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# Effect of Cash Flow Risk on Corporate Failures, and the Moderating Role of Earnings Management and Abnormal Compensation

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## Abstract

In this study, we find that United States firms' average cash flow risk (CFR) shows a significantly increasing trend over the past four decades or so. This does not portend well considering the significance of cash flows in maintaining a firm's financial health and going concern status. The *CFR* also increases dramatically for firms approaching financial distress or bankruptcy, suggesting its important role in predicting a firm's failure. Empirically, we find that *CFR* has a strong positive effect on a firm's financial distress likelihood. We also find that the association between *CFR* and financial distress is negatively moderated in firms with high earnings management and abnormal compensation. The results suggest that managers in firms with high *CFR* are more likely to use heuristics in form of earnings management. Thus, supporting the upper echelons theory related to managers under performance pressure. Meanwhile, consistent with the notion in the agency theory that financial incentives serve as effective monitoring mechanisms, compensation packages can incentivize better risk management practices and decrease the likelihood of a firm's failure. Our findings are also robust to alternative definitions of a firm's failure: financial constraints, presumed debt covenant violation and legal bankruptcy filings.

**JEL Classification:** M12; M41; G32; G33

**Keywords:** Financial distress; Cash flow risk; Bankruptcy; Earnings management; Abnormal compensation

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## 1. Introduction

Financial economists, in general, agree that cash flows help investors to assess firms' going concern status by providing information about their solvency position. In recent years, the importance of cash flow risk (*CFR*) is realised by credit rating agencies as well. For example, Fitch retained the rating of Wyndham Worldwide Corp. at BBB - even though its business surrounding was fickle. The reason is that Fitch affirmed Wyndham's effort that "Wyndham has modified its business model to decrease cash flow volatility".[1]

Intuitively, a firm's financial health is fundamentally driven by the stability of its cash flows. Thus, volatile cash flows should adversely affect its survival likelihood. Our empirical investigation shows that *CFR* of non-financial firms in the United States (U.S.) increase steeply as firms approach financial distress or bankruptcy, thus providing a perceivable and reliable signal in predicting a firm's failure (see Fig. 1). Moreover, Fig. 2 shows that the average *CFR* increased steadily and persistently over the past four decades or so, from about 0.2 in 1980 to about 9.5 in 2021. This upward trend of *CFR* is notable and contains time-varying information, which may help us to estimate firm failures more effectively. Firms with higher cash flow volatility are more likely to experience internal cash flow shortfall (Minton and Schrand 1999; Minton *et al.* 2002), which often leads to financial distress, thus threatening its going concern status. As such, *CFR* is a noteworthy contender in predicting corporate bankruptcy or firm failures.

**<Insert Figures 1 and 2>**

In light of the above discussion, we explore the explanatory power of *CFR* in predicting corporate failures using a sample of publicly traded U.S. firms over the period 1980 to 2021. Considering the limitations of bankruptcy as a failure indicator (see Gupta and Chaudhry 2019), we use the definition of financial distress proposed by Gupta and Chaudhry (2019) as the dependent variable to perform our empirical analysis.[2] In line with the existing literature (Huang 2009; Douglas *et al.* 2014; Hong *et al.* 2017), we employ a backward-looking estimate of *CFR*, the standard deviation of the ratio of operating cash flow to sales over the

[1] The report is available at https://www.fitchratings.com/research/corporate-finance/fitch-maintains-rating-watch-negative-on-wyndham-worldwide-corp-29-03-2018.
[2] Our results are also robust to alternative measures of firms' failure indicators including financial constraints, presumed covenant violation and legal bankruptcy. The test results are presented in section 4.5.



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past sixteen quarters with at least eight non-missing observations as a suitable predictor. Test results confirm that *CFR* is consistent and economically significant in predicting financial distress.

Although we find a positive, robust, and statistically significant relation between a continuous measure of *CFR* and the likelihood of firms experiencing financial distress, the coefficients of *CFR* remain relatively small, and its average marginal effects are relatively small as well. Thus, to improve its discriminatory power, we re-estimate our regression model with a transformed version of the *CFR* measure. Specifically, we employ a dummy variable *CFRH* which equals one, if a firm's *CFR* is above the median in a given year and industry and zero otherwise. The use of *CFRH* led to a dramatic rise in its discriminatory power, the magnitude of its coefficients, average marginal effects, and, hence, the economic significance. The explanatory power of our model also improved by around 7%.

Next, we investigate what firms do to minimize the adverse impact of high *CFR* on their failure likelihood. The firm's reaction to elevated risk can be assessed from two distinct viewpoints. First, due to career concerns and to avoid the likelihood of violating debt covenants (Habib *et al.* 2013), managers may engage in earnings management to reduce agency costs. In terms of the upper echelons theory, managers who face heavy job demands as a result of the firm's performance challenges are prone to utilizing heuristics (Hambrick 2007), thereby exhibiting a greater inclination towards income-seeking behavior (Hambrick and Mason 1982).

Thus, to investigate the theoretical prediction of the upper echelons theory, we investigate whether managers employ accrual and real earnings management (*AEM, REM*) to reduce the effect of *CFRH* on financial distress. Executives' choices in financial decisions are also significantly affected by their experiences, values, and personalities (Hambrick 2007). Due to the differences in managers' risk aversion, one may expect executives to undertake varying earnings management activities when they face high *CFR*. However, executives who are less risk-averse may engage in *AEM* and *REM* (Deng *et al.* 2018; Cai *et al.* 2019; Cai *et al.* 2020), to reduce financial distress likelihood. While, aggressive executives are also likely to engage in *AEM* or *REM* to smooth income or operating cash flows, and hide their unhealthy financial health, thereby reducing the probability of financial distress (Cai *et al.* 2019; Khuong 2020).



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Also, firms with high *CFR* may have stronger precautionary motivations to manipulate earnings (Sha *et al.* 2021) since they want to avoid future underinvestment problems and financial distress.

Second, in accordance with the agency theory, efficient boards may employ appropriate compensation incentives to align the interests of managers with those of the firm, thereby enabling managers to act as "good" stewards and mitigate high risk (Velte 2020). Accordingly, firms with efficient boards may adjust managers' compensation levels in response to high *CFR*, as monetary incentives are an effective means of aligning the interests of managers and shareholders. Thus, to investigate the theoretical prediction of the agency theory, we investigate whether abnormal compensation (*ACOMP*) of CEOs negatively moderates the relation between *CFRH* and financial distress. As boards in firms with high *CFR* are more likely to take preventive measures to manage the risk. Due to the interest alignment effect, managers with a higher or positive *ACOMP* are expected to pay more effort into managing the volatile cash flow.

In line with the predictions of the upper echelons theory, test results confirm that *AEM* and *REM* negatively moderate the relation between *CFRH* and financial distress. Suggesting that managers use earnings management successfully to reduce the impact of high *CFR* on firms' failure likelihood. Also confirming the predictions of the agency theory, we observe a negative moderating effect of *ACOMP*. Suggesting that compensation packages designed by boards that incentivize superior risk management help firms in reducing their failure likelihood, thereby, making managers act as good stewards of firms (Velte 2020).

Finally, as robustness checks, we explore the effect of *CFR* on alternative measures of financial distress (financial constraints and presumed covenant violation) and Chapter 11/7 bankruptcy filings, and find broadly similar results. Overall, our investigation suggests that the superior performance of *CFR* in predicting financial distress is robust to various definitions of firm failure or distress.

Overall, our contribution lies in providing a reliable, robust and stable predictor of financial distress, *CFR*, and what firms do to minimize its adverse impact on their financial health. The evidence reported in this study is expected to encourage managers and shareholders to pay attention to *CFR* when evaluating a firm's financial health. In addition, creditors and



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analysts may also benefit from paying more attention to executives' activities in firms facing higher levels of *CFR*. As we confirm that an efficient board and proper compensation levels do improve a firm's risk management practices, eventually leading to a reduced likelihood of a firm's failure.

## 2. Literature Review and Hypothesis Development

This section presents the rationale behind our choice of a firm's failure definition and *CFR* measure, and develops related hypotheses.

### 2.1 Defining Firm Failures

A firm's exit as a repercussion of underperformance is generally regarded as its failure/exit in the bankruptcy or firm failure literature (Chava and Jarrow 2004; Campbell *et al.* 2008). Firms that struggle to compete with their peers and sink into financial difficulties will eventually exit the market. The existing literature on bankruptcy or distress risk is extensive and concentrates particularly on modelling methodologies (Neves and Vieira 2006) and the selection of explanatory variables (Shumway 2001; Campbell *et al.* 2008). However, defining firm failures constitutes the premise of all empirical analyses.

