White Rose Research Online

eprints@whiterose.ac.uk
https://eprints.whiterose.ac.uk
Universities of Leeds, Sheffield and York

Deposited via The University of Sheffield.

White Rose Research Online URL for this paper:
https://eprints.whiterose.ac.uk/id/eprint/243309/

Version: Accepted Version

Article:
Li, X., Luo, D. and Reber, B. (2026) Reference-dependent preferences for lottery-like stocks: cash flow risk and credit market conditions. The Journal of Portfolio Management, 52 (8). pp. 122-144. ISSN: 0095-4918

https://doi.org/10.3905/jpm.2026.018

© 2026 For the purpose of open access, the author has applied a Creative Commons Attribution (CC BY) licence to any Author Accepted Manuscript version arising from this submission https://creativecommons.org/licenses/by/4.0/

Reuse
This article is distributed under the terms of the Creative Commons Attribution (CC BY) licence. This licence allows you to distribute, remix, tweak, and build upon the work, even commercially, as long as you credit the authors for the original work. More information and the full terms of the licence here: https://creativecommons.org/licenses/

Takedown
If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.

UNIVERSITY OF LEEDS
University of Sheffield
UNIVERSITY of York

Reference-dependent preferences for lottery-like stocks: Cash flow risk and credit market conditions

Xiafei Li[1], Di Luo[2], and Beat Reber[3]

September 2025

Abstract

Existing literature reports the financial distress risk anomaly that stocks with low financial distress risk outperform stocks with high financial distress risk. We find that the anomaly is much more pronounced among distressed stocks with high cash flow volatility or in bad credit times. Furthermore, the significant impact of distress risk on expected stock returns is not systematic for all stocks but is only for stocks with high cash flow volatility in bad credit times. We show that distressed stocks with high cash flow volatility or bad credit times have extremely strong lottery features. Our results indicate that the distress risk anomaly and the impact of distress risk on expected stock returns are mainly driven by these lottery-like stocks. Our findings are consistent with the reference-dependent preferences theory that investors' preferences for lottery-like distressed stocks depend on cash flow volatility and credit market conditions.

JEL classification: G02, G12, G33, E51

Keywords: The distress risk anomaly; cash flow volatility; credit market conditions; reference-dependent preference; lottery-like stocks

[1] Corresponding author at Keele Business School, Keele University, Keele, Staffordshire, United Kingdom, ST5 5BG. Email: x.li2@keele.ac.uk.

[2]Business School, University of Dundee, Nethergate, Dundee, DD1 4HN, UK. Email: dluo001@dundee.ac.uk.

[3] University of Sheffield Management School, Conduit Road, Sheffield S10 1FL. Email: Beat.Reber@sheffield.ac.uk.

1 Introduction

Asset pricing theories suggest that assets with higher risk should have higher returns. Consistent with this view, Chan and Chen (1991), Fama and French (1995, 1996), and Chen and Zhang (1998) argue that higher returns on stocks with small capitalization and high book-to-market ratio are the financial distress risk premiums because these stocks have high financial leverage, persistent low past earnings, and substantial low dividend. However, Dichev (1998), Griffin and Lemmon (2002), and Campbell et al. (2008, 2011) find that firms with high distress risk generate significantly lower returns than firms with low distress risk. This distress risk puzzle is in stark contrast to the asset pricing theories and is claimed as one of the prominent asset pricing anomalies by Griffin and Lemmon (2002) and Campbell et al. (2008).

Building on the theoretical foundation of reference-dependent preferences, we examine whether the distress risk anomaly and the impact of distress risk on expected stock returns are dependent on firm-level cash flow volatility and country-level credit market conditions. Our study is motivated by three strands of literature. First, extending from the prospect theory of Kahneman and Tversky (1979), several studies argue that investors' preferences for risky assets are sensitive to prior losses or gains relative to a reference point (Kőszegi and Rabin, 2006, 2007; O'Donoghue and Sprenger, 2018; Werner and Zank, 2019). As a result, investors are likely to overweight assets with prior gains and underweight assets with prior losses (Barberis et al., 2001; Bordalo et al., 2013). Conrad et al. (2014) show that distressed stocks tend to

be lottery-like stocks that have high idiosyncratic volatility, idiosyncratic skewness, and the highest daily returns (Kumar, 2009; Bali et al., 2011).

Second, according to the model of Merton (1974), default occurs when the value of a firm's assets falls below the default boundary. Rountree et al. (2008) report that cash flow volatility is negatively related to firm value, with a 1% increase in cash flow volatility leading to a 0.15% decrease in firm value. Therefore, a firm with high cash flow volatility is likely to have a greater likelihood that the firm value falls below the default boundary or increases to extremely high. Moreover, firms with high cash flow volatility are likely to produce negative earnings and experience internal cash shortfalls, which increase financial distress risk and even default (Minton and Schrand, 1999).

Third, an extensive body of literature has shown that poor credit market conditions reduce the supply of credit, and increase liquidity risk and refinancing risk.[1] For instance, the financial crisis of 2007-2008 led to a reduction in the supply of credit and an increase in selling pressure (Ivashina and Scharfstein, 2010; Cornett et al., 2011; Iyer et al., 2014). Therefore, poor credit market conditions increase firms' cost of debt and exacerbate default risk (Hackbarth et al., 2006; Pesaran et al., 2006; Almeida and Philippon, 2007; Chen, 2010).

We hypothesize that the distress risk anomaly and the impact of distress risk on the cross-section of expected stock returns are more pronounced among stocks with high cash flow volatility or under poor credit market conditions. Specifically, when cash flow volatility is high or in a poor credit market, distressed stocks have extremely strong lottery features. They earn

[1]See, for example, Ericsson and Renault (2006), Hackbarth et al. (2006), Brunnermeier and Pedersen (2009), Gilchrist and Zakrajšek (2012), He and Xiong (2012), Morris and Shin (2016), and Valenzuela (2016).

extremely high prior returns with large positive skewness. Investors have great preferences for these stocks and overprice them, which leads to very low subsequent returns. As a result, short-selling distressed stocks with high cash flow volatility or in a poor credit market would cause a significant distress risk anomaly. Moreover, the impact of distress risk on stock returns for these stocks is likely to be strong. Conversely, when cash flow volatility is low or in a good credit market, distressed stocks have relatively weak lottery features and investors would not overweight these stocks, resulting in average subsequent returns. Therefore, short-selling distressed stocks with low cash flow volatility or in a good credit market would lead to an insignificant distress risk anomaly and the impact of distress risk on stock returns for those stocks is likely to be weak.

Using U.S. common stocks from 1977 to 2014, we follow the methodology of Campbell et al. (2008) and estimate the failure probability of a stock as a proxy for distress risk. To investigate the impact of cash flow volatility on the distress risk anomaly, we employ a rolling approach of Bates et al. (2009) by calculating cash flow volatility as the standard deviation of the cash flow-to-assets ratio over the prior 24 months. We use a two-way independent sorts method based on stocks' failure probability and cash flow volatility to explore how the distress risk anomaly varies with the level of cash flow volatility. To examine the distress risk anomaly under different credit market conditions, we follow Campello and Chen (2010) and employ bank loan spread as a proxy for credit market conditions.

Consistent with our hypothesis, the strong distress risk anomaly is concentrated in stocks with high cash flow volatility or in bad credit times. The anomaly vanishes in stocks

with low cash flow volatility or in good credit times across most return performance measures. More importantly, distressed stocks with a high cash flow volatility or in bad credit times have extremely strong lottery features with the highest idiosyncratic volatility, positive skewness, and the maximum daily returns of Bali et al. (2011) among two-way sorted portfolios. The significant distress risk anomaly is mainly generated by short-selling these lottery-like stocks. Our results from Fama and MacBeth regressions show that the impact of distress risk on stock returns is significantly negative only for stocks with high cash flow volatility in bad credit times, but is insignificant for stocks with high cash flow volatility in good credit times and stocks with low cash flow volatility regardless of the credit market conditions. This pattern is robust to the sample excluding microcap stocks.

A growing body of literature has explored various explanations for the distress risk puzzle. For instance, Chava and Purnanandam (2010), George and Hwang (2010), and Garlappi and Yan (2011) attribute the puzzle to the use of noisy ex-post realized returns, the negative relation between leverage and stock returns, and expected shareholder recovery. Chen et al. (2010), O'Doherty (2012), and Li et al. (2017) show that the distress risk puzzle is associated with idiosyncratic volatility, conditional market risk, and risk-shifting, respectively. Hackbarth et al. (2015), Gao et al. (2017) and Chu et al. (2020) find that the puzzle can be partially explained by the U.S. Bankruptcy Reform Act of 1978, the temporarily overpriced distressed stocks, and the causal effect of limits to arbitrage. We differ from these studies by focusing on the behavioral explanation of reference-dependent preferences for the puzzle.

Our paper relates to the literature that examines investors' preferences for lottery-like stocks. Barberis and Huang (2008) develop a model and predict that investors have preferences for positively skewed stocks and overweight these stocks, leading to low subsequent returns. Kumar (2009) defines stocks with high idiosyncratic skewness as lottery-like stocks. Bordalo et al. (2013), Dertwinkel-Kalt and Köster (2020), and Cosemans and Frehen (2021) argue that the lower expected returns of lottery-like stocks are associated with their salient past returns. An et al. (2020) and Liu et al. (2020) report that the lottery-related anomalies of Boyer et al. (2010), Bali et al. (2011), and Conrad et al. (2014) are conditional on firms' earnings announcements and reference-dependent preferences.[2] Bali et al. (2020) propose a skewness factor based on growth option to explain the distress risk anomaly. Gao et al. (2021) attribute the return-skewness relation to variance-dependent skewness for lottery stocks.

We add to the recent literature by examining a behavioral explanation of reference-dependent preferences based on cash flow volatility and credit market conditions for the distress risk anomaly. Our results show that the distress risk anomaly is more pronounced for stocks with high cash flow volatility or in bad credit times, and vanishes in stocks with low cash flow volatility or in good credit times. The findings provide new insides into the distress risk anomaly and suggest that investors' preferences for distressed stocks depend on cash flow volatility and credit market conditions.

We also contribute to the literature on the pricing of financial distress risk. Fama and French (1993, 1996) and Vassalou and Xing (2004) show that distress risk is systematic

[2]Conrad et al. (2014), Bali et al. (2017), and Xu et al. (2019) find that lottery-like stocks with low future returns can also explain the distress risk, beta, and return asymmetry anomalies.

risk and negatively priced in the cross-sectional expected stock returns. We differ from these studies by splitting the full sample into subsamples based on stocks' cash flow volatility and credit market conditions. Our results demonstrate that the strong impact of distress risk on expected stock return is not systematic for all stocks, but is only for stocks with high cash flow volatility in bad credit times. Overall, our findings can be explained by the reference-dependent preferences that both the distress risk anomaly and the pricing of distress risk are dependent on cash flow volatility and credit market conditions.

