficient for strong IC groups is −0.023 and insignificant. Similar results are evident for the $DUVOL_{t+1}$ measure. The coefficients for *ABN_ARL2* are likewise positive and significant for the weak IC group alone (Columns (6) and (8)).

5.4 Additional tests

5.4.1 Alternative model for estimating ARL. In calculating the abnormal ARL following the residual approach, we used the actual number of days as our dependent variable. Since many studies also use the natural logarithm of the number of days (see Habib, Bhuiyan, Huang and Miah, 2019), we also used this variable as the dependent variable in calculating abnormal ARL. The coefficient on abnormal ARL following this approach is 0.094 ($p < 0.01$) and 0.105 ($p < 0.01$) for $SKEW_{t+1}$ and $DUVOL_{t+1}$ proxies, respectively, for the FFE regression specification. The coefficients continue to be positive and highly significant when additional explanatory variables are included in the regression to alleviate the omitted variable concern (untabulated).

5.4.2 Alternative sample period. We also considered an alternative sample period beginning from 2004 instead of 2002. The CICPA (2003) published the Guidance on the

Table V. Internal control environment, abnormal ARL and crash risk

Variables	Strong IC (1) *ABN_ARL1* $SKEW_{t+1}$ IC≥Median	Weak IC (2) *ABN_ARL1* $SKEW_{t+1}$ IC < Median	Strong IC (3) *ABN_ARL1* $DUVOL_{t+1}$ IC≥Median	Weak IC (4) *ABN_ARL1* $DUVOL_{t+1}$ IC < Median	Strong IC (5) *ABN_ARL2* $SKEW_{t+1}$ IC≥Median	Weak IC (6) *ABN_ARL2* $SKEW_{t+1}$ IC < Median	Strong IC (7) *ABN_ARL2* $DUVOL_{t+1}$ IC≥Median	Weak IC (8) *ABN_ARL2* $DUVOL_{t+1}$ IC < Median
$SKEW_t$	−0.045*** (−2.80)	−0.067*** (−4.28)	–	–	−0.048*** (−2.86)	−0.069*** (−4.06)	–	–
$DUVOL_t$	–	–	−0.070*** (−4.68)	−0.098*** (−7.16)	–	–	−0.071*** (−4.51)	−0.104*** (−6.93)
ABN_ARL_t	−0.023 (−0.52)	0.088** (2.33)	0.009 (0.25)	0.073** (2.46)	0.000 (0.17)	0.001* (1.90)	0.001 (1.22)	0.001** (2.34)
$TURN_t$	1.101*** (10.52)	0.608*** (7.60)	1.060*** (12.73)	0.593*** (8.96)	1.096*** (9.96)	0.677*** (7.91)	1.054*** (12.06)	0.644*** (9.14)
$SDRET_t$	−10.761*** (−9.70)	−9.393*** (−9.17)	−11.722*** (−12.31)	−9.491*** (−11.03)	−10.275*** (−8.93)	−9.600*** (−8.74)	−11.207*** (−11.33)	−9.580*** (−10.34)
RET_t	11.672*** (4.89)	22.559*** (10.04)	14.380*** (7.14)	21.016*** (10.23)	10.131*** (4.15)	19.725*** (8.01)	13.136*** (6.32)	19.462*** (8.54)
$SIZE_t$	−0.040** (−2.17)	−0.053** (−2.27)	−0.034** (−2.18)	−0.048** (−2.38)	−0.037* (−1.94)	−0.002 (−0.11)	−0.031* (−1.88)	−0.057*** (−2.60)
MB_t	−0.037*** (−4.86)	−0.015*** (−3.50)	−0.044*** (−6.91)	−0.017*** (−4.65)	−0.035*** (−4.47)	−0.012*** (−2.61)	−0.043*** (−6.44)	−0.014*** (−3.63)
LEV_t	0.217* (1.68)	0.309** (2.31)	0.233** (2.16)	0.316*** (2.93)	0.158 (1.19)	0.322** (2.41)	0.177* (1.65)	0.355*** (3.19)
$\lvert DAC\rvert_t$	−0.321 (−1.49)	−0.499** (−2.47)	−0.346** (−1.98)	−0.476*** (−2.91)	−0.345 (−1.54)	−0.328 (−1.51)	−0.390** (−2.17)	−0.374** (−2.12)
$\lvert REM\rvert_t$	0.078 (0.68)	0.173 (1.51)	0.030 (0.32)	0.073 (0.78)	0.094 (0.78)	0.066 (0.53)	0.017 (0.18)	0.019 (0.19)
$IOWN_t$	−0.030 (−0.50)	0.055 (0.85)	−0.014 (−0.28)	0.069 (1.32)	−0.023 (−0.37)	0.001 (0.02)	−0.001 (−0.02)	0.059 (1.05)
$ANALYST_t$	0.033** (2.29)	0.030** (2.10)	0.004 (0.38)	0.004 (0.29)	0.039*** (2.59)	0.025* (1.72)	0.006 (0.53)	0.015 (1.18)
$BSIZE_t$	−0.001 (−0.17)	0.016** (2.04)	−0.000 (−0.04)	0.017** (2.52)	−0.001 (−0.18)	0.010 (1.16)	−0.000 (−0.04)	0.014* (1.92)
$BIND_t$	−0.121 (−0.52)	0.288 (1.17)	−0.057 (−0.30)	0.211 (1.01)	−0.155 (−0.63)	0.168 (0.61)	−0.091 (−0.46)	0.119 (0.50)
$DUAL_t$	−0.019 (−0.59)	0.050 (1.55)	−0.012 (−0.45)	0.054** (2.13)	−0.026 (−0.73)	0.069** (1.96)	−0.014 (−0.52)	0.069** (2.53)
$BIG4_t$	0.083* (1.82)	0.169** (2.00)	0.070* (1.83)	0.215*** (2.97)	0.062 (1.31)	0.134 (1.50)	0.052 (1.33)	0.216*** (2.77)
$TOP10_t$	−0.016 (−0.64)	−0.009 (−0.31)	−0.015 (−0.71)	−0.005 (−0.24)	−0.011 (−0.41)	−0.011 (−0.39)	−0.015 (−0.68)	−0.005 (−0.22)
Constant	2.361*** (5.63)	2.398*** (4.81)	2.521*** (6.97)	2.416*** (5.58)	2.210*** (5.02)	1.503*** (4.80)	2.374*** (6.26)	2.694*** (5.69)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	No	No	No	No	No	No	No	No
Observations	4,031	4,162	4,031	4,162	3,738	3,898	3,738	3,898
Adjusted R^2	0.09	0.09	0.15	0.14	0.08	0.09	0.15	0.14