Previous studies primarily adopt legal bankruptcy events in conformity with related bankruptcy codes such as U.S. Chapter 7 or 11 fillings. Considering the declined number of legal bankruptcy filings and the significant number of out-of-court settlements, some studies employ other relevant events such as acquisition or delisting (Shumway 2001), or in-default credit ratings (Campbell *et al.* 2008) to supplement bankruptcy filings. However, the problem of these definitions of bankruptcy cannot be neglected. First, the number of U.S. firms filing for bankruptcy under Chapter 7 or Chapter 11 has decreased significantly in recent years. Thus, this gives misleading signals to investors regarding bankruptcy likelihood. Second, it is inappropriate to predict a combination of heterogeneous outcome variables, bankruptcy filings and other default events to proxy bankruptcy. Third, typically a long time lag exists between the legal default date and the real default moment due to the lengthy bankruptcy resolution process (Gupta and Chaudhry 2019). Stakeholders require a visible signal to recognize a firm's financial difficulties well in advance, since waiting until legal bankruptcy filings cause



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significant erosion in firm value. They may suffer huge losses if they are unable to identify and prepare for the forthcoming crisis. In this regard, an alternative measure to identify firms in financial distress/difficulties is appropriate.

Debt covenant violation is identified as an outstanding indicator of financial difficulties by auditing standards. Violations are technical defaults of financial debt covenants and signal increased financial difficulties (Bhaskar *et al.* 2017). Debt covenants state the restrictions based on accounting information such as interest coverage, leverage, current ratio, or net worth. Bhaskar *et al.* (2017) describe debt covenant violations as "trip wires". Although the restrictions in covenants do not imply that firms face financial difficulties (Dichev and Skinner 2002), firms are likely to experience financial difficulties when lenders react to the "tripped wire" by terminating the loan or restructuring. In this case, firms with violated covenants may suffer higher costs (Kim 2020) and experience financial difficulties or even declare bankruptcy (Bhaskar *et al.* 2017). Similarly, Jaggi and Lee (2002) use debt covenant violations to indicate the severity of financial distress.

Debt covenants state that firms are required to maintain threshold levels, specifically, the level of accounting-based metrics (Demerjian *et al.* 2020), to avoid increased credit risk. The violation of these metrics causes a negative impact on the firm's credit ratings due to inconsistencies in the performance (Graham *et al.* 2005), which further leads to riskier debts and worse future financial health. Therefore, firms that fail to maintain the thresholds are more likely to experience financial distress. Christensen and Nikolaev (2012) classify metrics of debt covenants into performance covenants (P-covenants) and capital covenants (C-covenants). Firms that fail to maintain both P-covenants and C-covenants are likely to experience persistent poor performance and be unable to maintain sufficient capital, which could potentially deteriorate their financial health.

Therefore, to examine firms' degree of financial distress, literature relies on the presumed violation of interest coverage ratio level (from P-covenants) and leverage ratio level (from C-covenants), since those metrics are broadly related to covenant contracts (Demerjian and Owens 2016). Firms with low-interest coverage levels and high leverage ratio levels are more likely to experience financial difficulties and find it harder to access external financing



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as they confront more difficulties in accessing new borrowing. As such, financial covenants used for estimating financial distress are minimum interest coverage covenants and maximum leverage ratio covenants (Demerjian and Owens 2016). However, the presumed covenants violation measure has an arguable problem that there is no consistent definition for "minimum" or "maximum" thresholds. The value of the threshold is changeable and customised in contracts. Therefore, studies using covenant violations have to customise the appropriate threshold under different requirements.

Another strand of literature uses a series of variations of firms' financial status and financial constraints, which are reflections of fundamental information, to predict financial distress. Such literature uses a firm's fundamental statements to infer its financial constraints, a measure of financial health (e.g. Farre-Mensa and Ljungqvist 2016). *KZ* index (Kaplan and Zingales 1997) is the most prominent measure of such financial constraints. Using five accounting variables, this index loads positively on leverage and market-to-book (*MB*) ratio and negatively on cash flow, dividends and cash. Therefore, the higher value indicates a firm is more constrained and facing higher financial stress. Similarly, Whited and Wu (2006) use another approach (*WW* index) including different accounting variables to reflect a firm's financial constraints. Firms with higher *WW* index values are classified as financially constrained and are more likely to be in distress.

Flagg *et al.* (1991) argue that a firm starts the failure process when it experiences a decline in "health". Financially distressed firms tend to have negative cash flows, reduced dividend payments, or loan default (Lau 1987; Flagg *et al.* 1991; Ward 1994), and those events signal a decline in "health". Many studies define financial distress following this framework. Turetsky and McEwen (2001) describe financial distress as a series of stages with a starting point which is the abnormal reduction of cash flow from operating activities. After this decline in financial health, they track different accounting characteristics such as decreasing dividends payment, loan default, or debt restructuring as subsequent distress processes. Franzen *et al.* (2007) also use accounting-based measures to evaluate the distress risk and highlight the popularity of using accounting information in the literature to proxy financial distress. Similarly, Bhaskar *et al.* (2017) use negative net incomes and operating cash flows to identify financially



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distressed firms. Due to deficient cash flows, firms are likely to suffer agency costs while seeking external capital, which leads to an underinvestment (Hong *et al.* 2019) and further deteriorates the firm's "health". Gupta and Chaudhry (2019) also depict a series of financial characteristics variations to predict financial distress.

As a consequence, we select a dynamic definition conditioned upon accounting and market information, which is proposed by Gupta and Chaudhry (2019), as the main definition of financial distress. Relying on financial fundamentals, a firm is supposed to be financially distressed in the year *t* if the following three conditions are satisfied:

*Condition 1*: Average market value declines in the years *t–1* and *t–2*.

*Condition 2*: Earnings before interest tax depreciation and amortisation are less than financial expenses in the years *t–1* and *t–2*.

*Condition 3*: Operating cash flow is less than financial expenses in the years *t–1* and *t–2*.

This financial distress measure outperforms from the following perspectives. First, Gupta and Chaudhry (2019) use average market value instead of market value on a given date to indicate a firm's average state. They also impose geometrically declining weights on a firm's market values to emphasise the importance of recent observations. Second, this measure comprehensively captures a firm's financial health from both the ability to meet financial commitment and the ability to repay the debts timely. A few studies pay less attention to the timing of cash inflows and outflows, which actually affects the on-time debt repayment (Pindado *et al.* 2008; Keasey *et al.* 2015). In this regard, the financial distress measure proposed by Gupta and Chaudhry (2019) overcomes the limitations we stated earlier and is more appropriate in estimating financial distress for our study.

In light of the above discussion, we employ the measure of financial distress proposed by Gupta and Chaudhry (2019) as a proxy to capture firms' failure or default to perform our empirical analysis. In addition, to establish the robustness of our findings, we also present our results employing alternative definitions of firm failure, namely, financial stress, presumed covenants violation, and legal bankruptcy filings, in Section 4.5.

### 2.2 Defining *CFR*



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According to bankruptcy laws in several countries, a firm is likely to go bankrupt or experience financial distress if one of the following two statuses is fulfilled. First, the firm confronts insufficient cash flows to pay the creditors, called cash flow shortage. Second, the firm is "overindebted" so that the value of its liabilities exceeds the assets value (Uhrig-Homburg 2005). Over-indebtedness is mentioned only in a few countries, such as Germany and Japan; however, cash flow shortage is required in almost all bankruptcy codes. Charitou *et al.* (2004) emphasize the importance of operating cash flow in estimating financial distress. Additionally, Minton *et al.* (2002) find that higher fundamental volatility results in lower future cash flows and earnings, leading to a high probability of cash flow shortage caused by poor information quality (Su 2013). Such a link implies that firms with higher *CFR* are perceived to experience cash flow shortfalls, which increases the probability of financial distress or bankruptcy. Moreover, Froot *et al.* (1993) illustrate that future cash flow performance is negatively related to *CFR*. A higher cost of capital may be generated based on the analysts' forecast of the firm's future unsatisfactory performance. Minton *et al.* (2002) supplement this argument and assert that cash flow volatility is positively associated with the cost of accessing external capital. In their investigation, *CFR* is measured as the coefficient of variation of a firm's quarterly operating cash flows. As such, high cash flow volatility not only causes internal insufficient cash flows over time but also increases the cost of capital, which, in turn, deteriorates the firm's cash flow shortage and exacerbates its financial distress.

*CFR* is also broadly used as a determinant of firms' yield spreads (Güntay and Hackbarth 2010; Tang and Yan 2010; Douglas *et al.* 2014; Molina 2015) due to the importance of fundamental information, which further influences firms' financial health. The intuition is that cash shortfall caused by *CFR* leads to lower payoffs to investors, which results in unexpected forecasts and a higher likelihood of financial distress. Tang and Yan (2010) find that *CFR* has a statistically significant relationship with spreads; this study measures *CFR* using the coefficient of variations of operating cash flows. Similarly, Molina (2015) shows a significant positive association between yield spreads and cash flow volatility calculated as the coefficient of variation of operating incomes. Douglas *et al.* (2014) document a strong economic effect of *CFR* on bond yield spreads especially for firms that are closer to default. In this investigation,



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*CFR* is measured as the standard deviation of operating cash flows scaled by different variables to proxy firm value. Based on these empirical results, we expect *CFR* to be positively associated with financial distress.

There are also alternative explanations for the expected positive relation between *CFR* and financial distress. Some academic studies empirically document the impact of *CFR* on credit ratings. Credit ratings indicate a firm's financial health. Rating agencies provide different levels of ratings to reduce the information asymmetry between investors and corporations. Higher credit ratings enhance a firm's reputation, thereby, affecting the cost of capital. In contrast, for lower-rated firms, debts are risky and vary with future cash flows (Güntay and Hackbarth 2010), which further increases the likelihood of experiencing financial distress as discussed above. Güntay and Hackbarth (2010) report that *CFR* (proxies by forecast dispersion) is related to credit rating downgrades, which, in turn, leads to credit risk along with higher bond credit spreads and influences the probability of financial distress.

