Financial Distress Risk Innovations and the Distress Risk-Return Relation*

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Abstract

We examine the puzzling negative relation between financial distress risk and the cross-section of expected returns. We find that the negative relation is most pronounced for up to six months after portfolio formation but after that, high distress stocks eventually earn persistently high returns. The negative relation during the first six months is driven by the most recent distress risk shocks to which investors initially underreact, causing temporary overpricing of distressed stocks. In the long run, the relation between distress risk and returns reflects the positive risk premium as distress risk innovations are fully incorporated into prices. We also find that the positive distress risk premium explains the size effect.

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1 Introduction

Is financial distress risk priced? Although the CAPM prescribes a single priced risk, a mismeasured market portfolio (Ferguson and Schockley, 2003) or time-varying investment opportunities (Merton, 1973) leave open the possibility of additional priced risks. Chan and Chen (1991) and Fama and French (1993, 1996) have suggested that distress risk may explain the nonzero returns of the size and value anomalies. This has motivated a large number of researchers to search for priced distress risk, often by examining the relationship between predicted default probability and subsequent returns. Most studies find that financial distress is negatively related to subsequent returns (see Dichev, 1998; Campbell, Hilscher, and Szilagyi, 2008, henceforth CHS, 2008; Avramov, Chordia, Jostova, and Philipov, 2009; George and Hwang, 2010; Garlappi and Yan, 2011; Gao, Parson, and Shen, 2017).[1] This is a counterintuitive result because distressed stocks are likely riskier than non-distressed stocks. CHS (2008) document that distressed stocks have higher standard deviations, market betas, and loadings on the size and value factors than non-distressed stocks. Hence, the expected return from distressed stocks should be at least as large as that from non-distressed stocks. Therefore, a better understanding of distress risk is important not just as a potential explanation of the size and book-to-market anomalies, but also in explaining the surprising negative relation between predicted default probability and returns.

In this paper, we examine the relation between financial distress risk and the cross-sectional stock returns. However, in contrast to prior work, we also consider the relation between distress risk *innovations* and subsequent returns. Such a relation can be caused by frictions and/or investor biases that lead to temporary price underreaction to risk innovations.[2] Empirically,

[1]However, other studies document the opposite results. Vassalou and Xing (2004) find that distress risk is positively priced, although this result appears to be driven by short-term return reversals (see Da and Gao, 2010). Using implied cost of capital to proxy for expected returns, Chava and Purnanandam (2010) find a positive cross-sectional relationship between expected stock returns and default risk. Kapadia (2011) finds that exposure to aggregate distress risk is positively priced in the cross-section of stock returns.

[2]Such biases and frictions include biased investor beliefs (Barberis, Shleifer, and Vishny, 1997; Daniel, Hirshleifer, and Subrahmanyam, 1998), slow information diffusion (Hong and Stein, 1999; Hong, Torous, and Valkanov, 2007), information capacity constraints (Sims, 2003); non-trivial transactions costs, and short-sale constraints.

prior studies find evidence of apparent underreaction in a wide variety of settings, which suggests that prices may underreact to risk innovations as well.[3] Also, there is ample evidence that investors underreact to innovations in volatility when setting option prices (Poteshman, 2001), market underreaction to the passage of time after merger announcement (Giglio and Shue, 2014), investor underreaction to stock level liquidity shocks (Bali, Peng, Shen, and Tang, 2014) and to idiosyncratic volatility innovations (Rachwalski and Wen, 2016). More recent work include Bali, Bodnaruk, Scherbina, and Tang (2017) who find investor underreaction to sudden increases in idiosyncratic volatility induced by firm-specific negative news. Provided distress risk is priced, underreaction to distress risk innovations should lead to predictable patterns in returns.