The rest of this paper is organized as follows. Section 2 develops our hypotheses. Section 3 describes the data used in this study, as well as the measures of financial distress risk and cash flow volatility. Section 4 presents the empirical results. Section 5 offers some concluding remarks.

2 Hypotheses Development

Reference-dependent preferences have become an important theory in behavioral economics since the prospect theory of Kahneman and Tversky (1979). The theory suggests that investors evaluate investment outcomes based on the prior performance of the investment relative to a reference point (Kőszegi and Rabin, 2006, 2007; O'Donoghue and Sprenger, 2018). Moreover, investors are more sensitive to prior losses than prior gains. They overweight securities with a high probability of lottery payoffs, leading to lower subsequent returns (Tversky and Kahneman, 1992; Barberis et al., 2001; Barberis and Huang, 2008; Kumar, 2009). Conrad et al. (2014) demonstrate that distressed stocks have lottery features with a high probability

of jackpot payoffs and are overpriced by investors. Wang et al. (2017), An et al. (2020), and Liu et al. (2020) provide empirical evidence that reference-dependent preferences can explain the lottery-related anomalies and the cross-sectional risk-return trade-off.

Several studies report a strong positive relation between cash flow volatility and default (Hackbarth et al., 2006; Tang and Yan, 2010). Moreover, numerous studies demonstrate that credit market conditions affect firms' default probability.[3] Kumar (2009) further shows that investors increase their demand for lottery-like stocks during economic downturns. These empirical findings suggest that the distress risk anomalies are likely to vary with cash flow volatility and credit market conditions. On the one hand, short-selling stocks with high cash flow volatility or under poor credit conditions are likely to produce large distress risk anomalies. This is because stocks with high cash flow volatility or under poor credit conditions are likely to generate lottery past payoffs and are overweighted by investors, in turn, they earn extremely low expected returns. On the other hand, short-selling stocks with low cash flow volatility or under good credit conditions would diminish the distress risk anomalies. Because stocks with low cash flow volatility or under good credit conditions are unlikely to produce lottery payoffs and investors have no preferences for them, the expected returns of these stocks are likely to be close to the average. We, therefore, expect to observe larger distress risk anomalies and a strong impact of distress risk on expected stock returns among stocks with high cash flow volatility or in bad economic times, and smaller distress risk anomalies and a weak impact of distress risk among stocks with low cash flow volatility and in good economic times.

[3]See, for example, Ericsson and Renault (2006), Hackbarth et al. (2006), Brunnermeier and Pedersen (2009), Gilchrist and Zakrajšek (2012), He and Xiong (2012), Morris and Shin (2016), Valenzuela (2016), Ivashina and Scharfstein (2010), Cornett et al. (2011), and Iyer et al. (2014).

3 Data and Measures

Our sample consists of all common shares (share codes 10 and 11) traded on the NYSE, AMEX, and NASDAQ between July 1977 and June 2014.[4] We obtain stock return data from the Center for Research in Security Prices (CRSP) and accounting data from the CRSP/Compustat Merged Database. We exclude financial firms (SIC codes between 6000 and 6999) from our sample. For delisted stocks, we use the CRSP delisting returns if they are available; otherwise, we follow Shumway (1997), Shumway and Warther (1999), and Beaver et al. (2007) and adjust for missing returns if the delisting is performance-related. We extract the data of the Fama and French (2015) five factors from Kenneth French's website[5] and obtain the returns on the market value of equity, profitability, and investment factors of the q-factor model of Hou et al. (2015) from Lu Zhang.[6]

3.1 Measure of distress risk

Campbell et al. (2008) develop a measure of distress risk, based on the failure probability score of a stock using a logit model, following Shumway (2001) and Chava and Jarrow (2004). By using market values, their method offers a more accurate approach for identifying distress risk because market value reflects investors' expectations about a firm's prospects, based on new information. Appendix A provides details of the distress risk measure.

[4]The sample period starts in July 1977 due to the limited data coverage for the distress measure and the independent double sort method.

[5]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

[6]We thank Professor Lu Zhang for providing the market value of equity, profitability, and investment factors.

3.2 Measure of cash flow volatility

Following Hou et al. (2015), we calculate cash flow as the ratio of income before extraordinary items (Compustat quarterly item IBQ), plus equity's share of depreciation (item DPQ), plus deferred taxes (if available, item $TXDIQ$) to the book value of the total assets (item ATQ). Cash flow volatility is calculated as the standard deviation of the cash flow-to-assets ratio for the prior 24 months, following Bates et al. (2009).

4 Empirical Results

4.1 Summary statistics and the return performance of distress risk portfolios

Table I reports summary statistics and correlation coefficients among the variables, including the distress risk measure (DR), the market capitalization of equity (MV), book-to-market ratio (B/M), momentum (MOM), gross profitability-to-assets ratio (GP), asset growth ratio (AG), and cash flow volatility (CFV). Appendix B provides descriptions of these variables. Table I shows that DR is negatively correlated with MV, GP, and AG, while positively correlated with B/M. The results suggest that firms with high distress risk tend to be small and value firms with lower profitability and low levels of investment in assets, while firms with low distress risk are large and growth firms with higher profitability and high levels of investment in assets. Consistent with Minton and Schrand (1999) and Hackbarth

et al. (2006), distress risk is positively correlated with cash flow volatility, with a correlation coefficient of 0.449, indicating that firms with high distress risk have higher cash flow volatility.

To investigate the return performance of distress risk portfolios, we follow Conrad et al. (2014) and form distress risk (DR) portfolios on a monthly basis. Specifically, at the end of each month of year t, we sort stocks based on their past month's distress risk (DR) measure and form decile portfolios using NYSE breakpoints. We hold the portfolios for the subsequent month and rebalance them every month during the sample period.

Table II reports the monthly average returns over the risk-free rate and abnormal returns of value-weighted distress risk portfolios from the time-series factor models. DR_1 represents the bottom distress risk portfolio that contains stocks with the lowest failure probability scores and DR_{10} represents the top distress risk portfolio that contains stocks with the highest failure probability scores. ΔDR represents the long-short portfolio that takes long positions in the bottom distress risk portfolio (DR_1) and short positions in the top distress risk portfolio (DR_{10}).

The abnormal returns are the intercepts of the capital asset pricing model (henceforth CAPM) of Sharpe (1964) and Lintner (1965), the Fama and French (1993) three-factor model

(henceforth FF3) and five-factor model (henceforth FF5), and the q-factor model of Hou et al. (2015) (henceforth HXZ) in the following equations, respectively:

$$R_{p,t} - R_{f,t} = \alpha_{CAPM} + \beta_{p,mkt}(R_{mkt,t} - R_{f,t}) + \varepsilon_{p,t}, \tag{1}$$

$$R_{p,t} - R_{f,t} = \alpha_{FF3} + \beta_{p,mkt}(R_{mkt,t} - R_{f,t}) + \beta_{p,smb}SMB_t + \beta_{p,hml}HML_t + \varepsilon_{p,t}, \tag{2}$$

$$\begin{aligned} R_{p,t} - R_{f,t} &= \alpha_{FF5} + \beta_{p,mkt}(R_{mkt,t} - R_{f,t}) + \beta_{p,smb}SMB_t + \beta_{p,hml}HML_t \\ &+ \beta_{p,rmw}RMW_t + \beta_{p,cma}CMA_t + \varepsilon_{p,t}, \end{aligned} \tag{3}$$

$$R_{p,t} - R_{f,t} = \alpha_{HXZ} + \beta_{p,mkt}(R_{me,t} - R_{f,t}) + \beta_{p,me}ME_t + \beta_{p,roe}ROE_t + \beta_{p,ia}IA_t + \varepsilon_{p,t}, \tag{4}$$

where $R_{p,t}$ is the return on portfolio p in month t, $R_{f,t}$ is the risk-free rate in month t, $R_{mkt,t}$ is the value-weighted return on all stocks listed on the NYSE, AMEX, and NASDAQ, SMB_t (Small-Minus-Big), HML_t (High-Minus-Low), RMW_t (Robust-Minus-Weak), and CMA_t (Conservative-Minus-Aggressive) are the differences between the returns on diversified portfolios of small and big stocks, high and low B/M stocks, stocks with robust and weak profitability, and stocks with conservative and aggressive investment, ME_t (Market value of Equity), ROE_t (Return-On-Equity), and IA_t (Investment-to-Assets) are the returns on the mimicking portfolios for size, profitability, and investment of the q-factor model of Hou et al. (2015).

O'Doherty (2012) finds that the distress risk effect can be explained by the conditional CAPM (henceforth CCAPM). Following his methodology, we examine the abnormal returns on distress risk portfolios from the CCAPM as follows:

$$\begin{aligned} R_{p,t} - R_{f,t} \;=\; & \alpha_{CCAPM} + \beta_{p,t}(R_{mkt,t} - R_{f,t}) + \beta_{p,t-1}(R_{mkt,t-1} - R_{f,t-1}) \\ + \;\; & \beta_{p,t-2}\sum_{i=2}^{4}(R_{mkt,t-i} - R_{f,t-i})/3 + \varepsilon_{p,t}, \end{aligned} \tag{5}$$

We run Equation (5) each month to obtain the estimated conditional risk $\hat{\beta}_{p,cmkt} = \hat{\beta}_{p,t} + \hat{\beta}_{p,t-1} + \hat{\beta}_{p,t-2}$. We then use the lagged estimates of $\hat{\beta}_{p,t}$, $\hat{\beta}_{p,t-1}$, and $\hat{\beta}_{p,t-2}$ to calculate the conditional alpha (α_{CCAPM}) based on Equation (5).

In line with Campbell et al. (2008, 2011), Table II shows that the returns decrease almost monotonically from portfolio DR_1 to portfolio DR_{10}. Moreover, DR_{10} significantly underperforms DR_1. These findings are consistent regardless of the return measures based on the asset pricing models above except for the CCAPM. For example, the long-short portfolio, ΔDR, earns an average excess return of 0.789% (t= 2.57) per month, α_{CAPM} of 1.202% (t= 4.47) per month, α_{FF3} of 1.497% (t= 6.47) per month, α_{FF5} of 0.94% (t= 4.08) per month, and α_{HXZ} of 0.441% (t= 2.18) per month. Consistent with the findings of Campbell et al. (2008), Stambaugh et al. (2012), and Chu et al. (2020), the significant abnormal returns on the long-short portfolio are mainly generated by short-selling stocks in DR_{10} except for the anomaly estimated from the HXZ model. The CCAPM estimates an insignificant abnormal return on the long-short portfolio, which is in line with the finding of O'Doherty (2012).

