Do narrative-related disclosures predict corporate failure? Evidence from UK non-financial publicly quoted firms

Abstract

By creating a comprehensive corporate failure-related lexicon, this paper explores the incremental explanatory power of narrative-related disclosures in predicting corporate failure. We find that corporate failure-related narrative disclosures significantly predict firms' failure up to two years ahead of actual failure. Additionally, we find that a financially distressed firm would become more vulnerable when financial constraints befall, which in turn would precipitate corporate failure. Various robustness tests assure the credibility of the explanatory ability of corporate failure-related narrative disclosures to predict corporate failure. Collectively, our results show the feasibility of these narrative-related disclosures in improving the explanatory power of models that predict corporate failure.

Keywords: Bankruptcy, Corporate failure, Financial distress risk, Narrative-related disclosures, UK.

1. Introduction

Several corporate failure (CF) prediction models are developed based on different modeling techniques which substantially apply a certain classical methodological approach (for a review see, Dimitras et al., 1996; Balcaen and Ooghe, 2006; Altman et al., 2017; Jayasekera, 2018) relying principally on accounting, market and/or macroeconomic indicators (e.g., Altman, 1968; Ohlson, 1980; Taffler, 1983; Goudie and Meeks, 1991; Charitou et al., 2004; Reisz and Perlich, 2007; Campbell et al., 2008; Tinoco and Wilson, 2013). However, after the collapse of major corporations (e.g., WorldCom, Enron and Lehman Brothers), growing attention has been paid to the prediction of business failures since stakeholders have become cautious about risk of business failure (Dean and Altman, 2007). Improving the ability to explain and predict CF, therefore, stands central in the literature (e.g., Balcaen and Ooghe, 2006; Jayasekera, 2018).

Remarkably, while there has recently been an increasing interest in studying the usefulness of qualitative information, little attention is paid toward employing qualitative information in CF prediction. Moreover, while the UK offers an "ideal" context for CF research (e.g., Taffler, 1984), prior research on the link between qualitative information and firm's status has mainly been conducted in the US context (a priori, due to data availability and the relative ease in obtaining qualitative data) and concerned the financial constraints (as detailed in Appendix A).[1] This paper addresses this gap by exploring the question of whether the narrative sections of annual reports communicate useful information to predict CF.[2] In doing so, this paper develops a textual measure for CF-related narrative disclosures (CF-Disclosure, hereafter) and examines its ability in predicting CF in the UK context. Thus, we expand prior literature in many aspects as follows.

First, a few studies have employed qualitative information revealed in the narrative sections of annual reports or 10-K filings (narrative-related disclosures) to test its predictive ability for

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[1] Financial distress and bankruptcy, as the main determinants of CF, are distinctive from financial constraints (see Whited and Wu, 2006; Senbet and Wang, 2012; Hoberg and Maksimovic, 2015; Farre-Mensa and Ljungqvist, 2016). Although financial constraints examination is not our main interest, our further analysis highlights whether financial constraints would promote the incidence of CF.

[2] Throughout the paper, CF refers to financial distress risk and bankruptcy.

financial constraints or to assess (but not to predict) bankruptcy and financial distress. For example, Kaplan and Zingales (1997) and Hadlock and Pierce (2010) use narrative-related disclosures of 10-K to construct indices so as to classify financially constrained firms. Furthermore, Hoberg and Maksimovic (2015) conclude that narrative sections have an incremental effect in predicting financial constraints. Utilizing the 10-K filing mandatory disclosure, Bodnaruk et al. (2015) indicate that there is a positive relationship between managers' belief of a firm's future financial constraints and the extent of 10-K narratives that reflect this outlook. In the same way, Holder-Webb and Cohen (2007) indicate that Management's Discussion and Analysis (MD&A) is the officially approved channel for managers to explain the source of financial distress to investors. In a contemporaneous paper complementary to ours, Gandhi et al. (2019), using an approach different from ours and employing a sample of the US banks, suggest the negative sentiment of 10-K narratives as a new proxy for bank distress. Still, particularly in the UK context, no previous study has examined the feasibility of the annual report narratives to directly predict CF and improve the explanatory power of the variables widely used in classical CF prediction models.

Second, there is a major difference between the insolvency laws in the UK (where it is creditor-friendly) and the US (where it is debtor-friendly). Consistent with the evidence of Davydenko and Franks (2008) that the bankruptcy code is a significant factor in studying CF, it seems important to investigate CF prediction outside the US. Second, disclosure type and regulations are also different in both countries. As opposed to the US, where narrative disclosure is highly regulated, narrative disclosure in the UK is mostly voluntary. These two types of disclosure are also provided under different enforcement laws since the common law is dominant in the UK while the code law is dominant in the US, which has more enforcement (Muñoz-Izquierdo et al., 2019). In this respect, prior research (e.g., Elshandidy et al., 2015) documents a significant impact of the legal system in explaining the observed variations in mandatory rather than voluntary disclosures, which are influenced more by firm-specific factors. In addition, compared to the US, the UK's companies do not file quarterly, and the UK's disclosure environment is less rich (Lennox et al., 2019). That is, management in UK companies is expected to consider annual report narratives as an important source for revealing information about the firm's prospects.

Third, UK companies are managed in corporate governance settings that are significantly different from their counterparts in the US (Short and Keasey, 1999; Franks and Mayer, 2002; Toms and Wright, 2005), and within less severe litigation risk (Lennox et al., 2019). Finally, despite the limited research on the relation between qualitative information and CF, the findings of research are, however, mixed within a line of research that looks at the information revealed related to going concern prospects either in mandatory or voluntary environments. For example, in mandatory environments where firms are required to provide information about going concern, the evidence shows less compliance (e.g., the Canadian context: Ontario Securities Commission, 2010) or limited usefulness in predicting CF (e.g., the UK context: Uang et al., 2006). In the US context, a recent study by Mayew et al. (2015) finds that the opinions of management about going concern revealed in MD&A of 10-K filings along with their tone have explanatory power in predicting whether a firm will cease as a going concern.

These distinctive aspects, collectively, motivate us to investigate the incremental explanatory power of narrative-related disclosures in predicting CF in the UK.[3] Our findings suggest that higher incidence of CF-Disclosure in the annual reports is strongly associated with a higher likelihood of CF. Specifically, we find that CF-Disclosure offers an incremental predictive ability relative to accounting, market and macroeconomic variables that are widely used in the classical CF prediction models. In an economic perspective, results show that the higher incidence of CF-Disclosure is associated with a 39.7% greater likelihood of CF within a year; 31.9% within two years. In addition, the predictive accuracy and explanatory power of CF-Disclosure alone is about 41% and 25% relative to that provided by accounting, market and macroeconomic variables combined in the year

[3] Our motive in visiting the UK is in line with, among others, that of Charitou et al. (2004) who clearly introduce the UK context, rather than the US, to be "the main motivation for [their] study" to the incremental information content of operating cash flows to predict CF. Nevertheless, we emphasize that our choice for the UK since it provides an ideal setting to conduct our research and thus, this does not limit generalizing our results to other regimes. Therefore, it seems reasonable to see the novelty of contribution provided by our paper as an extension of the US-based literature.

preceding the CF and the penultimate year, respectively. Incorporating CF-Disclosure into a base model (representing a classical CF prediction model) that contains accounting, market and macroeconomic indicators provides about 16% increase in the explanatory power relative to that provided by the base model for the year prior to CF; 9% for the two years prior to CF. Collectively, the results imply the feasibility of CF-Disclosure in enhancing the explanatory power of models that predict CF. Our results are robust to the inclusion of firm corporate governance factors that prior research shows to be related to CF.

These findings have theoretical and practical implications. Theoretically, in view of criticisms of CF prediction models based on financial ratios, academics can build on our paper to improve or revise these classical models. Our results can be sound not only for the UK but also for other countries (e.g., Germany which has an insolvency regime that, like the UK, reflects the legacy of the creditor-in-possession framework). Practically, the additional role of failure-related narratives in rendering early warning alerts is imperative to help interested parties (e.g., the Financial Reporting Council, stockholders and lenders) to take either preventative or remedial action. Information embedded in the annual reports' narratives can strengthen audit's analytical review, support the issuance of the qualified (going concern) audit opinion and thus reduce litigation and reputational loss risks.

Our paper contributes to CF literature as follows. Our paper advances extant literature on CF by suggesting the incremental role (explanatory ability) of the annual report narratives as a distinct indicator to objectively and directly predict CF. This paper also contributes to CF literature by creating a comprehensive CF-related wordlist. This wordlist aims to capture CF sentiment in annual report narratives, as well as assist future CF research to study the likelihood of CF beyond traditional CF models. Furthermore, our paper advances the extant evidence on CF (as summarized in Appendix A), which lacks generalization as it relied on a limited number of firm-year observations and/or concentrated on certain industries, is subjective as it relied principally on manual content analysis, and is outdated as it relied on old empirical data. Our research is largescale and relied on an objective textual method to capture the role of qualitative information in predicting CF. Our method can be applicable to different contexts (e.g., emerging economies), different industries (e.g., financial firms), cross-country (comparative evidence) with a minimum cost by relying on our algorithm. In addition, our paper augments CF literature, which for decades has suffered the major deficiency of overlooking the underlying theory of failure (Dean and Altman, 2007; Peat, 2007), by postulating the theoretical foundations for explaining the reasons for voluntary corporate failure disclosure. Having reasonable theoretical premises provides the initial validity of our work (Christenson, 1983).

The remainder of this paper proceeds as follows. Section 2 represents CF in the UK context. Section 3 discusses the theoretical considerations. Section 4 reviews relevant prior literature and develops the research hypothesis. Section 5 designs the research methodology including data description, measurement of variables and the multi-period logit model formulation. Section 6 discusses the empirical results, further analysis and robustness checks. Section 7 concludes, discusses limitations and suggests avenues for future research.

2. Corporate failure in the UK context

The UK context offers some unique features, e.g., the amount and quality of financial/non-financial information about corporate entities, as well as a CF rate among the highest in advanced countries, which provide the UK with an environment which is "ideal" for the assessment of company solvency and performance (Taffler, 1984; Charitou et al., 2004).

Furthermore, the UK insolvency law (e.g., Insolvency Act 1986 and Enterprise Act 2002) is different from the US Bankruptcy Code (e.g., Chapter 11) where the latter provides a protection to the debtor (distressed firm) by allowing it to stay upon the filing (continue as a going concern), whereas in the former, such opportunity to stay is not necessarily granted as an administrator would replace the management with the assumption that the insolvent firm has a concentrated creditor mass. Consequently, under the UK's insolvency regime, financially distressed firms are more likely to go bankrupt compared to those in the US. Similar to the UK, the European insolvency regimes have the legacy of creditor-in-possession frameworks, implying that debtors and creditors have exhausted all possible remedies. Therefore, liquidation, through selling the company or its assets, is assumed to be the principal means of resolving creditor claims (refer, for example, to Broude et al. (2007) and Fitch Ratings (2014) for a comparative study of insolvency regimes in the US, the UK, and the key markets in the EU).

The UK insolvency law contains a number of insolvency shelters including: (1) Company Voluntary Arrangement (CVA); (2) Administration; (3) Administrative Receivership (AR); (4) Creditors' Voluntary Liquidation (CVL); and (5) Compulsory Liquidation (CL).[4] As seen, regardless of the route by which an insolvent company would endeavor to survive, the UK's legacy assumption predicated on the creditor-in-possession framework remains dominant and basically suggests the formal insolvency process for settling the disputes between creditors and financially distressed firms.

This might explain why the UK experienced the highest number and rate of CFs in the world from the 1970s-1980s (it was almost double that of the US on average, e.g., Altman, 1984). During the 1980s several UK sectors (e.g., small industrial businesses) experienced high failure rates of 50% for a period of five years (Charitou et al., 2004). Agarwal and Taffler (2007) show that the number of UK firms at risk of failure is still growing and the high bankruptcies are expected to continue.[5] Given these statistics and the increasing criticism of Taffler's (1983) MDA-based model (Charitou et al., 2004; Jayasekera, 2018), there is a need to update CF prediction modeling after considering essential factors such as textual analysis, which will be grounded in theory and literature in the following section.

[4] For more details regarding the UK insolvency regime see for instance: Insolvency Service and Companies House. Available at: https://www.gov.uk/ and/or Accountant in Bankruptcy (AiB). Available at: https://www.aib.gov.uk/

[5] For UK companies' insolvency records, refer to: Insolvency Service and Companies House. Available at: https://www.gov.uk/ and Trading Economics. Available at: http://www.tradingeconomics.com/

3. Theoretical considerations for voluntary corporate failure disclosure

A theoretical analysis of how capital structure affects risk-related disclosure is introduced by Fatemi and Luft (2002) and the possibility that the changes in the financial structure can be linked with the managerial incentive to alter the firm's perceived risk is illustrated by Ross (1997). In addition to preserving their reputation, during financial distress exposure, managers (by signaling) attempt to mitigate information asymmetry to reduce the cost of finance; in this respect a potential CF-Disclosure can be considered as an effective tool (Francis et al., 2005; Holder-Webb and Cohen, 2007; Cheynel, 2013; Elshandidy and Shrives, 2016). In line with this view, capital need theory indicates that voluntary disclosure aids in achieving a company's need to raise capital at a low cost (Francis et al., 2005). Consequently, lowering asymmetry of capital market information to reduce the cost of capital represents a major incentive for managers to voluntarily disclose risk, particularly ahead of bankruptcy or during financial distress periods.