Based on the above discussions, previous studies that investigate a firm's financial health and *CFR* generally employ two categories of measure: (i) studies directly using cash flow-related accounting information to measure *CFR*, or (i) studies applying a potential proxy for *CFR*. Alnahedh *et al.* (2019) state that direct cash flow information contributes more accuracy when capturing uncertainty. Accordingly, we employ the direct measure of *CFR* to predict the likelihood of financial distress. The prevalent direct measure employs the standard deviation of cash flows to a scalar, such as book assets, sales, or book equity (Huang 2009; Douglas *et al.* 2014; Hong *et al.* 2017). To standardise firms' cash flows, we use sales as the proxy for firm size (Berk 1997) based on the following reason: first, recent studies (Huang 2009; Hong *et al.* 2017) use the ratio of cash flow to sales in their study and report significant results; second, Huang (2009) confirms that using sales as scalar can effectively reduce the autocorrelation in cash flows.

Overall, we expect *CFR* to have a positive effect on the probability of financial distress. Therefore, our hypothesis is as follows:

**H1:** *There is a positive association between CFR and financial distress.*

### 2.3 Moderating Effects of Earnings Management and Abnormal Compensation



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### 2.3.1 Moderating Effects of Earnings Management

Managers in firms facing high *CFR* are likely to take preventive measures to reduce the impact of volatile cash flows on the failure likelihood. Analysts and related stakeholders rely on this information to evaluate a firm's performance (Givoly *et al.* 2009), especially when firms are facing bankruptcy risks (Yoo and Pae 2017). Due to the greater scrutiny from outsiders and career concerns, managers may opportunistically exercise discretion over earnings to minimize the agency cost (Jiraporn *et al.* 2008) and satisfy the outsiders (Burgstahler and Dichev 1997). The managers will disseminate new reports aimed at enhancing and updating investors' perceptions regarding the financial well-being of the organization (Beyers *et al.* 2019). This resonates with the predictions of the upper echelons theory which posits that executives facing heavy challenges or performance difficulties are subjected to high job demands (Hambrick 2007). This can lead to non-rational decisions making by managers, including the utilization of opportunistic behaviours (Hambrick and Mason 1982; Ronen and Yaari 2008). This phenomenon is attributed to the fact that such managers may be more heavily influenced by their characteristics and experience (e.g. Arun *et al.* 2015; Harris *et al.* 2019; Cai *et al.* 2019).

Therefore, some risk-taking managers may intervene in financial statements to maintain the volatility of cash flow within a rational range in order to avoid its negative influence on the firm value. Managers of unhealthy firms or low growth potential (Li and Kuo 2017) may also have higher incentives to manipulate their financial performance, such as earnings (Saleh and Ahmed 2005; Charitou *et al.* 2011). Indeed, a manager's managerial risk aversion is associated with *AEM* (Faccio *et al.* 2016; Deng *et al.* 2018; Cai *et al.* 2019; Bouaziz *et al.* 2020), as well as *REM*. Executives who are less risk-averse are also likely to engage in *AEM* (Deng *et al.* 2018) to smooth income and reduce *CFR* (Cai *et al.* 2019). For risk-taking managers, they are likely to use *AEM* to reduce *CFR* instead of financial derivatives for hedging purposes (Barton 2001). Such activities decrease earnings and cash volatility, leading to a reduced level of bankruptcy probability (Sha *et al.* 2021). In addition, previous literature shows that *REM* has a direct effect on cash flow (Braam *et al.* 2015). Aggressive managers are likely to engage in *REM* when a firm has unpredictable volatility of cash flows, to help firms hide the worsening state of financial health (Khuong 2020). Additionally, managers in firms with weak internal



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governance are more susceptible to engaging in *REM* (Cheng *et al.* 2016) due to their stronger entrenchment power. Using *REM*, managers also try to smooth the earnings and firms' operating cash flows (Cai *et al.* 2020), which further decreases the probability of distress.

In addition, firms with high *CFR* may have stronger precautionary motivations to avoid future underinvestment problems and financial distress (Han and Qiu 2007; Sha *et al.* 2021). Prior literature documents that when firms face high *CFR*, they are more likely to reduce innovative investment to avoid strong financial constraints (Liu *et al.* 2017; Beladi *et al.* 2021) due to the precautionary motives. Therefore, these firms are more likely to undertake *AEM* to avoid unexpected changes to earnings and cash flow in financial statements (Sha *et al.* 2021) or undertake *REM* to directly affect their cash flows (Braam *et al.* 2015), expecting to reduce their default likelihood.

Thus, guided by the predictions of the upper echelons theory and the above discussion, our hypothesis is as follows:

**H2:** *Earnings Management negatively moderates the relation between CFRH and financial distress.*

**2.3.2 Moderating Effects of Abnormal Compensation**

In addition to *EM* activities, firms with efficient boards may also try to adjust compensation incentives in response to firms' high risk (Gormley *et al.* 2013). A firm's risk environment affects the structure of its executive's compensation level, which in turn alters the manager's incentives and corporate investments to manage the firm's risk (Gormley and Matsa, 2011). When firms face high risk, shareholders' interests and benefits may be negatively affected. Agency theory posits that monetary incentives are an effective means of aligning the interests of managers and shareholders. In this manner, the use of monetary incentives serves as a mechanism for mitigating the agency problem that arises from the inherent misalignment of interest between managers and shareholders. The value-maximizing financial decisions are therefore tied to the manager's compensation level, and board members may intervene when necessary to minimize value erosion.

Thus, boards may react by adjusting compensation levels in light of the increased risk to motivate managers to reduce the volatility and probability of financial distress (Gormley *et*



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*al.* 2013). Additionally, efficient internal governance is also reported to be an important determinant of a firm's cash flows (Cheng *et al.* 2016). Thus, managers are more likely to be encouraged to undertake active actions in managing *CFR* if their compensation structures incentivise them to do so. Accordingly, we expect firms with efficient boards to adjust compensation levels in response to high *CFR*. This alignment of interests is expected to result in managers making greater efforts to manage volatile cash flow, especially when they have a higher or positive *ACOMP*. To test this assertion, we examine whether the negative relation between *CFR* and financial distress is moderated by CEOs abnormal compensation (*ACOMP*).

Thus, guided by the predictions of the agency theory and the discussion above, our hypothesis is as follows:

**H3:** *ACOMP negatively moderates the relation between CFRH and financial distress.*

## 3. Data, Covariates and Summary Statistics

Our sample includes all U.S. domestic firms listed on NYSE, AMEX, and NASDAQ with available accounting and stock returns data. Accounting data are obtained from Compustat, and stock returns data from the Center for Research in Security Prices (CRSP). The sample is from 1980 to 2021. We exclude firms in financial services, transportation, community, public utilities, public administration and non-classifiable industrial sectors to maintain broad homogeneity in financial reporting and market competition within our sample.

### 3.1 Dependent Variable

As discussed in section 2.1, we employ the definition of financial distress proposed by Gupta and Chaudhry (2019) as the dependent variable.

### 3.2 Independent Variables

This section discusses all covariates employed in the subsequent empirical analysis.

#### 3.2.1 Cash Flow Risk

As a predictor variable, *CFR* incorporates more historical time series information. We measure *CFR* as the standard deviation of the ratio of operating cash flow to sales (as discussed in section 2.2) over the last sixteen quarters with a minimum of eight non-missing observations (Huang 2009; Hong *et al.* 2017). Cash flow from operations (*CFO*) is defined as the sum of



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earnings before extraordinary items, depreciation and amortisation, and change in working capital (Huang 2009). This definition examines the fluctuation of cash flow without the camouflage of other accounting variables documented in the accounting statements (Huang 2009). Consistent with the previous literature, we scale it by sales, which are used as a proxy for firm size (Berk 1997; Huang 2009). In order to match with other variables, we calculate the annual *CFR* based on the average of the calculated quarterly data.

Additionally, to assess the explanatory power and economic significance of *CFR*, we re-estimate our results with its transformed version. Specifically, we use a dummy variable *CFRH* that equals one if the firm's *CFR* exceeds the median level in a given year and industry, and zero otherwise. A firm having *CFRH* indicates a relatively high *CFR* than its industry peers.

### 3.2.2 Earnings Management and Abnormal Compensation

Following prior literature (Huang *et al.* 2017; Ferri *et al.* 2018), we use Collins *et al.* (2017) model to measure *AEM*. Specifically, we estimate the following equation:

$$\frac{ACC_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{ACC_{i,t-1}}{Assets_{i,t-1}} + \beta_2 \frac{(\Delta Sales - \Delta AR)_{i,t}}{Assets_{i,t-1}} + \sum_k \beta_{3,k} \frac{ROA_{Dum_{k,i,t}}}{Assets_{i,t-1}} + \sum_k \beta_{4,k} \frac{SG_{Dum_{k,i,t-1}}}{Assets_{i,t-1}} + \sum_k \beta_{5,k} \frac{MB_{Dum_{k,i,t-1}}}{Assets_{i,t-1}} + u_{i,t} \quad (1)$$

where *ACC* is total accruals, calculated as the sum of the change in accounts receivable, inventories, accounts payable, taxes, and other items from the cash flow statement, and *i* indexes firm and *t* indexes year. *Assets* is the book value of total assets, $\Delta Sales$ denotes the changes in sales, $\Delta AR$ denotes the changes in account receivables, dummy variables $ROA_{Dum_{k,i,t}}$, $SG_{Dum_{k,i,t-1}}$, $MB_{Dum_{k,i,t-1}}$ equals one if the variable belongs to the $k_{\text{th}}$ quintile in the aggregate data, and zero otherwise. Using Eq. (1), discretionary accruals are calculated as the residual from the regression estimated in a given year and industry. Each industry-year group has at least 20 observations, otherwise discarded.