To further assess the robustness of our results, we augment our asset pricing models with the lottery demand factor (FMAX) from Bali et al. (2017).[7] We find that including FMAX reduces the alpha spread on DR-sorted portfolios (ΔDR), though the spread remains statistically significant in most specifications.

Table III presents the mean of various firm characteristics and statistical properties of DR decile portfolios. The reported firm characteristics are DR, MV, B/M, GP, AG, CFV, *Leverage*, the ratio of research and development to sales ($R\&D$), and dividend payout ratio (PR). Following Bali et al. (2011) and Conrad et al. (2014), Table III also reports the average idiosyncratic volatility ($IVOL$), standard deviation (SD), skewness of daily returns of each stock over the next 12 months, and the averages of five highest daily returns during the month (MAX) of DR portfolios. The definitions and measures of firm characteristics and statistical properties are given in Appendix B. We estimate the time-series averages of cross-sectional means.

Table III confirms that firms in DR_{10} are small and value firms with the lowest MV and highest B/M among DR portfolios. They generate the lowest gross profits with the least asset growth, use stock repurchase to distribute profits to shareholders rather than paying dividends (low GP, AG, and negative PR), and have a high R&D ratio. Consistent with Conrad et al. (2014), stocks in DR_{10} have strong lottery features with higher idiosyncratic volatility, skewness, and maximum daily returns than stocks in other DR portfolios. More importantly, lottery-like stocks in DR_{10} have high cash flow risk. In contrast, firms in DR_1 are large and growth firms. They produce higher profits and pay more out in dividends.

[7] We thank an anonymous referee for suggesting this test.

In summary, our results are in line with the studies of Barberis and Huang (2008) and Conrad et al. (2014) that distressed stocks are lottery-like stocks. Investors have preferences for this type of stock and overprice them, leading to their low future returns and the strong distress risk anomaly.

4.2 Cash flow volatility and the financial distress risk anomaly

To examine whether the distress risk anomaly is dependent on cash flow volatility, we use a two-way portfolio sorts approach based on stocks' cash flow volatility and the distress risk measure. We examine the variation of excess returns and the abnormal returns from the factor models for two-way sorted portfolios. We also run Fama and MacBeth (1973) cross-sectional regressions to examine the impact of distress risk in stock returns for high and low cash flow volatility subsamples.

4.2.1 Two-way portfolio sorts

At the end of each month of year t, we sort all stocks in our sample into quintiles based on their lagged distress risk measures and independently sort all stocks into terciles based on their lagged cash flow volatility using NYSE breakpoints to ensure each portfolio has enough stocks. The intersections of the two groups produce 15 $DR\text{-}CFV$ portfolios. We hold the portfolios for the subsequent month and rebalance them monthly. Table IV presents the statistical properties of $DR\text{-}CFV$ portfolios. Subscript 1 indicates the bottom quintile or tercile and subscript 5 (3) indicates the top quintile (tercile). ΔDR again denotes the long-

short distress risk portfolio. In line with our hypothesis, distress stocks with a high cash flow volatility in portfolio DR_5-CFV_3 tend to be extreme lottery-like stocks because they have the highest idiosyncratic volatility, standard deviations, positive skewness, and average maximum returns across DR-CFV portfolios.

Table V reports the monthly average excess returns and abnormal returns on value-weighted two-way sorted portfolios. Ranking stocks by distress risk and holding cash flow volatility fixed, Table V shows that DR_5s uniformly underperform DR_1s across various measures of return except for the α_{HXZ} of CFV_1 and CFV_2, and the α_{CCAPM} of CFV_2. The magnitude and significance of the distress risk effect (the returns on portfolio ΔDR) increase with cash flow volatility. For instance, the α_{FF5} of ΔDR is 0.235% (t= 0.90) per month for CFR_1, 0.260% (t= 1.09) per month for CFR_2, and 0.905% (t= 3.92) per month for CFR_3. The α_{CCAPM} of ΔDR is 0.04% (t= 0.14) per month for CFR_1, and 0.627% (t= 2.38) per month for CFR_3. Consistent with our hypothesis, the results suggest that the distress risk anomaly varies strongly with the degree of cash flow volatility and is more pronounced for the portfolio that consists of stocks with high cash flow volatility.

Holding distress risk fixed, CFV_3 outperforms CFV_1 in DR_1 (firms with the lowest distress risk) and underperforms CFV_1 in DR_5 (firms with the highest distress risk), suggesting that the relation between cash flow volatility and stock returns varies with the level of distress risk. Overall, we find that distressed stocks with high cash flow volatility have strong lottery features and the distress risk anomaly is concentrated in these extreme lottery-like stocks.

Our results are in support of the behavioral explanation of reference-dependent preferences that investors have cash flow volatility-dependent preferences for distressed stocks.

4.2.2 Cross-sectional regressions

Fama and French (2008) argue that although the portfolio sorts approach provides a clear pattern of returns across different portfolios, the approach is hard to precisely identify the explanatory variables for average returns. We conduct Fama and MacBeth (1973) cross-sectional regressions in this subsection. Fama and French (2008) also point out that regression estimates based on all stocks can be driven by stocks with extreme values of the explanatory variables and extreme returns. To avoid this problem, we split the full sample into three subsamples according to stocks' cash flow volatility. Specifically, at the end of each month, we rank all stocks into terciles based on their lagged cash flow volatility using NYSE breakpoints and run the following cross-sectional regressions for the high and low cash flow volatility subsamples:

$$R_{i,t+1} - R_{f,\,t+1} = \gamma_0 + \gamma_1 DR_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} + \gamma_4 MOM_{i,t} + \varepsilon_{i,t+1}, \quad (6)$$

$$\begin{aligned} R_{i,t+1} - R_{f,\,t+1} &= \gamma_0 + \gamma_1 DR_{i,t} + \gamma_2 ln(MV)_{i,t} + \gamma_3 ln(B/M)_{i,t} + \gamma_4 MOM_{i,t} \\ &+ \gamma_5 GP_{i,t} + \gamma_6 AG_{i,t} + \varepsilon_{i,t+1}, \end{aligned} \quad (7)$$

where $R_{i,t+1}$ is the monthly returns from July of year t to June of year $t+1$, $R_{f,\,t+1}$ is the risk-free rate, DR is the distress risk variable, $ln(MV)$ is the natural logarithm of the market value of equity at the end of June of year t, $ln(B/M)$ is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year $t-1$ divided by the market value of

equity at the end of June of year t, MOM is the cumulative compounded stock returns of the previous 6 months from June of year t to May of year $t+1$, GP is the gross profitability ratio for the fiscal year ending in year $t-1$, and AG is the asset growth ratio for the fiscal year ending in year $t-1$. We expect that the coefficients on distress risk should be negative and greater in magnitude in the top cash flow volatility subsample than in the bottom subsample.

Table VI reports the estimates from Fama and MacBeth (1973) cross-sectional regressions. "Low" and "High" denote the subsamples that comprise stocks in the bottom and top terciles of cash flow volatility, respectively. "High-Low" is the difference between the top and bottom subsamples. After controlling for the size, book-to-market ratio, and momentum variables, the coefficients on distress risk are negative across the low and high cash flow volatility subsamples and are significant for the high subsample and insignificant for the low subsample. Furthermore, the coefficient on distress risk is strong for the high-low subsample. For instance, the coefficient on DR is -0.137 (t= -1.85) in the low cash flow volatility tercile and -0.382 (t= -5.45) in the high cash flow volatility tercile. The difference between high and low terciles is -0.244 (t= -3.95). These patterns remain after further controlling for the gross profitability and asset growth variables. The results suggest that the strong predictive power of distress risk for the cross-section of stock returns is dominated by stocks with high cash flow volatility.

To further examine whether the preference for lottery-like stocks contributes to the return premium associated with DR, we augment the Fama-MacBeth regressions in Table VI with the MAX variable, which is the average of the five highest daily returns during a

month following Bali et al. (2011), as a proxy for investor demand for lottery-type payoffs. The results indicate that including MAX attenuates both the magnitude and significance of the slope coefficient on DR across the high versus low cash flow risk subsamples. The results remain qualitatively similar when using MAX(1), as the highest daily returns during a month instead. This pattern suggests that a portion of the predictive power of DR is attributable to investors' willingness to hold stocks with lottery-like return distributions, consistent with prior evidence (e.g., Conrad et al., 2014; Bali et al., 2020).

4.3 Credit market conditions and the financial distress risk anomaly

He and Xiong (2012), Gilchrist and Zakrajšek (2012), Valenzuela (2016), and Chen et al. (2018) find that financial distress risk is highly influenced by credit market conditions. In this subsection, we explore how the distress risk anomaly varies with credit market conditions. Following Campello and Chen (2010), we use the bank loan spread between the bank prime loan rate and the 4-week Treasury bill rate to capture credit market conditions.[8] Specifically, we define a good credit time as a period with a reduction in the bank loan spread (negative change), and a bad credit time as a period with an increase in the spread (positive change). We then split the full sample period into the good and bad credit times subsamples and examine the performance of distress risk portfolios in the subsamples.

Table VII reports the monthly average excess returns and abnormal returns on value-weighted distress risk portfolios in good and bad credit times. Interestingly, the average excess

[8]We also use an alternative measure of commercial paper spread as a proxy for credit market conditions and conduct the same tests. The results are similar to those measured by bank loan spread.

returns on DR portfolios and the abnormal returns of DR_3 to DR_{10} in good credit times are greater than those of corresponding portfolios in bad credit times. However, the distress risk effects (the returns on ΔDR) are generally stronger in bad credit times than in good credit times. For instance, the α_{FF3} of ΔDR is 1.183% (t= 1.73) per month in good credit times and 1.742% (t= 7.14) per month in bad credit times. Moreover, short-selling distressed stocks in bad credit times contribute a large portion of the anomaly after adjusting for various risks with only one exception from the q-factor model of Hou et al. (2015). These results support our hypothesis that the distress risk anomaly is stronger in bad credit times than in good credit times.

Table VII also presents the results of the statistical properties of DR portfolios in good and bad credit times. Consistent with our hypothesis, DR_{10} in bad credit times has the largest idiosyncratic volatility, standard deviation, skewness, and MAX across DR portfolios among both good and bad credit times, indicating that distressed stocks in bad credit times tend to have extreme lottery features. The results further confirm the behavioral interpretation of the distress risk anomaly. In addition, investors also have credit market conditions-dependent preferences for distressed stocks.