According to Holder-Webb and Cohen (2007), managers have impetuses to relieve stakeholders' responses toward the financial distress risk by disclosing the event of distress risk. Furthermore, they argue that managers' incentives to disclose such information could be a function of the ethics-economic formula, which assumes that managers' intent to render a more complete disclosure that enables stakeholders to react wisely is driven by economic or ethical considerations. Additionally, legitimacy theory, which assumes that there is a "social contract" between firms and society which can be threatened or revoked, leading the firm to cease to exist if its legitimacy is in question (Mathews, 1993), can explain the incentives to reveal information about CF. Seeking to maintain or repair legitimacy, managers are motivated to voluntarily disclose any particular events that would have a detrimental effect on the firm's legitimacy (Suchman, 1995; Deegan, 2002). In so doing, the defensive impression management technique is used (Suchman, 1995; Ogden and Clarke, 2005; Samkin and Schneider, 2010) allowing managers to formulate a normalizing account (that is, deny, excuse, justify or explain the event, apologize or express remorse and guilt) and perform strategic restructuring (involving disassociation).[6]

Pursuant to legitimacy theory, where a firm's legitimacy is threatened, any strategy that managers implement to maintain or repair legitimacy "must" be accompanied by voluntary disclosure, especially in the annual reports (Deegan, 2002). In relation to legitimacy, legal compliance and the concept of accountability, which are consistent with the regulatory and cognitive legitimacy dimensions proposed by Scott (1995), offer a further explanation of managers' motive to employ voluntary narrative disclosure to report threats to a firm's legitimacy (Samkin and Schneider, 2010). With a belief in the responsibility to report, ethical management is pledged to completely disclose all relevant information regardless of the impact on the firm's image (Holder-Webb and Cohen, 2007). Otherwise, through the legitimacy process, managers of firms with a high level of public monitoring would have incentives to increase risk disclosure in order to reduce litigation and reputational risks (Cormier and Gordon, 2001; Oliveira et al., 2011a). Prior research (e.g., Skinner, 1994, 1997; Francis et al., 1994) indicates that managers' incentives to voluntarily disclose firms' prospects lie in obviating concurrent legal actions such as litigation risk, especially if the firm fails.

Overall, the theoretical framework based on a confluence of corporate structure theory and managers' incentives as formulated by signaling and legitimacy theories is consistent with the call by Roberts et al. (2005, p. 6) "for greater theoretical pluralism and more detailed attention to board processes and dynamics." Such a framework was also proposed by Aguilera (2005) and is adopted by some previous research such as Elshandidy and Shrives (2016) and Oliveira et al. (2011b).

4. Narrative-related disclosures and corporate failure: Hypothesis development

Since the seminal work by Beaver (1966) and Altman (1968), widespread literature classifies, assesses or predicts CF by developing financial distress and bankruptcy models. Nevertheless, prior

[6] Impression management is a conscious or unconscious attempt by managers to manage the real or imagined image of their firms (Neu et al., 1998; Samkin and Schneider, 2010).

research basically focuses on utilizing financial or accounting ratios (e.g., Altman, 1968; Ohlson, 1980; Taffler, 1983), testing market-based information (e.g., Black and Scholes, 1973; Merton, 1974; Reisz and Perlich, 2007), or studying macroeconomic determinants (e.g., Liu, 2004) to predict CF.

Meanwhile, due to several criticisms (e.g., Dimitras et al., 1996; Christidis and Gregory, 2010; Jayasekera, 2018), many serious drawbacks (e.g., Balcaen and Ooghe, 2006) and structural and assumption deficits (e.g., Agarwal and Taffler, 2008), the findings of previous CF research are debatable. That is why, on the one hand, recent studies (e.g., Campbell et al., 2008; Christidis and Gregory, 2010) resort to a so-called "combined approach" (Tinoco and Wilson, 2013) on the basis of incorporating variables from different aspects (such as accounting-based variables and market-based variables) in order to increase the predictive ability and accuracy of CF models.

On the other hand, the inclusion of non-accounting or qualitative measures in the classical failure prediction models is suggested by some authors (e.g., Ohlson, 1980; Zavgren, 1983; Keasey and Watson, 1987; Beaver et al., 2005; Shuai and Li, 2005). The majority of evidence (e.g., Hoberg and Maksimovic, 2015; Bodnaruk et al., 2015) related to employing qualitative data in prediction has been concentrated on financial constraints, suggesting a predictive contribution can go beyond the traditional financial-based measures.

Arguably, qualitative information provides useful content that can be employed to objectively and directly predict CF in addition to improving the explanatory power of the classical CF prediction models. Consistent with this notion, some studies shed light on the information content of the narrative-related disclosures and its usefulness in elucidating the source or the nature of financial distress and bankruptcy. Within the UK context, Smith and Taffler (2000) study manually the information content of the Chairman's statement and they find evidence of the ability of narrative disclosure to predict failure.[7] For a sample of financially distressed firms, Holder-Webb

[7] Furthermore, Clatworthy and Jones (2003) find systematic patterns in reporting good and bad news (in the Chairman's statements in the UK) regardless of company performance. In this, managers attribute good news to themselves, while blaming the external environment for bad news, which is consistent with impression management mentioned earlier (see footnote 6).

and Cohen (2007) measure the disclosure quality and find that on average firms increase the quality of disclosure in the year of distress onset, and that change in disclosure behavior is fundamentally driven by the managers' economic considerations, instead of ethical status. In addition, Hanley and Hoberg (2012) conclude that the likelihood of litigation risk is decreased by managers' strong strategic disclosure in the initial public offerings prospectus. This means that narrative-related disclosures regarding distress would be used to reduce the likelihood of litigation exposure. Supporting these purposes, the SEC, for example, designates the MD&A to present an exhaustive view of the firm's financial conditions and prospects. In the Australian context, Boo and Simnett (2002) investigate the tone of management's prospective comments in the annual report, and they find that the information content and tone of these comments are significantly associated with CF. Within the US context, using a different type of firms (financial rather than non-financial) and different type of outlet (10-Ks filings rather than annual reports), Gandhi et al. (2019) find that negative tone is significantly indicative of delisting probability, increase in loan loss, and decrease in future performance.

The above-mentioned papers use mostly the text tone (positive and/or negative) in annual reports/10-K filings to examine its association with CF. There is another line of research focusing on audit and/or management reports/opinions on the firm's ability to continue as going concern. For example, Uang et al. (2006) examine the information content of auditors' and managers' reports on going concern and find that audit opinions are more informative in predicting CF than managers' reports. They further find that managers of firms with effective governance monitoring are likely to convey messages consistent with those of auditors regarding going concern disclosures. Similarly, within the US context, a recent study by Mayew et al. (2015) analyzes the text of the MD&A section of 10-K filings to examine its ability to predict a firm's ability to continue. They find that the managers' going concern opinions revealed in the MD&A section, along with the tone of that section, are significantly indicative of a firm's ability to continue as a going concern. In another context, the Spanish, Muñoz-Izquierdo et al. (2019) find that auditor's report contains informational content which significantly explains the causes of CF.

Logically, we infer that the qualitative data contained within annual report narratives have an explanatory benefit that can be exploited to predict CF. Therefore, based on the above arguments, *ceteris paribus*, we hypothesize that management in firms with a prospect of failure will use a higher frequency of CF-related words in their annual report narratives.

Consistent with the literature on general disclosure (e.g., Skinner, 1994; Kothari et al., 2009; Bao et al., 2019) and/or timeliness of such disclosure (e.g., Clatworthy and Peel, 2016; Luypaert et al., 2016; Lukason and Camacho-Minano, 2019), managers' tendency to withhold bad news and/or delay annual reporting (particularly for financially distressed firms) may be seen as a competing argument (or implied as a plausible null hypothesis). However, managers' concerns owing to financial sanctions, as well as litigation risk and reputation loss when CF approaches are still supportive of our alternative hypothesis (above). Besides, the compliance levels with filing times are around 100% for publicly quoted firms (employed in our study) (e.g., Clatworthy and Peel, 2016). That said, the competing argument derived from this broad theme still plausibly motivates our research questions about: first, whether firms with significantly high levels of CF-Disclosure are more likely to fail; second, whether CF-Disclosure offers incremental predictive ability relative to that offered by the traditional CF predictors (i.e., accounting, market and macroeconomic variables that are widely used in the classical CF prediction models).[8]

5. Methodology

5.1. Sample selection and data collection

The present study investigates the contribution of CF-Disclosure to predict CF for a matched sample of non-financial publicly quoted firms in the UK over a period of sixteen years from January 2000 to December 2016. We choose this span for our sample because corporate governance data

[8] We thank the anonymous referee for suggesting this point to us.

starts to be available on the BoardEx database in 1999, while 2016 is chosen due to data availability. Following prior literature (e.g., Charitou et al. 2004), we establish our sample of Public Limited Companies (PLCs) whose shares are publicly traded under the UK Companies Act 2006, as well as Alternative Investment Market (AIM) companies. In addition, financial firms with Standard Industrial Classification Code (SIC) between 6000 and 6999 (i.e., finance, insurance and real estate) are excluded due to their distinctive regulations and accounting practices (e.g., Bodnaruk et al., 2015). In terms of failed firms, we include observations only for firms that failed during our sample span (i.e., from January 2000 to December 2016).

Our final sample comprises a group of 272 failed firms and a group of 272 matched healthy firms. We implement this technique because it provides a systematic method to define our sample of healthy firms (e.g., Charitou et al., 2004; Balcaen and Ooghe, 2006; Hsu and Wu, 2014).[9] In accordance with most previous CF literature (e.g., Hsu and Wu, 2014; for multiple references see Charitou et al., 2004), both groups are matched based on firm size (measured by total assets specified from the last complete filed account before CF) and industry classification (utilizing SIC). In every year of our sample, firms are coded zero until the failure event, when a failed firm takes one, which implies that healthy firms take zero in every year. Following prior research (e.g., Beaver et al., 2005; Peat, 2007; Mayew et al., 2015), this approach enables us to estimate a hazard model, or as known by survival analysis, as discrete-time logit model (shown later). Shumway (2001) indicates that considering multiple firm-year observations for both failed and healthy firms enhances efficiency, and mitigates the bias and inconsistency of the estimated coefficients as compared to a static model, particularly when the sample period is long, like ours.

Following prior literature (e.g., Campbell et al. 2008; Tinoco and Wilson 2013) we adopt a CF definition that incorporates the legal approach and financial distress approach. This definition

[9] Employing a matched control sample is a common practice in CF prediction research. Particularly in our paper, it helps to cut the cost of data collection because compared to financial data and the US 10-Ks (inclusively available at SEC EDGAR database), the manual collection of UK annual reports to retrieve qualitative data is substantially time and effort consuming.

is advantageous for considering the practical perspectives of CF and thus, improves the scope and predictive power of the empirical models (Campbell et al. 2008; Tinoco and Wilson 2013).[10] A firm is defined as *legally failed* (i.e., bankrupt) if its status is in administrative receivership, administration, company voluntary arrangement, voluntary liquidation, liquidation or when there is a cancellation of the firm and it is assumed valueless (e.g., Charitou et al., 2004; Christidis and Gregory, 2010). In addition to the previous legal approach, a firm is identified as *financially distressed* (financial approach) whenever it concurrently experiences, for two successive years, the following conditions (e.g., Pindado et al., 2008; Tinoco and Wilson, 2013): first, a negative growth in the market value; second, its financial expenses surpass its earnings before interest, taxes, depreciation and amortization. Applying these two measures jointly, besides requiring two consecutive years, provides a strong basis (the confluence and continuity of the two measures together) for regarding the firm as financially distressed. In order to ensure the accuracy of the analysis, the healthy group retains only the non-failed firms that are not exposed to financial distress.[11]

We gather the study's data from several sources as follows. Consistent with Charitou et al. (2004), the bankruptcy data are obtained from the UK Companies House – GOV.UK (https://www.gov.uk/government/organisations/companies-house) and the Bloomberg database. The accounting, market and macroeconomic data are collected from Datastream and Thomson One Banker (Worldscope), while the BoardEx database is used to compile the corporate governance data. Furthermore, the annual reports for UK publicly quoted firms are collected from multiple sources including the Thomson One Banker database, the Bloomberg database, the UK Companies House website, as well as the companies' official websites. In this respect, we operationalize the annual report as our source of narratives because it is perceived to be the major

[10] Technical insolvency (financial distress) and legal insolvency (bankruptcy) describe the practical definitions used for CF in the UK. See, for example, https://www.businessrescueexpert.co.uk/insolvency-vs-bankruptcy-uk/

[11] Both sets of failed and healthy firms are also traced to verify their fate and that the latter have not become failing over the next few years. Observations related to failed firms are excluded after the event of failure (e.g., Shumway, 2001; see also the dynamic logit model as set out in section 5.3. below).

and most credible source of information for the informed parties (Elshandidy and Neri, 2015). Diction version 7 is employed to extract the scores from the annual report narratives.

5.2. Variables measurement

5.2.1. Textual analysis proceedings and CF-Disclosure

This paper creates a comprehensive list of CF-related keywords to capture the CF sentiment in annual report narratives. In line with most prior textual analysis studies in accounting and finance (e.g., Bodnaruk et al., 2015), we adopt the *bag of words* method (Loughran and McDonald, 2011), in which the annual reports are parsed into a matrix composed of words and word count vectors.[12] Our approach is consistent with Loughran and McDonald's (2016) assertion of the importance of developing a wordlist in the context of each textual-subject study, as reliance on a wordlist that is derived from a different subject would probably cause spurious results (Loughran and McDonald, 2011).