We follow the investor underreaction model in Rachwalski and Wen (2016) to show that, in the presence of underreaction, distress risk innovations are negatively related to future returns. For example, suppose that distress risk is positively priced and that investors underreact to distress risk innovations. Then, immediately after a positive shock to a stock's distress risk, the representative investor's forecast of distress risk will be too low and the price of the stock will be too high. However, if underreaction is temporary, investors will eventually arrive at the correct distress risk forecast and stock price. Therefore, for some period of time after the shock, expected returns will be low as investors "correct" their underreaction. After the shock is fully priced, the stock's expected return will be higher than the pre-shock expected return because risk is higher.

We calibrate the model to deliver the empirical predictions for the distress risk-return relation. We simulate the long-run expected return response to a positive distress risk shock. Simulation results suggest that expected returns are negative for a few months after the shock, with the most negative return in month one. However, returns become positive over time as the shock gradually decays. This is consistent with a positive long-run price of distress risk,

[3]Prior research suggests that investors underreact to earnings announcements (Ball and Brown, 1968; Bernard and Thomas, 1990), prior returns (Jegadeesh and Titman, 1993), dividend news (Michaely, Thaler, and Womack, 1995), share repurchases (Ikenberry, Lakonishok, and Vermaelen, 1995), seasoned equity offerings (Loughran and Ritter, 1995), and news about related firms (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010).

but investors temporarily underreact to risk innovations.

We test our model by partitioning historical financial distress into recent (e.g. distress risk over the previous quarter) and distant (e.g. distress risk two quarters ago, or longer) components. Because distress risk is persistent, both recent and distant historical financial distress are informative about future distress risk. However, recent information may not be fully assimilated into prices, while distant information is more likely fully priced. Then, our model suggests that, controlling for distant distress risk, recent distress risk should be negatively related to subsequent returns. Also, controlling for recent financial distress, distant financial distress should be positively related to subsequent returns.

We empirically confirm the predictions of our model using portfolio analysis and stock-level cross-sectional regressions. In the portfolio analysis, we find that after controlling for "recent" financial distress, "distant" distress risk is positively related to future returns. In addition, after controlling for "distant" financial distress, "recent" distress risk is negatively related to future returns. The Fama-MacBeth (1973) regression results echo the portfolio analysis.

The underreaction model in Rachwalski and Wen (2016) also suggests that, provided the underlying price of distress risk is positive, any negative distress risk-return relationship should be temporary. Stocks with high distress risk may exhibit temporarily low returns because the level and recent change in distress risk are likely correlated. However, in the long-run (i.e. after the effects of temporary underreaction), the distress risk-return relation should be positive. We examine the returns of distress-sorted hedge portfolios for up to five years after portfolio formation and observe this return pattern. Consistent with prior studies, returns of some distress-sorted hedge portfolios are significantly negative for about a year. However, after this year, hedge portfolio returns are positive. This suggests that, after the temporary effects of underreaction have run their course, the underlying distress risk-return relation is positive. Prior studies generally focus on returns immediately after portfolio formation and may miss the long-run positive distress risk-return relation.

Our results are not driven by well-known return patterns (short-term reversals, momentum, and liquidity). The results are also robust to alternative measures of financial distress (use of

Ohlson's (1980) O-score rather than the predicted default measure of CHS (2008)), data filters that remove the smallest or most illiquid stocks from the sample, and alternative distant distress lag lengths. Finally, we generally report both equal- and value-weighted portfolio returns and obtain similar results. One limitation of our approach is that we do not observe investors' distress risk forecasts; this means that we cannot directly test whether or not these forecasts are consistent with the observed return patterns. Instead, we rely on return patterns to provide indirect support for our underreaction explanation of the distress risk-return relation. This leaves open the possibility that another stock characteristic, related to distress in the cross-section, is driving our results. To address this, we directly control for well-documented return patterns that could potentially fit the results; inference is generally similar.

We explore the relation between the size (SMB) and book-to-market (HML) hedge portfolios and distress risk. We construct a traded distress factor; this factor is a zero-cost hedge portfolio formed by taking a long position in stocks with high distant distress and a short position in stocks with low distant distress, controlling for recent distress (and underreaction). We find that SMB loads positively on distress risk. This is consistent with Chan and Chen (1991), who suggest that the size anomaly may be related to financial distress. However, we find that the HML portfolio loads negatively on the distress factor. Therefore, our distress factor cannot explain the value premium.