For *REM*, we use the model proposed by Roychowdhury (2006). Specifically, we use the sum of three components including *Abnormal production costs*, *Abnormal discretionary expenses* times minus one, and *Abnormal operating cash flow* times minus one, to measure *REM.* And the three components are estimated using the following equations:



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$$\frac{PROD_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t-1}}{Assets_{i,t-1}} + u_{i,t} \qquad (2)$$

$$\frac{DISX_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{Assets_{i,t-1}} + u_{i,t} \qquad (3)$$

$$\frac{CFO_{i,t}}{Assets_{i,t-1}} = \beta_0 + \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + u_{i,t} \qquad (4)$$

Prior literature shows that CEOs' compensation can be explained by their ability, effort, risk premium, and other economic determinants. The amount of pay that cannot be explained by these determinants is regarded as *ACOMP*. We follow prior research in developing a benchmark model to estimate expected and unexplained *ACOMP* (Core *et al.* 2008; Robinson *et al.* 2011; Alissa 2015). We estimate the expected compensation of the CEO by regressing the CEO's total compensation, which is the sum of salary, bonus, the value of restricted stock grants, the value of options granted during the year, and other annual pay (Core *et al.* 2008), on proxies for several economic determinants in a given year and industry, as follows:

$$Log(Total\ Compensation_{i,t}) = \beta_0 + \beta_1 Log(Tenure_{i,t}) + \beta_2(S\&P500_{i,t-1}) + \beta_3 Log(Sales_{i,t-1}) + \beta_4(BM_{i,t-1}) + \beta_5(RET_{i,t}) + \beta_6(RET_{i,t-1}) + \beta_7(ROA_{i,t}) + \beta_8(ROA_{i,t-1}) + u_{i,t} \qquad (5)$$

where $i$ indexes firm and $t$ indexes year. *Total Compensation* is described above. $Log(Tenure)$ is the logarithm of the CEO's tenure (in years). $S\&P500$ is a dummy variable that equals one for firms in the S&P500 index at the end of this year, and zero otherwise. $Log(Sale)$ is the logarithm of the firm's sales. *BM* is the book-to-market ratio at the end of year. *RET* is the firm's buy-and-hold return. *ROA* is the return on assets. The above OLS model includes fixed effects for years and 2-digit SIC codes of industries. We separate the actual total compensation of CEOs into two parts: the *Expected Compensation* estimated from Eq. (5), and the *ACOMP* (the residual obtained from the same equation). Therefore, we compute the *ACOMP* as:

$$ACOMP_{i,t} = Total\ Compensation_{i,t} - Expected\ Compensation_{i,t} \qquad (6)$$

### 3.2.3 Control Variables



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Prior academic studies have shown that many variables affect the likelihood of firms experiencing financial distress. Campbell *et al.* (2008) employ a fairly broad collection of explanatory variables, including both accounting and equity market variables, to predict the likelihood of firm failures. Indeed, models consisting of both accounting and market metrics outperform either accounting-based or market-based models (Das *et al.* 2009). Gupta and Chaudhry (2019) also address the complementary effect between accounting variables and market variables. In the investigation, they extend the set of covariates employed by Campbell *et al.* (2008) with two additional variables, financial expenses to sales and tax to market valued total assets. Moreover, to construct the parsimonious multivariate prediction model, they evaluate respective variables' average marginal effects and find five highly significant variables in predicting financial distress. In light of this, we employ the covariates suggested by Gupta and Chaudhry (2019) to proceed with our empirical analysis. In addition, considering the macroeconomic variation in specific industrial sectors and the duration dependency, we adopt two more control variables as well. Detailed definitions of firm-level explanatory variables and the two additional control variables are as follows:

i. *NIMTAAVG* – Weighted average of net income to market-valued total assets (*NIMTA*) over previous 3 years:

$$NIMTAAVG_{i,t} = \frac{1}{1.75}NIMTA_{i,t-1} + \frac{0.5}{1.75}NIMTA_{i,t-2} + \frac{0.25}{1.75}NIMTA_{i,t-3}$$

$$where, \qquad NIMTA_{i,t} = \frac{Net\ Income_{i,t}}{(Market\ Value\ of\ Equity_{i,t} +\ Total\ Liabilities_{i,t})}$$

ii. $EXRETAVG$ – The weighted average of monthly log excess returns relative to S&P 500 index:

$$EXRETAVG_{i,t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}\left(EXRET_{i,t-1} + \cdots + \phi^{11}EXRET_{i,t-12}\right)$$

$$where, \qquad EXRET_{i,t} = Log\left(1 + Equity\ Return_{i,t}\right) - \ Log\left(1 + Equity\ Return_{S\&P\ 500,t}\right)$$

iii. *FES* – Ratio of financial expense to sales:

$$FES_{i,t} = \frac{Financial\ Expense_{i,t}}{Sales_{i,t}}$$



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iv. *TMTA* – Ratio of income tax to market-valued total assets:

$$TMTA_{i,t} = \frac{Tax\ of\ Total\ Income_{\ i,t}}{Market\ Value\ of\ Equity_{i,t} + Total\ liabilities_{i,t}}$$

v. *CASHMTA* – Ratio of cash and short-term investments scaled by market value of total assets:

$$CASHMTA_{i,t} = \frac{Cash\ and\ Short\text{–}term\ Investments_{\ i,t}}{Market\ Value\ of\ Equity_{i,t} + Total\ Liabilities_{i,t}}$$

vi. *INDRISK* – Industry risk:

$$INDRISK_{i,t} = \frac{Number\ of\ firms\ with\ the\ interest\ event\ in\ each\ industry_{\ i,t}}{Total\ number\ of\ firm\ in\ each\ industry_{i,t}}$$

vii. *LNAGE* – The logarithm of firm's annual age[3]:

$$LNAGE_{i,t} = Log\left(age_{i,t}\right)$$

We expect *NIMTAAVG, EXRETAVG*, *TMTA* and *CASHMTA* to have a negative effect on the likelihood of financial distress, in contrast, *FES, INDRISK* and *LNAGE* are expected to be positively related to the likelihood of financial distress. *NIMTAAVG* represents a firm's profitability; firms with high profitability are related to lower insolvency probability. The market variable *EXRETAVG* is expected to affect the likelihood of financial distress negatively since distressed firms typically have lower returns compared to healthy ones. Firms with healthy financial status usually have a higher frequency and larger volume of business leading to more tax payments; therefore, *TMTA* is negatively associated with firm failures. As a proxy for liquidity, *CASHMTA* indicates a firm's liquid assets level, as the default probability increases if the firm holds fewer liquid assets. All variables are winsorised at their 1st and 99th percentiles to minimize the influence of outliers.

### 3.3 Summary Statistics

We report the summary statistics of all variables in Table 1 for financially distressed and healthy groups of firms to get a preliminary understanding of the differences among the firms' characteristics.

[3] The firm's age is measured as the duration of current year and first year in which firm has valid data in Compustat.



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**<Insert Table 1>**

We report mean, median, standard deviation, minimum value and maximum value of all covariates. Column 1 shows the list of variables used in our subsequent regression models, Column 2 states the healthy/distressed status of firms, and the remaining columns report descriptive statistics, which are comparable to previous literature (Campbell *et al.* 2008; Huang 2009; Gupta and Chaudhry 2019), with some differences in reasonable range due to the variations in samples.

Most notably, *CFR* exhibits a distinctly high mean value in the financially distressed group at 26.8, which is almost 8 times higher than their healthy counterparts (3.6), indicating that distressed firms have higher levels of volatile cash flows. Other covariates' descriptive statistics are similar to those reported by Gupta and Chaudhry (2019). Table 1 reports a distinct comparison of distressed and healthy firms' characteristics. For the distressed group, firms typically make losses (the mean of loss is about 27%, and the median loss is 19%), and have a relatively lower return as well as tax payment compared to healthy firms. Similar to Gupta and Chaudhry (2019), the mean of *FES* (0.242) and *INDRISK* (0.024) are slightly higher for the distressed group than for the healthy group. We check the correlation among those variables as well, and all covariates show low or moderate correlation with each other in untabulated results. The mean of *AEM*, *REM* and *ACOMP* are around zero since they are calculated as a residual of the regression model. We find that distressed firms are more likely to engage in upward *AEM* (0.029) and downward *REM* (-0.090).