The following procedures are applied to establish the wordlist (see figure 1). (1) We review CF academic studies (e.g., Dimitras et al., 1996; Charitou et al., 2004; Balcaen and Ooghe, 2006; Altman and Hotchkiss, 2010), the UK insolvency law (e.g., Insolvency Act 1986 and Enterprise Act 2002), the online information published at Insolvency Service and Companies House (https://www.gov.uk/), company news and announcements at Bloomberg Terminal and professionals online sites such as INVESTEGATE (http://www.investegate.co.uk/). This step enables us to identify the initial wordlist. (2) Following Elshandidy and Shrives (2016), the initial wordlist is expanded by including related synonyms using Roget's Thesaurus (http://www.roget.org/). (3) To develop the wordlist further, following prior research (e.g., Clatworthy and Jones, 2003; Kravet and Muslu, 2013), twenty annual reports for firms that failed after being financially distressed are randomly selected and carefully read to recognize words that are indicative of the CF. (4) To check the extent to which the CF identified words are featured, the

[12] For more information regarding the advantages of this method, refer to Loughran and McDonald (2016).

word is omitted if: a) it is not repeated in at least two annual reports, or b) it does not appear in at least one annual report, as well as any leading wordlists of risk-related disclosures (Elshandidy and Shrives, 2016). (5) Consistent with CF literature (e.g., Casey et al., 1986; Altman and Hotchkiss, 2010) and practical aspects of the UK insolvency law, the CF aggregate wordlist is assessed and classified into three categories, which are warning, reorganizational and statistical-related concepts.

[Insert Figure 1 about here]

The reorganizational group reflects the company's attempts to survive. The warning group reveals management signals to stakeholders. Both show consistency with management intentions to rehabilitate a distressed firm and warn related parties about a prospect of failure. This in turn is consistent with legitimacy and signaling theories. Besides, both groups are consistent with the context of liquidation (Chapter 7) and reorganization (Chapter 11) that is effectuated through the UK (US) CF procedures (e.g., Broude et al., 2007). The statistical group represents neutral words (such as significant, probable and differ) that reflect neither warning nor reorganization. Collectively, this ensures that the CF wordlist reliably connotes the context from which it is derived, i.e., the CF context. The final CF wordlist is presented in Appendix B. Notably, in line with Loughran and McDonald (2011) and Bodnaruk et al. (2015), the words require*, loss*, risk* and impairment* are the most frequent words contributing to CF-related measure.[13] In addition, as a further check of the validity of our wordlist, 76% of the wordlist of CF is correlated with the leading risk-related wordlists.[14] More specifically, since in a contemporaneous paper complementary to ours, Gandhi et al. (2019) use the negative wordlist of Loughran and McDonald (2011) and show the 10-K's negative sentiment as a proxy for financial distress in the US banks, we test the

[13] * Means any other derivatives from the original word, as consistent with previous wordlists suffixes are allowed. Although some loss, risk and fail derivatives do not meet the stage number 4/b, they are retained because these words have a strong echo in predicting CF (see Li, 2006).

[14] The aggregate risk, bad, good news and statistical wordlists of Elshandidy and Shrives (2016) are explicitly provided in their paper. Similarly, the papers of Kravet and Muslu (2013) and Campbell et al. (2014) contain their risk wordlists (with risk subcategories of financial, litigation, tax, other-systematic and other-idiosyncratic). Moreover, the six wordlists (negative, positive, uncertain, litigious, strong modal, and weak modal) of Loughran and McDonald (2011) and the constraining wordlist of Bodnaruk et al. (2015) are available at Bill McDonald's web page (http://www3.nd.edu/~mcdonald/Word_Lists.html).

correlation between the scores generated by our CF wordlist (comprising 267 words) and the negative wordlist of Loughran and McDonald (2011) (comprising 2,355 words). Results show that the correlation between the two wordlists is significantly high (around 62% at the 1% significance level), which implies that the two wordlists in common capture a large proportion of CF-Disclosure from the narrative sections of annual reports. The similarity with the work of Gandhi et al. (2019) provides further evidence of our wordlist's validity. Additionally, the negative wordlist of Loughran and McDonald (2011) is widely used in both the accounting and finance literature to measure the overall negative sentiment in business settings (e.g., Mayew et al., 2015; Loughran and McDonald, 2016). Consistent with the power law probability distribution (or so-called Zipf's law; see Loughran and McDonald (2016) for more details), this highly significant correlation suggests that our CF wordlist is important to identify words most related to CF in narratives' overall negative sentiment.[15]

To measure the *CF-Disclosure* score, as is typically done in textual analysis literature (see the review of Loughran and McDonald, 2016), we calculate the percentage of words indicating the likelihood of CF in the narrative sections of annual reports (i.e., number indicating the likelihood of CF scaled by the total number of words in the annual report). The reliability of the *CF-Disclosure* and its tones of warning and reorganization are statistically examined using Cronbach's alpha (Elshandidy and Shrives, 2016). The Cronbach's alpha of 87% for the computed scores of the *CF-Disclosure*, as well as its sub-tones, implies that the internal consistency between the *CF-Disclosure* and its sub-tones is high relative to the generally accepted value in social science of 70% (Elshandidy and Shrives, 2016). It is, therefore, concluded that the computed *CF-Disclosure* is reliable. To ensure the validity of our measure, we introduce Appendix C where we show how our

[15] We also test the incremental predictive and explanatory ability of our CF-related warning category against Loughran and McDonald's (2011) negative category, refer to the robustness checks in section 6. It is worth noting that having our CF wordlist generated within the failure context in the UK, on its own, avoids potential limitations related to using Loughran and McDonald's (2011) wordlists outside the US context (Ataullah et al., 2018).

wordlist performs in predicting two major collapses in the UK market in 2018-2019 (the cases of Carillion PLC and Thomas Cook PLC).

5.2.2. Control variables

Consistent with prior research (e.g., Charitou et al., 2004; Christidis and Gregory, 2010; Campbell et al., 2008; Tinoco and Wilson, 2013; Hsu and Wu, 2014; Darrat et al., 2016), we control for accounting-based variables (profitability, liquidity, leverage and performance). These are *ROA* (profitability) = net income/total assets, *Current Ratio* (liquidity) = current assets/ current liabilities, *Capital Structure* (leverage) = total debt/total equity capital, *Funds from Operations* (performance) = total funds from operations/total liabilities. Consistent with prior research, the present study expects that firms with higher profitability, liquidity and performance have a lower probability of failure, whereas higher leverage raises the possibility of failure.

We further control for market and macroeconomic-based variables following prior research (e.g., Agarwal and Taffler, 2008; Campbell et al., 2008; Christidis and Gregory, 2010; Tinoco and Wilson, 2013; Darrat et al., 2016). The market-based control variables are: *PRICE* = log firm's equity price, *Abnormal Returns* = the firm's cumulative annual returns minus the FTSE All Share return index for the same period of time, *Market Cap* = log the firm's market capitalization relative to the total market capitalization of the FTSE All Share index, *MB* = market value equity to book value equity and the *Volatility* of market returns is used as a measure of total risk, which is in turn measured by the standard deviation (sigma). Then, we add these two macroeconomic-based variables: the Retail Price Index (*RPI*) in base 100 as a measure of inflation rate in addition to the 3-Treasury Bill Rate (*TBR*) as a proxy for interest rates. Following the aforementioned studies, the present study expects that firms with larger market capitalization, higher stock price, abnormal stock returns and lower volatility, while market value is unusually low relative to book value, during lower levels of inflation and/or interest rate, are less likely to fail.

Additionally, we control for a number of different possible corporate governance variables that are broadly used in previous CF research (e.g., Daily and Dalton, 1994, 1995; Fich and Slezak, 2008; Platt and Platt, 2012; Hsu and Wu, 2014; Darrat et al., 2016). These variables include *Board Size* as measured by the log of the total number of board members, *Board Independence* as the proportion of independent non-executive directors to the board size, *CEO Turnover* as a dichotomous variable coded as one if the firm experienced a change in CEO and zero otherwise, *CEO Duality* as a dummy variable set to one if the CEO is also chairman of the board of directors or the executive chairman is present on the board and zero otherwise, and *Board Diversity* as captured by the proportion of female directors on the board of directors. Following the above-mentioned studies, the present study expects a negative (positive) relationship between board size, board independence, and board gender diversity (CEO turnover, and CEO duality) and the likelihood of CF.

Table 1 reports summary statistics for all explanatory variables for the final sample, which consists of 3,941 firm-year observations (272 healthy firms with 2,371 firm-year observations and 272 failed firms with 1,570 firm-year observations). Panels A, B and C of Table 1 present the descriptive statistics for the entire dataset, healthy firms and failed firms, respectively. To mitigate the outlier statistical problem, all continuous variables are winsorized at 1% on both tails (Shumway, 2001). The t-test statistics suggest that the means of all explanatory variables, except MB, are significantly different between the healthy and failed firms.[16] Table 2 displays the pair-wise correlations, where Pearson product moment correlations are displayed above the diagonal and Spearman rank-order correlations are displayed below. Collectively, *CF* is significantly correlated with the predicted signs with most control variables, where *CF* is coded as one if the firm is classified as failed and zero otherwise. Specifically, the *CF* variable is positively correlated with *CF-Disclosure* ($p < 0.01$). We also note that there is a positive correlation ($p < 0.01$) between the level

[16] Since multivariate analysis provides a better basis for drawing inferences related to the extent to which CF-Disclosure predicts CF and whether CF-Disclosure incrementally predicts CF over the classical CF prediction variables (e.g., Mayew et al., 2015), we turn our inferences to multivariate analyses, discussed later.

of aggregate *CF-Disclosure* and its sub-tones (untabulated for brevity), which thereby suggests that UK non-financial publicly quoted firms employ the tone in narrative-related disclosures to communicate their effort to face the probable failure or to convey a warning message about the CF likelihood.[17]

[Insert Table 1 about here]

[Insert Table 2 about here]

5.3. The empirical model

To estimate a multi-period (i.e., dynamic) logit model, we (following: Shumway, 2001; Chava and Jarrow, 2004; Campbell et al., 2008; Tinoco and Wilson, 2013; Darrat et al., 2016) employ a binary indicator of CF. The *CF* indicator is given a value of one if the company is classified as failed and zero otherwise. As pointed out earlier, we establish our analysis on both approaches to failure, i.e., the financial approach and the legal approach. Since there are multiple observations of the same firm, following Petersen (2009), we employ robust standard errors estimation and adjust standard errors clustered by firm. The present study's multi-period logit model is given by the following formula:

$$P_{i,t} = \frac{1}{1+\exp(-y_{i,t})} \quad Where,\ \mathrm{y}_{i,t} = \alpha + \beta' X_{i,t-1} = \alpha + \beta' \begin{bmatrix} X_{1,t-1} & \cdots & X_{1,t-j} \\ \vdots & \ddots & \vdots \\ X_{n,t-1} & \cdots & X_{n,t-j} \end{bmatrix}$$

$P_{i,t}$ denotes the conditional probability in time t that the firm i will fail within one year. This conditional probability is based on the observed value of $\mathrm{y}_{i,t}$, which is a linear set of the independent variables. $X_{1,t-1}$ denotes the value of the first independent variable at the year that immediately precedes *CF*, and so on. As a result, conditional on the observed values of our predictors, the multi-period logit model predicts the probability of *CF* during a year. Following prior studies (e.g., Tinoco and Wilson, 2013; Darrat et al., 2016), we estimate the probability of CF

[17] In addition, the correlation coefficients for both independent and control variables that are included in the logit analyses are also used to diagnose multicollinearity (untabulated). With Variance Inflation Factor (VIF) statistics less than 10 (or its alternate tolerance (TOL) statistics above 0.1), the unreported tests suggest that multicollinearity is not inherent in our logit regressions (Field, 2013). All unreported results are available upon request.

for one year and two years before the event of failure. The model description is identical when predicting for two years prior to *CF*.

6. Empirical results, further analysis and robustness checks

6.1. Empirical results

Panel A of Table 3 reports the results of logit regression models for examining the ability of *CF-Disclosure* to predict CF in a year and two years prior to CF, respectively. To that end, in one year and two years prior to CF, we introduce first Model 1 and Model 5 that give the impact of accounting, market and macroeconomic variables, as the base model, on CF. In one year before the CF, the results suggest that firms with larger market capitalization, higher profitability and stock prices, as well as lower leverage and volatility during low levels of inflation and interest rates are less likely to fail than other firms. In two years prior to CF, the signs of coefficients are not changed and results remain at the 1% significance level, except leverage and market capitalization, where significance is decreased to 5%, and abnormal returns, which becomes negatively significant at the 10% level. These results are consistent with our expectations and prior CF literature (e.g., Tinoco and Wilson, 2013).

[Insert Table 3 about here]

The following models report the *CF-Disclosure* estimates in a sequential fashion showing the incremental predictive ability of *CF-Disclosure* relative to the base model predictors. Following prior research (e.g., Chava and Jarrow, 2004; Campbell et al., 2008; Mayew et al., 2015), we, in a first round, also show the incremental explanatory ability and predictive accuracy using the McFadden Pseudo R^2 (Pseudo R^2) in addition to the p-values of the both Wald Chi-squared test (Wald χ^2 Test) and likelihood ratio test statistics (LRT). As a first step, we investigate the role of our main variable of interest, *CF-Disclosure*, alone. In Model 2 and Model 6 in a year and two years prior to CF, *CF-Disclosure* is significant at the 1% level (Z-statistics are 10.150 and 7.301, respectively). In addition, the Pseudo R^2 statistics suggest that *CF-Disclosure* alone has predictive accuracy and provides explanatory power of about 41% (0.069 under Model 2 / 0.167 under Model 1) and 25% (0.040 under Model 6 / 0.160 under Model 5) relative to that provided by accounting, market and macroeconomic variables combined.[18] This implies the feasible predictive ability of *CF-Disclosure* as compared to the CF predictors widely used in the classical models.