Our paper is related to previous studies along several different dimensions. A large strand of literature documents the negative relation between the level of financial distress and subsequent returns (Dichev, 1998; CHS, 2008). Our work extends these studies by documenting a short-lived negative relation between distress risk *innovations* and subsequent returns. In addition, we offer new empirical evidence on a positive relation between distress risk and *long-run* returns. We find that, starting in the second year after portfolio formation, returns of some distress-sorted hedge portfolios are positive. Documenting a positive long-run relation is important because distressed stocks are likely riskier than non-distressed stocks. Therefore, distressed stocks should earn a return at least as large as non-distressed stocks. Our results are consistent with this intuition.

Potential explanations of the negative relation between distress risk and expected returns include firm's endogenous choice of leverage (George and Hwang, 2010), violations of shareholder priority in bankruptcy (Garlappi and Yan, 2011), and investors' preference for skewed and lottery-like payoffs (Conrad, Kapadia, and Xing, 2014). In addition, Gao, Parson, and Shen (2017) propose an investor overconfidence explanation for the distress anomaly, and conclude that behavioral biases contribute to the temporary mispricing of financial distressed firms. Our work extends Gao, Parson, and Shen (2017) by showing that another specific form of behavioral biases — investor underreaction to risk innovations – also contributes to the negative risk-return relation. Our underreaction framework predicts that bad news would be incorporated into prices with a delay, due to investors underreaction. However, in the long run as more information is revealed, prices should reflect fundamental value and a positive distress risk premium. While the explanations in previous studies can explain the negative distress risk premium, they provide limited evidence in supporting the positive distress risk premium in the long-run. Our underreaction framework provides a new channel in understanding this dynamic relation, which allows us to reconcile a short-run negative distress risk-return relation with a positive underlying price of distress risk.

Finally, our work is also related to Fama and French (1993, 1996) who have suggested that distress risk may explain the nonzero returns of the size and value anomalies. Because we find that distress risk is positively related to subsequent returns after controlling for the effects of underreaction, we can empirically test the contention that the size and value premiums are due to financial distress risk. We provide evidence that distress risk is a plausible economic explanation of the nonzero returns of the SMB portfolio. However, we find no evidence that distress risk can explain the nozero returns of the HML portfolio.

The paper proceeds as follows. Secion 2 derives the empirical predictions of the investor underreaction model on the distress risk-return relation. Section 3 describes the data and our measures of recent and distant financial distress, and the empirical setup. Section 4 presents our empirical results on the cross-sectional price of distress risk. Section 5 explores the relation between financial distress, the size and value premium. Section 6 concludes.

2 A Simple Model of Investor Underreaction to Risk Innovations

In this section, we follow the underreaction model in Rachwalski and Wen (2016) and examine its implications of price underreaction to distress risk innovations. We then deliver the model's empirical implications for the distress risk-return relation.

2.1 Motivation of Investor Underreaction

Should prices underreact to risk innovations? There is apparent evidence of underreaction in a wide variety of settings (see Footnote 2). Then, it should not be surprising to find underreaction to risk innovations. First, distress risk estimates are not released in an easily processed form at a scheduled time (unlike, say, earnings). Instead, distress risk must be estimated from a variety of sources including market and accounting data. The relevant information set could easily be large, diverse, and continuously changing. Monitoring this information set in real time is likely a challenging task. If some of this information set is not monitored in real time, perhaps due to investor distraction (see Hirshleifer, Lim, and Teoh, 2009; DellaVigna and Pollet, 2009), then investors could easily underreact to risk innovations. Second, standard valuation techniques (e.g. discounting expected cash flows) may not be well-suited for distressed stocks, as many distressed stocks have negative earnings, high leverage, and volatile cash flows. Distressed stocks also have lower analyst coverage and institutional ownership (see CHS, 2008). This suggests that few investors have the skill to value these stocks correctly (see Baker and Wurgler, 2006), and that risk estimates of distressed stocks are relatively uncertain. This uncertainty, in particular the uncertainty associated with estimating default probabilities, may exacerbate underreaction (Zhang, 2006).