## 4. Role of *CFR* in Predicting Financial Distress

### 4.1 Panel Logit Regression

In line with the existing literature, we examine the probability of a firm's failure using panel logistic regression with random effects. Although hazard models are popular in previous academic studies, the discrete hazard model with logit link is actually a panel logistic model controlling for a firm's age (Gupta *et al.* 2018). Moreover, the panel logistic model achieves the essential required functions in empirical validation and is easier to understand. Thus, following Campbell *et al.* (2008) and Gupta and Chaudhry (2019), the marginal probability of a firm's financial distress over the next period is assumed to follow a logistic distribution:



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$$P(Y_{it} = 1) = \frac{1}{1 + \exp(-\alpha - \beta x_{i,t-1})} \tag{7}$$

where $Y_{it}$ is an indicator that equals one if the firm is financially distressed in time *t*, and $X_{i,t-1}$ is a vector of explanatory variables known at the end of the previous year. In addition, the higher value of $\alpha + \beta x_{i,t-1}$ suggests the higher likelihood of financial distress.

### 4.2 Baseline Multivariate Regression Model

The main objective of our empirical analysis is to investigate the effect of *CFR* on financial distress. Thus, we start with a baseline model that includes *NIMTAAVG*, *EXTRETAVG*, *FES*, *TMTA*, *CASHMTA*, *LNAGE* and *INDRISK* as explanatory variables, along with our variable of interest, *CFR*. Results are reported in Table 2. Model 1 presents the impact of *CFR* on financial distress. We find that the estimated coefficient of *CFR* is positive and significant at the 1% level. In addition, the average marginal effects (*AME*)[4] of *CFR* is 0.003 and significant. Consistent with our expectation, firm profitability, excess stock return and tax payment are negatively related to the distress risk, in contrast, a firm's financial expenses increase its probability of financial distress. All financial covariates are jointly significant in predicting the likelihood of financial distress of U.S. firms. In addition, Model 1 exhibits a classification performance of around 91% (measured using the area under the ROC curve)[5]. The result, therefore, implies that firms with high *CFR* are more likely to experience financial distress.

**<Insert Table 2>**

In addition, to address the potential endogeneity issue, we re-estimate our baseline model with the instrumental variable approach. We employ the Jackknife method by using the instrumental variable calculated as the mean of *CFR* in a given year, industry, and size excluding the firm itself. Model 2 in Table 2 reports the results and we find that the coefficient

[4] Average marginal effects are multiplied by 100 for expositional reasons.

[5] We evaluate the classification performance using a non-parametric classification measure, namely Area Under Receiver Operating Characteristic Curve (AUROC). The higher value of AUROC indicates the better performance of prediction model. For out-of-sample validation, we use observations from 1980 until 2017 to estimate our model, with the estimates, we predict the likelihood of financial distress for the year 2018; then we extend the observations from 1980 until 2018 to estimate our model and predict the likelihood of financial distress for the year 2019, and so on until 2021. We estimate the out-of-sample AUROC with these predicted likelihoods value from 2017 to 2021.



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of *CFR* remains positive and significant. This further supports that our findings are robust to endogeneity concerns.

Although *CFR* and its *AME* are statistically significant in Model 1, the magnitude of its coefficients and *AME* are relatively small, implying a relatively low change in the predicted probability due to a unit change in *CFR*. Therefore, we propose another version of *CFR* to improve Model 1's performance, a dummy variable capturing firms with high *CFR*, *CFRH*. Specifically, the new dummy variable *CFRH* equals one if the firm's *CFR* is higher than the median in a given year and industry, and zero otherwise. *CFRH* focuses more on the group with relatively high *CFR*. Column 3 in Table 2 presents the results. We find that *CFRH* has much higher magnitudes of coefficients and also much larger *AME* compared to the continuous *CFR* in Column 1. Therefore, *CFRH* is significant in predicting the likelihood of financial distress as expected. The coefficient of *CFRH* is positive and significant at the 1% level with a magnitude of 1.393. The *AME* (in percentages) of *CFRH* is 1.195, which is much higher than the one in Model 1. The high value of *AME* suggests considerable economic significance.

In addition to the increased economic significance, our proposed multivariate regression delivers a noticeable improvement in explanatory power over the models discussed in the previous section. We report McFadden's pseudo-*R–squared* to make the comparison. The *R–squared* increased from 0.212 to 0.284, which is about 7% improvement in the explanatory power. The high value of AUROC, around 92%, indicates excellent classification performance. Therefore, our final baseline model (with *CFRH*) to predict financial distress is as follows:

$$\boldsymbol{Financial\ Distress_{i,t}} = \beta_0 + \boldsymbol{\beta_1} \times \boldsymbol{CFRH_{i,t}} + \beta_2 \times NIMTAAVG_{i,t} + \beta_3 \times EXRETAVG_{i,t-1} + \beta_4 \times FES_{i,t-1} + \beta_5 \times TMTA_{i,t-1} + \beta_6 \times CASHMTA_{i,t-1} + \beta_7 \times LNAGE_{i,t-1} + \beta_8 \times INDRISK_{i,t-1} \quad (8)$$

### 4.3 Moderating Role of Earnings Management (Test of H2)

In this section, we investigate the moderating effect of *AEM* and *REM* on the relation between *CFRH* and financial distress. In addition, we also test the moderating role of *EM* using another version of *CFR*. Specifically, *CFRD* is a dummy variable which equals one if a firm is in the top decile of *CFR* in a given year and industry. Fig. 3 shows the mean of different decile groups.



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We find that the top decile has the highest value, around 32, of average *CFR*, however, the value of other groups' average *CFR* range within 2. Therefore, to account for this extreme skewness in the distribution of *CFR*, besides *CFRH* we also use *CFRD* in our moderation analysis.

**<Insert Figure 3>**

**<Insert Table 3>**

To analyse the moderating effect of *AEM* or *REM*, we employ dummy variables, *HAEM*, *PAEM*, *HREM* and *PREM*. *HAEM* (*HREM*) equals one if the *AEM* (*REM*) is above the median of industry-year, and zero otherwise. *PAEM* (*PREM*) equals one if the *AEM* (*REM*) is nonnegative, and zero otherwise. Panel A of Table 3 reports the results using *CFRH*. We find that the coefficient of interaction terms $CFRH \times HAEM$ and $CFRH \times PAEM$ are negative and significant at 0.01 level with values -1.094 and -0.997, respectively. The results indicate that executives in firms facing high *CFR* may engage in *AEM* to reduce the probability of financial distress. Thus, the empirical results support the hypothesis predicted by the upper echelons theory that managers who are facing high job demands, such as the challenge of firm performance, are more susceptible to being affected by their personal characteristics when making financial decisions (Hambrick 2007). However, for *REM*, we find that the coefficient of interaction terms $CFRH \times HREM$ and $CFRH \times PREM$ are insignificant or weakly significant at 0.1 level. The plausible explanation is that managers exhibit a greater tendency towards inflating earnings or strategically timing a firm's information releases, with the aim of manipulating firm's performance through *AEM* than *REM* as *AEM* is timelier (Edmans et al. 2017). In addition, there might not be much room or time left to do *REM* for managers in firms with high *CFR*.

Panel B reports the results using *CFRD* in our baseline model. We find that the coefficient of interaction terms $CFRD \times HAEM$ and $CFRD \times PAEM$ are negative and significant at 0.01 level with values -1.479 and -1.471, respectively. In addition, the coefficient of interaction terms $CFRD \times HREM$ and $CFRD \times PREM$ are negative and significant at 0.01 level (-1.327 and -1.431, respectively). The results indicate that, for firms facing extremely high



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*CFR*, the managers are more likely to be more aggressive and engage in accruals and real earnings management to reduce the likelihood of financial distress, since they face greater job demand suggested by upper echelons theory. Thus, overall we find convincing evidence that earnings management negatively moderates the relation between *CFR* and financial distress. Thereby affirming the upper echelons theory's prediction that when top managers are faced with intense job demands, such as the need to improve company performance, they are prone to utilizing heuristics in their financial decision-making.

**4.4 Moderating Role of *ACOMP* (Test of H3)**

In this section, we investigate the moderating effect of *ACOMP* on the relation between *CFRH* and *CFRD*, and financial distress. We employ the model proposed by Core *et al.* (2008) to measure *ACOMP*. Similarly, we employ two dummy variables to analyse the moderating effect, *HACOMP* and *PACOMP*. *HACOMP* equals one if *ACOMP* is above the median in a given year and industry, and zero otherwise. *PACOMP* equals one if *ACOMP* is non-negative, and zero otherwise. Panel A of Table 4 reports the results using *CFRH*, while Panel B of Table 4 reports the results using *CFRD*. The coefficients of interaction terms *CFRH* × *HACOMP* and *CFRH* × *PACOMP* are negative and significant (-1.071, -1.190) at 0.01 level. Similarly, the coefficients of interaction terms *CFRD* × *HACOMP* and *CFRD* × *PACOMP* are negative and significant at 0.01 level with values -1.561 and -1.577, respectively.

**<Insert Table 4>**

Such results suggest that when firms face high or extremely high *CFR*, some boards may respond effectively by adjusting compensation structures to motivate executives to put more effort into managing the high *CFR*. Considering the interest alignment effect, board members adjust executives' *ACOMP* to a higher level to align managers' interests with firms' interests. Therefore, executives with high and positive *ACOMP* may have higher incentives to reduce the risk and thereby reducing the probability of financial distress. Overall, in line with the predictions of the agency theory, we find that boards are effective in adjusting compensation levels in response to higher *CFR*. This alignment of interests encourages managers to put more effort into managing volatile cash flows.



