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In anticipation of a downturn: The role of impression management in buffering against failure

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Abstract

The COVID-19 pandemic has triggered a surge in worldwide business failures. Firms have been actively searching for solutions to survive the crisis and improve business resilience in the post-crisis phase. In developing strategic responses to the risks of failing to get through the “black swan” event, tactics such as impression management may be selected by managers to mitigate contemporary challenges. This paper aims to uncover the actions taken by organisations to manage financial information and market perceptions. It compares the effects of the strategies in normal and unprecedented situations. The empirical analysis of delisting events suggests that the application of impression management is associated with lower delisting risks; however, the effects of such tactics are attenuated in the presence of macro-environmental shocks. Further analyses of market reaction reveal that investors seem to discount all information at the time of disclosure during the pandemic, making the market reaction to impression management less favourable. This provides further support for the reduced efficiency of impression management in alleviating delisting risks following the COVID-19 pandemic. Our results have important implications for firms' development of strategies in response to external turbulence..

Keywords: business failure; COVID-19 pandemic; impression management; delisting

1. Introduction

Throughout the COVID-19 pandemic, many businesses have been battered by globally disrupted economic activities. The pandemic has triggered a labour shortage, disrupting global supply chains and increasing uncertainties in industrial markets (Matthews, Rutherford, Edmondson, & Matthews, 2022). Consequently, the past three years have led to a shocking number of businesses, small and large and across multiple nations and industries, ceasing operations or experiencing extreme difficulties with survival (Amankwah-Amoah, Khan, & Osabutey, 2021; Kalemli-Ozcan, Gourinchas, Penciakova, & Sander, 2020). Undoubtedly, adverse environmental conditions precipitate business failures and urgent scholarly attention is required to understand the impact of such exogenous factors and how to mitigate failure risks (Amankwah-Amoah, Khan, & Wood, 2021; Amankwah-Amoah & Wang, 2019).

Academics and professionals must address how organisations can survive the unprecedented crisis or revitalise their businesses following the external shock (Amankwah-Amoah, Khan, & Osabutey, 2021). An expanding body of literature has suggested that failure cannot be understood through a single lens; instead, investigating strategic management and its connections with entrepreneurship, supply chain management, and other business dimensions is warranted (Ketchen & Craighead, 2020). Alongside awaiting public policy decisions by governmental bodies, firms are expected to proactively develop strategies to achieve organisational agility. For example, research suggests changing business models through open innovation, digitalisation, and coopetition (Crick & Crick, 2020; Li, Wang, Ye, Chen, & Zhan, 2022). However, our understanding of new or conventional solutions' effectiveness in navigating the pandemic remains limited. Current enquiries into the problem remain at the conceptual level, and there is little empirical evidence surrounding the efficacies of different strategies (e.g., Arslan, Golgeci, Khan, Al-Tabbaa, & Hurmelinna-Laukkanen, 2021; Hartmann & Lussier, 2020). This is concerning, particularly with the existential threat of a volatile crisis.

Facing the risks of detrimental changes in the macro-environment, firms are motivated or urged to take strategic actions to reduce the risks of business failure. Impression

management is a commonly adopted method. It refers to “any action purposefully designed and carried out to influence an audience's perceptions of an organisation” (Elsbach, Sutton, & Principe, 1998, p. 68). Prior literature provides ample evidence that firms experiencing financial difficulties are incentivised to engage in impression management by managing their earnings numbers (e.g. Walker, 2013) and communicating financial information to outsiders (e.g. Merkl-Davies & Brennan, 2007). These tactics are part of corporate communication through which positive messages and signals are sent to the market. Existing literature has discussed the diverse applications of impression management in organisational and marketing strategies (Fisk & Grove, 1996); however, the efficacy of impression management in preventing business failure remains underexplored, particularly in the context of severe external shocks (Alo, Ail, Zahoor, Arslan, & Golgeci, 2023). Understanding such strategic actions in normal times and during a global crisis is necessary.

This study investigates the strategic use of impression management for mitigating failure risks during a global crisis (focusing on the COVID-19 pandemic). Despite the ample evidence on impression management, little is known about its role in mitigating failure risks. Agency theory suggests that investors are likely to be misled, at least in the short term, by the strategic distortion of disclosure and reported earnings. Therefore, impression management could function as an effective way to alleviate business failure. However, salience theory and heuristic bias suggest that investors may overstate the impact of the pandemic in their decision-making process, leading to over-pessimism. Consequently, they may choose to discount positive information even if it is unlikely to be affected by the pandemic. If so, the effectiveness of impression management in mitigating failure risks is likely to be attenuated.

Drawing on a dataset of listed firms in China under a unique policy of special treatment that identifies firms with delisting risks, we examine how impression management relates to business failure risks, especially during the pandemic. We are particularly interested in two prevalent impression management strategies: strategic tone management and earnings management. Using the delisting risk warning issued by stock exchanges in mainland China, we construct an indicator for delisting risk and regress this on proxies of tone management in the management discussion and analysis (MD&A) section. We find that

strategic tone management is negatively related to delisting, but this favourable impact has been weakened during the pandemic. Second, we obtain evidence about the implications of earnings management for delisting risk. Specifically, accrual-based earnings management appears to be more effective than real earnings management when managing delisting risk, potentially due to its relatively low cost and timeliness. Like strategic tone management, earnings management effectively mitigates the risk of delisting; however, such effort appears to be partially diluted by severe macro-environmental shocks.

Additionally, we examine the market reaction to impression management to understand the attenuated effectiveness in mitigating delisting risks. There is no evidence that investors react to impression management around the time of disclosure. However, we find that tone management and accrual-based earnings management have had a reduced effect in mitigating delisting risk during the COVID-19 pandemic. Furthermore, we show that although investors do not immediately react to disclosure, they react gradually after a disclosure. Specifically, they can potentially see through and adjust for the accrual-based earnings management; however, they are still misled (unable or unwilling to adjust for) by tone management and real earnings management. Moreover, we show that long-term market reaction to tone management is mainly driven by reaction to B2B firms, which could result from their relatively lower visibility and investor familiarity given the dominance of retail investors in the Chinese stock market.

This study makes two distinctive contributions. First, we contribute to the business failure literature by linking impression management to businesses under failure risks. This moves beyond the extant literature's primary focus on the antecedents or consequences of business failure by bringing new perspectives to managing failure risks; these are concerned with firms' strategic choices driven by the discrepancies between performance and organisational aspirations. Second, the study responds to the call for research on adverse environmental factors and their effects on business failure (Amankwah-Amoah & Wang, 2019). Focusing on the COVID-19 pandemic, we empirically investigate the efficacy of strategies in mitigating failure risks before and during the pandemic. The findings can advise industrial markets on using similar approaches in the post-pandemic world or future crises.

2. Related Literature and Hypothesis Development

2.1 Managing Failure Risks During Crises

Scholars have defined organisational failure or business failure in various ways, with a common understanding that a failure often refers to firms ceasing operations altogether or undergoing temporary performance turbulence (Amankwah-Amoah, 2016). Two primary approaches have been proposed to explain the causes of business failure: the deterministic perspective and the voluntarist perspective (Amankwah-Amoah, 2016). While these two streams of research respectively regard the macro and micro factors as more important, the interactions between the driving forces cannot be ignored (Amankwah-Amoah & Wang, 2019). The COVID-19 pandemic has illuminated their prolonged impact in a changing landscape where internal and external resources require rapid mobilisation (Sheng, Amankwah-Amoah, Khan, & Wang, 2021).

During the COVID-19 pandemic, research has identified several pathways to enhance business resilience and refrain from closing doors to the market in a global crisis. For example, Crick and Crick (2020) highlight the collaborative activities of companies during the pandemic and remark on the implications of the coopetition paradox on business performance. Liljenberg (2022) presents an interesting discussion about the contextual agility that entails organisations' market sense-making abilities and preparedness to respond to environmental dynamics in practice and strategic adaption. In addition, some firms have strategically used conventional approaches, such as impression management (e.g. Pan, McNamara, Lee, Halebian, & Devers, 2018; Talbot & Boiral, 2018), to blunt sensitivity to organisational dysfunction or environmental changes.

Firms in distress will likely take strategic actions to lower the risk of failure by, for example, managing or manipulating their underlying financial performance or influencing investors' perceptions and interpretations of firm performance. This can be understood through the theoretical lens of organisational aspirations. Shinkle (2012) states that aspirations refer to organisational goals, reference points, or desired performance levels. This theory suggests that real performance relative to aspirations influences firms' strategic intentions and actions. Firms intend to take more risks and engage in strategic adjustments when

underperforming compared to when their performance is better than their aspirations (Shinkle, 2012).

The environmental changes posed by a global crisis will heighten firms' incentives to act strategically. This is due to the market lacking confidence and being sensitive to the available information. Firms, especially those operating on the razor's edge, are motivated to communicate strategically with their stakeholders to stabilise the market. Scholars in the strategic management and entrepreneurship fields have discussed how failure can be communicated. They have further highlighted how entrepreneurs respond to failure through tactics such as impression management (e.g., Dobusch, Köster, Schäfer, & Seckler, 2022; Shepherd & Haynie, 2011; Ucbasaran, Shepherd, Lockett, & Lyon, 2013). The information presented to the market is managed or manipulated to highlight favourable cues and eliminate unfavourable cues, justifying the courses of action that led to failure (Caldwell & O'Reilly III, 1982). Firms craft failure narratives, which are used to manage the impression of an organisation after closure (Dobusch et al., 2022).