Next, we run Fama and MacBeth (1973) cross-sectional regressions of monthly excess returns in Equations (6) and (7) for the good and bad credit times subsamples. Table VIII shows that the coefficients of distress risk are significantly negative in bad credit times, but they are indistinguishable from zero in good credit times. For example, after controlling for the size, book-to-market ratio, momentum, gross profitability, and asset growth variables, the

coefficient on DR is -0.102 (t= -0.62) in good credit times and is -0.244 (t= -2.65) in bad credit times. The results imply that the strong impact of distress risk on stock returns is driven by poor credit market conditions.

We finally conduct a further analysis in Table VIII by including MAX in the Fama-MacBeth regressions across different credit market conditions. Consistent with our findings in Table VI, controlling for investors' lottery demand reduces the slope coefficient on DR, suggesting that lottery preferences partially drive the DR premium.

4.4 The impact of distress risk conditional on cash flow volatility and credit market conditions

Our previous results indicate that both cash flow volatility and credit market conditions affect the predictability of distress risk for the cross-section of stock returns. In this subsection, we further investigate how cash flow volatility and credit market conditions work together to influence the predictive power of distress risk. Following the methods in Table VI and Table VIII, we form three cash flow volatility subsamples and run Fama and MacBeth (1973) cross-sectional regressions of Equation (7) for the low and high cash flow volatility groups in good and bad credit times separately.

Table IX shows that the coefficients on distress risk are insignificant in both low and high cash flow volatility subsamples in good credit times, However, in bad credit times, the coefficient is significantly negative in the high cash flow volatility subsample and is insignificant in the low cash flow volatility subsamples. For instance, in bad credit times, the coefficient

on DR is -0.281 (t= -3.20) for the high cash flow volatility subsample and -0.79 (t= -0.92) for the low subsample. The differences between high and low subsamples are statistically significant in both good and bad credit times. Overall, the results are consistent with our hypothesis that the strong predictive power of distress risk for stock returns is not systematic for all stocks, but it is driven by stocks with high cash flow volatility in bad credit times.

4.5 Robustness tests

Brennan et al. (1998) argue that the standard Fama and MacBeth (1973) approach may suffer from a measurement error problem, which is associated with the factor loadings. The authors advocate that using risk-adjusted returns as the dependent variable in Fama and MacBeth (1973) cross-sectional regression can avoid the errors-in-variables problem. We follow their approach and calculate the risk-adjusted returns based on the Fama and French (1993) three-factor model from the following equation:

$$\begin{aligned} R^*_{i,t} &= R_{i,t} - R_{f,t} - \beta_{i,m} f_{MKT,t} - \beta_{i,s} f_{SMB,t} - \beta_{i,h} f_{HML,t} \\ &= \alpha_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{8}$$

where $R^*_{i,t+1}$ is the monthly percentage risk-adjusted returns between July of year t and June of year $t+1$, which is the sum of the average intercept ($\alpha_{i,t}$) and residual ($\varepsilon_{i,t}$) from the time-series regression using the 36-month rolling window. We perform Fama and MacBeth (1973) cross-sectional regressions in the same way as those reported in Table IX by using the risk-adjusted returns as the dependent variable. Panel A of Table X shows that employing risk-adjusted returns does not change the pattern that the coefficients on distress risk are

larger in magnitude and significance in the high cash flow volatility subsample than in the low cash flow volatility subsample in both good and bad credit times.

Fama and French (2008) argue that microcap stocks account for about 60% of all stocks, which can affect portfolio returns. The premium in microcap stocks tends to be unprofitable in practice due to high transaction costs. Following their study, we define stocks with a market capitalization below 20% of the total market capitalization of NYSE stocks as microcaps. To eliminate the impact of microcap stocks on the relation between distress risk and stock returns, we follow Green et al. (2017) by excluding microcap stocks from our sample and conducting the cross-sectional regressions of Table IX again. The results in Panel B of Table X mirror the pattern in Table IX that the impact of distress risk on stock returns is dominated by stocks with high cash flow volatility in bad credit times.

5 Conclusion

We examine the reference-dependent preferences explanation based on cash flow volatility and credit market conditions for the distress risk anomaly. We find that distressed stocks with a high cash flow volatility or in bad credit times have strong lottery features, such as the highest idiosyncratic volatility, positive skewness, and maximum daily returns among distress risk portfolios. Moreover, the distress risk anomaly is large among stocks with high cash flow volatility and in bad credit times, while it is small among stocks with low cash flow volatility and in good credit times.

The existing literature shows that distress risk is negatively priced in the cross-section of stock returns (Vassalou and Xing, 2004; George and Hwang, 2010; Li et al., 2017). We find that the impact of distress risk varies with the degree of cash flow volatility and credit market conditions. Specifically, the predictive power of distress risk for the cross-section of expected returns is significantly negative only for stocks with high cash flow volatility in bad credit times but is insignificant for stocks with low cash flow volatility and in good credit times. Overall, our findings are in support of the reference-dependent preferences interpretation that the distress risk anomaly is due to investors' preferences for distressed stocks, but their preferences are dependent on cash flow volatility and credit market conditions.

References

Almeida, H. and T. Philippon (2007). The risk-adjusted cost of financial distress. *Journal of Finance 62*(6), 2557–2586.

An, L., H. Wang, J. Wang, and J. Yu (2020). Lottery-related anomalies: The role of reference-dependent preferences. *Management Science 66*(1), 473–501.

Bali, T. G., S. J. Brown, S. Murray, and Y. Tan (2017). A lottery-demand-based explanation of the beta anomaly. *Journal of Financial and Quantitative Analysis 52*(6), 2369–2397.

Bali, T. G., N. Cakici, and R. F. Whitelaw (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics 99*, 427–446.

Bali, T. G., L. D. Viva, N. Lambertides, and L. Trigeorgis (2020). Growth options and related stock market anomalies: Profitability, distress, lotteryness, and volatility. *Journal of Financial and Quantitative Analysis 55*(7), 2150–2180.

Barberis, N. and M. Huang (2008). Stocks as lotteries: The implications of probability weighting for security prices. *American Economic Review 98*(5), 2066–2100.

Barberis, N., M. Huang, and T. Santos (2001). Prospect theory and asset prices. *The Quarterly Journal of Economics 116*(1), 1–53.

Bates, T. W., K. M. Kahle, and R. M. Stulz (2009). Why do U.S. firms hold so much more cash than they used to? *Journal of Finance 64*(5), 1985–2021.

Beaver, W., M. McNichols, and R. Price (2007). Delisting returns and their effect on accounting-based market anomalies. *Journal of Accounting & Economics 43*(2/3), 341–368.

Bordalo, P., N. Gennaioli, and A. Shleifer (2013). Salience and asset prices. *American Economic Review 103*(3), 623–628.

Boyer, B., T. Mitton, and K. Vorkink (2010). Expected idiosyncratic skewness. *Review of Financial Studies 23*(1), 169–202.

Brennan, M. J., T. Chordia, and A. Subrahmanyam (1998). Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics 49*(3), 345–373.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Campbell, J. Y., J. Hilscher, and J. A. N. Szilagyi (2008). In search of distress risk. *Journal of Finance 63*(6), 2899–2939.

Campbell, J. Y., J. Hilscher, and J. A. N. Szilagyi (2011). Predicting financial distress and the performance of distressed stocks. *Journal of Investment Management 9*(2), 14–34.

Campello, M. and L. Chen (2010). Are financial constraints priced? evidence from firm fundamentals and stock returns. *Journal of Money, Credit and Banking 42*(6), 1185–1198.

Chan, K. and N. Chen (1991). Structural and return characteristics of small and large firms. *Journal of Finance 46*(4), 1467–1484.

Chava, S. and R. A. Jarrow (2004). Bankruptcy prediction with industry effects. *Review of Finance 8*, 537–569.

Chava, S. and A. Purnanandam (2010). Is default risk negatively related to stock returns? *Review of Financial Studies 23*(6), 2523–2559.

Chen, H. (2010). Macroeconomic conditions and the puzzles of credit spreads and capital structure. *Journal of Finance 65*(6), 2171–2212.

Chen, H., R. Cui, Z. He, and K. Milbradt (2018). Quantifying liquidity and default risks of corporate bonds over the business cycle. *Review of Financial Studies 31*(3), 852–897.

Chen, J., L. Chollete, and R. Ray (2010). Financial distress and idiosyncratic volatility: An empirical investigation. *Journal of Financial Markets 13*, 249–267.

Chen, N. and F. Zhang (1998). Risk and return of value stocks. *Journal of Business 71*(4), 501–535.

Chu, Y., D. Hirshleifer, and L. Ma (2020). The causal effect of limits to arbitrage on asset pricing anomalies. *Journal of Finance 75*(5), 2631–2672.

Conrad, J., N. Kapadia, and Y. Xing (2014). Death and jackpot: Why do individual investors hold overpriced stocks? *Journal of Financial Economics 113*(3), 455–475.

Cornett, M. M., J. J. McNutt, P. E. Strahan, and H. Tehranian (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics 101*(2), 297–312.

Cosemans, M. and R. Frehen (2021). Salience theory and stock prices: Empirical evidence. *Journal of Financial Economics 140*(2), 460–483.

Dertwinkel-Kalt, M. and M. Köster (2020). Salience and skewness preferences. *Journal of the European Economic Association 18*(5), 2057–2107.

Dichev, I. D. (1998). Is the risk of bankruptcy a systematic risk? *Journal of Finance 53*(3), 1131–1147.

Ericsson, J. and O. Renault (2006). Liquidity and credit risk. *Journal of Finance 61*(5), 2219–2250.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*(1), 3–56.

Fama, E. F. and K. R. French (1995). Size and book-to-market factors in earnings and returns. *Journal of Finance 50*(1), 131–155.

Fama, E. F. and K. R. French (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance 51*(1), 55–84.

Fama, E. F. and K. R. French (2008). Dissecting anomalies. *Journal of Finance 63*(4), 1653–1678.

Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116*(1), 1–22.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy 81*(3), 607–636.

Gao, P., C. A. Parsons, and J. Shen (2017). The global relation between financial distress and equity returns. *Review of Financial Studies 31*(1), 239–277.

Gao, X., K. G. Koedijk, and Z. Wang (2021). Volatility-dependent skewness preference. *Journal of Portfolio Management DOI: https://doi.org/10.3905/jpm.2021.1.295*.

Garlappi, L. and H. Yan (2011). Financial distress and the cross-section of equity returns. *Journal of Finance 66*(3), 789–822.

George, T. J. and C.-Y. Hwang (2010). A resolution of the distress risk and leverage puzzles in the cross section of stock returns. *Journal of Financial Economics 96*(1), 56–79.

Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *The American Economic Review 102*(4), 1692–1720.

Green, J., J. R. M. Hand, and X. F. Zhang (2017). The characteristics that provide independent information about average U.S. monthly stock returns. *Review of Financial Studies 30*(12), 4389–4436.