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### 4.5 Alternative Definitions of Firm Failure

Besides the main results reported above, we also conduct several robustness checks to gain deeper insight into the effect of *CFR* on the likelihood of firms facing financial distress. To further provide evidence of the extent to which our results are robust, we use four alternative definitions to identify a firm's financial difficulties. First, we use two definitions for financial constraints, the *KZ* index and the *WW* index. Using *KZ* index, a firm's degree of financial constraints is estimated by five variables: cash flow, market-to-book, leverage, dividends, and cash holdings (Lamont *et al.* 2001; Kothari *et al.* 2016). A higher index value indicates a firm is more likely to be in financial distress. We use a dummy variable *FSKZ* which equals one if a firm is in the top quartile based on the *KZ* index in a given year and industry indicating the financial stress, and zero otherwise. *WW* index is another measure of the financial stress which uses several variables as well: cash flow to assets, dividend, long-term debt to assets, total assets, sales growth, and industry sales growth (Whited and Wu 2006). Similarly, we use a dummy variable *FSWW* which equals one if a firm is in the top quartile based upon the *WW* index in an industry-year group, indicating that the firm is more likely to be financially stressed, and zero otherwise.

Second, we proxy firms that are financially distressed if they are presumed to violate debt covenant conditions. Considering the discussion before, firms with either a high leverage ratio or low-interest coverage are more likely to experience financial difficulties and hardship in accessing external financing. These two violated metrics indicate firms have persistent poor performance and insufficient capital level, which may lead to financial distress or bankruptcy. Therefore, firms with low-interest coverage and high leverage ratios are supposed to have covenant violations. Specifically, we classify firms in the bottom quartile of the interest coverage ratio and the top quartile of the leverage ratio in a given year as covenant-violation groups of firms. The leverage ratio is defined as the sum of short-term debt and long-term debt to total assets, and the interest coverage ratio is calculated as earnings before interest and taxes (*EBIT*) to interest expenses.

We also employ legal bankruptcy as a failure definition by identifying firms that filed



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for Chapter 11/7 bankruptcy in the Compustat[6] database. We separately estimate our prediction models for these four alternative definitions of firm failures using Eq. (8). The response variable in both models has binary outcomes. Table 5 reports the estimation results with these alternative measures for a 1-year prediction horizon.

**<Insert Table 5>**

Columns 2 and 3 in Table 5 report the result for *FSKZ* and *FSWW* as failure definitions, respectively. As we see, *CFRH* remains significant at 1% level with values of 0.116 and 0.900, respectively. Column 4 presents the results for presumed covenant violation as failure definition. Similarly, the key variable *CFRH* is positive and significant with a value of 0.348. Turning to firms that filed for bankruptcy, we find the result is qualitatively unchanged and the coefficient of *CFRH* is also positive and significant at 1% level, 1.137. Such results suggest that firms that filed for bankruptcy have suffered high *CFR* and significant erosion in firm value already. However, we find that the value of *R-squared* is lower compared to the models employing the financial distress definition in our main results, which indicates that our model performs better in predicting financial distress.

In view of our empirical findings, we have a strong motivation to believe in the superior performance of *CFRH* in predicting firm failures; the overall explanatory power of our model is robust to alternative failure definitions.

## 5. Additional Tests

We also conduct a few additional tests. We focus on whether corporate governance mechanisms play a role in moderating the relation between *CFR* and financial distress. Prior literature shows that firms' risk is more likely to be reduced or controlled in firms with a strong governance structure (Ahmad *et al.* 2021; Boachie and Mensah 2022), therefore, we re-estimate our baseline model with different variables indicating the level of firm's corporate governance mechanisms. Specifically, we have tried the corporate governance score from Refinitiv and MSCI (KLD), takeover index (Cain *et al.* 2017), board co-option (Coles *et al.* 2014) and different board characteristics including board independence, board size, and board tenure, etc.

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[6] We use code "*TL*" in *"Status Alert"* variable in Compustat to identify whether the firms filed for bankruptcy.



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However, we fail to find consistent and significant effects of corporate governance in moderating the association between *CFR* and financial distress.

## 6. Conclusion

In this study, we explore the association between *CFR* and financial distress of U.S. listed firms. Our principal results make three main contributions to the literature on corporate failure and *CFR*. First, our test results show a positive significant effect of *CFR* on financial distress. Second, although we find a superior and statistically significant role of *CFR* in predicting the likelihood of financial distress, the magnitude of its *AME* remains relatively small. Therefore, we improve our model with *CFRH*. Such binary transformation raises the discriminatory power of *CFR* and the explanatory power of our model dramatically. Third, we find that the effect of *CFRH* on financial distress is moderated negatively in firms with higher and positive *AEM*, *REM* and *ACOMP*. The results suggest that managers in companies with a high level of *CFR* tend to rely more on heuristics in the form of earnings management. This aligns with the upper echelons theory, which posits that managers facing significant performance pressure are more likely to be influenced by their personal characteristics in their decision-making. On the other hand, boards may offer compensation packages to encourage better risk management practices, as agency theory argues that financial incentives are effective in serving as a monitoring tool.

We also document that the significance of *CFR* is robust to alternative definitions of firm failure such as financial constraints, presumed covenant violation and legal bankruptcy filings. In addition, we argue that our definition to identify a firm's financial difficulties outperforms legal bankruptcy filings, since waiting until bankruptcy filing may lead to significant losses to stakeholders and unexpected erosion in the firm value. Also, some cases of "strategic bankruptcy" may mislead stakeholders and conceal the real financial health of firms (Gupta *et al.* 2019). In general, these results provide strong empirical support for the significance of *CFR* as a financial distress predictor.

The findings of this study have some limitations that should be considered. First, as the agency theory suggests, internal and external corporate governance should serve as an effective mechanism for mitigating agency conflicts. Therefore, the effect of *CFRH* on financial distress should be moderated by corporate governance metrics. Nonetheless, our findings do not



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consistently support this hypothesis, and further studies are needed to gain a deeper insight into this matter. Second, while our findings are generalizable to U.S. firms, caution should be taken in applying the results to non-U.S. firms. Given the substantial variations in corporate governance, regulatory authority, and information ecosystems across countries (La Porta et al. 1997; La Porta et al. 1998), researchers may consider those factors as potential moderators when exploring the effect of *CFR* on firm failures across different countries.



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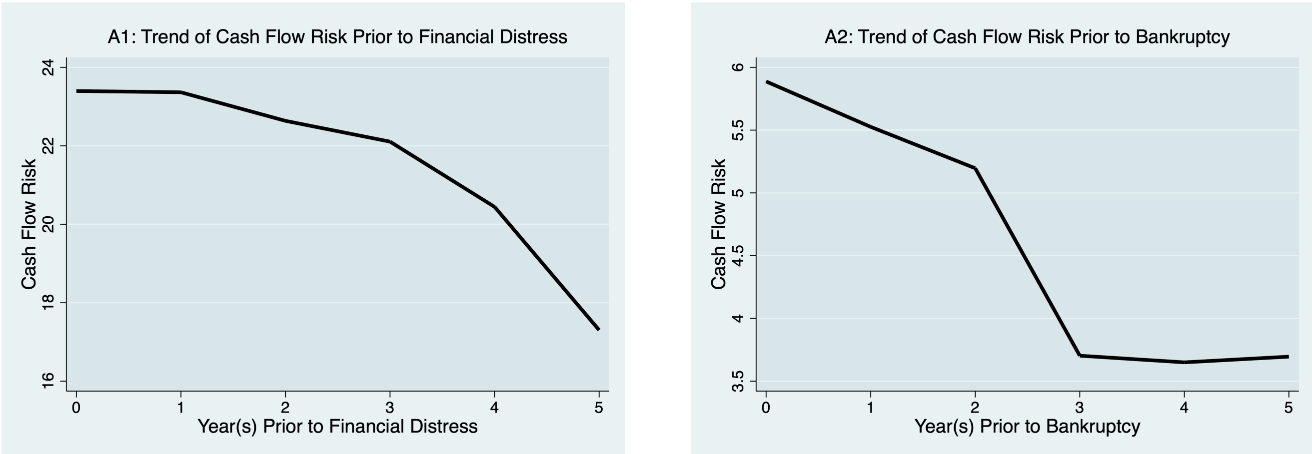
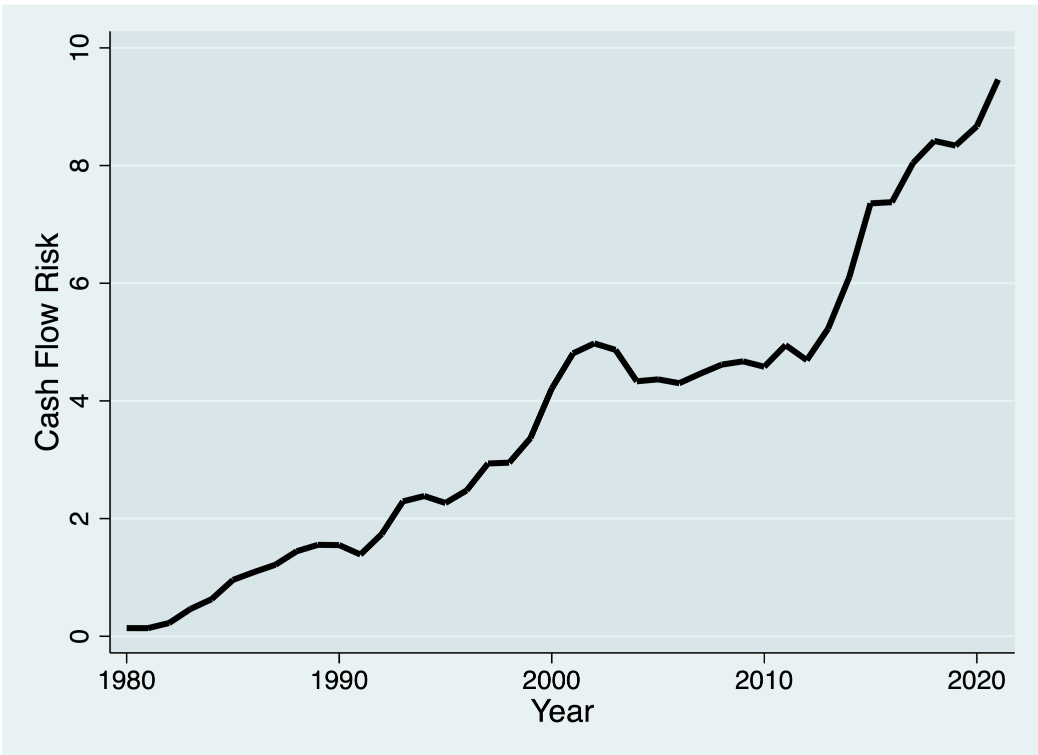
## List of Figures and Tables