Although there has been extensive discussion about firms' strategic presentation of information after business failures, little attention has been given to organisations' strategic communications at the pre-failure stage. Tactics like impression management are considered devices for firms to communicate to the markets and establish a positive corporate reputation. Organisational reputation is the generalised favourability of firms (Lange, Lee, & Dai, 2011), and firm performance is a critical determinant of reputation (Fombrun & Shanley, 1990). Driven by corporations' self-presentation motives (Highhouse, Brooks, & Gregarus, 2009), firms are incentivised to present favourable cues in corporate disclosure, particularly when facing failing risks.

2.2 Impression Management During a Crisis

Impression management is a widely used tactic in business and management that “describes efforts by an actor to create, maintain, protect, or otherwise alter an image held by a target audience” (Bolino, Kacmar, Turnley, & Gilstrap, 2008, p. 1080). At the organisational level, impression management can be direct or indirect and assertive or

defensive (Mohamed, Gardner, & Paolillo, 1999). Direct impression management aims to disclose positive information about the organisation, and indirect techniques try to manage information associated with the organisation. Organisations may choose assertive tactics to proactively shape images or respond to threats to organisational images (Parhankangas & Ehrlich, 2014).

Organisations use various techniques to influence stakeholders' perceptions of performance and manage impressions. For example, studies have demonstrated that firms tend to manage the tone reflected by corporate financial disclosures (e.g. Bolino et al., 2008). A positive tone signals managerial confidence (e.g. Lee, Hwang, & Chen, 2017; Yan, 2015). In general, managers are selective in news release media (Washburn & Bromiley, 2014); they time the release of disclosures (Graffin, Halebian, & Kiley, 2016) and exert their discretion over their content, layout, and presentation (Merkl-Davies & Brennan, 2007). Alongside strategic tone management, managers under pressure may directly manage or manipulate corporate performance (i.e., earnings number) to mask negative news and mislead stakeholders about the underlying economic performance, also referred to as earnings management. This paper will focus on two commonly adopted strategies in impression management: tone management and earnings management.

2.2.1 Managing Impression via Strategic Tone Management

The tone of communication has received considerable attention in the management and marketing literature (e.g., Wang et al., 2018; Pitt, Plangger, Botha, Kietzmann, & Pitt, 2019). In the following analyses, we concentrate on the tone of the annual report's MD&A section. The MD&A section allows managers to evaluate the firm's performance, financial condition, risk, and prospects. According to prior literature (e.g. Davis & Tama-Sweet, 2012), the sentiment of the MD&A section is generally consistent with the firm's profitability. Firms are motivated to present information positively, even if the tone of their textual disclosure is disproportionate to their current financial performance and position (Huang, Teoh, & Zhang, 2014). When a firm experiences operational and financial difficulties, the motive for self-presentation is stronger. When corporate disclosure is publicised, it delivers information to financial markets. A positive tone in the disclosure

can influence outsiders' perceptions of the firm. Therefore, we suggest the following hypothesis:

H1a: Strategic tone management is negatively associated with the probability of receiving delisting risk warnings from stock exchanges.

We are more interested in the effectiveness of impression management when affected by global crises, such as the COVID-19 pandemic. Due to the highly vulnerable market sentiments, it is likely that any failure to provide positive information or valid justification for negative information during the downturns could cause markets to overreact. Therefore, managers might have stronger incentives to use impression management during the pandemic as a 'damper', reducing business failure's speed (or acceleration).

However, when facing extreme exogenous shocks, impression management may be less effective than normal. First, this will likely result from market pessimism following the shocks because negative events negatively impact the economy (e.g., Carter & Simkins, 2004). Given the negative consequences of the pandemic on firm operations and stock return, investors may become more pessimistic and discount positive information even without the pandemic's influence. Second, from an irrational perspective, heuristics bias may induce incomplete decision-making based on immediate information rather than all relevant available information (Tversky & Kahneman, 1973). Finally, according to salience theory (e.g., Bordalo, Gennaioli, & Shleifer, 2022), the COVID-19 pandemic is arguably the most salient event of the past three years, which may potentially attract excessive attention from the public. Consequently, investors may overreact to the pandemic and overestimate its negative impacts when making investment decisions. This suggests that although not all firms have been substantially affected by the pandemic, the influence of the pandemic is likely to be overweighted in investors' decision-making process. The capital market may universally discount positive information during the pandemic, making impression management less effective in mitigating failure risks. Therefore, we develop the following hypothesis:

H1b: The effect of strategic tone management in mitigating failure risks is weakened during the COVID-19 pandemic.

2.2.2 Managing Impression via Earnings Management

Like tone management, earnings management could also function as an effective way to mitigate failure risks. Prior marketing literature has examined a similar concept to earnings management: myopic management (e.g., Mizik, 2010; Srinivasan & Ramani, 2019), mainly focusing on its short-term orientation. It is defined as “the practice in which management overemphasizes short term goal achievement (i.e. meeting or beating quarterly earnings estimates) at the expense of strategies that offer superior return, but in the longer run” (Agnihotri & Bhattacharya, 2021, p.147). However, considering the negative impact of the pandemic on business operations, managers would be incentivised to employ all available devices to enhance desirable aspects or obfuscate less desirable aspects of the firm. Therefore, our analyses extend the notion of myopic management to a broader sense of earnings management to capture managers' reactions in anticipation of business failures. Specifically, we focus on two main methods of earnings management: accrual-based earnings management (AEM) and real earnings management (REM), which function as substitutes (Zang, 2012). AEM usually involves managerial discretion over accounting choices and earnings reporting choices, while REM refers to manipulating real economic activities. By manipulating earnings numbers or real activities, firms with failure risks could increase their chance of meeting financial targets and avoiding being treated differently and therefore delisted. Therefore, we hypothesise the following:

H2a: Earnings management is negatively associated with the probability of receiving delisting risk warnings from stock exchanges.

Like tone management, we expect earnings management to be less effective during the COVID-19 pandemic. Fig. 1 depicts a conceptual illustration of the hypothesised relationships between impression management and business failure, as documented in H1 and H2. Alongside the theoretical reasoning presented above, the reduced effectiveness of earnings management may also result from its increased costs after the outbreak and

national lockdown. Despite prior studies providing ample evidence for AEM and REM, managers have specific preferences for AEM and REM under different circumstances. According to Zang (2012), there is a trade-off between AEM and REM; the former is preferred by managers when the firm is in financial difficulties. Roychowdhury (2006) documents three methods of REM: sales manipulation, overproduction, and the reduction of discretionary expenditures. Notably, these options have been significantly restricted by the COVID-19 pandemic because sales and production have declined due to governmental restrictions and lockdowns. Furthermore, discretionary expenditures have also decreased due to national lockdowns, limiting the extent they can be managed downwards. Therefore, it is likely that AEM has become more prominent than REM during the pandemic. More importantly, despite the evidence on the effectiveness of AEM in meeting earnings benchmarks, it is less likely to function as expected following national lockdowns. In particular, COVID-19 control measures confine the available AEM options, limiting the scope and extent to which earnings can be managed. Therefore, we hypothesise:

H2b: The effect of earnings management in mitigating failure risks is weakened during the COVID-19 pandemic.

[Insert Figure 1 Here]

3. Research Design

3.1 Business Failure in the Context of the Chinese Stock Market

We focus on business failure for listed firms, called delisting, and examine our hypotheses in the context of the Chinese stock market to take advantage of China's specific special treatment (ST) policy. Delisting has significant negative impacts because delisted firms lose access to capital markets and suffer from reduced liquidity. Prior studies have identified that firms have strong incentives to avoid delisting (e.g. Chu, Du, & Jiang, 2011; Jiang & Wang, 2008).

Firms close to involuntary delisting are not always distinguishable, and financial data on near-delisting firms are often incomplete and unreliable. Furthermore, we are interested in

how firms could retaliate when facing business failure rather than what leads to failure. Therefore, instead of examining the outcome of delisting, we focus on the intermediate state of delisting by exploiting the Chinese stock market's ST policy, which provides a clear indicator of delisting risk.

According to the rules of stock listing issued by the Shanghai and Shenzhen stock exchanges, a delisting risk warning will be issued to a company in the form of a ‘*ST’ (special treatment) suffix before the short name of its stocks. This warning will be issued on a stock when an abnormality occurs in the listed firm's financial condition. This may include, for example, negative net profits in the past two consecutive years, a stock price below nominal value (changed to below 1 RMB in 2020) for 20 consecutive trading days, a market value below 300 million RMB for 20 consecutive trading days, negative net assets, revenue less than a certain amount, a disclaimer of opinion or adverse opinion, significant errors or falsehoods in the financial statements, the violation of laws, or a failure to disclose a periodic report. After receiving a delisting risk warning, the stock listing of a listed firm may be terminated by the stock exchange if the firm fails to meet all the conditions in the following year.¹ If it meets the conditions, its stock's delisting risk warning will be lifted. The rationale behind the ST policy is that ST firms are performing poorly and need to be delisted to protect investor interests (Jiang & Wang, 2008). ST indicates the danger of involuntary delisting, and the stock will be deregistered if there is no improvement.

We deployed the delisting risk warning as a proxy for firms at risk of business failure to measure business failure risk. *ST* was constructed as a dummy indicator for delisting risk; it equalled 1 if a listed firm received a delisting risk warning in year $t+1$ and 0 otherwise. Next, as the outbreak started in late December 2019, we used the end of 2019 as the cut-off point and developed a dummy indicator, *POST*, which takes the value of 1 after 2019 and 0 otherwise.

¹ The *Rules Governing the Listing of Stocks on Shanghai Stock Exchange* and *Rules Governing the Listing of Stocks on Shenzhen Stock Exchange* have been revised several times in recent years (last revised in 2022). The detailed criteria for issuing and lifting a delisting risk warning and the termination of the listing have been modified.