Notes: Robust *t*-statistics in parentheses. Variable definitions are in Table AI. *,**,***Statistically significant at the 10, 5 and 1 levels, respectively (two-tailed test)

Practice Criteria for Certified Public Accountants of China No. 5 – Audit Report. This document provides detailed guidance on audit report dates, facilitating the determination of the appropriate audit report date. Untabulated results using both abnormal ARL measures reveal that the coefficients are positive and statistically significant at $p < 0.01$ for both of the crash risk measures (e.g. the coefficients on *ABN_ARL1* and *ABN_ARL2* are 0.108 ($p < 0.01$) and 0.0016 ($p < 0.01$), respectively) for the $SKEW_{t+1}$ crash measure.

6. Conclusion

We test empirically whether abnormal ARL increases the risk of a future crash. Using a large sample from China, we document a significantly positive association between current-period abnormal ARL and future price crash risk. The finding is consistent with the prediction that excessively long ARL often signals financial reporting quality issues emanating from bad news hoarding by the management. Delayed disclosures of negative news increase heterogeneous investor beliefs and the risk of price crash. We extend our main proposition further by examining whether the positive association is more pronounced for firms with ineffective IC environments. Our results support this prediction. The findings confirm that a strong IC environment signals a strong and reliable management representation and, hence, a higher level of information transparency. This, in turn, leads to a lower abnormal ARL-induced risk of stock price crash. Our study extends the scant literature on the consequences of ARL, and provides some useful insights for the Chinese regulatory authorities when considering the appropriateness of the current filing deadline for listed firms. Finally, the significant moderating effect of the IC environment as documented in this study may have practical implications for the Board of Directors in improving their corporate governance policies and practices.

Notes

1. Habib, Hasan and Jiang (2018) provided a systematic review of the determinants and consequences of crash risk, and identified that earnings manipulation, tax avoidance and the creation of a poor corporate governance framework are some of the mechanisms used by managers for concealing bad news.
2. Andreou *et al.* (2017) documented that CEOs have strong financial incentives to hoard bad news in their early career stage, and this increases the likelihood of future stock price crashes. This negative impact of CEO age on stock crash risk is strongest when board monitoring is compromised owing to CEO duality and greater organizational complexity.
3. As at November 12, 2018, the total market capitalization in Shanghai Stock Exchange (2018) is CNY 27,827.5bn (equivalent to $4,002.15bn), and the total market capitalization in Shenzhen Stock Exchange (2018) is CNY 17,247.2bn (equivalent to $2,480.6bn). Both of these two stock exchanges have been ranked among the top 10 by market capitalization internationally as of April 30, 2018 (WFE, 2018).
4. Our IC index score is close to what has been documented in prior Chinese studies. For example, Li (2015) reported an average score of 672.2 for the sample period 2009–2012. Lin and Yu (2015) documented an average IC score of 685.46 for the sample period 2008–2011.