**Figure 1**
**Time trend of cash flow risk 5 years prior to financial distress and bankruptcy**




**Notes:** This figure exhibits the annual average of cash flow risk (*CFR*) over the 5-year periods prior to financial distress and bankruptcy filings for U.S. firms.

**Figure 2**
**Time trend of cash flow risk**




**Notes:** This figure exhibits the annual average of cash flow risk (*CFR*) over the period 1980 to 2021 for U.S. firms.



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**Table 1**
**Sample description**

This table reports summary statistics for all covariates used in the multivariate analysis. To facilitate comparison, summary statistics are reported separately for healthy and financially distressed groups of firms. All variables are winsorised at their 1st and 99th percentile values. The sample is based on the annual data of U.S. firms from 1980 to 2021.

| Variable | Status | Mean | Standard Deviation | Minimum | Median | Maximum |
|---|---|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| *CFR* | Healthy | 3.601 | 18.895 | 0.012 | 0.200 | 166.697 |
| | Distressed | 26.849 | 49.876 | 0.014 | 3.454 | 166.697 |
| *NIMTAAVG* | Healthy | -0.073 | 0.226 | -1.286 | 0.006 | 0.197 |
| | Distressed | -0.271 | 0.265 | -1.286 | -0.191 | 0.197 |
| *EXRETAVG* | Healthy | -0.009 | 0.051 | -0.180 | -0.006 | 0.132 |
| | Distressed | -0.011 | 0.081 | -0.180 | -0.011 | 0.132 |
| *FES* | Healthy | 0.089 | 0.336 | 0.000 | 0.016 | 2.672 |
| | Distressed | 0.242 | 0.598 | 0.000 | 0.023 | 2.672 |
| *TMTA* | Healthy | 0.018 | 0.036 | -0.086 | 0.005 | 0.166 |
| | Distressed | -0.001 | 0.019 | -0.086 | 0.000 | 0.166 |
| *CASHMTA* | Healthy | 0.118 | 0.172 | 0.000 | 0.054 | 0.920 |
| | Distressed | 0.237 | 0.233 | 0.000 | 0.166 | 0.920 |
| *LNAGE* | Healthy | 2.137 | 1.002 | 0.000 | 2.197 | 4.357 |
| | Distressed | 2.427 | 0.561 | 1.386 | 2.303 | 4.007 |
| *INDRISK* | Healthy | 0.008 | 0.011 | 0.000 | 0.004 | 0.067 |
| | Distressed | 0.024 | 0.015 | 0.000 | 0.020 | 0.067 |
| *AEM* | Healthy | -0.007 | 0.080 | -2.185 | -0.007 | 1.186 |
| | Distressed | 0.029 | 0.021 | -2.108 | 0.030 | 0.703 |
| *REM* | Healthy | 0.027 | 0.716 | -1.515 | -0.063 | 2.821 |
| | Distressed | -0.090 | 0.709 | -1.515 | -0.173 | 2.822 |
| *ACOMP* | Healthy | -0.002 | 0.604 | -4.883 | 0.000 | 5.601 |
| | Distressed | -0.028 | 0.720 | -2.550 | 0.001 | 1.956 |



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**Table 2**
**Baseline multivariate regression of financial distress**

This table reports multivariate regression estimates employing financial distress as the dependent variable and covariates including *CFR, NIMTAAVG, EXTRETAVG, FES, TMTA, CASHMTA*, *LNAGE* and *INDRISK*. All variables are winsorised at their 1st and 99th percentile values. Model 1 is the multivariate model with *CFR*, Model 2 is the multivariate model of instrumental variable estimates. The instrumental variable is the mean of the *CFR* in a given year, industry and firm size, excluding the firm itself (jackknife average). Model 3 is the multivariate model with a dummy variable *CFRH*, which equals one if a firm's *CFR* is above the median in a given year and industry. The coefficient of average marginal effect (*AME*) is multiplied by 100 for expositional purposes. N = 0 represents the number of healthy firms. N = 1 represents the number of financially distressed firms. AUROC-W is the within-sample area under the ROC curve and AUROC-H is the out-of-sample area under the ROC curve. The sample is based on annual data of U.S. firms from 1980 to 2021. ***, **, * indicate significance at the 1, 5, and 10 % levels, respectively.

| Variable | | *Financial Distress* | |
|---|---|---|---|
| (1) | (2) | (3) | (4) |
| | Model 1 | Model 2 | Model 3 |
| ***CFR*** | **0.004***** | **0.020***** | |
| | (3.872) | (8.210) | |
| ***CFRH*** | | | **1.393***** |
| | | | (14.242) |
| *AME × 100* | 0.003*** | - | 1.195*** |
| *NIMTAAVG* | -2.725*** | -1.245*** | -2.415*** |
| | (-18.692) | (-9.703) | (-17.482) |
| *EXTRETAVG* | -10.844*** | 2.204*** | -10.688*** |
| | (-21.149) | (9.343) | (-21.476) |
| *FES* | 0.355*** | -0.563*** | 0.321*** |
| | (4.629) | (-4.797) | (5.066) |
| *TMTA* | -10.632*** | -5.448*** | -9.007*** |
| | (-9.954) | (-12.329) | (-8.642) |
| *CASHMTA* | 2.694*** | 0.706*** | 2.489*** |
| | (16.811) | (7.960) | (16.218) |
| *LNAGE* | -0.020 | 0.074*** | 0.210*** |
| | (-0.369) | (3.842) | (4.072) |
| *INDRISK* | 27.803*** | 6.435*** | 28.539*** |
| | (12.826) | (6.331) | (13.597) |
| Model's goodness of fit and prediction performance measure | | | |
| Chi2 | 2433.120 | 1751.210 | 2569.441 |
| Log likelihood | -5595.167 | -378882.180 | -5669.862 |
| *R*-square | 0.212 | - | 0.284 |
| AUROC-W | 0.913 | - | 0.915 |
| AUROC-H | 0.900 | - | 0.887 |
| N = 0 | 84,852 | 87,718 | 84,852 |
| N = 1 | 1,543 | 1,543 | 1,543 |



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**Table 3**

**Multivariate regression of financial distress with earnings management as moderator**

This table reports multivariate regression estimates employing financial distress as the dependent variable. The regression employs different variables including *PAEM*, *HAEM*, *PREM*, and *HREM* with *CFRH* as interaction terms. Panel A is the multivariate regression with a dummy variable *CFRH*, which equals one if a firm's *CFR* is above the median in a given year and industry. Panel B is the multivariate regression with a dummy variable *CFRD,* which equals one if a firm is in the top decile of *CFR* in a given year and industry. N = 0 represents the number of healthy firms. N = 1 represents the number of financially distressed firms. The sample is based on annual data of U.S. firms from 1980 to 2021. ***, **, * indicate significance at the 1, 5, and 10 % levels, respectively.