3.2 Data and Sample Selection

To test our hypotheses, we obtained data for all A-share listed companies in China from the Chinese Stock Market and Accounting Research (CSMAR) database. We began with firm financial data and matched this with ST status, textual attributes of management commentary, and board of director characteristics based on stock ID and fiscal year. To explore the impact of the COVID-19 pandemic, we focused on the period between 2017 and 2021. After eliminating missing values, our final sample comprised 12,023 firm-year observations for 3252 unique listed companies from 2017 to 2021.² Of the 12,023 firm-year observations, 236 (1.96%) were subject to the delisting risk warning (with an ‘ST’ status).³ Table 1 shows the distribution of our firm-year observations over the sample period. There is a clear upward trend in the number of listed firms even during the pandemic, suggesting the rapid expansion of the Chinese stock market.

[Insert Table 1 Here]

3.3 Impression Management

3.3.1 Strategic Tone Management

Firms engage in impression management through various disclosure documents, such as earnings press releases (Davis, Piger, & Sedor, 2012), conference calls (Frankel, Mayew, & Sun, 2010), and MD&A sections (Davis & Tama-Sweet, 2012), to opportunistically influence the perceptions of investors about firms' performances and prospects. To measure impression management, we focused on standard, almost costless, and relatively subtle tactics commonly used in prior studies (e.g. Merkl-Davies & Brennan, 2007; Kim, Xiong, & Kim, 2018): discretionary disclosure strategies. Specifically, we focused on managerial discretion over the textual attributes of corporate disclosure. Following Davis and Tama-Sweet (2012), we analysed the MD&A section in annual reports where managers evaluate the firm's performance, financial condition, risk, and prospects. As a useful supplement to

² We found qualitatively similar results after excluding firms in the financial industry.

³ Before sample selection, ST firms amounted to 4% of the initial sample (19,843). The smaller proportion of ST firms in the final sample was due to missing variables resulting from trading suspension.

the financial statements, MD&A sections describe and explain significant events and changes in the period from the firm management perspective. They also provide managers' evaluation of the macroeconomics, industrial trends, risks, and uncertainties that may affect future performance.

Our analysis examined a series of textual attributes, starting with tone. The sentiment of corporate disclosure is generally consistent with a firm's profitability. However, tone may be used to convey new information or for impression management purposes. The latter case corresponds to the idea of tone management documented by Huang et al. (2014), which occurs when the tone of a firm's textual disclosure is disproportionate to its financial performance and position. Managers have frequently used tone management to influence outsiders' perceptions.

Following Huang et al. (2014), we measured the tone of an MD&A section as the difference between the number of positive words and negative words divided by the total number of positive and negative words in an MD&A section. As tone may be used to convey new information rather than impression management, a 'manipulated' tone must be isolated from a normal tone. Therefore, we decomposed the tone of MD&A into a truthful tone that reflects current and expected future performance and a strategically distorted tone that reflects tone management. Specifically, we estimated the normal tone using the following equation adapted from Li (2010) and Huang et al. (2014), which controls for tone determinants, including performance, growth, risks, and complexity:

$$TONE_{jt} = \alpha + \beta_1 EARN_{jt} + \beta_2 BHR_{jt} + \beta_3 SIZE_{jt} + \beta_4 BTM_{jt} + \beta_5 STD_BHR_{jt} + \beta_6 STD_EARN_{jt} + \beta_7 AGE_{jt} + \beta_8 LOSS_{jt} + \beta_9 \Delta EARN_{jt} + \varepsilon_{jt}, \quad (1)$$

where *EARN* is measured as earnings before extraordinary items scaled by lagged total assets; *BHR* is the buy and hold annual stock returns; *SIZE* is the natural logarithm of total asset at fiscal year-end; *BTM* is book-to-market ratio measured at the end of fiscal year *t*; *STD_BHR* is the standard deviation of monthly stock return in year *t*; *AGE* is the number of years since established; *LOSS* equals 1 if earnings before extraordinary items is negative, and 0 otherwise; $\Delta EARN$ is the change earnings before extraordinary items from year *t*-1

to year t scaled by lagged total assets. The model is estimated using annual data and the results are presented in Table 2. The residual of the regression, namely abnormal positive tone ($ABTONE$), is the proxy for tone management. Consistent with Huang et al. (2014), $EARN$ is positively associated with the tone whereas the coefficients on BTM and $LOSS$ are negative. Moreover, our results suggest that stock return and firm size are positively related to the tone of MD&A section. Greater stock return and earnings volatility are generally negative signals as reflected by the negative coefficients.

[Insert Table 2 Here]

Alongside the $ABTONE$, we further constructed a $\Delta TONE$, which captured the changes in MD&A tone from year $t-1$ to year t . A positive $\Delta TONE$ may be associated with improved performance or impression management. Furthermore, four other textual attributes were constructed: word count (WC), the total number of unique words (UWC), sentence count (SC), and similarity ($SAME$) between the MD&A of year t and year $t-1$. To enable easier comparison of the magnitude and economic significance, we followed Bernard and Thomas (1990) and Huang et al. (2014) and reconstructed impression management variables by taking the annual decile rankings (1 to 10) of $\Delta TONE$ and $ABTONE$ minus 1; these were then scaled by 9. Therefore, the new variables $R\Delta TONE$ and $RABTONE$ ranged from 0 to 1.

3.3.2 Earnings Management

Following prior literature, we estimated discretionary accruals using the following modified Jones model by Dechow, Sloan, and Sweeney (1995) to measure the magnitude of AEM.

$$\frac{DACC_t}{TA_{t-1}} = \alpha_0 + \alpha_1 \left(\frac{1}{TA_{t-1}} \right) + \beta_1 \left(\frac{\Delta S_t}{TA_{t-1}} \right) + \beta_2 \left(\frac{PPE_t}{TA_{t-1}} \right) + \varepsilon_t, \quad (2)$$

where $DACC_t$ is the difference between earnings before extraordinary items and cash flow from operation in year t ; TA_{t-1} is the total assets in year $t-1$; ΔS_t is the change in revenue

from year $t-1$ to year t ; PPE_t is the gross property, plant, and equipment at the end of year t . Discretionary accruals is then measured as residuals from this equation.

For real activities manipulation, we followed the approach in Roychowdhury (2006) and estimated two different types of real activities manipulation: overproduction and abnormal reduction in discretionary expenditures.⁴ To estimate the normal level of production costs, we run the following regression by industry year⁵:

$$\frac{PROD_t}{TA_{t-1}} = \alpha_0 + \alpha_1 \left(\frac{1}{TA_{t-1}} \right) + \beta_1 \left(\frac{S_t}{TA_{t-1}} \right) + \beta_2 \left(\frac{\Delta S_t}{TA_{t-1}} \right) + \beta_3 \left(\frac{\Delta S_{t-1}}{TA_{t-1}} \right) + \varepsilon_t, \quad (3)$$

where $PROD_t$ is the sum of the cost of goods sold in year t and the change in inventory from year $t-1$ to year t ; S_t is the net sales in year t ; ΔS_{t-1} is the change in net sales from year $t-2$ to year $t-1$.

Similarly, following Roychowdhury (2006), we used the following equation to estimate the normal level of discretionary expenditures:

$$\frac{DISEXP_t}{TA_{t-1}} = \alpha_0 + \alpha_1 \left(\frac{1}{TA_{t-1}} \right) + \beta \left(\frac{S_{t-1}}{TA_{t-1}} \right) + \varepsilon_t, \quad (4)$$

where $DISEXP_t$ is the sum of discretionary expenditures in year t and S_{t-1} is the net sales in year $t-1$. All regressions are estimated cross-sectionally by industry-year grouping with at least 15 observations available. The abnormal level of production costs and discretionary expenses were then measured as the residuals from the above three equations. Additionally, abnormal discretionary expenses were multiplied by minus one so that higher values indicate greater level of earnings management. Furthermore, to test the joint effect of the above real activity manipulation, we further constructed a comprehensive *REM* indicator to combine these two individual proxies following Zang (2012). Similarly, all earnings

⁴ We do not include abnormal cash flow from operations here because the net effect is ambiguous as noted in Roychowdhury (2006) and Zang (2012).

⁵ We use the first digit of the 2012 industry classification by the CSRC.

management variables are further transformed into *RAEM*, *RABPROD*, *RABDISEXP*, and *RREM*, with a value ranging between 0 and 1.

4. Empirical Results

4.1 Descriptive Statistics

Table 3 presents the summary statistics for the variables used in our primary analyses. According to Panel A of Table 3, firms with a delisting risk warning only constituted 2% of our sample. The average *TONE* of 0.272 suggests a positive tone of MD&A, and the average $\Delta TONE$ of 0.014 indicates that firms generally had a more optimistic tone than last year. This is consistent with the overwhelming optimism documented in prior studies. The abnormal positive tone (*RABTONE*) had considerable variation within the final sample.

Table 3 Panel B presents a comparison between normal firms and *ST* firms. According to the difference in mean, non-*ST* firms appeared to have a more positive tone, greater *RAEM*, and abnormal product costs (*RABPROD*). However, they had a lower abnormal discretionary expense (*RABDISEXP*). Interestingly, on average, non-*ST* firms had higher tone management and accrual-based earnings management, partially corroborating the effectiveness of managers' strategies to buff business failure.

Table 3 Panel C presents an additional comparison between pre- and post-outbreak. Firms were less likely to receive a delisting risk warning after the COVID-19 pandemic began. However, there was a more positive tone, a more positive change in tone, and a higher level of tone management during the pandemic. Accrual-based and real earnings management were lower after the pandemic began.