Griffin, J. M. and M. L. Lemmon (2002). Book-to-market equity, distress risk, and stock returns. *Journal of Finance 57*(5), 2317–2336.

Hackbarth, D., R. Haselmann, and D. Schoenherr (2015). Financial distress, stock returns, and the 1978 Bankruptcy Reform Act. *Review of Financial Studies 28*(6), 1810–1847.

Hackbarth, D., J. Miao, and E. Morellec (2006). Capital structure, credit risk, and macroeconomic conditions. *Journal of Financial Economics 82*, 519–550.

He, Z. and W. Xiong (2012). Rollover risk and credit risk. *Journal of Finance 67*(2), 391–430.

Hou, K., C. Xue, and L. Zhang (2015). Digesting anomalies: An investment approach. *Review of Financial Studies 28*(3), 650–705.

Ivashina, V. and D. Scharfstein (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics 97*(3), 319–338.

Iyer, R., J.-L. Peydró, S. da Rocha-Lopes, and A. Schoar (2014). Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007–2009 Crisis. *Review of Financial Studies 27*(1), 347–372.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica 47*(2), 263–292.

Kumar, A. (2009). Who gambles in the stock market? *Journal of Finance 64*(4), 1889–1933.

Kőszegi, B. and M. Rabin (2006). A model of reference-dependent preferences. *Quarterly Journal of Economics 97*(4), 1047–1073.

Kőszegi, B. and M. Rabin (2007). Reference-dependent risk attitudes. *The American Economic Review 97*(4), 1047–1–73.

Li, K., J. Lockwood, and H. Miao (2017). Risk-shifting, equity risk, and the distress puzzle. *Journal of Corporate Finance 44*, 275–288.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics 47*(1), 13–37.

Liu, B., H. Wang, J. Yu, and S. Zhao (2020). Time-varying demand for lottery: Speculation ahead of earnings announcements. *Journal of Financial Economics 138*, 789–817.

Merton, R. C. (1974). On the pricing of corporate debt: the risk structure of interest rates. *Journal of Finance 29*, 449–470.

Minton, B. A. and C. Schrand (1999). The impact of cash flow volatility on discretionary investment and the costs of debt and equity financing. *Journal of Financial Economics 54*, 423–460.

Morris, S. and H. S. Shin (2016). Illiquidity component of credit risk - The 2016 Lawrence R. Klein lecture. *International Economic Review 57*(4), 1135–1148.

O'Doherty, M. S. (2012). On the conditional risk and performance of financially distressed stocks. *Management Science 58*(8), 1502–1520.

O'Donoghue, T. and C. Sprenger (2018). *Chapter 1 - Reference-dependent preferences, Handbook of Behavioral Economics*, Volume 1 of *Applications and Foundations 1*. p1-77: Elsevier Science.

Pesaran, M. H., T. Schuermann, B.-J. Treutler, and S. M. Weiner (2006). Macroeconomic dynamics and credit risk: a global perspective. *Journal of Money, Credit, and Banking 38*, 1211–1262.

Rountree, B., J. Weston, and G. Allayannis (2008). Do investors value smooth performance? *Journal of Financial Economics 90*, 237–251.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance 19*(3), 425–442.

Shumway, T. (1997). The delisting bias in CRSP data. *Journal of Finance 52*(1), 327–340.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business 74*(1), 101–124.

Shumway, T. and V. A. Warther (1999). The delisting bias in CRSP's Nasdaq data and its implications for the size effect. *Journal of Finance 54*(6), 2361–2379.

Stambaugh, R. F., J. Yu, and Y. Yuan (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics 104*, 288–302.

Tang, D. Y. and H. Yan (2010). Market conditions, default risk and credit spreads. *Journal of Banking & Finance 34*, 743–753.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*(4), 297–323.

Valenzuela, P. (2016). Rollover risk and credit spreads: Evidence from international corporate bonds. *Review of Finance 20*(2), 631–661.

Vassalou, M. and Y. Xing (2004). Default risk in equity returns. *Journal of Finance 59*(2), 831–868.

Wang, H., J. Yan, and J. Yu (2017). Reference-dependent preferences and the risk–return trade-off. *Journal of Financial Economics 123*, 395–414.

Werner, K. M. and H. Zank (2019). A revealed reference point for prospect theory. *Economic Theory 67*, 731–773.

Xu, Z., T. Chevapatrakul, and X. Li (2019). Return asymmetry and the cross section of stock returns. *Journal of International Money and Finance 97*, 93–110.

Table I Descriptive statistics

This table reports the mean, standard deviation (SD), minimum (Min), median, maximum (Max), and correlation coefficients between the variables of a distress risk measure (DR), measured by the failure probability score of stocks (Campbell et al., 2008), the market capitalization of equity (MV, measured in million dollars), book-to-market ratio (B/M), momentum (MOM), gross profitability ratio (GP), asset growth ratio (AG), cash flow risk (CFR), and leverage ($Leverage$). Appendix A provides a detailed measure of DR. Appendix B provides definitions for the remaining variables. We report the Spearman rank correlations in this table. The sample includes non-financial ordinary common stocks for the period from 1977 to 2014.

Descriptive statistics								
	DR	$MV(\$m)$	B/M	MOM	GP	AG	CFR	$Leverage$
Mean	-7.987	1968	0.845	0.134	0.369	0.163	0.030	0.228
SD	1.449	11726	1.493	0.540	0.327	1.063	0.073	0.199
Min	-11.806	0.040	0.000	-0.995	-18.871	-1.000	0.000	0.000
Median	-8.381	142	0.600	0.064	0.342	0.068	0.013	0.206
Max	-2.162	547363	191.497	65.056	4.853	233.360	16.402	6.746
Spearman correlations								
$MV(\$m)$	-0.450	1.000						
B/M	0.219	-0.316	1.000					
MOM	-0.192	0.106	-0.239	1.000				
GP	-0.229	-0.038	-0.196	0.053	1.000			
AG	-0.261	0.240	-0.267	-0.079	0.054	1.000		
CFR	0.449	-0.378	-0.079	-0.079	-0.010	-0.183	1.000	
$Leverage$	0.263	0.069	0.128	0.011	-0.234	-0.017	-0.136	1.000

Table II Returns on distress risk decile portfolios

This table reports the value-weighted monthly average excess returns ($R_{p,t} - R_{f,t}$) and abnormal returns on distress risk (DR) portfolios. The abnormal returns are the intercepts of the capital asset pricing model (CAPM), Fama and French (1993) three-factor model (FF3), Fama and French (2015) five-factor model (FF5), q-factor model of Hou et al. (2015) (HXZ), and the conditional CAPM (CCAPM) of O'Doherty (2012). At the end of each month of year t, we sort stocks into deciles based on their lagged DR using NYSE breakpoints and hold the portfolios for the subsequent month. DR_1 represents a portfolio that comprises stocks with the lowest DR. DR_{10} represents a portfolio that contains stocks with the highest DR. ΔDR represents the long-short portfolio that takes long positions in DR_1 and short positions in DR_{10}. The sample period covers July 1977 to June 2014.

	DR_1	DR_2	DR_3	DR_4	DR_5	DR_6	DR_7	DR_8	DR_9	DR_{10}	ΔDR
$R_{p,t} - R_{f,t}$	0.897	0.730	0.667	0.616	0.677	0.546	0.488	0.701	0.575	0.108	0.789
	(4.11)	(3.54)	(3.19)	(2.96)	(3.01)	(2.36)	(1.84)	(2.50)	(1.74)	(0.27)	(2.57)
α_{CAPM}	0.337	0.169	0.090	0.048	0.057	-0.089	-0.221	-0.040	-0.289	-0.865	1.202
	(3.14)	(2.20)	(1.26)	(0.62)	(0.75)	(-1.09)	(-2.10)	(-0.33)	(-1.93)	(-3.79)	(4.47)
α_{FF3}	0.436	0.225	0.141	0.083	0.021	-0.112	-0.319	-0.157	-0.429	-1.062	1.497
	(4.21)	(2.91)	(2.00)	(1.10)	(0.27)	(-1.33)	(-3.23)	(-1.26)	(-3.07)	(-5.81)	(6.47)
α_{FF5}	0.337	0.058	0.024	0.007	0.007	-0.111	-0.247	-0.011	-0.144	-0.602	0.940
	(2.84)	(0.74)	(0.31)	(0.09)	(0.08)	(-1.25)	(-2.30)	(-0.08)	(-0.96)	(-3.59)	(4.08)
α_{HXZ}	0.257	-0.043	0.037	-0.007	0.053	-0.030	-0.087	0.222	0.148	-0.184	0.441
	(2.07)	(-0.52)	(0.40)	(-0.08)	(0.59)	(-0.31)	(-0.78)	(1.70)	(0.95)	(-1.23)	(2.18)
α_{CCAPM}	0.168	0.120	0.148	0.123	0.177	-0.066	-0.084	0.172	-0.026	-0.324	0.492
	(1.47)	(1.43)	(1.67)	(1.31)	(1.92)	(-0.73)	(-0.75)	(1.28)	(-0.15)	(-1.29)	(1.68)

Table III Firm characteristics and statistical properties of distress risk portfolios

This table reports the mean of firm characteristics and statistical properties of distress risk (DR) portfolios. At the end of each month of year t, we sort stocks into deciles based on their lagged DR using NYSE breakpoints and hold the portfolios for the subsequent month. The DR portfolios are rebalanced monthly. DR_1 represents a portfolio that comprises stocks with the lowest DR. DR_{10} represents a portfolio that contains stocks with the highest DR. The reported firm characteristics are market capitalization of equity (MV, in million dollars), book-to-market ratio (B/M), gross profitability ratio (GP), asset growth ratio (AG), cash flow risk (CFR), leverage ($Leverage$), research and development-to-sales ratio ($R\&D$), and dividend payout ratio (PR). The reported statistical properties are the average idiosyncratic risk ($IVOL$), standard deviation (SD), skewness, and maximum daily returns (MAX) of DR portfolios. $IVOL$ is the standard deviations of residuals from the Fama and French (1993) three-factor model over the prior 12 months with a minimum of 100 days. SD and skewness are estimated from the daily returns of each stock over the next 12 months following Conrad et al. (2014). MAX is the average of the five highest daily returns during a month following Bali et al. (2011). They are the time-series averages of cross-sectional means. Appendix A provides a detailed measure of DR. Appendix B provides definitions for the remaining variables. The sample period covers July 1977 to June 2014.