| Variables | *Financial Distress* | | | |
|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) |
| **Panel A: Multivariate regression of financial distress with *CFRH*** | | | | |
| *CFRH* | 2.541*** | 2.437*** | 2.037*** | 2.306*** |
| | (5.271) | (5.902) | (5.346) | (5.348) |
| *HAEM* | 2.242*** | | | |
| | (4.888) | | | |
| ***CFRH× HAEM*** | **-1.094**** | | | |
| | (-2.231) | | | |
| *PAEM* | | 1.878*** | | |
| | | (4.798) | | |
| ***CFRH× PAEM*** | | **-0.997**** | | |
| | | (-2.365) | | |
| *HREM* | | | 1.478*** | |
| | | | (3.977) | |
| ***CFRH× HREM*** | | | **-0.469** | |
| | | | (-1.195) | |
| *PREM* | | | | 1.587*** |
| | | | | (3.753) |
| ***CFRH× PREM*** | | | | **-0.766*** |
| | | | | (-1.738) |
| Controls | Yes | Yes | Yes | Yes |
| Model's goodness of fit and prediction performance measure | | | | |
| Chi2 | 1793.293 | 2230.320 | 1867.54 | 2237.31 |
| Log likelihood | -5305.397 | -5947.015 | -5392.415 | -5953.065 |
| *R*-square | 0.347 | 0.299 | 0.297 | 0.289 |
| N = 0 | 63,997 | 93,433 | 66,222 | 93,433 |
| N = 1 | 1,469 | 1,584 | 1,484 | 1,584 |
| **Panel B: Multivariate regression of financial distress with *CFRD*** | | | | |
| *CFRD* | 2.802*** | 2.803*** | 2.630*** | 2.743*** |



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| | | | | |
|---|---|---|---|---|
| | (7.876) | (8.817) | (9.800) | (10.293) |
| *HAEM* | 1.656*** | | | |
| | (7.860) | | | |
| ***CFRD×HAEM*** | **-1.479*****  | | | |
| | (-4.138) | | | |
| *PAEM* | | 1.458*** | | |
| | | (7.522) | | |
| ***CFRD×PAEM*** | | **-1.471***** | | |
| | | (-4.595) | | |
| *HREM* | | | 1.378*** | |
| | | | (7.410) | |
| ***CFRD×HREM*** | | | **-1.327***** | |
| | | | (-4.841) | |
| *PREM* | | | | 1.243*** |
| | | | | (6.845) |
| ***CFRD×PREM*** | | | | **-1.431***** |
| | | | | (-5.276) |
| Controls | Yes | Yes | Yes | Yes |
| Model's goodness of fit and prediction performance measure | | | | |
| Chi2 | 1922.66 | 2341.75 | 1968.39 | 2323.760 |
| Log likelihood | -5057.129 | -5677.359 | -5145.790 | -5686.696 |
| *R*-square | 0.276 | 0.243 | 0.255 | 0.234 |
| N = 0 | 61,577 | 87,813 | 63,624 | 87,813 |
| N = 1 | 1,423 | 1.537 | 1,438 | 1.537 |



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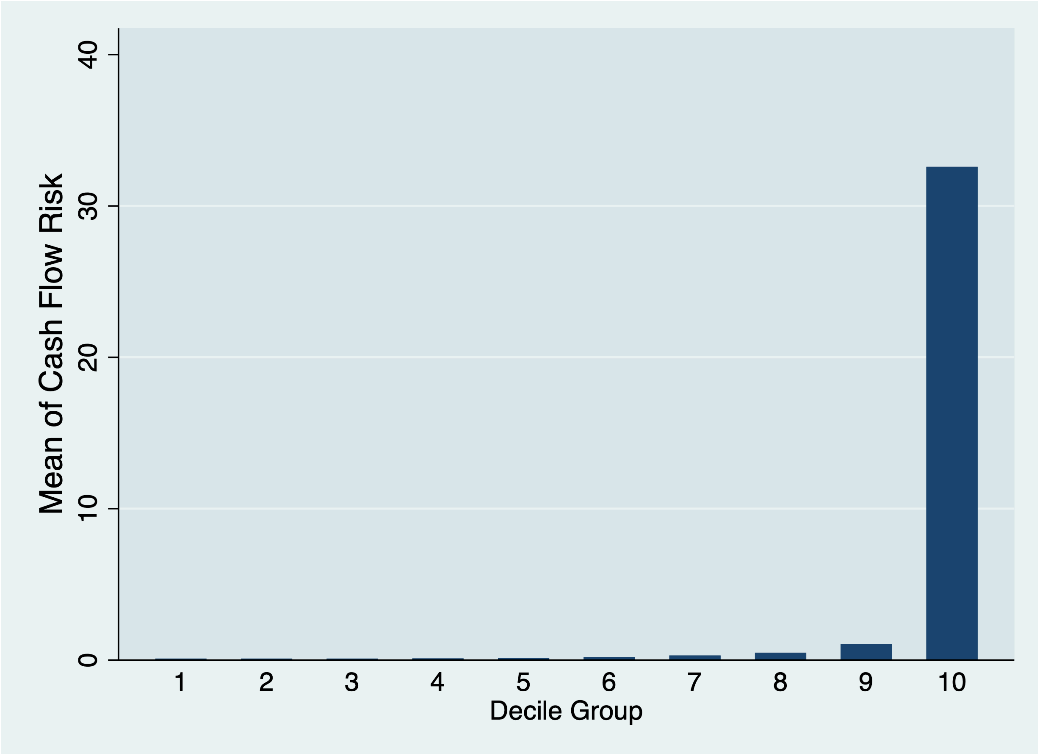
**Figure 3**
**Mean of cash flow risk over decile groups**




**Notes:** This figure exhibits the average cash flow risk (*CFR*) of different decile groups the over period 1980 to 2021 for U.S. firms.

**Table 4**
**Multivariate regression of financial distress with abnormal compensation as moderator**

This table reports multivariate regression estimates employing financial distress as the dependent variable. The regression employs different variables including *PACOMP* and *HACOMP* with *CFRH* as interaction terms. Panel A is the multivariate regression with a dummy variable *CFRH*, which equals one if a firm's *CFR* is above the median in a given year and industry. Panel B is the multivariate regression with a dummy variable *CFRD,* which equals one if a firm is in the top decile of *CFR* in a given year and industry. N = 0 represents the number of healthy firms, and N = 1 represents the number of financially distressed firms. The sample is based on annual data of U.S. firms from 1980 to 2021. ***, **, * indicate significance at the 1, 5, and 10 % levels, respectively.

| Variables | *Financial Distress* | |
|---|---|---|
| (1) | (2) | (3) |
| **Panel A: Multivariate regression of financial distress with *CFRH*** | | |
| *CFRH* | 2.503*** | 2.633*** |
| | (6.409) | (5.930) |
| *HACOMP* | 1.770*** | |
| | (4.780) | |
| ***CFRH× HACOMP*** | **-1.071*** ** | |



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| | | |
|---|---|---|
| | (-2.670) | |
| *PACOMP* | | 1.826*** |
| | | (4.326) |
| ***CFRH× PACOMP*** | | **-1.190*****  |
| | | (-2.632) |
| Controls | Yes | Yes |
| Model's goodness of fit and prediction performance measure | | |
| Chi2 | 1793.293 | 2230.320 |
| Log likelihood | -5305.397 | -5947.015 |
| *R*-square | 0.347 | 0.299 |
| N = 0 | 63,997 | 93,433 |
| N = 1 | 1,469 | 1,584 |

| **Panel B: Multivariate regression of financial distress with *CFRD*** | | |
|---|---|---|
| *CFRD* | 2.896*** | 2.924*** |
| | (8.792) | (8.458) |
| *HACOMP* | 1.185*** | |
| | (6.692) | |
| ***CFRD× HACOMP*** | **-1.561***** | |
| | (-4.702) | |
| *PACOMP* | | 1.150*** |
| | | (6.131) |
| ***CFRD× PACOMP*** | | **-1.577***** |
| | | (-4.535) |
| Controls | Yes | Yes |
| Model's goodness of fit and prediction performance measure | | |
| Chi2 | 1924.031 | 2326.160 |
| Log likelihood | -5053.379 | -5692.588 |
| *R*-square | 0.242 | 0.229 |
| N = 0 | 61,184 | 87,813 |
| N = 1 | 1,420 | 1,537 |



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**Table 5**

**Multivariate regression of financial distress with alternative definitions of firm failure**

This table reports multivariate regression estimates employing alternative definitions of firm failures: financial stress (*FSKZ* and *FSWW*), presumed covenant violation (*DC*) and legal bankruptcy filings (*Bankrupt*). All variables are winsorised at their 1st and 99th percentile values. N = 0 represents the number of healthy firms. N = 1 represents the number of financially distressed firms. The sample is based on annual data of U.S. firms from 1980 to 2021. ***, **, * indicate significance at the 1, 5, and 10 % levels, respectively.

| Variable | *FSKZ* | *FSWW* | *DC* | *Bankrupt* |
|---|---|---|---|---|
| (1) | (2) | (3) | (4) | (5) |
| ***CFRH*** | **0.116*** ** | **0.900*** ** | **0.348*** ** | **1.137*** ** |
| | (3.289) | (18.695) | (7.266) | (3.940) |
| Controls | Yes | Yes | Yes | Yes |
| | | Model's goodness of fit and prediction performance measure | | |
| Chi2 | 4302.732 | 4490.350 | 926.151 | 121.972 |
| Log likelihood | -24843.605 | -18276.820 | -14125.281 | -767.919 |
| $R$-square | 0.171 | 0.167 | 0.046 | 0.056 |
| N = 0 | 83,348 | 85,023 | 89,521 | 94,857 |
| N = 1 | 11,669 | 9,994 | 5,496 | 160 |



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