[Insert Table 3 Here]

4.2 Delisting Risk and Impression Management

We first investigated whether the delisting risk was associated with tone management and, more importantly, whether the COVID-19 pandemic moderated this relationship. We

examined the relationship between impression management and delisting risk using the following regressions:

$$\begin{aligned} \text{Pr } (ST)_{jt+1} = & \alpha + \beta_1 TM_{jt} + \beta_2 POST_{jt} + \beta_3 TM \times POST_{jt} + \text{Controls} + \text{YearFE} \\ & + \text{IndFE} + \varepsilon_{jt}, \end{aligned} \quad (5)$$

where tone management (*TM*) is measured as either *RATONE* or *RABTONE*, which is the abnormal positive tone estimated from equation (1); *POST* is an indicator for the COVID-19 outbreak, which takes the value of 1 on and after fiscal year 2020, and 0 otherwise; A series of control variables are included. *SIZE* is measured as the natural logarithm of the market value at the end of year *t*; *LV* is measured as total debt scaled by total asset; *Growth* is the change in revenue from year *t-1* to year *t* scaled by revenue in year *t-1*. *DIR_NUM* is the total number of directors; *FEMALE* is the proportion of female directors and top management; *DIR_IND* is the portion of independent directors; *II_OWN* is the institutional investor ownership, measured as the proportion of shares owned by institutional investors. We also include industry and year-fixed effects in the regressions and estimate with robust standard errors clustered at the firm level. Results are presented in Table 4 Panel A.

Consistent with H1a, Column (2) of Table 4 suggests a significant negative association between delisting risk warning and tone management. The coefficient on *RABTONE* was negative (-1.391) and significant at the 1% level. This suggests that managers who engage in a greater level of strategic tone management are less likely to receive a delisting risk warning. Column (4) presents the results of the relationship between *RABTONE* and *POST*. The coefficient on *RABTONE* remained negative and significant, while the interaction term *RABTONE* × *POST* was positive (0.979) and significant at the 5% level. This indicates that controlling for other factors, tone management has been less effective in mitigating delisting risk warnings since the COVID-19 pandemic began, corroborating H1b.

The results for control variables generally align with prior literature. Larger firms and firms with a higher growth rate are less likely to receive delisting risk warnings, while firms with higher leverage that experience a loss are more likely to receive delisting risk warnings.

[Insert Table 4 Here]

We conducted further analyses to reveal whether other textual attributes of the MD&A section related to the level of probability of receiving a delisting risk warning. We tested the length, unique words, and similarity of the MD&A section. The results are presented in Table 4 Panel B. We used the number of words and sentences to capture the length of MD&A. To capture changes in the MD&A sections over time, we obtained a similarity measure between this year's and the previous year's MD&A sections directly from CSMAR. Instinctively, the similarity of firms without significant changes should be relatively high. As expected, these attributes were negatively associated with the probability of receiving a delisting risk, suggesting that firms with higher delisting risks are likely to have shorter MD&A sections, use fewer words, and be less similar to the previous year's MD&A. Specifically, the coefficient on SIMILARITY was negative (−6.096) and significant at the 1% level. More importantly, the interaction term $SIMILARITY \times POST$ was positive (7.647) and significant, indicating the impact of similarity on the probability of receiving delisting risk warnings during the pandemic. This further supports H1b, suggesting that impression management has been constrained during the pandemic to mitigate business failure.

4.3 Delisting Risk and Earnings Management

Next, we investigated whether delisting risk is associated with earnings management and whether this relationship has been affected by the COVID-19 pandemic. We tested whether *AEM* and *REM* levels relate to the probability of receiving delisting risk warnings using the same regression design, with *RABTONE* replaced by earnings management proxies. The model specification was as follows:

$$\begin{aligned} \Pr (ST)_{jt+1} = & \alpha + \beta_1 EM_{jt} + \beta_2 POST_{jt} + \beta_3 EM \times POST_{jt} + \text{Controls} + \text{YearFE} \\ & + \text{IndFE} + \varepsilon_{jt}, \end{aligned} \quad (6)$$

where earnings management (*EM*), represents discretionary accrual (*RAEM*), abnormal production costs (*RABPROD*), abnormal discretionary expenses (*RABDISEXP*), or *RREM*. Table 5 Panel A presents the results. Panel B shows the interaction between earnings management proxies and *POST*.

As shown in Table 5 Panel A Column (1), the coefficient of *RAEM* (-0.470) was negative and significant at the 10% level, suggesting that accrual-based earnings management effectively meets the earnings benchmark and avoids delisting risk warnings. All three real earnings management proxies were insignificant. The results remained consistent when we added two comprehensive earnings management proxies, *RAEM* and *RREM*, in the same regression, as shown in Panel A Column (5). Table 5 Panel B shows our test of the conditional effects of earnings management when affected by the pandemic. Consistently, *RAEM* at year t was negatively associated with the probability of receiving a delisting risk warning in the next year. These findings suggest that *AEM* plays a more critical role in addressing delisting risk, while *REM* does not play a significant role.

Furthermore, as expected, coefficients on the interaction term between *RAEM* and *POST* were positive and significant at the 5% level in Columns (1) and (5). This is consistent with H2b that the effect of (accrual-based) earnings management on mitigating delisting risk has been reduced by the COVID-19 pandemic. This corroborates that extreme environmental shocks potentially constrain the scope and extent that managers can manipulate earnings numbers.

[Insert Table 5 Here]

4.4 Market Reaction to Impression Management

We have documented the attenuated role of impression management in mitigating business failure risk. Our results were consistent with our theoretical reasoning. If rational investors anticipate the increased use of impression management tactics during the pandemic, they will likely discount tone and earnings management. Consequently, we would observe a negative or no market reaction during disclosure. However, a positive market reaction would be expected if investors cannot see through the managed tone and earnings. To test the competing views above, we used the following regression model adopted from Huang et al. (2014):

$$CR[-1, +1] = \alpha + \beta_1 TM_{jt} + \beta_2 TM \times POST_{jt} + \beta_3 EM_{jt} + \beta_4 EM \times POST_{jt} + \text{Controls} \\ + YearFE + FirmFE + \varepsilon_{jt}, \quad (7)$$

where the dependent variable $CR[-1, +1]$ is the 3-day cumulative stock return from one day prior to the disclosure of the annual report to one day after the disclosure. We control for firm characteristics that may affect stock return, including ST , $SIZE$, book-to-market ratio (BTM), BHR , STD_BHR , STD_EARN as well as firm and year fixed effects. The model was estimated using robust standard error clustered at the firm level. Table 6 presents the results. We first regressed stock return on impression management proxies; then, we added interactions between these proxies and $POST$ to the model.

In Column (1), all impression management proxies were insignificant. In contrast, in Column (2), the coefficients on the interaction term $RABTONE \times POST$ and $RAEM \times POST$ were negative and significant at 1% and 5%, respectively. This implies that investors do not react (unable or unwilling) to information at the time of disclosure. However, they have discounted all information after the outbreak of the COVID-19 pandemic, as indicated by the negative and significant coefficients of the interaction terms. This evidence supports the reduced market reaction to impression management during the pandemic, aligning with H1b and H2b.

To further assess the effect attenuation, we tested whether investors react to impression management after disclosing the annual report. We replaced the 3-day stock return around the disclosure, $CR[-1, +1]$, in Equation (7) with a 60-day stock return, $CR[+2, +61]$, starting from the second day after the disclosure. We re-estimated the regression. If investors gradually see through these tactics after the disclosure, we predict a negative effect on market reaction.

The results are presented in Columns (3) and (4) of Table 6. Clearly, investors react to impression management after disclosing an annual report. Specifically, there was a positive reaction to tone management and real earnings management, while there was a negative reaction to accrual-based earnings management. These findings show that investors are potentially misled by impression and real earnings management but not by accrual-based earnings management. This is because an abnormal tone is often difficult to detect, and real earnings management is usually indistinguishable from genuine error. Further analyses of the interaction terms reveal a positive reaction to real activity manipulation during the

pandemic, implying that investors have been misled by real earnings management during the pandemic.

[Insert Table 6 Here]

4.5 Business-to-business (B2B) versus Non-B2B Firms

Next, we are interested in whether the above effects vary across B2B and non-B2B firms given the distinct audiences they target. B2B firms often deal with a limited number of businesses customers instead of individual customers, and thus care more about trust and loyalty (Wang & Xu, 2017). Consequently, they may exhibit different patterns of impression management when facing crisis. As such, we first identified B2B firms following prior studies (e.g., Mishra, Ewing, & Pitt, 2020; Srinivasan, Lilien, & Sridhar, 2011) and about 59% (41%) of our final sample are classified as B2B (non-B2B) firms.⁶ We then constructed and interacted two dummy indicators for B2B firms and non-B2B firms with our proxies for impression management and re-estimate model (5) and (6). The results (ubtabulated) do not reveal any significant differences regarding the effects of impression management between these two groups of firms. However, we do find something interesting about the market reaction after re-estimating model (7) and the results are presented in Table 7. Specifically, market reactions to earnings management appear to be similar for both B2B and non-B2B firms whereas the 60-day positive stock return to tone management is mainly driven by B2B firms as evidenced by the positive and significant coefficient on the interaction term between *B2B* and *RABTONE*. Prior literature suggests that due to the nature of business transactions, B2B firms are less active on social media (Swani, Brown, & Milne, 2014). Arguably, B2B firms may be relatively less visible to individuals compared to non-B2B firms and thus the market may be less familiar with these firms considering the dominance of retail investors in the Chinese stock market.

⁶ Notably, the classification of B2B firms in prior literature is generally based on industry classification and there is substantial variation across studies and contexts. For instance, Srinivasan et al. (2011) use the U.S. firm's primary four digit SIC code to identify B2B industries whereas a detailed list of B2B industries is directly provided in Mishra et al. (2020). We combine the two lists together and identify B2B industries using the 2012 CSRC industry classification.