2.2 The Model

We follow the underreaction model in Rachwalski and Wen (2016) and assume that the price of the stock follows,

$$p_t = \frac{d}{r_t^*} = \frac{d}{\gamma FD_t^*}, \tag{1}$$

where p_t is the price, d is the expected future dividend, r_t^* is the discount rate or required return, and FD_t^* is the "priced" distress risk as perceived by investors. γ is a positive risk aversion parameter that maps distress risk to discount rates.

Under the model, priced or perceived distress risk (FD_t^*) may differ from true distress risk (FD_t). We assume that true distress risk follows an AR(1) process,

$$log(FD_{t+1}) = c + \varphi log(FD_t) + \epsilon_{t+1}, \tag{2}$$

where $\varphi \in (0, 1)$ and the error term is white noise $\epsilon \sim N(0, \sigma_\epsilon^2)$. Under this specification, true distress risk is persistent and each stock reverts to its long-run mean distress risk. We assume that the representative investor cannot, or does not, react to ϵ, possibly because ϵ is not observed. Therefore, this information cannot be directly incorporated into prices.

Priced or perceived distress risk (FD^*) evolves according to

$$FD_{t+1}^* = FD_t^* + \Theta(FD_t - FD_t^*), \tag{3}$$

Investors base their distress risk estimates on last period's forecast (FD_t^*) and the forecast error ($FD_t - FD_t^*$). Θ governs the speed with which investors update their forecasts and we consider $\Theta \in (0, 1)$. Under this specification, investors temporarily underreact to risk innovations. However, in the absence of additional shocks (ϵ), priced or perceived distress risk will eventually converge with true distress risk. When $FD_t = FD_t^*$, p_t is determined solely by true distress risk (i.e., underreaction does not occur); this can be interpreted as the equilibrium stock price.

Under this model, the expected gross return,

$$
\begin{aligned}
E_t(R_{t+1}) &= E_t\left(\frac{p_{t+1}+d}{p_t}\right) \\
&= E_t\left(\frac{FD_t^*}{FD_{t+1}^*}+\gamma FD_t^*\right) \\
&= E_t\left[\frac{FD_t^*}{FD_t^*+\Theta(FD_t-FD_t^*)}+\gamma FD_t^*\right],
\end{aligned} \tag{4}
$$

will depend on the representative investor's distress risk forecast error $(FD_t - FD_t^*)$ as well as the priced or perceived level of distress risk (FD_t^*). It is straightforward to show that if perceived distress risk is too low (i.e., $FD_t > FD_t^*$), then next period's expected return will be low (relative to the case where $FD_t = FD_t^*$). This low expected return corresponds to an expected increase in priced distress risk and the discount rate, which reduces the price of the stock. Also, holding $FD_t - FD_t^*$ constant, higher perceived distress risk will be associated with higher expected returns.

2.3 Empirical Implications

The model implies that, controlling for the distress risk forecast error $(FD_t - FD_t^*)$, priced or perceived distress risk is positively related to subsequent returns,

$$\frac{\partial E_t(R_{t+1})}{\partial FD_t^*} > 0, \tag{5}$$

Also, controlling for the level of priced distress risk, recent innovations in distress risk are negatively related to subsequent returns. Since innovations in distress risk are positively related to true distress risk, equation (4) is equivalent to testing,

$$\frac{\partial E_t[R_{t+1}]}{\partial FD_t} < 0, \tag{6}$$

where R_{t+1} is the time $t+1$ gross return.