In Model 3 and Model 7, representing our expanded model, *CF-Disclosure* is added as the key explanatory variable to the variables of the base model. In both models in a year and two years prior to CF, *CF-Disclosure* is significant at the 1% level (Z-statistics are 6.811 and 4.655, respectively). To put this in an economic perspective, we estimate the average marginal effects (unreported).[19] With a standard deviation of 0.385, the marginal effects of the *CF-Disclosure* are 0.097 and 0.076 in the year preceding the CF and the penultimate year, respectively. That is, other things being equal, a one-standard-deviation increase in the *CF-Disclosure* is associated with a 39.7% (0.097 * 0.385 / CF binary dependent sample mean of 0.094) greater likelihood of CF within a year. Similarly, a one-standard-deviation increase in the *CF-Disclosure* is associated with a 31.9% greater likelihood of CF within two years. Thus, the presence of more CF-related words in the annual report narratives is associated with a higher probability of CF in the first or second following year. These results support the study's hypothesis.

These results are consistent with signaling and legitimacy theories as where a firm's solvency is in question, managers are motivated to signal threats to the firm's legitimacy in order to formulate a normalizing account, perform strategic restructuring, mitigate information asymmetry, reduce stakeholders' responses and lessen litigation and reputational risks. Furthermore, our findings support previous arguments (e.g., Holder-Webb and Cohen, 2007) that annual report narratives provide the official channel for managers to disclose potential CF to stakeholders. These results confirm prior studies' (e.g., Ohlson, 1980; Shuai and Li, 2005) call for the recognition of qualitative variables to enhance the predictive power of CF models.

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[18] Caution should be exercised in interpreting the Pseudo R^2. However, its values are comparable and indicative when the evaluated models have the same dataset context and outcome variable.
[19] Marginal effects are the average of discrete or partial changes in the quantities of interest (i.e., the probability of CF) evaluated for each observation (Bartus, 2005).

Furthermore, the Pseudo R^2 statistics in addition to the p-values of the both Wald χ^2 Test and LRT report the significance of incorporating the *CF-Disclosure* variable into the traditional base model. Relative to the base model (Models 1 and 5), the p-values reported under Model 3 and Model 7 for one year and two years prior to CF, respectively, indicate the high significance of *CF-Disclosure* at the 1% level. Besides, the enhancement in Pseudo R^2 statistic by about 16% (from 0.167 for Model 1 to 0.193 for Model 3) for the year prior to CF, as well as by about 9% (from 0.160 for Model 5 to 0.174 for Model 7) for the two years prior to CF underscores the incremental explanatory ability of *CF-Disclosure.*

Taken all together, these findings empirically indicate that annual report narratives are an important factor in predicting the likelihood of CF. The theoretical implications of this finding contribute in enriching the continuing discussion about the usefulness of information conveyed in annual report narratives (e.g., Elshandidy et al., 2018) by underscoring its importance in predicting CF and improving or revising CF classical prediction models. These implications are also extended to the auditors to strengthen audit's analytical review, especially for the sake of going concern reporting. In addition, the results have practical implications for investors and other market participants who are likely to look for early warning alerts of CF. In Models 3 and 7, the control variables that are included in the base model retain their statistical significance, except capital structure and market capitalization, which become significant at the 5% and 10% levels in one year and two years prior to CF, respectively.

Model 4 and Model 8 include further corporate governance factors (*board size, board independence, CEO turnover, duality role and gender diversity*), which were of interest in previous CF studies such as Daily and Dalton (1994, 1995), Fich and Slezak (2008), and Hsu and Wu (2014). This inclusion is important to revise our results from possible endogeneity attributable to omitted variables (Darrat et al., 2016), as well as considering the influence of conventional corporate governance factors that appear in the prior CF literature. The exhibited models for one year and two years prior to CF indicate, as before, that the positive relationship between *CF-Disclosure* and the likelihood of CF remains highly significant with a stable Z-statistic at the 1% level, even in the presence of corporate governance attributes. Thus, this finding suggests that the present study's key variable of *CF-Disclosure* is a powerful and consistent predictor over time of the possibility of CF. Regarding corporate governance control variables, interestingly none is statistically significant in its association with the likelihood of CF, either for the penultimate year or the year preceding the CF. Only for one-year prior to CF, *CEO Turnover* is statistically significant at the 5% level (Z-statistic of 2.435), which suggests that CEO instability increases for failed firms (Daily and Dalton, 1995). In sum, the observed corporate governance results are consistent with the findings of Hsu and Wu (2014) related to board composition in the UK context.

Panel B of Table 3 displays a comparison of model performance statistics from the base model (Model 1 and Model 5 in panel A) and the expanded model that includes *CF-Disclosure* (Model 3 and Model 7 in panel A) as estimated in a year and two years prior to CF. Following prior CF research (e.g., Chava and Jarrow, 2004; Agarwal and Taffler, 2008; Tinoco and Wilson, 2013; Darrat et al., 2016) this paper employs five widely used measures to assess the model's fit and predictive ability: Pseudo R^2 (reported under panel A), Wald χ^2 Test, Hosmer and Lemeshow goodness-of-fit test (H&L Test), LRT and Area Under the Receiver Operating Characteristic (ROC) Curve (AUC).

Typically, the higher absolute values of the Pseudo R^2 statistic, as a proportion of change in terms of the log likelihood, imply that the model, as a whole, provides a superior fit to the data. The Wald χ^2 Test restricts the parameters of interest to zero and checking if the fit of the model is significantly reduced. Similarly, LRT compares the difference between the nested models. Accordingly, if the difference is statistically significant, it is indicative that the unconstrained model statistically fits the data better than the constrained model; thus, including the variables is imperative. AUC gauges the discriminating ability and accuracy of the model relative to the perfect model with a value of 1. AUC shows the probability of detecting true and false outcomes for an entire range of possible cut-points. Thus, it is a complete and leading measure to assess the model's ability to discriminate between the subjects of the binary outcomes, with a higher score suggesting better predictive ability (Hosmer et al., 2013). In the H&L Test the sample is divided up, as is commonly done (e.g., Tinoco and Wilson, 2013), into ten groups (g) based on the predicted probabilities. For this partition, the Pearson chi-square statistic compares the predicted frequency and the observed frequency. Thus, the more closely these frequencies match, the better fitted is the model to predict the binary outcome (i.e., CF) (Agresti, 2002).[20]

With the exception of the H&L Test statistics, panel B of Table 3 shows that both base and expanded models have significant performance in predicting CF for a year and two years before CF. However, the superior statistics for the expanded model (relative to the base model) clearly indicate that adding the *CF-Disclosure* variable contributes positively and significantly to the performance of the CF prediction models (the AUC of the model contains *CF-Disclosure* alone is virtually 85% of the base model). This, in other words, also means that it is preferable to consider *CF-Disclosure* alongside the traditional accounting, market and macroeconomic variables in order to increase the CF prediction ability.

In terms of H&L Test statistics, in t - 1, the large chi-square (14.710) with a p-value slightly above 0.05 implies that the base model hardly fits the data. In t - 2, the chi-square exceeds 15 and the p-value is significantly lower than 0.05, obviously suggesting that the base model does not fit well. This, in turn, implies that the base model lacks other explanatory variables needed to accurately discriminate between the binary response (i.e., the *CF*). Turning to the expanded model, in both t - 1 and t - 2, the small chi-square (<15) and the large p-value (>0.05) clearly suggest that the model fit is good. Therefore, it can be concluded that incorporating the *CF-Disclosure* variable significantly assists the traditional variables in adequately discriminating between failed and healthy firms and better predicting CF. We also check the external validity of our multi-period logit model by undertaking an out-of-sample-period *ex-ante* test (Charitou et al., 2004). Our validation sample

[20] The H&L Test statistic approximately follows a chi-squared distribution with g−2 degrees of freedom and a good fit yields a large p-value. Therefore, a small chi-square (<15) and a large p-value (>0.05) indicate that the model fits the data well (Tinoco and Wilson, 2013).

takes place in the 2011-2016 period. In t -1 and t - 2, the predictive ability of the base model is 73.80% and 72.66%, and of the expanded model is 76.22% and %74.71%, respectively.

6.2. Further analysis

Motivated by the present study's theoretical foundation, in addition to considering the difficulty in distinguishing financial constraints from CF in some of the previous research (Whited and Wu, 2006), we investigate whether financial constraints would promote the incidence of *CF*. We thus use Bodnaruk et al.'s (2015) financial constraints wordlist to calculate the percentage of words that indicate financial constraints in annual reports narratives (i.e., *FC-proxy*).[21] The '*Further*' models of Table 3 illustrate that failed firms suffer severely from financial constraints in the year that directly precedes the failure (Z-statistic is 3.119 at the 1% significance level). The variable's unreported marginal effect of 0.170 indicates that it has a non-trivial economic impact on CF (18.9%). However, in two years prior to the CF, the *FC-proxy* statistically shows an insignificant role in the CF. Simultaneously, *CF-Disclosure* is significantly associated with the probability of CF in both the year that directly precedes the CF (Z-statistic is 4.757 at the 1% significance level; economically 28.7%) and the penultimate year (Z-statistic is 4.112 at the 1% significance level; economically 30.3%). These results, consequently, confirm our supposition that a financially distressed firm becomes more vulnerable when financial constraints take place, which as a result, would promote the incidence of CF. In the same context, this evidence provides empirical support to prior research (e.g., Senbet and Wang, 2012) showing that a firm can be financially distressed without being financially constrained.

6.3. Robustness checks

We validate our findings and test the robustness in various ways. First, to account for the effect of the recent financial crisis (2007-2008), we employ dummy variables for the periods prior,

[21] The multicollinearity (unreported) tests suggest that the predictors remain independent and do not suffer this problem after adding *FC-proxy*.

during and post the crisis. Based on Models 1 and 2 of Table 4, the results suggest that the probability of failure has significantly increased both during and after the crisis relative to before the crisis. Yet, our earlier findings individually and collectively remain strongly consistent. These results are consistent with the UK's companies' insolvency records and the evidence of Agarwal and Taffler (2007) on growing bankruptcies in the UK.

Turning to Model 3 of Table 4, the coefficient estimates of *CF-Disclosure*, (*CF-Disclosure* + *CF-Disclosure*Crisis*) and (*CF-Disclosure* + *CF-Disclosure*PostCrisis*) report the sign and the significance of the relationship between *CF-Disclosure* and the likelihood of CF considering the impacts of the period pre, during and post-crisis, respectively. The evidence clearly indicates that *CF-Disclosure* is positively and significantly able to capture the probability of CF before, during and after the financial crisis at the 10-1% level of significance. Moreover, the positive and significant sums of the parameters of (*CF-Disclosure* + *CF-Disclosure*Crisis*) and (*CF-Disclosure* + *CF-Disclosure*PostCrisis*) indicate that firms increasingly use annual report narratives to communicate potential CF during and after the financial crisis (relative to before the financial crisis), respectively. To sum up, it can be argued that the annual report narrative-related disclosures imply a very strong alarm for CF with a 90-99% confidence level, before, during and after the financial crisis.[22]

[Insert Table 4 about here]

Second, following Chava and Jarrow (2004), we validate our results by investigating the influence of industry effects. Thus, in Table 5 we run the logit models with an intercept and slope dummy variables for each specific industry grouping. Further, for one year and two years before CF, slope shifting dummies for *CF-Disclosure* are applied in Models 3 and 4 to test the link between the industry groupings and *CF-Disclosure*. Chava and Jarrow (2004) indicate that the original four-digit industry separation is too fine for estimation purposes. Therefore, we follow them and

[22] To verify this conclusion, we also employ the difference-in-differences test to investigate the significance of differences in *CF-Disclosure* between the failed and the healthy firms before, during and after the financial crisis. The unreported results are in line with our previous results at the 1% significance level. Notably, we run our test for the interactions between *CF-Disclosure* and crisis dummy variables for only one year before CF since going further would lead to incongruous inferences as the period of the financial crisis is only two years.

combine the four-digit SIC code into three unique groups as follows: *IND1* represents miscellaneous industries (SIC code is in the ranges 1–1000, 1500–1800, 5000–6000, 7000–8900), *IND2* represents manufacturing and mineral industries (SIC code is in the ranges 1000–1500, 2000–4000), and *IND3* represents transportation, communications and utilities (SIC code is in the range 4000–5000). In addition, as mentioned earlier, the finance, insurance and real estate sector (SIC code is in the range 6000-6999) is excluded from our analysis.

In Table 5, it is observed that the *CF-Disclosure* findings remain consistent with our original results discussed earlier. Focusing on Models 3 and 4 where *IND3* is employed as the base value, the resulting estimates report the significance of *IND1*. It is, therefore, suggested that *IND1* is the industry group most exposed to CF, followed by *IND2* and *IND3*, respectively. With respect to the interactions between *CF-Disclosure* and industry groups, *CF-Disclosure* is positively significant in all industry groups, suggesting that *CF-Disclosure* retains its predictive power to capture the probability of CF in all industry groups. Moreover, the signs and slope dummies illustrate that *CF-Disclosure* is more sensitive to the likelihood of CF in *IND3* and *IND2*, respectively, compared to *IND1*.

[Insert Table 5 about here]

Third, to further test the robustness of our results, we perform a univariate analysis for *CF-Disclosure* in order to determine its discriminating ability using the analysis of variance (ANOVA) F-test. We also conduct multiple discriminate analysis (MDA) to check the total significance of the expanded (and the base) discriminant model. The Wilks' lambda statistic in panel A of Table 6 suggests that *CF-Disclosure* is able to explain 4‰ (1 - 0.996) of the total variability between the failed and healthy firms.[23] In line with that, the F-test statistic suggests that *CF-Disclosure* has a high ability to discriminate between the failed and the healthy firms at the 1% significance level.