Taken together, tone management by B2B firms would be relatively more difficult for investors to see through and adjust for, thereby leading to a greater positive market reaction.

[Insert Table 7 Here]

4.6 Severity of the Pandemic

We further considered the severity of the pandemic in the region where a firm is located. Instinctively, firms in more severe areas are more likely to be adversely affected by the pandemic. Therefore, we obtained the annual number of confirmed COVID-19 cases in each city and province and matched this to our firm-year sample. The data on confirmed cases began in 2020. We estimated similar regressions to our main tests. However, our analyses (untabulated) did not find any evidence that severity plays an important role. This may be because restrictions and lockdowns were adopted nationally due to the widespread nature of COVID-19. Therefore, firms in an area with fewer confirmed cases have still been significantly affected by the pandemic.

4.7 Additional Analyses

In previous sections, we have explored how firms deal with delisting risk warnings issued by the stock exchanges. A natural follow-up question concerns how effective the two strategies are in helping firms with delisting risks avoid being delisted. To examine the impact of impression management on delisting events, we identified a sample of firms that have been forced to delist. Within our sub-sample of 526 firm-year with delisting risk, only 23 of the 284 unique firms have been delisted to date. This is primarily due to missing information on delisted firms. Many had been suspended for trading for years before the delisting or had failed to disclose their annual report in time. Unsurprisingly, there was no significant association between impression management and delisting events in the sample of ST firms. Firms in extreme financial difficulties are generally under more robust scrutiny from investors and regulators. They will likely make the media headlines, leaving little room for earnings management. Furthermore, tone management alone will not help in this situation because the distressing financial statements would attract most market attention.

Due to the mechanism of delisting risk warning, firms currently labelled ST may remain in this status until removed by the stock exchanges. Therefore, ST status in year t may be correlated with ST status in year $t + 1$. Therefore, we added a dummy indicator of the ST status in year t to our models; the results remained broadly consistent.

Another concern is that firms may anticipate future financial difficulties and try to ‘take a bath’ in the current period. This may lead to poor financial conditions documented in annual reports, leading to firms receiving a delisting risk warning from the stock exchange. However, as this is temporary, managers could reverse this and inflate their earnings in the following period, lifting the risk warning. This ‘artificial’ delisting risk warning does not necessarily reflect a failing business and may have interfered with our tests. We identified ST firms with negative *AEM* to eliminate their influence and excluded them from our sample. The rationale is that firms, except those who intend to take a bath, are unlikely to manage their earnings downwards when risking business failure. Our results remained consistent after excluding these firms.

5. Discussions and Conclusions

The COVID-19 pandemic, as an unexpected exogenous shock, brought challenges to firms. It could change how managers deal with business failure risks. When the COVID-19 pandemic began, restrictions were introduced to stop the spread of the virus, interfering with the operation of many businesses. Given their large size and scale, listed companies are more likely to be affected.

This paper analysed impression management's efficacy in alleviating business failure risks. We regarded business failure as firms with delisting risk and considered two impression management approaches: tone management and earnings management. Our results show that firms more engaged in strategic tone management are less likely to receive delisting risk warnings. However, the favourability created by tone management is reduced by widespread environmental shocks. Similarly, earnings management is effective in meeting earnings benchmarks and avoiding delisting risk warnings; however, the effectiveness of this tactic is weakened during highly turbulent times. Further analyses of the market

reaction to impression management reveal that investors discount all information during disclosure when affected by the pandemic. This partially explains the attenuated effects of impression management.

5.1 Theoretical Implications

This study makes the following contributions to research. First, we have contributed to the business failure literature by exploring how impression management is associated with business failure. We have analysed businesses with a risk of failure and assessed how they could use tactics to mitigate delisting risks. This has provided a new perspective to studying business failure by investigating financial disclosure information at the strategic level. Second, the study has responded to the call for research on adverse environmental factors and their effect on business failure (Amankwah-Amoah & Wang, 2019). Within the COVID-19 context, we empirically investigated the efficacy of the two impression management strategies to mitigate failure risks before and during the pandemic. The results indicate that investors have universally discounted information during the pandemic, attenuating the effect of impression management, and this finding corroborates prior research on information asymmetry, limited attention, and investor sophistication. Furthermore, drawing on agency theory, salience theory, and heuristic bias to explain such phenomenon extends the application of these theoretical perspectives to understanding business failure in global challenges.

5.2 Practical Implications

Our findings provide information about using similar approaches in the post-pandemic world or future crises. We have found consistent evidence that managing impressions through tone and earnings management is vital in mitigating delisting risks. However, such effects appear to have been weakened by the COVID-19 pandemic. Therefore, managers and stakeholders should be cautious in managing impressions when affected by severe external shocks. Managers may want to consider a more diverse strategy for managing stakeholders' perceptions during a global crisis.

Notably, our study focuses on the context of listed firms, potentially limiting our findings' generalisability to small and unlisted firms.

5.3 Future Research

It would be helpful to understand what determines managers' preferences for impression management. It would be interesting to assess whether the strategic choices related to impression management tactics in anticipation of business failure are conditional on other firm characteristics. Future studies could also investigate different textual attributes or textual disclosures. Furthermore, we have focused on the risk of business failure. It would be valuable to investigate the role of impression management in the transition from failing business to business failure.

References

- Agnihotri, A., & Bhattacharya, S. (2021). CEO narcissism and myopic management. *Industrial Marketing Management*, 97, 145-158.
- Amankwah-Amoah, J. (2016). An integrative process model of organisational failure. *Journal of Business Research*, 69(9), 3388–3397.
- Amankwah-Amoah, J., Khan, Z., & Osabutey, E. L. C. (2021). COVID-19 and business renewal: Lessons and insights from the global airline industry. *International Business Review*, 30(3), 101802.
- Amankwah-Amoah, J., Khan, Z., & Wood, G. (2021). COVID-19 and business failures: The paradoxes of experience, scale, and scope for theory and practice. *European Management Journal*, 39(2), 179–184.
- Amankwah-Amoah, J., & Wang, X. (2019). Business Failures around the World: Emerging Trends and New Research Agenda. *Journal of Business Research*, 98, 367–369.
- Bolino, M. C., Kacmar, K. M., Turnley, W. H., & Gilstrap, J. B. (2008). A multi-level review of impression management motives and behaviors. *Journal of Management*, 34(6), 1080-1109.
- Bordalo, P., Gennaioli, N., & Shleifer, A. (2022). Salience. *Annual Review of Economics*, 14, 521-544.
- Caldwell, D. F., & O'Reilly III, C. A. (1982). Responses to failure: The effects of choice and responsibility on impression management. *Academy of Management Journal*, 25(1), 121-136.
- Carter, D. A., & Simkins, B. J. (2004). The market's reaction to unexpected, catastrophic events: the case of airline stock returns and the September 11th attacks. *The Quarterly Review of Economics and Finance*, 44(4), 539-558.

- Chu, A. G., Du, X., & Jiang, G. (2011). Buy, lie, or die: An investigation of Chinese ST firms' voluntary interim audit motive and auditor independence. *Journal of Business Ethics*, 102, 135-153.
- Crick, J. M., & Crick, D. (2020). Coopetition and COVID-19: Collaborative business-to-business marketing strategies in a pandemic crisis. *Industrial Marketing Management*, 88(May), 206–213.
- Davies, D., & Brennan, N. (2007). Discretionary disclosure strategies in corporate narratives: Incremental information or impression management. *Journal of Accounting Literature*, 26(1), 116-196.
- Davis, A.K., Piger, J.M. and Sedor, L.M. (2012). Beyond the numbers: Measuring the information content of earnings press release language. *Contemporary Accounting Research*, 29 (3), pp. 845-868.
- Davis, A.K. and Tama-Sweet, I. (2012). Managers' use of language across alternative disclosure outlets: earnings press releases versus MD&A. *Contemporary Accounting Research*, 29 (3), pp. 804-837.
- Dechow, P., Sloan, R. and Sweeney, A. (1995). Detecting earnings management. *The Accounting Review*, pp.193-225.
- Dobusch, L., Köster, N., Schäfer, E., & Seckler, C. (2022). Open about organizational failure: A communication perspective on postmortem impression management. *Long Range Planning*, 55(6), 102176.
- Elsbach, K. D., Sutton, R. I., & Principe, K. E. (1998). Averting expected challenges through anticipatory impression management: A study of hospital billing. *Organization Science*, 9(1), 68-86.
- Fombrun, C., & Shanley, M. (1990). What's in a name? Reputation building and corporate strategy. *Academy of Management Journal*, 33(2), 233-258.

- Frankel, R., Mayew, W.J. and Sun, Y. (2010). Do pennies matter? Investor relations consequences of small negative earnings surprises. *Review of Accounting Studies*, 15 (1), pp. 220-242.
- Graffin, S. D., Halebian, J., & Kiley, J. T. (2016). Ready, AIM, acquire: Impression offsetting and acquisitions. *Academy of Management Journal*, 59(1), 232-252.
- Highhouse, S., Brooks, M. E., & Gregarus, G. (2009). An organizational impression management perspective on the formation of corporate reputations. *Journal of Management*, 35(6), 1481-1493.
- Huang, X., Teoh, S. H., & Zhang, Y. (2014). Tone management. *The Accounting Review*, 89(3), 1083-1113.
- Jiang, G., & Wang, H. (2008). Should earnings thresholds be used as delisting criteria in stock market?. *Journal of Accounting and Public Policy*, 27(5), 409-419.
- Kalemli-Ozcan, S., Gourinchas, P.-O., Penciakova, V., & Sander, N. (2020). COVID-19 and SME Failures. *IMF Working Papers*, 20(207). <https://doi.org/10.5089/9781513557748.001>
- Ketchen, D. J., & Craighead, C. W. (2020). Research at the Intersection of Entrepreneurship, Supply Chain Management, and Strategic Management: Opportunities Highlighted by COVID-19. *Journal of Management*, 46(8), 1330–1341.
- Kim, M., Xiong, G., & Kim, K. H. (2018). Where does pride lead? Corporate managerial hubris and strategic emphasis. *Journal of the Academy of Marketing Science*, 46, 537-556.
- Lange, D., Lee, P. M., & Dai, Y. (2011). Organizational reputation: A review. *Journal of Management*, 37(1), 153-184.
- Lee, J. M., Hwang, B. H., & Chen, H. (2017). Are founder CEOs more overconfident than professional CEOs? Evidence from S&P 1500 companies. *Strategic Management*

Journal, 38(3), 751-769.