2.4 Calibration and Expected Return Response

In this section, we calibrate the model to generate empirical predictions for the distress risk-return relation under investor underreaction. Figure 1 plots the long-run response of expected return to a one-standard deviation shock to distress risk, which occurs at month zero, for various Θ values (0.05, 0.2, 0.6, 0.95). Higher Θ corresponds to less investor underreaction (i.e., they adjust their forecast errors quickly to true level). Using empirical data on distress risk (discussed in the data section) and the calibrated parameters $c = 0.14$, $\varphi = 0.85$, $\sigma_\epsilon = 0.2$, and $\gamma = 3$, we show the long-run response of expected returns to a positive distress risk shock in Figure 1.

The return pattern in Figure 1 suggests that with distress risk shocks, expected returns are negative for a few months, with the most negative return in month one. However, returns become positive over time as the shock gradually decays. A reasonable interpretation of this return pattern is that the negative returns in the short-run are likely attributable to a transitory friction (i.e., underreaction to risk innovations), while the long-run (equilibrium) price of distress risk is positive. Overall, Figure 1 is consistent with the model's implications of investor underreaction to distress risk innovations, which results in predictable negative returns for a period of time as the shock is gradually incorporated into prices. However, in the long run, as the price adjusts to incorporate the shock, the expected return will reflect the underlying risk. We empirically confirm these predictions.

3 Data

3.1 Stock Sample, Filters

We obtain stock data from CRSP and Compustat. Following CHS (2008), we eliminate all stocks with a lagged price less than one dollar from the sample. This sort of filter is intended to remove the smallest and most illiquid stocks from the sample. The filter also partially addresses concerns that the distress anomaly may be confined to a small subset of the stock market (and may be difficult to exploit due to short selling constraints and low liquidity associated with this subset). We use CRSP delisting returns where appropriate (following Shumway, 1997 and Price, Beaver, and McNichols, 2007). We exclude financial firms (SIC codes 6000 through 6999). We require that each stock-month observation has sufficient accounting and market data to compute recent and distant financial distress defined as below.

3.2 Measures of Financial Distress

We primarily measure financial distress using CHS's (2008) failure probability. CHS show this measure is a relatively accurate predictor of corporate default.[4] However, as a robustness check, we also report results using Ohlson's (1980) O-score.

3.3 "Recent" and "Distant" Financial Distress

If underreaction is important, the choice of the historical data used to calculate financial distress will be important. For this reason we distinguish between "recent" financial distress (RD, defined as predicted default probability using all information up to the current quarter t) and "distant" financial distress (DD, defined as the predicted default probability using information up to quarter $t - s$). We will refer to s as the RD-DD threshold, as s separates the data into partitions used to estimate RD and DD. Although we will focus on a two-quarter RD-DD threshold throughout much of the paper, we will also examine thresholds of two and four quarters.[5] To illustrate, when $s = 4$, RD is the predicted default probability calculated using data up to the current quarter (time t). DD is the predicted default probability calculated using data up to time $t - 4$. Note that the threshold is equal to the DD lag length (e.g. when $s = 4$, DD equals RD lagged 4 quarters).

We use RD and DD to test equations (5) and (6). We measure FD^*, perceived financial

[4]CHS show their measure predicts corporate failure more accurately, at both short and long horizons, than either static models (Beaver, 1966; Altman, 1968; Ohlson, 1980) or the structural default model of Merton (1974).

[5]We focus on the two-quarter threshold to be conservative and allow quarterly accounting information to become publicly available. Our results remain similar when using the one-quarter threshold where we measure RD using the most recent quarter data.

distress, with DD, to the extent that distant information is more likely to be fully priced. Provided the RD−DD threshold is sufficiently long, investors will have fully incorporated the information contained in DD into prices. We measure FD with RD using most recent information. In the presence of underreaction, investors may have not fully assimilated the information contained in RD into prices. Then RD contains information about subsequent returns related to predictable corrections to underreaction.

3.4 RD- and DD-Sorted Portfolios

In this section we examine the mean returns of RD- and DD-sorted portfolios. This section highlights the conditional nature of distress risk-return relation. Each month, we identify firms that release earnings. We use the information from the earnings report and market data to calculate recent distress (RD) for each of these firms. We also record financial distress calculated one year prior (DD) for each of these firms. We then form sequentially-sorted portfolios (by RD then DD, and separately by DD then RD).[6]

Table 1 reports mean equal-weighted portfolio returns for the month subsequent to portfolio formation.[7] Financial distress is measured by CHS failure probability in Panel A and O-score in Panel B. Our discussion focuses on CHS failure probability, although results are similar when using O-score.