[Insert Table 6 about here]

[23] The value of Wilks' lambda has a range from 0 to 1. A lower value of Wilks' lambda implies a greater ability to discriminate between the groups (i.e., between the failed and healthy firms). The after *CF-Disclosure* unexplained total variability (0.996) would probably, at the first glance, appear too large. However, this proportion is marginally larger than its counterpart (0.995) for Altman's (1968) original Z-score model, that contains five popular financial ratios, tested in the UK context (for more details see Almamy et al., 2016).

In terms of the MDA, panel B in Table 6 reports the estimates resulting from our expanded model (which involves the variables in Model 3 of Table 3) in addition to the base model (which involves the variables in Model 1 of Table 3). The Wilks' lambda statistic of the expanded model (0.767) implies that the model has a high significance in discriminating between the failed and the healthy firms at the 1% significance level. Besides, the reduction in the unexplained proportion of the groups' total variability from 0.772, as is indicated for the base model, to 0.767, as is indicated for the expanded model, implies that *CF-Disclosure* contributes to the discriminating model. These results, in sum, accord with the previous findings derived from the logit analysis.

Fifth, as we noted earlier, Gandhi et al. (2019) in a contemporaneous paper, using an approach different from ours, show a significant association between the negative sentiment category proposed by Loughran and McDonald (2011), as a proxy for financial distress, and a US bank's omission of dividends and experience of lower return on assets (ROA) in the following year. Similarly, we check *CF-Disclosure* ability to predict dividend omission and ROA decrease in the subsequent year. In Model 1 and Model 2 of Table 7, the significantly positive (negative) coefficient on *CF-Disclosure* with a Z(T)-statistic of 3.674 (-2.827) at the 1% significance level suggests that *CF-Disclosure* is significantly predictive of a following year dividends omission and lower ROA due to a firm's financial distress. In unreported tests to predict dividend omission and ROA using the negative sentiment category of Loughran and McDonald (2011), our sample fails to find significant result for ROA. A plausible reason for this insignificant result is that the negative category of Loughran and McDonald (2011) does not recognize CF-related reorganization tone, which we find negatively significant with ROA with a T-statistic of -2.585 at the 5% level.

In Model 3 and Model 4 of Table 7, we replace the aggregate score of *CF-Disclosure* with Loughran and McDonald's (2011) negative category (which contains 2,355 words) and our warning category to predict CF (which contains 196 words). As expected, the overall pessimistic sentiment in the annual report narratives is significantly related to higher probability of subsequent CF (under Model 3, *Negative_Tone* is significantly positive with a Z-statistic of 7.915 at the 1% level). Model 4 reveals a relatively higher predictive ability of our CF-related warning category (*Warning_Tone* is significantly positive with a Z-statistic of 8.046 at the 1% level). Additionally, the marginally higher Pseudo R^2 higher (0.207 > 0.203) illustrates the accuracy of our CF wordlist in capturing the warning messages conveyed in annual report narratives about the CF likelihood. Overall, results suggest that our CF wordlist is well-established for the CF context, and importantly complementary to Loughran and McDonald's (2011) negative wordlist to identify words most related to CF in the overall negative sentiment narratives.

Sixth, we use a multinomial logit model (which is often referred to as conditional logit model) to clarify the predictive power of *CF-Disclosure* to capture the probability of CF while recognizing financial distress (*FD*) and bankruptcy (*BR*) risks separately. For both tests in a year and two years prior to *CF*, Table 8 indicates that *CF-Disclosure* retains its high significance (at the 1% level) in predicting the probability of *FD* (Z-statistics are 5.707 and 4.388, respectively) and *BR* (Z-statistics are 4.630 and 2.972, respectively). Collectively, the qualitatively immutable and systematic inferences provided by Table 8 are consistent with our previous results. This also demonstrates the power and practicality of the CF definition that includes the financial distress and bankruptcy risks (Campbell et al., 2008; Tinoco and Wilson 2013).

[Insert Table 8 about here]

Furthermore, above, we use a multinomial logit model because the categories of our dependent variable convey no natural ordering. In unreported tests, however, we *assume* that our dependent variable conveys ordinal categories (bankruptcy, financial distress, or healthy) hypothetically like that, for instance, of a firm's credit ratings (*say*: in default, speculative, or investment) (e.g., Ashbaugh-Skaife et al., 2006). Accordingly, we estimate an ordered logit model investigating the ability of *CF-Disclosure* to predict the probability of failure in such a setting. The untabulated results (Z-statistics are 6.856 and 4.747 at the 1% level for tests in one year and two years prior to *CF*, respectively) are collectively consistent with those previously drawn from our prior analyses. Besides, we rerun all models presented in Table 3 using two sub-samples in which we consider financial distress and bankruptcy separately. All unreported results are robust and consistent with that derived from the previous analyses (*CF-Disclosure* is significant at the 1% level in predicting the probability of either *FD* or *BR*). As a final robustness check, controlling for unobserved heterogeneity, the unreported results of our principal analyses with year and industry fixed effects collectively and generally are consistent. Overall, our sensitivity tests illustrate that our inferences are robust to using alternative measures and estimation procedures.[24]

7. Conclusion

This paper contributes to the literature on CF prediction by examining the predictive ability of narrative-related disclosures. To gauge narrative-related disclosures, we established a comprehensive list of CF-related keywords capturing the CF sentiment in annual report narratives. Regarding CF-Disclosure and CF prediction, we find that greater incidence of CF-Disclosure in the annual reports is strongly associated with a higher likelihood of CF, in both the year immediately prior to failure and the penultimate year. Our study also provides evidence suggesting that CF-Disclosure offers an incremental predictive ability relative to accounting, market and macroeconomic variables that are widely used in the classical CF prediction models. Thus, CF-Disclosure is feasible in enhancing the explanatory power of the models that predict CF. Additionally, we observe that a financially distressed firm becomes more vulnerable when financial constraints occur, which thereby would accelerate the CF incident. Various robustness tests verify the credibility of the incremental explanatory power of CF-Disclosure for CF prediction.

Despite the importance of our results, they should be interpreted taking into consideration the following limitations. First, despite the rational premise of our legal and financial definition of CF, it could be a consequence of various reasons such as an ethical problem of management, like

[24] Predicting CF for one year and/or two years before the event of failure is common in literature because data availability for failed companies is limited; most typically have three firm-year observations prior to CF (e.g., Darrat et al., 2016). Interestingly, our untabulated results from a limited sample show that CF-Disclosure can predict CF up to six years in advance, which accords with the trend presented in Appendix C for the Carillion case. Although this predictive ability is consistent with the forward-looking pattern of narrative disclosures, it should be viewed with caution as it is likely to be linked to firms that have a higher ability to exist longer.

committing fraud (Hsu and Wu, 2014). Second, annual reports are used because they represent a key source of information for investors. However, other outlets of corporate communication (e.g., financial analysts' reports, conference calls and/or online resources) could contain unique signals of the likelihood of failure. Third, our paper adopts a quantity-based methodology in measuring CF-Disclosure, without gauging the quality. These limitations might provide avenues for future research on CF.

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Table 1
Descriptive statistics

Panel A: Entire data set

Variable	Obs.	Mean	S.D.	Median	Q1	Q3
Accounting, market and macroeconomic control variables (serve as a base model):						
ROA	3941	-3.812	28.220	4.400	-4.950	9.010
Current Ratio	3941	2.458	3.385	1.450	0.990	2.360
Capital Structure	3941	25.255	31.896	17.940	0.330	39.030
Funds from Operation	3941	-0.132	1.212	0.138	-0.021	0.281
PRICE	3941	4.352	1.797	4.554	3.314	5.587
Market Cap	3941	6.938	0.559	6.930	6.715	7.173
Abnormal Returns	3941	0.159	13.505	-0.775	-6.652	5.759
MB	3941	2.429	4.285	1.560	0.880	2.890
Volatility	3941	0.497	0.247	0.435	0.316	0.626
TBR	3941	2.713	2.174	3.871	0.389	4.746
PRI	3941	213.288	27.711	208.500	188.200	242.000
CF- Disclosure:						
CF-Disclosure	3941	2.527	0.385	2.517	2.254	2.783
Corporate governance control factors:						
Board Size	3941	1.834	0.335	1.792	1.609	2.079
Board Independence	3941	0.347	0.234	0.400	0.167	0.500
CEO Turnover	3941	0.103	0.304	0.000	0.000	0.000
Duality Role	3941	0.285	0.451	0.000	0.000	1.000
Gender Diversity	3941	0.051	0.093	0.000	0.000	0.100

	Panel B: Healthy firms				**Panel C: Failed firms**				Difference
Variable	Obs.	Mean	S.D.	Median	Obs.	Mean	S.D.	Median	t-statistics
ROA	2371	3.196	17.409	6.110	1570	-14.395	36.821	-1.510	20.115***
Current Ratio	2371	2.345	2.971	1.530	1570	2.629	3.922	1.335	-2.587***
Capital Structure	2371	23.706	26.843	18.110	1570	27.595	38.174	17.730	-3.753***
Funds from Operation	2371	0.074	0.923	0.180	1570	-0.443	1.497	0.034	13.394***
PRICE	2371	4.679	1.600	4.840	1570	3.857	1.958	4.052	14.441***
Market Cap	2371	6.983	0.489	6.958	1570	6.869	0.646	6.882	6.290***
Abnormal Returns	2371	0.709	11.645	-0.548	1570	-0.671	15.875	-1.380	3.143***
MB	2371	2.474	3.719	1.620	1570	2.360	5.021	1.425	0.816
Volatility	2371	0.429	0.213	0.374	1570	0.599	0.259	0.563	-22.515***
TBR	2371	2.278	2.164	0.501	1570	3.370	2.020	4.476	-15.911***
PRI	2371	218.834	28.748	222.700	1570	204.911	23.733	199.900	15.929***
CF-Disclosure	2371	2.495	0.379	2.493	1570	2.574	0.390	2.549	-6.268***
Board Size	2371	1.869	0.320	1.792	1570	1.781	0.349	1.792	8.221***
Board Independence	2371	0.371	0.225	0.400	1570	0.310	0.243	0.333	8.177***
CEO Turnover	2371	0.083	0.276	0.000	1570	0.134	0.341	0.000	-5.133***
Duality Role	2371	0.274	0.446	0.000	1570	0.301	0.459	0.000	-1.847*
Gender Diversity	2371	0.056	0.097	0.000	1570	0.044	0.085	0.000	3.974***

This table presents summary statistics for all independent variables and scores over the period 2000 to 2016. The entire sample of 544 firms comprises 272 failed firms matched with 272 healthy firms. *ROA* is the return on assets as a measure of firm profitability = net income/total assets. *Current Ratio* is a measure of firm liquidity = current assets/current liabilities. *Capital Structure* is measured by firm leverage = total debt/total equity. *Funds from Operation* is a measure of firm performance = total funds from operations/total liabilities. *PRICE* is measured as the log of firm's equity price. *Market Cap* measures the firm's relative value as the log of the firm's market capitalization relative to the total market capitalization of the FTSE All Share index. *Abnormal Returns* represents the firm's cumulative annual returns minus the FTSE All Share return index for the same period of time. *Volatility* is the sigma of market returns used as a measure of total risk, which is in turn measured by the standard deviation. *MB* is market to book ratio = market value equity/book value equity. *RPI* is the Retail Price Index (RPI) in base 100 as a measure of the inflation rate. *TBR* is the 3-Treasury Bill Rate as a proxy for interest rates. *CF-Disclosure* is the aggregate information regarding CF, measured by the percentage of words that indicate the likelihood of CF in the narrative sections of annual reports. *Board Size* is measured by the log of the total number of board of directors. *Board Independence* is measured by the proportion of independent non-executive directors to the board size. *CEO Turnover* is a dichotomous variable coded as one if the firm experienced a change in CEO and zero otherwise. *Duality Role* is a dummy variable set to one if the CEO is also chairman of the board of directors or executive chairman presents on the board and zero otherwise. *Gender Diversity* is measured by the proportion of female directors on the board of directors. In addition, for these variables, t-statistics report the differences between healthy and failed firms. *, ** and ***indicate significance at the 0.1, 0.05 and 0.01 levels, respectively. All continuous variables are winsorized at 1% on both tails.