- Li, F. (2010). The information content of forward - looking statements in corporate filings—A naïve Bayesian machine learning approach. *Journal of Accounting Research*, 48 (5), pp. 1049-1102.
- Li, L., Wang, Z., Ye, F., Chen, L., & Zhan, Y. (2022). Digital technology deployment and firm resilience: Evidence from the COVID-19 pandemic. *Industrial Marketing Management*.
- Liljenberg, A. (2022). Contextual agility informing market shaping. *Industrial Marketing Management*, 102(September 2020), 229–239.
- Matthews, R., Rutherford, B. N., Edmondson, D., & Matthews, L. (2022). Uncertainty in industrial markets: The COVID-19 pandemic. *Industrial Marketing Management*, 102(December 2021), 364–376.
- Mishra, S., Ewing, M. T., & Pitt, L. F. (2020). The effects of an articulated customer value proposition (CVP) on promotional expense, brand investment and firm performance in B2B markets: A text based analysis. *Industrial Marketing Management*, 87, 264-275.
- Mizik, N. (2010). The theory and practice of myopic management. *Journal of Marketing Research*, 47(4), 594-611.
- Mohamed, A. A., Gardner, W. L., & Paolillo, J. G. (1999). A taxonomy of organizational impression management tactics. *Journal of Competitiveness Studies*, 7(1), 108.
- Pan, L., McNamara, G., Lee, J. J., Halebian, J., & Devers, C. E. (2018). Give it to us straight (most of the time): Top managers' use of concrete language and its effect on investor reactions. *Strategic Management Journal*, 39(8), 2204-2225.
- Parhankangas, A., & Ehrlich, M. (2014). How entrepreneurs seduce business angels: An impression management approach. *Journal of Business Venturing*, 29(4), 543-564.

- Pitt, C. S., Plangger, K. A., Botha, E., Kietzmann, J., & Pitt, L. (2019). How employees engage with B2B brands on social media: Word choice and verbal tone. *Industrial Marketing Management*, 81, 130-137.
- Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3), pp.335--370.
- Sheng, J., Amankwah-Amoah, J., Khan, Z., & Wang, X. (2021). COVID-19 Pandemic in the New Era of Big Data Analytics: Methodological Innovations and Future Research Directions. *British Journal of Management*, 32(4), 1164–1183.
- Shepherd, D. A. and Haynie, J. M. (2011). Venture failure, stigma, and impression management: A self - verification, self - determination view. *Strategic Entrepreneurship Journal*, 5(2), 178-197.
- Shinkle, G. A. (2012). Organizational aspirations, reference points, and goals: Building on the past and aiming for the future. *Journal of management*, 38(1), 415-455.
- Srinivasan, R., Lilien, G. L., & Sridhar, S. (2011). Should firms spend more on research and development and advertising during recessions?. *Journal of Marketing*, 75(3), 49-65.
- Srinivasan, R., & Ramani, N. (2019). With power comes responsibility: How powerful marketing departments can help prevent myopic management. *Journal of Marketing*, 83(3), 108-125.
- Swani, K., Brown, B. P., & Milne, G. R. (2014). Should tweets differ for B2B and B2C? An analysis of Fortune 500 companies' Twitter communications. *Industrial marketing management*, 43(5), 873-881.
- Talbot, D., & Boiral, O. (2018). GHG reporting and impression management: An assessment of sustainability reports from the energy sector. *Journal of Business Ethics*, 147, 367-383.

- Tversky, A., & Kahneman, D. (1973). Availability: A heuristic for judging frequency and probability. *Cognitive psychology*, 5(2), 207-232.
- Ucbasaran, D., Shepherd, D. A., Lockett, A., & Lyon, S. J. (2013). Life after business failure: The process and consequences of business failure for entrepreneurs. *Journal of Management*, 39(1), 163-202.
- Walker, M. (2013). How far can we trust earnings numbers? What research tells us about earnings management. *Accounting and Business Research*, 43(4), pp.445--481.
- Wang, F., & Xu, B. (2017). Who needs to be more visible online? The value implications of web visibility and firm heterogeneity. *Information & Management*, 54(4), 506-515.
- Washburn, M., & Bromiley, P. (2014). Managers and analysts: An examination of mutual influence. *Academy of Management Journal*, 57(3), 849-868.
- Yan, S. (2015). Managerial attitudes and takeover outcomes: Evidence from corporate filings. *Journal of International Financial Markets, Institutions and Money*, 35, 30-44.
- Zang, A. (2012). Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review*, 87(2), pp.675-703.

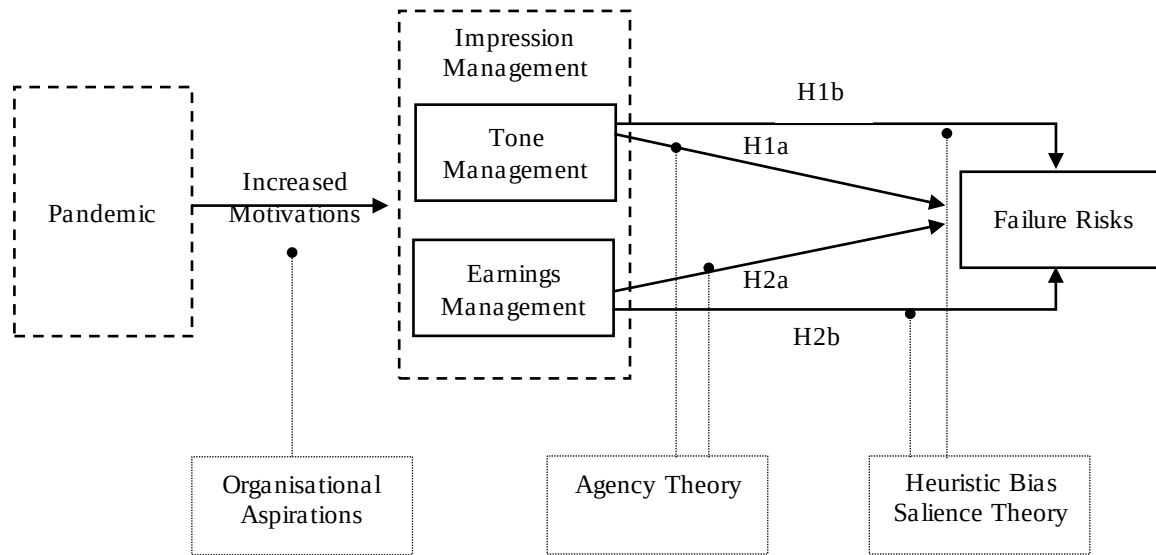


Figure 1. Conceptual Illustration

Table 1 Sample Distribution

Year	$ST=0$	$ST=1$	Total
2017	2,030	33	2,063
2018	2,206	39	2,245
2019	2,227	79	2,306
2020	2,692	42	2,734
2021	2,632	43	2,675
Total	11,787	236	12,023

Table 2 Expected Tone of the MD&A Section

DV:	(1) <i>TONE</i>
<i>EARN</i>	0.047*** [2.634]
<i>BHR</i>	0.009*** [3.009]
<i>SIZE</i>	0.012*** [10.131]
<i>BTM</i>	-0.018*** [-5.901]
<i>STD_BHR</i>	-0.056** [-2.377]
<i>STD_EARN</i>	-0.091*** [-5.683]
<i>AGE</i>	-0.001*** [-2.861]
<i>LOSS</i>	-0.051*** [-15.965]
<i>ΔEARN</i>	-0.037*** [-2.722]
<i>Constant</i>	0.119*** [6.074]
<i>N</i>	12,023
<i>Adj. R²</i>	0.071

Note: *t*-statistics in parentheses and *, **, and *** indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. This table reports the expected tone model, Equation (1), and OLS regression results are presented. The dependent variable, *TONE*, is measured as the difference between the number of positive and negative words in the MD&A section, scaled by the total of positive and negative words. All continuous variables are winsorized at the 1st and 99th percentiles. Variables are defined in Appendix I.