Table 1 demonstrates that sequential sorts are helpful in clarifying the relationship between distress risk and mean returns. The column means of Panel A1 (where stocks are sorted by DD, then RD) reveal little relation between DD and subsequent returns. The extreme DD portfolios exhibit little difference in mean returns (0.72 for DD1, 0.68 for DD5). Therefore, an unconditional sort on DD suggests that DD is unrelated to subsequent returns. However, the column means of Panel A2 (where stocks are sorted by RD, then DD) reveal an economically large and monotonic relation between DD and subsequent returns (with extreme portfolio returns of 0.50 and 1.31). The column means of Panel A2 are formed using a sequential sort,

[6]We use a sequential sort rather than an independent sort because RD and DD are highly correlated. An independent sort leaves certain portfolios (e.g. RD1, DD5) sparsely populated.

[7]The sample period for our study is 1977 to 2014 since quarterly Compustat data is sparse before this date.

where stocks are sorted into RD quintiles then DD quintiles within each RD quintile. Because the first sort is on RD, each DD quintile must contain stocks from each RD quintile; this is one way to control for RD when examining the DD-return relation. In Panel A1, the first sort is on DD, so there is no such control for RD. Therefore, controlling for RD reveals a positive DD-return relation.

Similarly, controlling for DD reveals a stronger relation between RD and subsequent returns. Comparing the row means of Panel A1 and A2, controlling for DD increases the absolute value of the difference in the extreme portfolio mean returns (from 0.74 to 1.21). However, the negative RD-return relation is economically large even when using a single sort on RD (this is consistent with prior work, such as Dichev, 1998 and CHS, 2008). Importantly, RD and DD have opposing conditional relationships with subsequent returns, although the DD-return relation is only apparent when appropriate controls are applied.

We will refer to the portfolios corresponding to the row means of Panel A1 and the column means of Panel A2 as RDS1-RDS5 and DDS1-DDS5, respectively. The "S" indicates a sequential sort. For example, RDS portfolios are formed by first sorting stocks on DD into quintiles, then within each DD quintile, stocks are further sorted into sub-quintiles by RD. RDS1 is the portfolio of stocks with the lowest RD within each DD portfolio, and RD5 is the portfolio of stocks with the highest RD within each DD portfolio.[8]

3.5 Descriptive Statistics

Table 2 reports descriptive statistics of the sequentially- and single-sorted DD and RD portfolios (again, using a two-quarter RD-DD threshold). The DD and RD columns report the annualized 12-month failure probability (CHS, 2008) associated with each portfolio (e.g. the RD5 portfolio contains stocks with an average failure probability of 1.14% based on recent distress and 0.63% based on distant distress). Table 2 offers evidence that predicted failure probability tracks realized corporate failures. The DELIST column reports the share of firms delisted from CRSP

[8]Similarly, DDS portfolios are formed by first sorting stocks on RD into quintiles, then within each RD quintile, stocks are further sorted into sub-quintiles by DD. DDS1 is the portfolio of stocks with the lowest DD within each RD portfolio, and DDS5 is the portfolio of stocks with the highest DD within each RD portfolio.

due to bankruptcy, liquidation or performance within 12 months of portfolio formation for each quintile. For example, on average 77.4% of delisted firms are in the RD5 quintile while 2.27% are in the RD1 quintile. Therefore, high predicted failure probability is associated with high future corporate failures (as demonstrated by CHS).

Table 2 demonstrates that a single sort on DD is very similar to a sort on RD (and the reverse); both DD and RD increase in a similar way from RD1 to RD5 and from DD1 to DD5. This occurs because financial distress, not surprisingly, exhibits positive autocorrelation. Sequential sorts break the tight link between DD and RD. The DDS portfolios exhibit substantial variation in DD and little variation in RD. Similarly, the RDS portfolios exhibit substantial variation in RD but little variation in DD.