	DR_1	DR_2	DR_3	DR_4	DR_5	DR_6	DR_7	DR_8	DR_9	DR_{10}
DR	-9.744	-9.291	-9.096	-8.930	-8.769	-8.595	-8.388	-8.103	-7.614	-5.999
MV(\$m)	3764	4327	3902	3198	2420	2152	1736	1198	542	188
B/M	0.688	0.580	0.608	0.651	0.699	0.756	0.810	0.886	0.985	1.345
GP	0.469	0.471	0.437	0.412	0.391	0.373	0.364	0.356	0.343	0.278
AG	0.153	0.166	0.170	0.180	0.184	0.181	0.185	0.186	0.172	0.113
CFR	0.016	0.014	0.013	0.013	0.014	0.015	0.017	0.020	0.027	0.063
$Leverage$	0.095	0.147	0.180	0.207	0.225	0.242	0.255	0.271	0.282	0.294
$R\&D$	0.101	0.075	0.053	0.060	0.070	0.125	0.229	0.523	2.607	7.099
PR	0.434	0.464	0.226	0.244	0.152	0.169	0.156	0.138	0.001	-0.247
$IVOL$	2.142	2.141	2.167	2.230	2.333	2.464	2.686	3.016	3.680	5.585
SD	2.411	2.437	2.457	2.500	2.597	2.732	2.941	3.264	3.970	6.112
$Skewness$	0.509	0.357	0.377	0.377	0.413	0.456	0.515	0.595	0.747	0.987
MAX	2.790	2.885	2.912	2.978	3.088	3.246	3.481	3.866	4.633	6.941

Table IV The statistical properties of two-way sorted portfolios based on distress risk and cash flow risk

This table reports the average idiosyncratic risk ($IVOL$), standard deviation (SD), skewness, and maximum daily returns (MAX) of two-way sorted portfolios based on distress risk (DR) and cash flow risk (CFR). $IVOL$ is the standard deviations of residuals from the Fama and French (1993) three-factor model over the prior 12 months with a minimum of 100 days. SD and skewness are estimated from the daily returns of each stock over the next 12 months following Conrad et al. (2014). MAX is the average of the five highest daily returns during a month following Bali et al. (2011). At the end of each month of year t, we sort stocks into quintiles based on their lagged distress risk measures (DR) and independently sort stocks into terciles based on their lagged cash flow risk (CFR) using NYSE breakpoints. The intersections of the two groups produce DR-CFR portfolios. We hold the portfolios for the subsequent month and rebalance them monthly. DR_1 is the bottom distress risk quintile. DR_3 is the third distress risk quintile. DR_5 is the top distress risk quintile. ΔDR represents the long-short portfolio that takes long positions in DR_1 and short positions in DR_5. CFR_1 is the bottom cash flow risk tercile. CFR_2 is the middle cash flow risk tercile. CFR_3 is the top cash flow risk tercile. The sample period covers July 1977 to June 2014.

	DR_1	DR_2	DR_3	DR_4	DR_5
			IVOL		
CFR_1	1.809	1.832	1.942	2.303	3.568
CFR_2	2.079	2.157	2.330	2.712	4.074
CFR_3	2.503	2.598	2.825	3.256	5.217
			SD		
CFR_1	2.098	2.117	2.200	2.543	3.877
CFR_2	2.365	2.435	2.589	2.966	4.451
CFR_3	2.763	2.864	3.094	3.517	5.674
			Skewness		
CFR_1	0.363	0.287	0.320	0.458	0.745
CFR_2	0.446	0.398	0.414	0.550	0.807
CFR_3	0.531	0.452	0.555	0.614	0.935
			MAX		
CFR_1	2.474	2.537	2.637	3.062	4.607
CFR_2	2.778	2.912	3.111	3.540	5.196
CFR_3	3.195	3.370	3.630	4.117	6.446

Table V Returns on two-way sorted portfolios based on distress risk and cash flow risk

This table reports the monthly average excess returns ($R_{p,t} - R_{f,t}$) and abnormal returns on two-way sorted portfolios based on distress risk (DR) and cash flow risk (CFR) (See the captions of Tables II for descriptions of the abnormal returns). At the end of each month of year t, we sort stocks into quintiles based on their lagged distress risk measures (DR) and independently sort stocks into terciles based on their lagged cash flow risk (CFR) using NYSE breakpoints. The intersections of the two groups produce DR-CFR portfolios. We hold the portfolios for the subsequent month and rebalance them monthly. DR_1 is the bottom distress risk quintile. DR_3 is the third distress risk quintile. DR_5 is the top distress risk quintile. ΔDR represents the long-short portfolio that takes long positions in DR_1 and short positions in DR_5. CFR_1 is the bottom cash flow risk tercile. CFR_2 is the middle cash flow risk tercile. CFR_3 is the top cash flow risk tercile. The sample period covers July 1977 to June 2014.

	DR_1	DR_2	DR_3	DR_4	DR_5	ΔDR
			$R_{p,t} - R_{f,t}$			
CFR_1	0.779	0.652	0.739	0.665	0.771	0.009
	(3.88)	(3.23)	(3.52)	(2.63)	(2.23)	(0.03)
CFR_2	0.831	0.799	0.630	0.684	0.774	0.057
	(3.64)	(3.68)	(2.66)	(2.44)	(2.20)	(0.21)
CFR_3	1.013	0.677	0.485	0.529	0.215	0.799
	(4.22)	(2.80)	(1.80)	(1.77)	(0.57)	(3.05)
			α_{CAPM}			
CFR_1	0.257	0.121	0.194	0.031	-0.048	0.305
	(2.67)	(1.32)	(1.95)	(0.24)	(-0.24)	(1.28)
CFR_2	0.254	0.228	0.005	-0.025	-0.083	0.337
	(2.21)	(2.33)	(0.05)	(-0.19)	(-0.43)	(1.32)
CFR_3	0.394	0.050	-0.226	-0.245	-0.736	1.130
	(3.52)	(0.43)	(-1.94)	(-1.79)	(-3.88)	(4.86)
			α_{FF3}			
CFR_1	0.274	0.146	0.099	-0.139	-0.317	0.591
	(2.94)	(1.69)	(1.11)	(-1.12)	(-1.65)	(2.61)
CFR_2	0.348	0.225	-0.073	-0.174	-0.316	0.664
	(3.15)	(2.23)	(-0.73)	(-1.33)	(-1.74)	(2.81)
CFR_3	0.506	0.116	-0.152	-0.310	-0.856	1.362
	(4.58)	(1.04)	(-1.34)	(-2.27)	(-5.55)	(6.34)
			α_{FF5}			
CFR_1	0.026	0.003	-0.001	-0.138	-0.210	0.235
	(0.29)	(0.03)	(-0.01)	(-1.05)	(-0.94)	(0.90)
CFR_2	0.257	0.092	-0.120	-0.105	-0.003	0.260
	(2.16)	(0.85)	(-1.07)	(-0.76)	(-0.02)	(1.09)
CFR_3	0.438	0.079	-0.061	-0.140	-0.466	0.905
	(3.43)	(0.65)	(-0.50)	(-0.95)	(-3.12)	(3.92)
			α_{HXZ}			
CFR_1	-0.072	-0.054	0.020	-0.035	0.102	-0.174
	(-0.83)	(-0.57)	(0.22)	(-0.23)	(0.38)	(-0.58)
CFR_2	0.126	0.129	0.010	0.139	0.296	-0.170
	(1.01)	(1.00)	(0.08)	(1.01)	(1.72)	(-0.72)
CFR_3	0.370	0.110	0.029	0.122	-0.110	0.480
	(2.77)	(0.84)	(0.21)	(0.88)	(-0.84)	(2.27)
			α_{CCAPM}			
CFR_1	0.165	0.126	0.199	0.199	0.126	0.040
	(1.58)	(1.29)	(1.84)	(1.37)	(0.55)	(0.14)
CFR_2	0.195	0.198	0.112	0.026	0.273	-0.078
	(1.54)	(1.80)	(0.99)	(0.18)	(1.12)	(-0.25)
CFR_3	0.290	0.110	-0.053	-0.068	-0.337	0.627
	(2.26)	(0.72)	(-0.39)	(-0.43)	(-1.55)	(2.38)

Table VI Fama and MacBeth (1973) regressions for the high and low cash flow risk subsamples

For each month from July of year t to June of year $t+1$, we estimate the average coefficients from Fama and MacBeth cross-sectional regressions of the monthly excess returns on the distress risk variable (DR) plus control variables. The control variables are size ($ln(MV)$), book-to-market ($ln(B/M)$), momentum (MOM), gross profitability (GP), and asset growth (AG). $ln(MV)$ is the natural logarithm of the market value of equity at the end of June of year t, $ln(B/M)$ is the natural logarithm of the ratio of the book value of equity for the fiscal year ending in year $t-1$ divided by the market value of equity at the end of December of year $t-1$, MOM is the cumulative compounded stock returns of the previous 6 months from June of year t to May of year $t+1$. GP is computed as the ratio of revenue (annual item $REVT$) net of costs of goods sold (item $COGS$) to book value of total assets. AG is computed as the ratio of the change in the book value of total assets from the fiscal year ending in year $t-2$ to the fiscal year ending in $t-1$, divided by the book value of total assets in year $t-2$, MAX is the average of the five highest daily returns. At the end of each month of year t, we sort stocks into terciles based on their lagged cash flow risk using NYSE breakpoints and form the cash flow risk subsamples. Low represents the bottom cash flow risk subsample. High represents the top cash flow risk subsample and High-Low represents the difference between the top and the bottom cash flow risk subsamples. Independent variables are winsorized at the 1% level. The sample period covers July 1977 to June 2014.