Table 3 Summary Statistics

Panel A: Summary Statistics						
Variable	N	Mean	Min	Median	Max	SD
<i>Dependent Variable</i>						
<i>ST</i>	12,023	0.020	0	0	1	0.139
<i>CR[-1, +1]</i>	12,023	-0.006	-0.191	-0.006	0.184	0.066
<i>CR[+2, +62]</i>	12,023	0.037	-0.434	0.011	0.765	0.228
<i>Variable of Interest</i>						
<i>TONE</i>	12,023	0.272	-0.070	0.282	0.525	0.122
<i>ΔTONE</i>	12,023	0.014	-0.219	0.011	0.272	0.093
<i>ABTONE</i>	12,023	0.000	-0.297	0.009	0.238	0.116
<i>RΔTONE</i>	12,023	0.500	0	0.444	1	0.319
<i>RABTONE</i>	12,023	0.500	0	0.444	1	0.319
<i>WC</i>	12,023	9.370	8.380	9.360	10.40	0.427
<i>WC</i>	12,023	8.690	7.690	8.670	9.760	0.431
<i>SC</i>	12,023	4.920	3.710	4.920	6.060	0.486
<i>Similarity</i>	12,023	0.944	0.773	0.952	0.990	0.036
<i>AEM</i>	12,023	-0.020	-1.160	0.002	0.541	0.204
<i>ABPROD</i>	12,023	0.001	-0.215	-0.012	0.330	0.084
<i>ABDISEXP</i>	12,023	0.000	-0.319	0.016	0.102	0.071
<i>REM</i>	12,023	0.000	-0.534	0.001	0.433	0.063
<i>POST</i>	12,023	0.450	0	0	1	0.498
<i>RAEM</i>	12,023	0.500	0	0.444	1	0.319
<i>RABPROD</i>	12,023	0.500	0	0.444	1	0.319
<i>RABDISEXP</i>	12,023	0.500	0	0.444	1	0.319
<i>RREM</i>	12,023	0.500	0	0.444	1	0.319
<i>Control Variable</i>						
<i>EARN</i>	12,023	0.040	-2.670	0.037	2.350	0.093
<i>BHR</i>	12,023	0.080	-0.587	-0.009	1.980	0.463
<i>SIZE</i>	12,023	15.80	14.20	15.60	18.90	0.998
<i>BTM</i>	12,023	0.553	0.058	0.453	2.100	0.387
<i>STD_BHR</i>	12,023	0.115	0.040	0.102	0.339	0.054
<i>STD_EARN</i>	12,023	0.040	0	0.020	1.700	0.071
<i>AGE</i>	12,023	20.50	10	20	34	5.210
<i>LOSS</i>	12,023	0.209	0	0	1	0.407
<i>ΔEARN</i>	12,023	0.012	-2.680	0.007	2.290	0.105
<i>GROWTH</i>	12,023	0.162	-0.588	0.110	2.240	0.375
<i>DIR_NUM</i>	12,023	11.20	5	10	23	3.430
<i>FEMALE</i>	12,023	0.197	0	0.185	0.500	0.112
<i>DIR_IND</i>	12,023	0.371	0.182	0.364	0.600	0.087
<i>II_OWN</i>	12,023	0.419	0.002	0.434	0.897	0.242

Panel B: Comparison Between the Normal Firms and ST Firms

Variables	<i>ST=0</i>		<i>ST=1</i>		Mean Diff
	N	Mean	N	Mean	
<i>POST</i>	11,787	0.452	236	0.36	0.092***
<i>TONE</i>	11,787	0.274	236	0.153	0.122***
<i>RΔTONE</i>	11,787	0.5	236	0.472	0.029
<i>RABTONE</i>	11,787	0.503	236	0.346	0.157***
<i>RAEM</i>	11,787	0.504	236	0.318	0.186***
<i>RABPROD</i>	11,787	0.501	236	0.436	0.065***
<i>RABDISEXP</i>	11,787	0.499	236	0.565	-0.067***
<i>RREM</i>	11,787	0.5	236	0.49	0.011
<i>CR[-1, +1]</i>	11,787	-0.006	236	-0.049	0.043***
<i>CR[+2, +62]</i>	11,787	0.038	236	-0.008	0.046***

Panel C: Comparison Between the Pre- and Post-outbreak of the coronavirus

Variables	<i>POST=0</i>		<i>POST=1</i>		Mean Diff
	N	Mean	N	Mean	
<i>ST</i>	6,614	0.023	5,409	0.016	0.007***
<i>TONE</i>	6,614	0.262	5,409	0.284	-0.022***
<i>RΔTONE</i>	6,614	0.434	5,409	0.581	-0.147***
<i>RABTONE</i>	6,614	0.475	5,409	0.531	-0.056***
<i>RAEM</i>	6,614	0.517	5,409	0.48	0.037***
<i>RABPROD</i>	6,614	0.499	5,409	0.501	-0.002
<i>RABDISEXP</i>	6,614	0.508	5,409	0.49	0.017***
<i>RREM</i>	6,614	0.505	5,409	0.493	0.012**
<i>CR[-1, +1]</i>	6,614	-0.007	5,409	-0.006	-0.001
<i>CR[+2, +62]</i>	6,614	-0.017	5,409	0.103	-0.120***

Table 4 Tone Management and Delisting Risk

Panel A: Tone and Delisting Risk				
DV	(1) <i>ST</i>	(2) <i>ST</i>	(3) <i>ST</i>	(4) <i>ST</i>
<i>RΔTONE</i>	0.465* [1.939]		0.315 [1.008]	
<i>RABTONE</i>		-1.391*** [-4.951]		-1.782*** [-5.124]
<i>RΔTONE</i> × <i>POST</i>			0.428 [0.874]	
<i>RABTONE</i> × <i>POST</i>				0.979** [2.025]
<i>POST</i>			-0.701 [-1.563]	-0.585 [-1.584]
<i>SIZE</i>	-1.198*** [-7.520]	-1.153*** [-7.593]	-1.198*** [-7.515]	-1.159*** [-7.622]
<i>LV</i>	2.244*** [4.156]	2.264*** [4.362]	2.244*** [4.169]	2.279*** [4.378]
<i>LOSS</i>	2.321*** [10.339]	2.294*** [10.284]	2.319*** [10.347]	2.293*** [10.289]
<i>GROWTH</i>	-0.612* [-1.751]	-0.391 [-1.315]	-0.610* [-1.752]	-0.376 [-1.273]
<i>DIR_NUM</i>	0.095*** [4.181]	0.096*** [4.229]	0.095*** [4.230]	0.096*** [4.238]
<i>FEMALE</i>	1.089 [1.415]	0.922 [1.199]	1.092 [1.418]	0.959 [1.242]
<i>DIR_IND</i>	0.448 [0.473]	0.583 [0.613]	0.431 [0.454]	0.567 [0.596]
<i>AGE</i>	0.009 [0.477]	0.008 [0.456]	0.009 [0.470]	0.009 [0.468]
<i>II_OWN</i>	0.893** [1.985]	0.677 [1.438]	0.879** [1.967]	0.687 [1.456]
<i>Industry FE</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	10.417*** [4.007]	10.644*** [4.314]	10.497*** [4.039]	10.857*** [4.389]
<i>N</i>	12,023	12,023	12,023	12,023
<i>pseudo R²</i>	0.295	0.309	0.296	0.311

Panel B: Additional Textual Attributes and Delisting Risk

DV	(1) <i>ST</i>	(2) <i>ST</i>	(3) <i>ST</i>	(4) <i>ST</i>
<i>WC</i>	-0.318 [-1.197]			
<i>WC</i> × <i>POST</i>	0.190 [0.487]			
<i>WC_UNQ</i>		-0.314 [-1.187]		
<i>WC_UNQ</i> × <i>POST</i>		0.197 [0.510]		
<i>SC</i>			-0.374* [-1.682]	
<i>SC</i> × <i>POST</i>			0.140 [0.425]	
<i>SIMILARITY</i>				-6.096*** [-2.714]
<i>SIMILARITY</i> × <i>POST</i>				7.647* [1.826]
<i>POST</i>	-1.993 [-0.539]	-1.929 [-0.567]	-0.857 [-0.514]	-7.475* [-1.906]
<i>Controls</i>	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	13.177*** [3.922]	12.935*** [3.991]	11.945*** [4.434]	16.464*** [5.066]
<i>N</i>	12023	12023	12023	12023
pseudo <i>R</i> ²	0.294	0.294	0.295	0.297

Note: z-statistics in parentheses and *, **, and *** indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. This table reports the results of Equation (5) focusing on the impact of tone management on the probability of receiving delisting risk warning. Logit regression results are reported based on robust standard errors clustered by listed firms. The dependent variable *ST* is an indicator which takes the value of 1 if the firm receives a delisting risk warning in the next year, and 0 otherwise. The independent variable in Panel A is *RABTONE* whereas Panel B presents results on additional textual attributes. Industry and year fixed effects are controlled in all regressions. All continuous variables are winsorized at the 1st and 99th percentiles. Variables are defined in Appendix I.

Table 5 Earnings Management and Delisting Risk

Panel A					
DV	(1) <i>ST</i>	(2) <i>ST</i>	(3) <i>ST</i>	(4) <i>ST</i>	(5) <i>ST</i>
<i>RAEM</i>	-0.470* [-1.792]				-0.462* [-1.708]
<i>RABPROD</i>		-0.318 [-1.187]			
<i>RABDISEXP</i>			0.240 [0.756]		
<i>REM</i>				-0.110 [-0.504]	-0.054 [-0.238]
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	10.867*** [4.224]	10.859*** [4.253]	10.633*** [4.144]	10.859*** [4.242]	10.879*** [4.241]
<i>N</i>	12,023	12,023	12,023	12,023	12,023
<i>pseudo R²</i>	0.295	0.294	0.294	0.294	0.295

Panel B

DV	(1) <i>ST</i>	(2) <i>ST</i>	(3) <i>ST</i>	(4) <i>ST</i>	(5) <i>ST</i>
<i>RAEM</i>	-1.008*** [-2.697]				-0.960** [-2.517]
<i>RAEM</i> × <i>POST</i>	1.242** [2.575]				1.162** [2.377]
<i>RABPROD</i>		-0.243 [-0.751]			
<i>RABPROD</i> × <i>POST</i>		-0.199 [-0.436]			
<i>RABDISEXP</i>			-0.058 [-0.163]		
<i>RABDISEXP</i> × <i>POST</i>			0.859* [1.713]		
<i>REM</i>				-0.415 [-1.442]	-0.311 [-1.038]
<i>REM</i> × <i>POST</i>				0.834* [1.845]	0.709 [1.558]
<i>Controls</i>	Yes	Yes	Yes	Yes	Yes
<i>Industry FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	11.462*** [4.514]	10.818*** [4.210]	10.614*** [4.129]	10.896*** [4.245]	11.453*** [4.517]
<i>N</i>	12,023	12,023	12,023	12,023	12,023
<i>pseudo R</i> ²	0.298	0.294	0.295	0.295	0.299

Note: z-statistics in parentheses and *, **, and *** indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. This table reports the results of Equation (6) focusing on the impact of earnings management on the probability of receiving delisting risk warning. Logit regression results are reported based on robust standard errors clustered by listed firms. The dependent variable *ST* is an indicator which takes the value of 1 if the firm receives a delisting risk warning in the next year, and 0 otherwise. The independent variables of earnings management are measured as annual decile rank of the residuals from Equation (2)-(4) minus 1 then scaled by 9. Industry and year fixed effects are controlled in all regressions. All continuous variables are winsorized at the 1st and 99th percentiles. Variables are defined in Appendix I.