Table 2
Pearson (top) and Spearman (bottom) correlation coefficients

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 CF		**-0.283**	**0.034**	**0.058**	**-0.188**	**-0.226**	**-0.113**	**-0.043**	-0.015	**0.214**	0.025	**0.038**	**0.208**	**-0.167**	**-0.115**	**0.094**	0.015	-0.025
2 ROA	**-0.273**		**-0.069**	-0.024	**0.536**	**0.292**	**0.153**	**0.043**	**-0.101**	**-0.432**	**-0.038**	0.017	**-0.203**	**0.263**	**0.216**	**-0.086**	**-0.053**	**0.103**
3 Current Ratio	**-0.064**	**0.055**		**-0.271**	**-0.468**	**-0.139**	**0.048**	0.002	-0.015	**0.123**	0.005	0.017	**-0.067**	**-0.140**	**-0.150**	**-0.038**	0.022	**-0.068**
4 Capital Structure	-0.020	**0.048**	**-0.498**		**0.113**	**0.087**	**-0.066**	-0.019	**-0.052**	**-0.048**	**0.051**	**-0.053**	**0.076**	**0.144**	**0.131**	**0.066**	-0.015	0.011
5 Funds from Operation	**-0.256**	**0.739**	**0.119**	**-0.095**		**0.289**	**0.055**	0.012	**-0.092**	**-0.322**	**-0.056**	**0.039**	**-0.085**	**0.226**	**0.235**	-0.024	-0.031	**0.100**
6 PRICE	**-0.209**	**0.424**	**-0.045**	**0.178**	**0.357**		**-0.033**	-0.023	**0.188**	**-0.469**	0.028	-0.010	**-0.210**	**0.458**	**0.351**	-0.028	-0.028	**0.104**
7 Market Cap	**-0.115**	**0.176**	**0.045**	-0.028	**0.141**	-0.003		**0.163**	**-0.146**	**-0.040**	**-0.120**	0.005	**-0.154**	**0.053**	0.007	**-0.062**	**0.051**	0.015
8 Abnormal Returns	**-0.045**	**0.090**	0.015	-0.011	**0.075**	0.005	**0.148**		-0.031	0.024	**-0.128**	**0.080**	0.014	-0.009	0.020	**-0.033**	-0.009	**0.050**
9 MB	**-0.083**	**0.221**	**0.053**	**0.047**	**0.144**	**0.387**	**-0.172**	**-0.058**		-0.003	0.016	0.002	**-0.055**	**0.082**	**0.049**	-0.020	**-0.034**	**0.056**
10 Volatility	**0.209**	**-0.453**	0.010	**-0.160**	**-0.399**	**-0.520**	**-0.076**	-0.029	**-0.212**		-0.025	**-0.037**	**0.235**	**-0.346**	**-0.262**	**0.075**	**0.099**	**-0.145**
11 TBR	**0.047**	-0.012	-0.018	**0.059**	**-0.085**	0.005	**-0.144**	**-0.129**	**0.061**	-0.018		**-0.848**	**-0.315**	0.022	**-0.127**	0.011	**0.092**	**-0.190**
12 RPI	**0.053**	0.008	**0.045**	**-0.078**	**0.054**	-0.004	0.016	**0.101**	**-0.036**	**-0.041**	**-0.768**		**0.356**	**-0.059**	**0.125**	0.021	**-0.110**	**0.232**
13 CF-Disclosure	**0.198**	**-0.308**	**-0.144**	**0.050**	**-0.278**	**-0.204**	**-0.145**	0.013	**-0.160**	**0.233**	**-0.283**	**0.375**		**-0.199**	-0.001	**0.100**	-0.020	**0.062**
14 Board Size	**-0.151**	**0.268**	**-0.105**	**0.229**	**0.211**	**0.464**	**0.068**	0.025	**0.205**	**-0.365**	0.018	**-0.072**	**-0.193**		**0.377**	0.007	**-0.089**	**0.144**
15 Board Independence	**-0.109**	**0.234**	**-0.087**	**0.213**	**0.211**	**0.346**	0.017	**0.052**	**0.107**	**-0.266**	**-0.136**	**0.137**	0.016	**0.360**		0.021	**-0.202**	**0.186**
16 CEO Turnover	**0.094**	**-0.107**	**-0.032**	0.026	**-0.078**	-0.028	**-0.059**	**-0.034**	**-0.041**	**0.076**	0.005	0.021	**0.096**	0.011	0.020		0.004	0.016
17 Duality Role	0.015	**-0.065**	-0.023	**-0.036**	-0.018	-0.026	0.030	-0.027	**-0.084**	**0.088**	**0.078**	**-0.114**	-0.017	**-0.100**	**-0.209**	0.004		**-0.067**
18 Gender Diversity	**-0.039**	**0.146**	**-0.051**	**0.064**	**0.116**	**0.163**	0.027	**0.056**	**0.112**	**-0.181**	**-0.197**	**0.225**	**0.060**	**0.216**	**0.226**	0.008	**-0.073**	

This table reports the correlation coefficients for regression variables. Bold text indicates significance based on two-tailed t-tests, at the 0.05 level or better. All continuous variables are winsorized at 1% on both tails. Refer to Table 1 and Appendix D for the variable descriptions, measures, and sources.

Table 3
Logit regressions and model performance measures
Panel A: Logit regression of CF indicator on CF-Disclosure, corporate governance and complete predictor variables

VARIABLES	One year prior to CF					Two years prior to CF				
	Model 1	Model 2	Model 3	Model 4	*'Further'*	Model 5	Model 6	Model 7	Model 8	*'Further'*
ROA	-0.011***		-0.011***	-0.010***	-0.010***	-0.014***		-0.014***	-0.014***	-0.014***
	(-5.041)		(-5.508)	(-5.113)	(-5.159)	(-5.778)		(-6.153)	(-6.009)	(-6.014)
Current Ratio	-0.002		0.011	0.011	0.009	0.003		0.014	0.014	0.014
	(-0.086)		(0.584)	(0.580)	(0.484)	(0.141)		(0.641)	(0.624)	(0.612)
Capital Structure	0.005***		0.004**	0.004**	0.004**	0.004**		0.003*	0.004*	0.004*
	(2.903)		(2.326)	(2.497)	(2.528)	(2.304)		(1.783)	(1.892)	(1.890)
Funds from Operation	-0.081		-0.093	-0.088	-0.105*	-0.055		-0.059	-0.060	-0.063
	(-1.285)		(-1.550)	(-1.459)	(-1.722)	(-0.800)		(-0.878)	(-0.901)	(-0.935)
PRICE	-0.252***		-0.221***	-0.198***	-0.190***	-0.219***		-0.202***	-0.200***	-0.199***
	(-5.146)		(-4.683)	(-4.199)	(-4.008)	(-4.450)		(-4.216)	(-4.215)	(-4.186)
Market Cap	-0.348***		-0.234**	-0.229**	-0.208**	-0.274**		-0.188*	-0.181	-0.180
	(-3.340)		(-2.249)	(-2.182)	(-1.994)	(-2.494)		(-1.708)	(-1.644)	(-1.641)
Abnormal Returns	-0.003		-0.003	-0.003	-0.003	-0.009*		-0.008*	-0.008*	-0.008*
	(-0.855)		(-0.872)	(-0.874)	(-0.841)	(-1.736)		(-1.724)	(-1.724)	(-1.726)
MB	-0.017		-0.010	-0.008	-0.008	0.001		0.007	0.007	0.007
	(-1.210)		(-0.726)	(-0.587)	(-0.581)	(0.077)		(0.553)	(0.549)	(0.541)
Volatility	1.178***		0.943***	0.866***	0.868***	1.141***		0.944***	0.995***	0.995***
	(3.882)		(3.290)	(2.992)	(3.007)	(3.727)		(3.206)	(3.271)	(3.269)
TBR	0.307***		0.328***	0.311***	0.302***	0.401***		0.422***	0.421***	0.419***
	(5.297)		(5.758)	(5.440)	(5.397)	(7.297)		(7.665)	(7.658)	(7.592)
RPI	0.027***		0.022***	0.021***	0.017***	0.033***		0.031***	0.031***	0.030***
	(5.985)		(5.049)	(4.749)	(3.632)	(7.101)		(6.638)	(6.419)	(5.857)
FC-proxy					2.432***					0.300
					(3.119)					(0.347)
CF-Disclosure		1.857***	1.362***	1.308***	1.011***		1.427***	0.988***	1.011***	0.974***

		(10.150)	(6.811)	(6.682)	(4.757)		(7.301)	(4.655)	(4.789)	(4.112)
Board Size				-0.358	-0.357				0.243	0.239
				(-1.240)	(-1.231)				(0.870)	(0.856)
Board Independence				-0.311	-0.310				-0.491	-0.492
				(-0.949)	(-0.929)				(-1.413)	(-1.414)
CEO Turnover				0.460***	0.464***				0.168	0.168
				(2.870)	(2.894)				(0.816)	(0.815)
Duality Role				-0.122	-0.112				-0.142	-0.141
				(-0.759)	(-0.692)				(-0.906)	(-0.899)
Gender Diversity				0.557	0.676				0.675	0.698
				(0.679)	(0.823)				(0.768)	(0.799)
Constant	-6.477***	-7.164***	-9.972***	-8.956***	-8.471***	-8.600***	-5.863***	-11.250***	-11.650***	-11.530***
	(-4.111)	(-14.193)	(-6.057)	(-5.098)	(-4.789)	(-5.385)	(-11.215)	(-6.482)	(-6.376)	(-6.221)
Observations	3,941	3,941	3,941	3,941	3,941	3,441	3,441	3,441	3,441	3,441
LRT (p-value)			< 0.001					< 0.001		
Wald χ^2 Test (p-value)			< 0.001	< 0.001	< 0.001			< 0.001	< 0.001	< 0.001
Pseudo R^2	0.167	0.069	0.193	0.198	0.203	0.160	0.040	0.174	0.177	0.177
Panel B: Model performance measures										
Wald χ^2 Test:										
χ^2 [11,12,11,12][a]	292.300		353.170			240.510		287.530		
(p-value)	< 0.001		< 0.001			< 0.001		< 0.001		
H&L Test:										
χ^2 [8][a]	14.710		4.710			16.880		13.06		
(p-value)	0.065		0.789			0.031		0.1100		
LRT:										
χ^2 [1][a]			64.650					21.670		
(p-value)			< 0.001					< 0.001		
AUC[b]	0.808	0.696	0.819	0.817	0.820	0.797	0.648	0.800	0.808	0.808
External validity	0.738		0.762			0.727		0.747		

Panel A of this table reports the results from logit CF prediction models. The *'Further'* model reports the results of further analysis inspecting the role of financial constraints. *FC-proxy* is the percentage of words that indicate financial constraints in annual reports narratives. LRT is the likelihood ratio test statistics between the Base Model and the Expanded Model that includes *CF-Disclosure* in one and two years prior to CF (i.e., Model 1 and Model 3, and Model 5 and Model 7, respectively). Wald χ^2 Test represents the significance of including the *CF-Disclosure* parameter in the model. Robust standard errors are adjusted for clustering at the firm level. Z-statistics are in parentheses. Significance level: *** $p<0.01$, ** $p<0.05$ and * $p<0.1$. Refer to Table 1 and Appendix D for the variable descriptions, measures, and sources.
The performance statistics of Base Model (1 and 5) and Expanded Model (3 and 7) are reported in Panel B for a year and two years prior to CF. Pseudo R^2 (reported under Panel A), Wald χ^2 Test and H&L Test are calculated individually for each model. In terms of H&L Test, each model's covariates are tested under the criteria that a small chi-square (<15) and a large p-value (>0.05) infer that the model fits the covariates well so that it can be employed appropriately to predict the binary outcome (i.e., CF). LRT is the likelihood ratio test statistics between the base and the complete models in a year and two years prior to CF. The AUC measures the model power to discriminate between failed and healthy firms with a higher score suggesting improved predictive ability. External validity reports models' predictive ability using an out-of-sample-period *ex-ante* test. [b] For comparison purpose, AUC reports the area under the curve for the four models using the same observations under H0: the under-curves areas are equal. The overall p-value <0.001 for the four models, as well as models in t - 1 and t - 2 demonstrates the strong rejection of the null hypothesis. AUC of other models is also denoted. [a] The degrees of freedom for each estimated model are represented in brackets.

Table 4
Logit regression of CF indicator on complete predictor variables with the financial crisis effects

VARIABLES	One year prior to CF	Two years prior to CF	One year prior to CF
	Model 1	Model 2	Model 3
Crisis	0.980***	0.845***	0.521*
	(4.160)	(3.180)	(1.942)
PostCrisis	1.136***	0.634*	0.318
	(3.665)	(1.762)	(0.864)
CF-Disclosure	1.285***	1.016***	0.992***
	(6.580)	(4.835)	(4.303)
*CF-Disclosure*Crisis*			0.347***
			(3.014)
*CF-Disclosure*PostCrisis*			0.383*
			(1.758)
Constant	-6.306***	-10.363***	-4.349**
	(-3.362)	(-4.602)	(-2.021)
'*Base & CG controls*'	Included	Included	Included
Observations	3,941	3,941	3,941
Pseudo R^2	0.207	0.182	0.212
AUC	0.820	0.810	0.822

This table reports the results from logit CF prediction models over the sample period 2000–2016 considering the financial crisis effects. Relative to the period before the crisis, *Crisis* (*PostCrisis*) is a dummy variable that takes a value of one for years 2007 and 2008 (years 2009 to 2016) and zero otherwise. In one year and two years prior to CF, Models 1 and 2 are estimated to examine the impact of the financial crisis on the ability of *CF-Disclosure* variable to predict CF. For Model 3, parameter estimates for *CF-Disclosure, CF-Disclosure*Crisis* and *CF-Disclosure*PostCrisis* indicate the link between CF-Disclosure and CF pre, during and post-crisis, respectively. '*Base & CG controls*' indicates the inclusion of accounting, market, macroeconomic, and corporate governance control variables shown in Model 4, Panel A of Table 3. Robust standard errors are adjusted for clustering at the firm level. Z-statistics are in parentheses. Significance level: *** p<0.01, ** p<0.05 and * p<0.1. Refer to Table 1 and Appendix D for the variable descriptions, measures, and sources.