	Constant	DR	$ln(MV)$	$ln(B/M)$	MOM	GP	AG	MAX
Low	0.689	-0.137	-0.151	0.033	0.016			
	(0.84)	(-1.85)	(-4.50)	(0.42)	(0.09)			
	0.796	-0.033	-0.000	0.179	0.193			-0.090
	(1.13)	(-0.48)	(-3.48)	(2.65)	(1.08)			(-2.97)
High	-0.718	-0.382	-0.269	0.282	0.092			
	(-0.89)	(-5.45)	(-5.94)	(3.74)	(0.78)			
	-0.808	-0.217	-0.000	0.286	0.116			-0.057
	(-1.09)	(-3.18)	(-2.81)	(4.40)	(0.95)			(-2.81)
High-Low	-1.406	-0.244	-0.118	0.249	0.076			
	(-2.39)	(-3.95)	(-3.04)	(3.42)	(0.47)			
	-1.604	-0.184	0.000	0.107	-0.077			0.034
	(-2.56)	(-2.87)	(0.83)	(1.41)	(-0.47)			(1.19)
Low	0.831	-0.095	-0.133	0.068	0.025	0.489	-0.262	
	(1.03)	(-1.26)	(-4.03)	(0.90)	(0.14)	(3.04)	(-1.86)	
	1.140	0.033	-0.000	0.209	0.207	0.746	-0.208	-0.104
	(1.62)	(0.48)	(-3.30)	(3.32)	(1.18)	(4.56)	(-1.45)	(-3.53)
High	-0.813	-0.395	-0.258	0.237	0.022	0.047	-0.568	
	(-1.01)	(-5.71)	(-5.65)	(3.09)	(0.19)	(0.28)	(-5.48)	
	-0.828	-0.226	-0.000	0.248	0.042	0.242	-0.687	-0.058
	(-1.12)	(-3.34)	(-2.79)	(3.89)	(0.37)	(1.49)	(-6.48)	(-2.92)
High-Low	-1.643	-0.300	-0.125	0.169	-0.003	-0.443	-0.306	
	(-2.83)	(-4.98)	(-3.31)	(2.34)	(-0.02)	(-2.28)	(-1.90)	
	-1.967	-0.259	0.000	0.039	-0.165	-0.504	-0.479	0.046
	(-3.17)	(-4.12)	(0.47)	(0.51)	(-1.02)	(-2.53)	(-3.03)	(1.65)

Table VII The returns and statistical properties of distress risk portfolios in good and bad credit times

This table reports the value-weighted monthly average excess returns ($R_{p,t} - R_{f,t}$), abnormal returns, idiosyncratic risk ($IVOL$), standard deviation (SD), skewness, and maximum daily returns (MAX) of distress risk (DR) portfolios in good and bad credit times (See the captions of Tables II and IV for descriptions of the abnormal returns, $IVOL$, SD, skewness, MAX). At the end of each month of year t, we sort stocks into deciles based on their lagged DR using NYSE breakpoints and hold the portfolios for the subsequent month. DR_1 represents a portfolio that comprises stocks with the lowest DR. DR_{10} represents a portfolio that contains stocks with the highest DR. ΔDR represents the long-short portfolio that takes long positions in DR_1 and short positions in DR_{10}. We use the bank loan spread between the bank prime loan rate and the 4-week Treasury bill rate to identify good and bad credit times. A good credit time is a period with a negative change in the bank loan spread, and a bad credit time is a period with a positive change in the bank loan spread. The sample period covers July 1977 to June 2014.

	DR_1	DR_2	DR_3	DR_4	DR_5	DR_6	DR_7	DR_8	DR_9	DR_{10}	ΔDR
Good credit times											
$R_{p,t} - R_{f,t}$	1.349	1.107	1.216	1.276	1.475	1.244	1.878	2.075	1.806	1.949	-0.600
	(3.10)	(2.62)	(2.81)	(3.02)	(2.92)	(2.49)	(2.78)	(3.10)	(2.15)	(1.85)	(-0.70)
α_{CAPM}	0.457	0.168	0.197	0.316	0.280	0.085	0.302	0.555	-0.092	-0.281	0.738
	(1.65)	(0.76)	(1.19)	(1.76)	(1.63)	(0.42)	(1.23)	(1.81)	(-0.23)	(-0.44)	(0.95)
α_{FF3}	0.504	0.187	0.190	0.353	0.218	0.047	0.234	0.411	-0.381	-0.679	1.183
	(1.69)	(0.87)	(1.19)	(1.93)	(1.48)	(0.23)	(1.05)	(1.52)	(-1.10)	(-1.33)	(1.73)
α_{FF5}	0.323	0.062	0.097	0.314	0.123	0.143	0.422	0.477	0.204	0.061	0.262
	(0.95)	(0.28)	(0.54)	(1.69)	(0.81)	(0.78)	(1.75)	(1.83)	(0.69)	(0.12)	(0.39)
α_{HXZ}	0.270	-0.014	0.109	0.239	0.221	-0.010	0.276	0.562	-0.056	-0.033	0.302
	(1.02)	(-0.06)	(0.63)	(1.22)	(1.12)	(-0.05)	(1.03)	(2.01)	(-0.22)	(-0.08)	(0.59)
α_{lcmkt}	0.110	0.027	0.249	0.320	0.418	0.082	0.508	0.865	0.250	0.268	-0.159
	(0.38)	(0.14)	(1.54)	(1.60)	(2.16)	(0.36)	(2.13)	(2.39)	(0.68)	(0.42)	(-0.20)
$IVOL$	2.099	2.061	2.099	2.165	2.230	2.365	2.591	2.916	3.543	5.287	
SD	2.414	2.391	2.453	2.504	2.568	2.693	2.905	3.219	3.900	5.810	
$Skewness$	0.384	0.269	0.323	0.323	0.358	0.385	0.451	0.513	0.726	1.124	
Max	2.816	2.817	2.889	2.969	3.024	3.190	3.433	3.799	4.509	6.462	
Bad credit times											
$R_{p,t} - R_{f,t}$	0.889	0.698	0.621	0.530	0.581	0.444	0.289	0.476	0.419	-0.168	1.056
	(3.57)	(2.97)	(2.60)	(2.22)	(2.30)	(1.69)	(0.99)	(1.53)	(1.15)	(-0.38)	(3.18)
α_{CAPM}	0.366	0.175	0.084	-0.002	0.015	-0.143	-0.345	-0.199	-0.356	-1.030	1.395
	(3.06)	(2.06)	(1.04)	(-0.02)	(0.17)	(-1.56)	(-2.97)	(-1.51)	(-2.15)	(-4.05)	(4.69)
α_{FF3}	0.514	0.237	0.136	0.030	-0.052	-0.189	-0.455	-0.371	-0.509	-1.228	1.742
	(4.58)	(2.73)	(1.68)	(0.35)	(-0.61)	(-2.04)	(-4.22)	(-2.91)	(-3.27)	(-6.32)	(7.14)
α_{FF5}	0.418	0.045	0.024	-0.064	-0.059	-0.184	-0.400	-0.204	-0.270	-0.777	1.195
	(3.16)	(0.52)	(0.27)	(-0.66)	(-0.65)	(-1.85)	(-3.42)	(-1.45)	(-1.57)	(-4.37)	(4.82)
α_{HXZ}	0.313	-0.054	0.037	-0.067	0.006	-0.040	-0.181	0.117	0.135	-0.272	0.585
	(2.11)	(-0.57)	(0.33)	(-0.66)	(0.06)	(-0.37)	(-1.46)	(0.80)	(0.71)	(-1.72)	(2.52)
α_{CCAPM}	0.194	0.129	0.143	0.063	0.140	-0.109	-0.193	0.043	-0.052	-0.456	0.650
	(1.52)	(1.36)	(1.38)	(0.59)	(1.32)	(-1.08)	(-1.53)	(0.30)	(-0.26)	(-1.67)	(2.06)
$IVOL$	2.158	2.165	2.189	2.252	2.363	2.496	2.717	3.049	3.723	5.662	
SD	2.418	2.455	2.467	2.508	2.612	2.751	2.961	3.287	4.001	6.198	
$Skewness$	0.539	0.378	0.391	0.391	0.426	0.473	0.531	0.614	0.754	0.957	
Max	2.788	2.903	2.922	2.985	3.106	3.265	3.498	3.889	4.672	7.063	

Table VIII Fama and MacBeth (1973) regressions in good and bad credit times

For each month from July of year t to June of year $t+1$, we estimate the average coefficients from Fama and MacBeth cross-sectional regressions of the monthly excess returns on the distress risk variable (DR) plus the control variables for the good and bad time subsamples. The control variables are size ($ln(MV)$), book-to-market ($ln(B/M)$), momentum (MOM), gross profitability (GP), asset growth (AG), and the average of the five highest daily returns (MAX) (See the captions of Table VI for descriptions of the control variables). We use bank loan spread to identify good and bad credit times (See the captions of Table VII for the definitions). Independent variables are winsorized at the 1% level. The sample period covers July 1977 to June 2014.

Constant	DR	$ln(MV)$	$ln(B/M)$	MOM	GP	AG	MAX
			Good credit times				
1.093	-0.095	-0.000	0.142	-0.309			
(0.62)	(-0.58)	(-3.43)	(2.05)	(-1.27)			
1.480	-0.058	-0.000	0.144	-0.315			-0.063
(0.90)	(-0.37)	(-3.50)	(2.07)	(-1.34)			(-0.02)
0.991	-0.102	-0.000	0.140	-0.349	0.196	-0.223	
(0.56)	(-0.62)	(-3.57)	(2.01)	(-1.42)	(0.51)	(-2.19)	
1.402	-0.062	-0.000	0.142	-0.355	0.192	-0.233	-0.289
(0.86)	(-0.41)	(-3.65)	(2.04)	(-1.49)	(0.50)	(-2.29)	(-0.07)
			Bad credit times				
-1.620	-0.255	-0.000	0.330	0.258			
(-1.67)	(-2.78)	(-3.08)	(5.31)	(1.99)			
-0.931	-0.203	-0.000	0.301	0.292			-7.254
(-1.17)	(-2.69)	(-3.19)	(4.97)	(2.33)			(-3.24)
-1.609	-0.244	-0.000	0.313	0.207	0.455	-0.488	
(-1.67)	(-2.65)	(-3.05)	(5.20)	(1.66)	(3.25)	(-5.81)	
-0.891	-0.189	-0.000	0.286	0.241	0.467	-0.479	-7.485
(-1.12)	(-2.48)	(-3.18)	(4.85)	(2.02)	(3.34)	(-5.67)	(-3.36)

Table IX Fama and MacBeth (1973) regressions for the cash flow risk subsamples in good and bad credit times

For each month from July of year t to June of year $t+1$, we estimate the average coefficients from Fama and MacBeth cross-sectional regressions of the monthly excess returns on the distress risk variable (DR) plus the control variables for the low, high, and high-low subsamples in good and bad times. The control variables are size ($ln(MV)$), book-to-market ($ln(B/M)$), momentum (MOM), gross profitability (GP), and asset growth (AG)(See the captions of Table VI for descriptions of the control variables). At the end of each month of year t, we sort stocks into terciles based on their lagged cash flow risk using NYSE breakpoints and form the cash flow risk subsamples. Low represents the bottom cash flow risk subsample. High represents the top cash flow risk subsample and High-Low represents the difference between the top and the bottom cash flow risk subsample. We use bank loan spread to identify good and bad credit times (See the captions of Table VII for the definitions). Independent variables are winsorized at the 1% level. The sample period covers July 1977 to June 2014.