Table 6 Market Reaction to Impression Management

DV	(1) <i>CR [-1, +1]</i>	(2) <i>CR [-1, +1]</i>	(3) <i>CR [+2, +61]</i>	(4) <i>CR [+2, +61]</i>
<i>RABTONE</i>	0.001 [0.293]	0.006 [1.408]	0.026** [2.464]	0.026** [2.233]
<i>RABTONE</i> × <i>POST</i>		-0.011*** [-2.578]		-0.000 [-0.026]
<i>RAEM</i>	-0.002 [-0.641]	0.004 [1.186]	-0.036*** [-4.989]	-0.026*** [-2.725]
<i>RAEM</i> × <i>POST</i>		-0.010** [-2.236]		-0.017 [-1.254]
<i>RREM</i>	-0.001 [-0.349]	-0.002 [-0.791]	0.021*** [3.013]	0.005 [0.608]
<i>RREM</i> × <i>POST</i>		0.003 [0.585]		0.037*** [2.803]
<i>ST</i>	-0.049*** [-6.210]	-0.048*** [-6.096]	-0.092*** [-4.283]	-0.092*** [-4.295]
<i>SIZE</i>	-0.013*** [-4.184]	-0.012*** [-3.867]	-0.132*** [-14.121]	-0.131*** [-14.020]
<i>BTM</i>	0.009 [1.600]	0.010* [1.771]	-0.118*** [-7.631]	-0.119*** [-7.652]
<i>BHR</i>	0.004* [1.739]	0.004 [1.496]	0.046*** [6.236]	0.045*** [6.069]
<i>STD_BHR</i>	0.026 [1.430]	0.027 [1.532]	-0.192*** [-3.734]	-0.191*** [-3.704]
<i>STD_EARN</i>	-0.018 [-1.001]	-0.018 [-0.984]	-0.011 [-0.235]	-0.011 [-0.223]
<i>Firm FE</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes
<i>Constant</i>	0.199*** [4.021]	0.180*** [3.599]	2.020*** [13.383]	2.012*** [13.277]
<i>N</i>	12,023	12,023	12,023	12,023
<i>Adj R²</i>	0.026	0.028	0.352	0.352

Note: t-statistics in parentheses and *, **, and *** indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. This table reports the results of Equation (7) focusing on the impact of impression management on stock returns. Fixed effect panel regression results are reported based on robust standard errors clustered by listed firms. The dependent variable *CR*[-1, +1] and *CR*[+2, +61] are 3-day and 60-day cumulative stock returns. The independent variables are tone and earnings management proxies. Firm and year fixed effects are included in all regressions. All continuous variables are winsorized at the 1st and 99th percentiles. Variables are defined in Appendix I.

Table 7 B2B versus Non-B2B Firms

DV:	(1) <i>CR</i> [-1, +1]	(1) <i>CR</i> [+2, +61]
<i>B2B</i> × <i>RABTONE</i>	0.006 [1.396]	0.035*** [2.685]
<i>NonB2B</i> × <i>RABTONE</i>	-0.006 [-1.180]	0.013 [0.950]
<i>B2B</i> × <i>RAEM</i>	-0.000 [-0.125]	-0.045*** [-4.923]
<i>NonB2B</i> × <i>RAEM</i>	-0.004 [-0.938]	-0.020* [-1.871]
<i>B2B</i> × <i>RREM</i>	-0.001 [-0.255]	0.015* [1.671]
<i>NonB2B</i> × <i>RREM</i>	-0.001 [-0.257]	0.028*** [2.727]
<i>Controls</i>	Yes	Yes
<i>Firm FE</i>	Yes	Yes
<i>Year FE</i>	Yes	Yes
<i>Constant</i>	0.200*** [4.048]	2.022*** [13.412]
<i>N</i>	12,023	12,023
<i>Adj. R²</i>	0.027	0.352

Note: *t*-statistics in parentheses and *, **, and *** indicate $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. This table reports the results of Equation (7) focusing on the differential impact of impression management on stock returns between B2B and non-B2B firms. Fixed effect panel regression results are reported based on robust standard errors clustered by listed firms. The dependent variable *CR*[-1, +1] and *CR*[+2, +61] are 3-day and 60-day cumulative stock returns. The independent variables are interaction terms between indicators of B2B/non-B2B and impression management proxies. Firm and year fixed effects are included in all regressions. All continuous variables are winsorized at the 1st and 99th percentiles. Variables are defined in Appendix I.

Appendix I: Variable definitions

Variable	Definition
Dependent variable	
<i>ST</i>	A dummy variable, which equals to one if firm <i>j</i> 's stock is in the status of special treatment, and zero otherwise.
<i>CR</i> [-1, +1]	3-day cumulative return around the disclosure of annual report.
<i>CR</i> [+2, +61]	60-day cumulative return starting from the second day after the disclosure of annual report.
Variables of interest	
<i>TONE</i>	The difference between the number of positive words and the number of negative words, scaled by the total of positive and negative words in the MD&A section.
$\Delta TONE$	Change in <i>TONE</i> from year <i>t-1</i> to <i>t</i> .
<i>RA</i> <i>TONE</i>	Annual decile rank of $\Delta TONE$ minus 1 and then divided by 9.
<i>AB</i> <i>TONE</i>	The residual from Equation (1).
<i>RAB</i> <i>TONE</i>	Annual decile rank of <i>AB</i> <i>TONE</i> minus 1 and then divided by 9.
<i>AEM</i>	Accrual-based earnings management, measured as the residual from Equation (2).
<i>RAEM</i>	Annual decile rank of <i>AEM</i> minus 1 and then divided by 9.
<i>ABR</i> <i>POD</i>	Abnormal production costs, measured as the residual from Equation (3).
<i>RAB</i> <i>PROD</i>	Annual decile rank of <i>ABR</i> <i>POD</i> minus 1 and then divided by 9.
<i>AB</i> <i>DIS</i> <i>EXP</i>	Abnormal discretionary expenditures, measured as the residual from Equation (4) multiplied by minus one.
<i>RAB</i> <i>DIS</i> <i>EXP</i>	Annual decile rank of <i>AB</i> <i>DIS</i> <i>EXP</i> minus 1 and then divided by 9.
<i>REM</i>	Real earnings management, calculated as the sum of <i>ABR</i> <i>POD</i> and <i>AB</i> <i>DIS</i> <i>EXP</i> .
<i>RREM</i>	Annual decile rank of <i>REM</i> minus 1 and then divided by 9.
<i>WC</i>	Word count, defined as the total number of words in the MD&A section.
<i>UWC</i>	The number of unique words in the MD&A section.
<i>SC</i>	Sentence count, defined as the total number of sentences in the MD&A section.
<i>SIMILARITY</i>	Textual similarity to the previous year's MD&A section, obtained directly from CSMAR.
<i>POST</i>	A dummy indicator for the outbreak of coronavirus, which is set to 1 after 2019, and 0 otherwise.
<i>B2B</i>	A dummy variable, which equals to one if firm <i>j</i> 's is in B2B industries, and zero otherwise.
<i>NonB2B</i>	A dummy variable, which equals to one if firm <i>j</i> 's is not in B2B industries, and zero otherwise.
Control variables	
<i>EARN</i>	Earnings before extraordinary items scaled by total assets at the end of year <i>t</i> .
<i>BHR</i>	Buy-and-hold stock returns for year <i>t</i> .
<i>SIZE</i>	Natural logarithm of total assets at the end of year <i>t</i> .
<i>BTM</i>	Book-to-market ratio at the end of year <i>t</i> .
<i>STD_BHR</i>	The standard deviation of monthly stock return in year <i>t</i> .
<i>STD_EARN</i>	The standard deviation of <i>EARN</i> over the past three years.
<i>AGE</i>	The number of years since the firm was established.
<i>LV</i>	Total liabilities divided by total assets at the end of year <i>t</i> .

<i>LOSS</i>	A dummy variable, which is set to one if earnings before extraordinary items is negative in year t , and zero otherwise.
<i>$\Delta EARN$</i>	Change in <i>EARN</i> from year $t-1$ to t .
<i>GROWTH</i>	Sales growth, measured as change in sales from year $t-1$ to t divided by sales in year $t-1$.
<i>DIR_NUM</i>	The number of directors of firm j in year t .
<i>FEMALE</i>	The proportion of female directors and top executives.
<i>DIR_IND</i>	The number of independent directors scaled by the total number of directors in year t .
<i>II_OWN</i>	Institutional investor ownership.