Table 5
Logit regression of CF indicator on complete predictor variables with the industry effects

VARIABLES	One year prior to CF	Two years prior to CF	One year prior to CF	Two years prior to CF
	Model 1	Model 2	Model 3	Model 4
IND1	-0.387	-0.464	5.938**	4.963*
	(-1.158)	(-1.263)	(2.256)	(1.796)
IND2	-0.634*	-0.683*	4.139	2.957
	(-1.847)	(-1.826)	(1.603)	(1.077)
CF-Disclosure	1.257***	0.949***	3.020***	2.402***
	(6.496)	(4.607)	(3.648)	(2.724)
*CF-Disclosure*IND1*			-2.180**	-1.921**
			(-2.481)	(-2.075)
*CF-Disclosure*IND2*			-1.608*	-1.241
			(-1.874)	(-1.354)
Constant	-8.200***	-10.824***	-13.426***	-15.043***
	(-4.477)	(-5.730)	(-4.466)	(-4.615)
'*Base & CG controls*'	Included	Included	Included	Included
Observations	3,941	3,441	3,941	3,441
Pseudo R^2	0.201	0.180	0.205	0.184
AUC	0.819	0.811	0.821	0.814

This table reports the results from logit CF prediction models with the inclusion of industry effects. Consistent with Chava and Jarrow (2004), Models 3 and 4 are estimated in one year and two years prior to CF, respectively. *IND1* represents miscellaneous industries (SIC code is in the ranges 1–1000, 1500–1800, 5000–6000, 7000–8900), *IND2* represents manufacturing and mineral industries (SIC code is in the ranges 1000–1500, 2000–4000)) and *IND3* represents transportation, communications and utilities (SIC code is in the range 4000–5000). '*Base & CG controls*' indicates the inclusion of accounting, market, macroeconomic, and corporate governance control variables shown in Model 4, Panel A of Table 3. Robust standard errors are adjusted for clustering at the firm level. Z-statistics are in parentheses. Significance level: *** p<0.01, ** p<0.05 and * p<0.1. Refer to Table 1 and Appendix D for the variable descriptions, measures, and sources.

Table 6
F-Test summary and Wilks' Lambda for CF-Disclosure, base and complete models, as well as the classification results

Panel A: The univariate analysis for the key variable CF-Disclosure			
Variable	Wilks' lambda	F	p-value
CF-Disclosure	0.996	16.890	< 0.001

Panel B: The multiple discriminate analyses for the overall significance of the discriminant models				
Model	Test of function(s)	Wilks' lambda	Chi-square	p-value
Base Model	1	0.772	1127.045	< 0.001
Expanded Model	1	0.767	1156.584	< 0.001

Panel A of this table reports the results of the analysis of variance (ANOVA) F-test for the *CF-Disclosure* key variable on an individual basis to test for the discriminating ability. Panel B reports the explanatory results as well as the significance resulting from the multiple discriminate analyses (MDA). Wilk's lambda is used to test the significance of the discriminant functions (i.e., the class centers separation in addition to the proportion of variance); when the value of Wilks' lambda for a function is small, the function is significant. F-test statistic is the ratio of variances. The Base Model incorporates the variables in Model 1, Panel A of Table 3. The Expanded Model incorporates the variables in Model 3, Panel A of Table 3. Refer to Table 1 and Appendix D for the variable descriptions, measures, and sources.

Table 7
Logit and fixed effects panel regressions using alternative proxies

VARIABLES	Model 1	Model 2	Model 3	Model 4
	Dividend_Omission$_{it+1}$	*ROA$_{it+1}$*	*CF$_{it+1}$*	*CF$_{it+1}$*
CF-Disclosure	0.703***	-5.199***		
	(3.674)	(-2.827)		
Negative_Tone			2.337***	
			(7.915)	
Warning_Tone				1.914***
				(8.046)
Constant	-1.624	5.566	-9.324***	-9.901***
	(-1.221)	(0.495)	(-5.202)	(-5.547)
'*Base & CG controls*'	Included	Included	Included	Included
Observations	3,941	3,708	3,941	3,941
Pseudo (R^2)	0.313	(0.293)	0.203	0.207

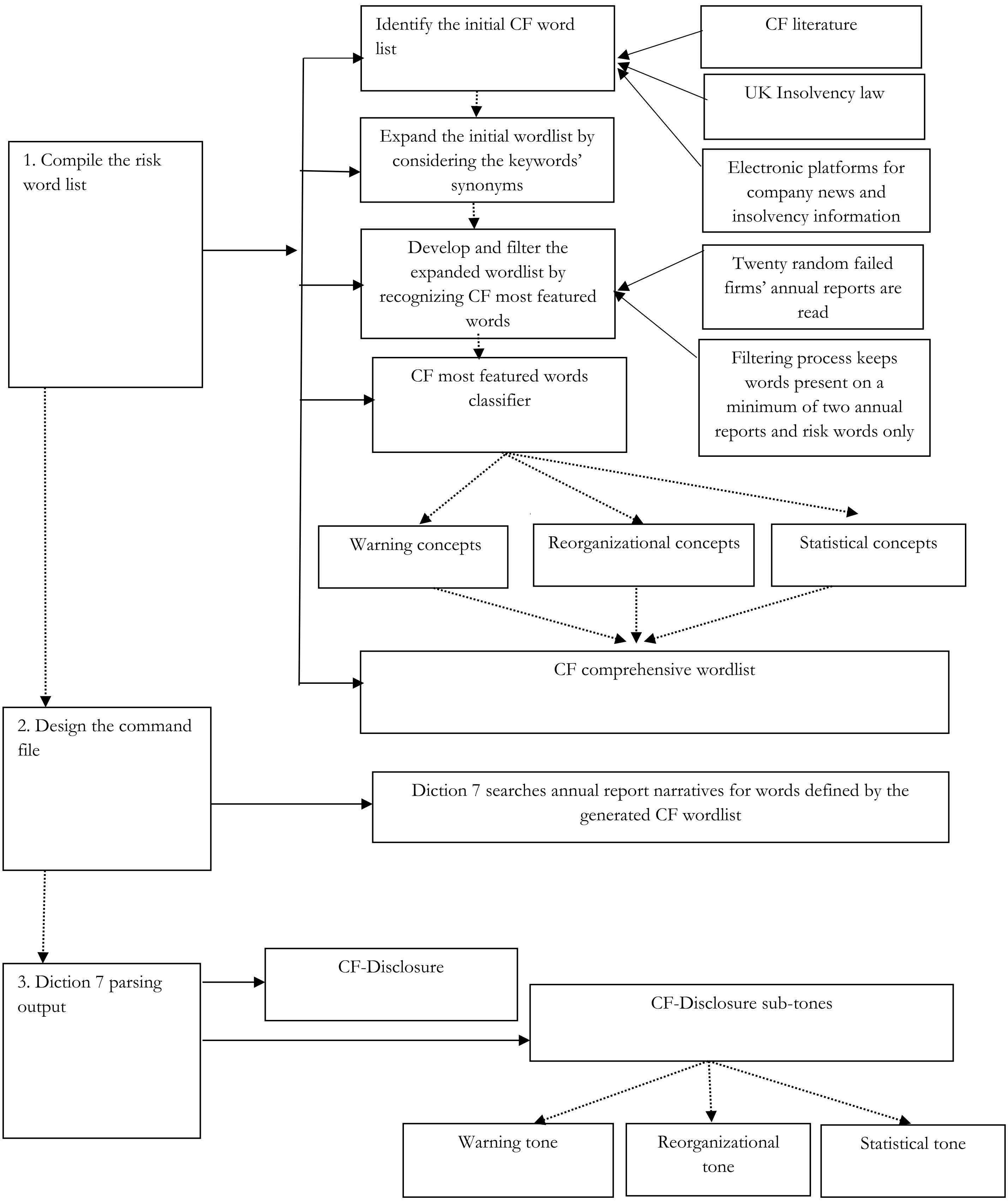
This table reports the results from logit (Models 1, 3, and 4) and fixed effects (Model 2) panel estimations. In Models 1 and 2 we replace our *CF* indicator with *Dividend_Omission* and *ROA* as financial distress indicators, respectively. In Models 3 and 4 we replace the *CF-Disclosure* with the negative sentiment category proposed by Loughran and McDonald (2011) and our warning category, respectively. *Dividend_Omission* is a dummy variable that equals one if the firm does not pay dividends in the subsequent year, and zero otherwise. *ROA* is the subsequent year return on assets = net income/total assets. *Negative_Tone* is the percentage of negative words in the annual report narratives captured using Loughran and McDonald's (2011) negative wordlist (http://www3.nd.edu/~mcdonald/Word_Lists.html). *Warning_Tone* represents a CF-Disclosure subgroup that reveals management warning signals captured by the percentage of warning words in the annual report narratives. '*Base & CG controls*' indicates the inclusion of accounting, market, macroeconomic, and corporate governance control variables shown in Model 4, Panel A of Table 3. Robust standard errors are adjusted for clustering at the firm level. Z(T)-statistics are in parentheses. Significance level: *** p<0.01, ** p<0.05 and * p<0.1. Refer to Table 1 and Appendix D for the variable descriptions, measures, and sources.

Table 8
Multinomial logit regression of financial distress (FD) and bankruptcy (BR) on CF-Disclosure

VARIABLES	One year prior to *FD/BR*		Two years prior to *FD/BR*	
	Model 1	Model 2	Model 3	Model 4
	FD	*BR*	*FD*	*BR*
CF-Disclosure	1.865***	0.985***	1.649***	0.683***
	(5.707)	(4.630)	(4.388)	(2.972)
Constant	-2.071	-14.719***	-6.222*	-16.325***
	(-0.812)	(-6.274)	(-1.941)	(-7.753)
'*Base & CG controls*'	Included		Included	
Observations	3,941		3,441	
Pseudo R^2	0.205		0.186	

This table reports the results from multinomial logit financial distress/bankruptcy prediction models. Thus, it shows the link between the CF-Disclosure variable and the probability of CF while financial distress and bankruptcy risks are recognized separately. Financial distress (FD) is defined as whenever a firm simultaneously experiences, for two consecutive years, the following conditions: first, negative growth in the market value; second, its financial expenses surpass its earnings before interest, taxes, depreciation, and amortization. Bankruptcy (BR) is defined as when a firm's status is under administrative receivership, administration, company voluntary arrangement, voluntary liquidation, liquidation or when there is a cancellation of the firm and it is assumed valueless. *'Base & CG controls'* indicates the inclusion of accounting, market, macroeconomic, and corporate governance control variables shown in Model 4, Panel A of Table 3. Robust standard errors are adjusted for clustering at the firm level. Z-statistics are in parentheses. Significance level: *** p<0.01, ** p<0.05 and * p<0.1. Refer to Table 1 and Appendix 4 for the variable descriptions, measures, and sources.

Figure 1. Textual analysis procedures to capture CF-Disclosure



This figure describes the three main steps taken to generate CF-Disclosure and CF-Disclosure sub-tones. A detailed discussion can be found in Section 5.2.

Appendix A

Summary of empirical work, presented in chronological order, on the relation between qualitative information and firm's status

Panel A: Accounting and finance domain

Study name (year)	Journal	Jurisdiction	Sample	Approach
Tennyson et al. (1990)	JBFA	USA	46 firms during 1978-1980.	Using automated textual analysis for the 10-Ks' president's letters and the management analysis, authors identify different themes (e.g., internal operations, growth and expansion) and link them to bankrupt and non-bankrupt firms.
Kaplan and Zingales (1997)	QJE	USA	49 low-dividend paying firms during 1970-1984.	Using automated textual analysis for the 10-Ks' the Liquidity and Capitalization Resource Subsection (CAP+LIQ) in the Management Discussion and Analysis (MD&A) section, authors use the firms' qualitative information to classify each firm-year into one of five categories based on its financial constraint status in order to investigate whether firm's financial (health or constraints) status interrupts the association between the firm's investment and cash flow.
Smith and Taffler (2000)	AAAJ	UK	66 manufacturing and construction firms during 1978-1985.	Using automated textual analysis for the chairman's discretionary statement, authors employ form oriented and meaning oriented means of analysis to explain corporate failure. Notably, authors call future research to examine the incremental explanatory ability of the discretionary narrative disclosure to that obtained by financial variables alone. They also invite future research to examine beyond the chairman's statement because narrative-related disclosure was a very recent innovation in UK reporting practice of the time of the study.
Boo and Simnett (2002)	ABACUS	Australia	140 non-financial firms during 1990-1991.	Using manual textual analysis for content of management's prospective comments in financially distressed companies, authors categorize management's comments into optimistic, pessimistic, mixed or silent and find that management's prospective comments are useful to predict firms' future viability.
Uang et al. (2006)	EFM	UK	179 non-financial firms during 1994-2000.	Using automated textual analysis for the tone of the going concern statements by management and auditor, authors examine whether auditor and management going concern narratives signal the severity of subsequent outcomes appropriately. They find the tone of the auditor does, while that of the management does not.
Holder-Webb and Cohen (2007)	JBE	USA	136 non-financial firms during 1990-1995.	Using a proprietary index based on SEC reporting requirements and practitioner guidelines, authors measure the quality of MD&A disclosures for a sample of firms entering financial distress in an effort to determine whether changes in the disclosure appear to be motivated primarily by economic or ethical concerns.
Hadlock and Pierce (2010)	RFS	USA	1,848 non-financial firm-year observations during 1995–2004.	Using manual textual analysis for the 10-Ks, authors use qualitative data as a means to categorize a firm's financial constraints. Then, the qualitative categories are incorporated with some proper financial ratios. Using this qualitatively determined financial constraint status, authors employ ordered logit models predicting constraints as a function of different quantitative explanatory variables.
Hoberg and Maksimovic (2015)	RFS	USA	52,438 non-financial firm-year observations during 1997–2009.	Using automated textual analysis for the 10-Ks' CAP+LIQ in the MD&A section, authors acquire continuous measures of financial constraints to investigate the association between the different external finance constraints and firms' characteristics, besides studying the link between these constraints and investment and issuance policies following unexpected negative shocks.