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Appendix 1

Variables	Explanation
$CRASH_{t+1}$	In this study, two measures of firm-specific crash risk are used, consistent with Chen *et al.* (2001). These measures are based on the firm-specific weekly returns, estimated as the residuals from the market model. The detailed estimation procedure for the two crash risk measures, *SKEW* and *DUVOL* are explained in the text (Equations (1)–(3))
ARL_DAY_t	The number of calendar days from fiscal year-end to the date of the auditor's report
ABN_ARL1_t	A dummy variable coded 1 for firm-year observations in the top 10% of the ARL_DAY distribution, and 0 otherwise
ABN_ARL2_t	We take the residual from the ARL determinants model detailed in Table AII. We regress ARL on some of the known determinants of ARL based on prior research. A positive (negative) residual implies an abnormally long (short) ARL
$ICINDEX_t$	The index is constructed by DIB Enterprise Risk Management Technology Co. Ltd The DIB index, annually published since 2008, is a composite index constructed on five dimensions of internal control: IC strategies, operational efficiency, financial reporting quality, legal compliance and asset safety
$TURN_t$	$TURN_{t-1}$ is the average monthly share turnover for the current fiscal year minus the average monthly share turnover for the previous fiscal year, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month
RET_t	Past one-year weekly returns
$SDRET_t$	Standard deviation of firm-specific weekly returns over the fiscal year, and denotes stock volatility, as stocks that are more volatile are likely to be more crash prone
$SIZE_t$	Natural log of total assets
MB_t	Market value of equity divided by the book value of equity
LEV_t	Total long-term debt divided by total assets
ROA_t	Net income divided by total assets
$\vert DAC \vert_t$	Absolute discretionary accruals calculated using the modified Jones model controlling for firm performance (Dechow *et al.*, 1995; Kothari *et al.*, 2005), and should be associated with crash risk positively (Hutton *et al.*, 2009). We estimate the following equation for all firms in the same industry (CSRC industry category) with at least eight observations for an industry in a particular year: $ACC_{i,t}/TA_{i,t-1} = \gamma_0(1/TA_{i,t-1}) + \gamma_1[\Delta SALES_{i,t} - \Delta RECEIVABLE_{i,t}/TA_{i,t-1}] + \gamma_2(PPE_{i,t}/TA_{i,t-1}) + \gamma_3(ROA_{i,t-1}) + \varepsilon_{i,t}$ (A1), where *ACC* is total accruals calculated as earnings before extraordinary items and discontinued operations minus operating cash flows; *TA* is total assets in year $t-1$; $\Delta SALES$ is change in sales from year $t-1$ to year t; $\Delta RECEIVABLE$ is change in accounts receivable from year $t-1$ to year t; *PPE* is gross property plant and equipment; *ROA* is return on assets measured as earnings before extraordinary items and discontinued operations for the preceding year divided by total assets for the same year. The coefficient estimates from Equation (A1) are used to estimate the non-discretionary component of total accruals (*NDAC*) for our sample firms. The discretionary accruals are then the residuals from equation (A1), i.e. $DAC = ACC\text{-}NDAC$
REM_t	We follow prior literature in developing our *REM* proxies (Roychowdhury, 2006); abnormal levels of cash flow from operations (*ACFO*); abnormal production costs (*APROD*); and abnormal discretionary expenses (*ADISX*). *ACFO* are computed by estimating the following regression model within each two-digit SIC industry and year: $CFO/TA_{t-1} = \gamma_0(1/TA_{t-1}) + \gamma_1(SALES/TA_{t-1}) + \gamma_2(\Delta SALES/TA_{t-1}) + \varepsilon$ (A2), where *CFO* is cash flows from operations. *ACFO* is the residual of model (A2). We multiply the residuals from the estimation model by −1 so that higher values of *ACFO* indicate income-increasing *REM*. To estimate the abnormal production cost (*APROD*) we follow Roychowdhury (2006) and use the following model: $PROD/TA_{t-1} = \gamma_0(1/TA_{t-1}) + \gamma_1(SALES/TA_{t-1}) + \gamma_2(\Delta SALES/TA_{t-1}) + \gamma_3(\Delta SALES_{t-1}/TA_{t-1}) + \varepsilon$ (A3), where *PROD* is production cost measured as the sum of cost of goods sold and change in inventory. We use the residual from equation (A3) as our measure of *APROD*. A high value