	Constant	DR	$ln(MV)$	$ln(B/M)$	MOM	GP	AG
				Good credit times			
Low	3.243	0.183	-0.000	-0.044	-0.321	0.814	0.204
	(1.53)	(0.85)	(-2.60)	(-0.61)	(-0.76)	(2.00)	(0.83)
High	0.217	-0.218	-0.000	0.221	-0.466	0.048	-0.266
	(0.13)	(-1.39)	(-2.37)	(1.83)	(-1.78)	(0.10)	(-1.73)
High-Low	-3.026	-0.401	-0.000	0.265	-0.145	-0.767	-0.470
	(-2.11)	(-2.34)	(-1.67)	(2.03)	(-0.43)	(-1.46)	(-1.67)
				Bad credit times			
Low	-0.248	-0.079	-0.000	0.277	0.219	0.708	-0.306
	(-0.28)	(-0.92)	(-2.99)	(3.53)	(1.07)	(3.69)	(-1.75)
High	-1.678	-0.281	-0.000	0.284	0.103	0.267	-0.773
	(-1.73)	(-3.20)	(-2.51)	(3.76)	(0.77)	(1.51)	(-6.08)
High-Low	-1.430	-0.202	0.000	0.006	-0.116	-0.440	-0.468
	(-2.05)	(-2.87)	(0.49)	(0.07)	(-0.61)	(-1.89)	(-2.42)

Table X Robustness tests from Fama and MacBeth (1973) regressions

For each month from July of year t to June of year $t+1$, we estimate the average coefficients from Fama and MacBeth cross-sectional regressions of the monthly risk-adjusted returns in Panel A or excess returns in Panel B on the distress risk variable (DR) plus the control variables for the low, high, and high-low subsamples in good and bad credit times. The control variables are size ($ln(MV)$), book-to-market ratio ($ln(B/M)$), momentum (MOM), gross profitability (GP), and asset growth (AG) (See the captions of Table VI for descriptions of the control variables). At the end of each month of year t, we sort stocks into terciles based on their lagged cash flow risk using NYSE breakpoints and form the cash flow risk subsamples. Low represents the bottom cash flow risk subsample. High represents the top cash flow risk subsample and High-Low represents the difference between the top and the bottom cash flow risk subsample. We use bank loan spread to identify good and bad credit times (See the captions of Table VII for the definitions). The risk-adjusted return is based on the Fama and French (1993) three-factor model, which is the sum of the intercept and the residuals from the time-series regression using the 36-month rolling window. Stocks with a market capitalization below 20% of the total market capitalization of NYSE stocks are defined as microcap stocks. Independent variables are winsorized at the 1% level. The sample period covers July 1977 to June 2014.

	Constant	DR	$ln(MV)$	$ln(B/M)$	MOM	GP	AG
Panel A: Risk-adjusted returns							
Good credit times							
Low	-0.544	-0.080	-0.000	-0.063	-0.399	0.787	0.201
	(-0.42)	(-0.53)	(-1.57)	(-0.91)	(-1.00)	(2.46)	(0.90)
High	-3.323	-0.395	-0.000	0.234	-0.333	0.315	-0.215
	(-3.03)	(-3.17)	(-0.33)	(1.94)	(-1.38)	(0.74)	(-1.69)
High-Low	-2.779	-0.316	0.000	0.298	0.066	-0.472	-0.416
	(-2.19)	(-2.16)	(0.20)	(2.22)	(0.19)	(-1.07)	(-1.66)
Bad credit times							
Low	-1.923	-0.201	-0.000	0.158	0.029	0.644	-0.184
	(-3.54)	(-3.28)	(-2.34)	(3.00)	(0.15)	(4.14)	(-1.36)
High	-3.185	-0.384	-0.000	0.178	-0.117	0.208	-0.459
	(-5.11)	(-5.69)	(-3.19)	(3.24)	(-0.76)	(1.28)	(-4.09)
High-Low	-1.261	-0.182	-0.000	0.020	-0.146	-0.436	-0.276
	(-2.14)	(-2.96)	(-1.05)	(0.28)	(-0.91)	(-2.28)	(-1.68)
Panel B: Excluding microcap stocks							
Good credit times							
Low	3.270	0.170	-0.000	-0.049	-0.614	0.441	-0.007
	(1.18)	(0.59)	(-2.34)	(-0.39)	(-1.43)	(0.95)	(-0.03)
High	-0.764	-0.288	-0.000	0.239	-0.159	0.133	-0.059
	(-0.31)	(-1.21)	(-1.42)	(1.04)	(-0.54)	(0.30)	(-0.40)
High-Low	-4.034	-0.459	-0.000	0.288	0.454	-0.308	-0.052
	(-2.24)	(-2.23)	(-0.72)	(1.43)	(1.28)	(-0.76)	(-0.20)
Bad credit times							
Low	-0.929	-0.151	-0.000	0.182	0.268	0.587	-0.157
	(-0.89)	(-1.47)	(-2.54)	(1.74)	(1.07)	(2.64)	(-0.76)
High	-3.648	-0.459	-0.000	0.445	0.420	0.389	-0.489
	(-3.24)	(-4.46)	(-2.18)	(2.77)	(2.32)	(1.55)	(-3.77)
High-Low	-2.718	-0.308	0.000	0.263	0.152	-0.198	-0.332
	(-3.36)	(-3.67)	(0.59)	(1.81)	(0.66)	(-0.72)	(-1.50)

Appendix A: Measure of distress risk

Following the methodology of Campbell et al. (2008), we calculate the failure probability score for the distress risk (DR) of stock from the following equation:

$$\begin{aligned} DR_t &= -9.164 - 20.264NIMTAAVG_t + 1.416TLMTA_t - 7.129EXRETAVG_t + 1.411SIGMA_t \\ &- 0.045RSIZE_t - 2.132CASHMTA_t + 0.075MB_t - 0.058PRICE_t, \end{aligned} \tag{A-1}$$

where

$$NIMTAAVG_{t-1,t-12} = \frac{1-\varphi^3}{1-\varphi^{12}} NIMTA_{t-1,t-3} + \cdots + \varphi^9 NIMTA_{t-10,t-12}, \tag{A-2}$$

and

$$EXRETAVG_{t-1,t-12} = \frac{1-\varphi}{1-\varphi^{12}} EXRET_{t-1} + \cdots + \varphi^{11} EXRET_{t-12}, \tag{A-3}$$

$\varphi = 2^{-1/3}$.

$NIMTA$ is the profitability ratio of net income (Compustat quarterly item NIQ) divided by the sum of market equity (share price times the number of shares outstanding from CRSP) and total liabilities (item LTQ).

$NIMTAAVG$ is the moving average of $NIMTA$, which is a better predictor of bankruptcy because a long history of losses is more reliable in predicting bankruptcy than one large quarterly loss in a single month.

$EXRET = ln(1 + R_{i,t}) - ln(1 + R_{S\&P500,t})$ is the monthly log excess return on each firm's equity relative to the S&P 500 index.

$EXRETAVG$ is the moving average of $EXRET$, which is a better predictor of bankruptcy because a sustained decline in stock market value is more reliable in predicting bankruptcy than a sudden stock price decline in a single month.

$TLMTA$ is the leverage ratio of total liabilities divided by the market value of total assets.

$SIGMA$ is the annualized standard deviation for a three-month rolling sample: $\sqrt{\frac{252}{N-1}\sum_{k\in\{t-1,t-2,t-3\}} r_k^2}$, where k is the index of trading days in months $t-1$, $t-2$, and $t-3$, r_k is the firm-level daily return, and N is the total number of trading days in the three months. If there are fewer than five nonzero observations over the three months in the rolling window, $SIGMA$ is assigned as missing.

$RSIZE$ is the relative size of a firm measured as the ratio of the log market value of equity to that of the S&P 500 index.

$CASHMTA$ is the cash ratio of cash plus short-term investments (Compustat quarterly item $CHEQ$) divided by the sum of market equity and total liabilities (item LTQ).

MB is the market-to-book ratio of the market value of equity divided by the book value of equity. Following Campbell et al. (2008), we add 10% of the difference between the market and book equity to the book value of total assets. This allows the book value of equity to be increased for extremely small stocks. For firm-month observations that still have negative book equity after this adjustment, we use \$1 to replace the negative values to ensure that the market-to-book ratios of all firms are non-negative.

$PRICE$ is the log price per share of each firm, truncated above at \$15. For stocks with prices less than \$1, we eliminate them at the portfolio formation date. We winsorize the variables on the right-hand side of the equation (A-1) at the $1st$ and $99th$ percentiles of their distributions each month.

Appendix B: Firm characteristics

AG: asset growth ratio, computed as the ratio of the change in the book value of total assets from the fiscal year ending in year $t-2$ to the fiscal year ending in $t-1$, divided by the book value of total assets in year $t-2$.

B/M: book-to-market equity, the ratio of the book value of equity to the market value of equity. Following Davis et al. (2000), the book value of equity is calculated as the shareholders' equity (data item SEQ), plus balance sheet deferred taxes and investment tax credits (annual item $TXDITC$) (if available), less the book value of the preferred stock (in the following order: data item $PSTKRV$ or data item $PSTKL$ or data item $PSTK$) from the Compustat. The B/M ratio of year t is the book value of equity for the fiscal year ending in year $t-1$, divided by the market value of equity at the end of December in year $t-1$ from the CRSP.

CFR: cash flow risk, calculated as the standard deviation of a ratio of income before extraordinary items (Compustat quarterly item IBQ), plus equity's share of depreciation (item DPQ), plus deferred taxes (if available, item $TXDIQ$) to the book value of total assets (ATQ) over the prior 24 months.

GP: gross profitability ratio, computed as the ratio of the revenue (annual item $REVT$) net of costs of goods sold (item $COGS$) to the book value of total assets.

$IVOL$: The idiosyncratic volatility of a stock, calculated as the standard deviations of residuals from the Fama and French (1993) three-factor model over the prior 12 months with a minimum of 100 days.

Leverage: leverage, the ratio of the sum of long-term debt (data item $DLTT$) and debt in current liabilities (data item DLC) to the book value of total assets.

MAX: the average of the five highest daily returns during a month following Bali et al. (2011).

MOM: momentum, computed as the cumulative compounded stock returns of the previous 6 months from June of year t to May of year $t+1$.

MV: market capitalization of equity, calculated by the share price at the end of June in year t times the number of shares outstanding from the CRSP.

PR: payout ratio, calculated as the total distributions including dividends paid to preferred stocks (data item DVP), common stocks (data item DVC), and share repurchases (data item $PRSTKC$) divided by the operating income before depreciation (data item $OIBDP$).

$R\&D$: research & development to sales ratio, calculated as the ratio of research & development expense (data item XRD) to sales (data item $SALE$).

ROA: return on asset ratio, calculated as the ratio of the operating income before depreciation (data item $OIBDP$) to the book value of total assets (data item AT).

SD: standard deviation of daily returns of each stock over the next 12 months.

Skewness: skewness of daily returns of each stock over the next 12 months.