Bodnaruk et al. (2015)	JFQA	USA	51,533 non-financial firm-year observations during 1997–2011.	Using automated textual analysis for the 10-Ks, authors use qualitative information to first create financial constraints wordlist, then use their wordlist to construct a measure of financial constraints as the percentage of constraining words in 10-K narratives. Finally, they use that measure to directly predict financial constraints events (dividend omissions, dividend increases, equity recycling, and underfunded pension plans).
Mayew et al. (2015)	AR	USA	45,725 firm-year observations during 1995–2012.	Using the mandatory going concern opinion by the management under FASB's requirements, as well as the overall linguistic tone of the MD&A utilizing LM (2011) negative and positive wordlists, authors measure a firm's ability to continue as a going concern.
Gandhi et al. (2019)	JBF	USA	6,223 bank-year observations during 1997-2014.	Using LM (2011) negative wordlist, authors examine the link between the proportion of negative words in the US banks' 10-Ks and four separate variables of financial distress (subsequent distressed delisting, dividends omission, loan losses, and ROA) to introduce negative sentiment in banks' 10-K narratives as a new proxy for bank distress.
Muñoz-Izquierdo et al. (2019)	JBR	Spain	808 non-financial firm-year observations during 2004–2014.	Using manual textual analysis for comments disclosed in auditor's unqualified opinions, unqualified opinions with emphasis paragraphs, and qualified opinions, authors indicate that auditor's report can reveal the causes of business failure, where 11 causes are studied.
Panel B: Machin learning domain*				
Study name (year)	Journal	Jurisdiction	Sample	Approach
Cecchini et al. (2010)	DSS	USA	156 manufacturing firms during 1994-1999.	Using a complex vector space model, authors analyze the textual content in MD&A disclosures to predict bankruptcy and fraud outcomes. To predict bankruptcy, the algorithm they use incorporates word sense disambiguation that considers the context of a sentence and employs the WordNet program to create a concept score to identify classifiers of bankrupt and non-bankrupt firms. Later, a Support Vector Machine classification method is used to identify phrases that ultimately discriminate between bankrupt and non-bankrupt firms.
Shirata et al. (2011)	JETA	Japan	180 firms during 1999-2005.	Using text mining methods (morphological analysis and conditional probability), authors analyze the sentences in annual reports and extract key phrases/descriptions, where they show that a distinguishing between bankrupt firms and non-bankrupt firms can be done using some particular expressions when appear together with the word "dividend" or "retained earnings".
Yang et al. (2018)	JETA	USA	168 firms from 2014.	Using SAS Text Miner and a latent semantic analysis algorithm, authors extract high-frequency words, related concept links, and topics from MD&As to identify differences in textual expressions used by bankrupt and non-bankrupt firms. They only observe that some high-frequency words appear to suggest differences between bankrupt and non-bankrupt firms regarding their financial position and ongoing status.
Mai et al. (2019)	EJOR	USA	94,994 firm-year observations during 1994–2014.	Designing a deep learning approach, i.e., a machine learning paradigm that combines multiple layers of neural networks to learn representations of data with multiple levels of abstraction, authors employ different model set-ups using varying input data (based on an end-to- end machine-learning model, in which the learning algorithm goes directly from the raw textual input to the prediction) and find that MD&A information content is useful for bankruptcy prediction. They also suggest

				that a simple deep learning model using an average of the embedding layer is better than other data mining models when textual information is used.
Tang et al. (2020)	JF	China	424 firms during 2014-2018.	Extracting valuable features by using the wrapper-based method, followed by constructing multiple single classifiers, ensemble classifiers, and deep learning models, authors propose a framework (incorporating the integration of financial, management, and textual factors) to reveal the financial distress features of listed Chinese firms. Their experiment results (which indicate the superiority of ensemble classifiers and deep learning models) suggest that management and textual factors are the key factors in the financial distress prediction of listed Chinese companies.

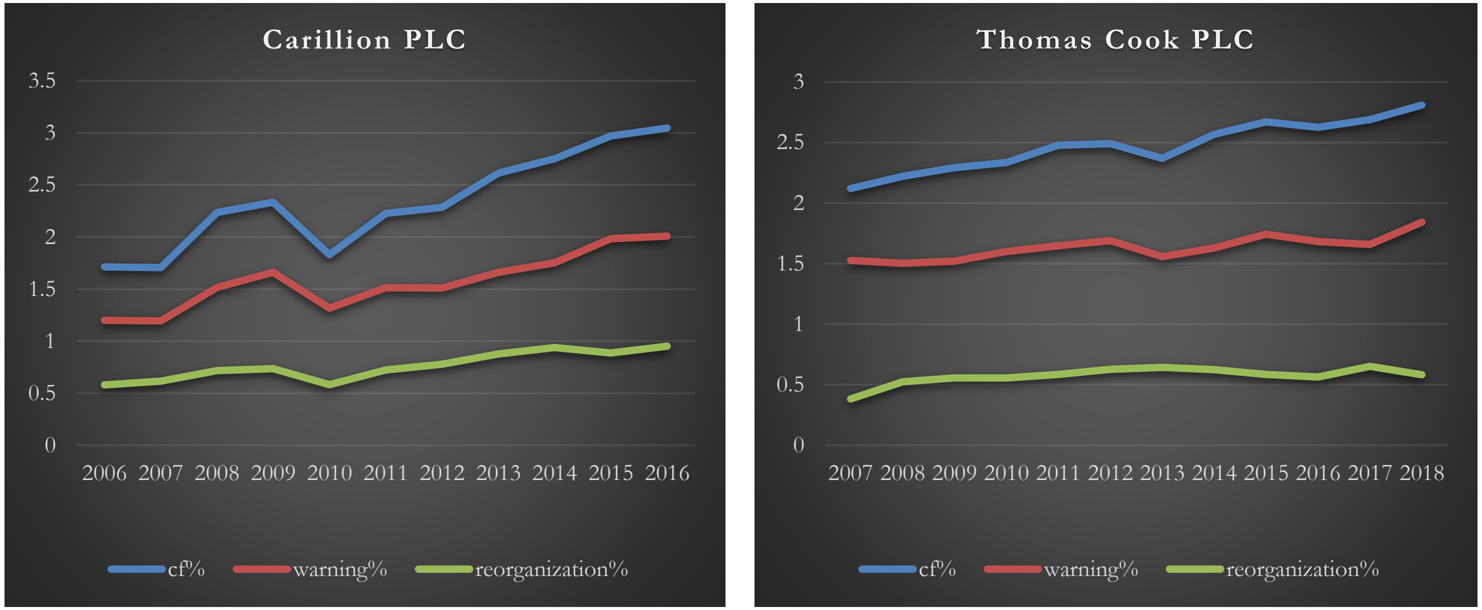
Appendix A gives a summary of recent research on the relation between narratives and CF.
* There are various methods for modeling using machine learning methods, with several purported advantages (e.g., improved predictive performance). However, machine learning methods are "black boxes" preventing from understanding the role of each independent variable and thus, making results interpretation a big problem. Additionally, many of these methods are complex (and potentially add more noise than signal) and have many important drawbacks. Refer, for example, to Loughran and McDonald (2016) and Jayasekera (2018) for more detailed discussion.

Appendix B
The final wordlist of corporate failure

Administration Administrator Adverse Adversely Affect Affected Affecting Against Agreed Agreeing Agreement Agreements Anticipate Anticipated Appoint Appointed Appointing Appointment Bankruptcy Believe Believed Cancel Cancellation Canceled Challenge Challenges Challenging Change Changes Closed Commitment Commitments Committed Competition Competitive Competitors Complaints Compliance Complied Complies Comply Complying Concern Concerning Conditional Conflict Conflicted Conflicts Constrain Constraint Constraints Contract Contracted Contracts Contractual Court Courts Covenant Covenants Critical Damage Damaged Damages Damaging Decline Declined Declining Decrease Decreased Default Defer Delay Delays Delist Delisted Delisting Depend Dependent Depending Depends Depressed Differ Differed Differing Differs Difficult Difficulties Disappointing Discontinued Dispute Disputed Diversified Diversify Divestment Doubt Doubtful Downturn Draw-down Drawn down Drop Exposed Exposure Exposures Facilities Facility Fail Failed Failing Failings Fails Failure Failures Fall Fallen Falling Falls Fell Fluctuation Fluctuations Forced Fragile Hazardous Hazards Hindered Illiquid Illiquidity Impaired Impairment Impairments Imposed Inability Incur Incurred Injunctions Instability Insufficient Join Joined Lack Lacked Left Legal Legislation Less Likelihood Likely Limitations Limited Limits Liquidated Liquidating Liquidation Liquidator Litigation Lose Loses Losing Loss Losses Lost Low Lower Lowest Material Materially Misstatement Misstatements Mitigate Mitigated Mitigation Necessary Need Needed Needs Negative Negatively Negotiate Negotiated Negotiating Negotiations Non-compliance Obligation Obligations Obstacles Opportunities Opportunity Penalties Poor Poorly Potential Potentially Pressure Pressures Problems Recession Reduce Reduced Reducing Reduction Reductions Refinancing Renegotiate Renegotiated Reorganization Reorganized Require Required Requirement Requirements Requires Requiring Resignation Resignations Resigned Resolution Resolutions Restricted Restrictions Restructure Restructured Restructuring Retired Reverse Reversed Revised Revocation Risk Riskier Riskiest Riskiness Risks Risky Sever Severe Severely Significance Significant Significantly Slow Slower Slowly Step down Stepped down Strategic Strategies Strategy Suffered Susceptible Suspend Suspended Suspension Suspensive Termination Threat Tight Tough Turmoil Unable Uncertain Uncertainties Uncertainty Unexpected Unfortunately Unpaid Viable Volatile Volatility

This list presents CF-related keywords used to capture the CF sentiment in annual report narratives. The total sum of words is 267. Words classification according to their connotations is available from the authors upon request.

Appendix C
Validity examination of CF wordlist on the cases of Carillion PLC and Thomas Cook PLC
Figure 2



This figure gives the timeline of CF sentiment in annual report narratives of two sudden high-profile corporate collapses in the UK. Carillion PLC went into liquidation on 15 January 2018 (*it is officially the largest ever trading liquidation in the UK*; www.gov.uk/). Thomas Cook PLC (the world's most iconic travel brand) went into liquidation on 23 September 2019. Data based on the last available annual reports. The percentage of words are scaled by the total number of words in the annual report.

Appendix D
Variable descriptions, measures, sources, and examples of prior literature

	Sort	Variable	Definition and measurement	Source	Ex. sign	Examples of relevant literature
Control variables (and represent the base model)	Dependent	Corporate Failure	Binary outcome variable, one = event of financial distress or bankruptcy; zero = otherwise.	Coded	(N/A)	Tinoco and Wilson (2013)
	Accounting	*ROA*	Return on Assets is a measure for firm profitability = net income/total assets.	Worldscope	(-)	Campbell et al. (2008)
		Current Ratio	It is a measure of firm liquidity = current assets/current liabilities.	Worldscope	(-)	Chava and Jarrow (2004)
		Capital Structure	Measured by firm leverage = total debt/total equity.	Worldscope	(+)	Darrat et al. (2016)
		Funds from Operation	It is a measure of firm performance = total funds from operations/total liabilities.	Worldscope	(-)	Almamy et al. (2016)
	Market	*PRICE*	Measured as the log of firm's equity price.	Datastream	(-)	Tinoco and Wilson (2013)
		Abnormal Returns	It is the firm's cumulative monthly abnormal returns on an annual basis = the firm's cumulative annual returns minus the FTSE All Share return index for the same period of time.	Datastream	(-)	Tinoco and Wilson (2013)
		Market Cap	Measures the firm's relative value as log the firm's market capitalization relative to the total market capitalization of the FTSE All Share index	Worldscope	(-)	Mayew et al. (2015)
		Volatility	Sigma of market returns is used as a measure of total risk, which is in turn measured by the standard deviation.	Datastream	(+)	Mayew et al. (2015)
		MB	Represents market to book ratio = Market value equity/book value equity.	Datastream	(+)	Campbell et al. (2008)
	Macroeconomic	*RPI*	Represents the Retail Price Index (RPI) in base 100 as a measure of inflation rate.	Datastream	(+)	Tinoco and Wilson (2013)
		TBR	Represents the 3-Treasury Bill Rate (TBR) as a proxy for interest rates.	Datastream	(+)	Tinoco and Wilson (2013)
Corporate governance control variables	Corporate Governance	*Board Size*	Measured by the log of the total number of board of directors.	BoardEx	(-)	Platt and Platt (2012)
		Board Independence	Measured by the proportion of independent non-executive directors to the board size.	BoardEx	(-)	Daily and Dalton (1994)
		CEO Turnover	It is a dichotomous variable coded as one if the firm experienced a change in CEO and zero otherwise.	BoardEx	(+)	Daily & Dalton (1995)
		Gender Diversity	Measured by the proportion of female directors on the board of directors.	BoardEx	(-)	Darrat et al. (2016)
		Duality Role	It is a dummy variable set to one if the CEO is also chairman of the board of directors or executive chairman presents on the board and zero otherwise.	BoardEx	(+)	Daily and Dalton (1994)
Narrative-related disclosures	Corporate failure related narrative disclosures	*CF-Disclosure*	It reflects the aggregate information regarding corporate failure that can be found in the narrative sections of annual reports. This typically relates to the discussion sections, which exclude the financial statements but include the notes to the accounts. The scores are generated based on textual analysis using Diction version 7 to count the number of words that exists in the final CF-related narratives wordlist. The score is calculated by the percentage of words	Annual Reports via Thomson one/Bloomberg using Diction 7	(+)	Hypothesized (as discussed in Section 4)

indicating the likelihood of corporate failure in the narrative sections of annual reports.