(continued)

Table AI.
Variable definitions

Variables	Explanation
	of *APROD* indicates higher *REM*, as production costs are abnormally high when managers use overproduction opportunistically to lower the cost of goods sold. To compute abnormal discretionary expenses (*ADISX*), we estimate the following regression and use its residual value to measure *ADISX*: $DISX/TA_{t-1} = \gamma_0(1/TA_{t-1}) + \gamma_1(SALES_{t-1}/TA_{t-1}) + \varepsilon$ (A4), where *DISX* is discretionary expenses (advertising expense, R&D and SG&A expenses). We multiply the residuals from the estimation model (A4) of *DISX* by −1 so that higher values of *ADISX* indicate income-increasing *REM*
$IOWN_t$	Proportion of institutional shareholdings over total outstanding shares
$ANALYST_t$	Natural log of number of analysts following a firm
$BSIZE_t$	Number of board directors
$BIND_t$	Proportion of independent board members over total number of board members
$DUAL_t$	A dummy variable coded 1 if the CEO is also the Chairman of the board, and 0 otherwise
$BIG4_t$	A dummy variable coded 1 for top 4 INTERNATIONAL audit firms based on audit revenue among all listed companies during sample years, and 0 otherwise
$TOP10_t$	A dummy variable coded 1 for top 10 LOCAL audit firms based on audit revenue among all listed companies during sample years, and 0 otherwise
$LARGE\_OWN_t$	Total number of shareholdings by the largest shareholder divided by the total number of company outstanding shares
SOE_t	An indicator variable coded 1 if the firm is a state-owned enterprise (SOE), and 0 otherwise
$LEGAL_t$	Measures the legal enforcement of property rights, defined as the number of patents applied for and approved per engineer in a region; a higher score means stronger legal enforcement
CAP_t	The access to stock market financing in a region, calculated as the total market capitalization of all listed companies in a region relative to regional GDP
CPC_t	A dummy variable coded 1 if any members of the CPC committee are also directors, supervisors or senior executives; otherwise it is 0 (Li and Chan, 2016)
$PERK\_EXC_t$	Actual perk consumption minus expected perk consumption, whereby the latter is derived by regressing perks consumption (scaled by revenue) on the natural log of total compensation for all firm employees, firm size, and the natural log of total income per capita of the region in which the firm is located (Xu *et al.*, 2014)
$DONAT_t$	The natural logarithm of donation expenditures (Zhang *et al.*, 2016)

Table AI.

Appendix 2

Variables	Predicted sign	(1) ARL_DAY
SIZE	+	−0.565* (−1.79)
BIG4	−	−0.205 (−0.17)
TOP10	−	1.196* (1.85)
LN_AF	+	5.295*** (9.43)
OPINION	+	1.246*** (6.00)
MB	+	−0.329*** (−3.33)
LEV	+	−11.911*** (−4.17)
LOSS	+	6.573*** (9.97)
ST	+	3.096*** (2.91)
IOWN	−	−4.275*** (−2.91)
ANALYST	−	−2.198*** (−7.38)
AC	−	−0.806 (−0.93)
BSIZE	?	−0.145 (−0.85)
BIND	−	−3.060 (−0.60)
DUAL	+	1.528** (2.08)
COMPLEX	+	6.962*** (3.51)
LN_SEG	+	−0.555 (−0.95)
Industry		Yes
Year		Yes
Observations		13,595
Adjusted R^2		0.11

Notes: Robust *t*-statistics in parentheses. *LN_AF* is the natural log of total audit fees. *OPINION* is a dummy variable coded 1 for firm-year observations with modified audit opinion, and 0 otherwise. Special treatment (*ST*) firms are coded 1 for firms with negative cumulative earnings for two consecutive years or companies that had negative earnings for one year but the current year shareholders' equities are below registered capital, or companies that received the auditors' "going concern opinion." *AC* is a dummy variable coded 1 if the firm has an audit committee and 0 otherwise. *COMPLEX* is the sum of accounts receivable and inventories divided by total assets. *LN_SEG* is the natural log of the number of business segments the firm is operating in. Other variables are defined as before. *,**,***Statistically significant at the 10, 5 and 1 levels, respectively (two-tailed test)

Table AII.
Determinants of audit report lag in China

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