Persistence in distress risk implies that DD and RD are correlated. Empirically, the correlation is quite high; the time series average of the DD-RD cross-sectional correlation is 0.85. Because DD and RD are positively correlated but have opposing partial relationships with mean returns, a single measure of financial distress (e.g. calculating financial distress over the most recent quarter) cannot fully reveal the relation between distress and subsequent returns.

Table 2 contains additional portfolio descriptive statistics. On average, distressed stocks are small, volatile, have positive skewness, and are illiquid. Also, distressed stocks exhibit positive skewness, which may appeal to certain investors (Barberis and Huang, 2008; Bali, Cakici, and Whitelaw, 2011).

4 The Cross-Sectional Price of Financial Distress

In this section, we explore the relation between financial distress and the cross-sectional stock returns. Our model suggests that priced or perceived distress risk is positively related to subsequent returns,

$$\frac{\partial E_t(R_{t+1})}{\partial FD_t^*} > 0, \tag{7}$$

Also, our model suggests that true financial distress is negatively related to subsequent returns,

$$\frac{\partial E_t(R_{t+1})}{\partial FD_t} < 0, \tag{8}$$

Our empirical proxy for true historical financial distress (FD_t) is estimated using the most recent data. And our empirical proxy for perceived distress risk (FD_t^*) is estimated using more distant data, to the extent that distant information is more likely to be fully assimilated into prices. True distress risk may differ from perceived distress risk since our model assumes that investor cannot, or slowly react to distress risk shocks. We empirically confirm the predictions of the underreaction model using portfolio analysis and stock-level cross-sectional regressions.

4.1 Portfolio Analysis

In this section, we examine the distress risk-return relation using portfolio level analysis. Table 3 reports mean returns of the hedge (high minus low distress) portfolio for each sorting procedure (DD, RD, DDS and RDS). Equal- and value-weighted returns are reported for three RD-DD thresholds. Focusing on Panel A, where distress is measured by CHS failure probability, the DD hedge portfolio returns are often negative and never statistically significant. In contrast, the DDS hedge portfolio returns are always positive and highly significant for all thresholds. After controlling for predictable returns related to the adjustment period (captured by RD), the DD-return relation is positive. This is consistent with a positive price of distress risk.

The RD hedge portfolio returns are significant for most thresholds and always negative. This is consistent with Dichev (1998) and CHS (2008), who find that firms with high financial distress deliver abnormally low returns. The RDS hedge portfolio returns are always more negative, more significant, and larger in absolute value than the corresponding RD hedge portfolio returns. For example, in Panel A the equal-weighted RDS hedge portfolio using a two-quarter RD-DD threshold exhibits a return of -1.21% per month, while the RD hedge portfolio exhibits a return of -0.71%. By controlling for distant financial distress, we uncover a stronger negative relationship between recent financial distress and stock returns. Results are similar in Panel B, where distress is measured by O-score.

Table 4 reports regressions of the RDS and DDS hedge portfolio returns on the Fama and French (1996) factors (MKT, SMB, and HML) and the Fama and French factors with a momentum factor (WML). As above, results are reported for both equal- and value-weighted returns and for thresholds of 2, 4, and 6 quarters. Alphas are similar to the raw portfolio returns. The DDS hedge portfolio earns a significant positive returns for most of the thresholds. The RDS hedge portfolio always earns highly significant negative returns. For example, when using the CHS predicted failure probability and a two-quarter threshold, the DDS hedge portfolio generates an equal-weighted three-factor alpha of 0.69% monthly (with a robust t-statistic of 4.08). Using the same setup, the RDS hedge portfolio generates an equal-weighted three-factor alpha of -1.49% monthly. Overall, these results suggest that commonly-used factors cannot explain the nonzero mean returns of the RDS and DDS hedge portfolios.

Although a positive DD-return relation is consistent with a positive distress risk-return relation, we are not comfortable asserting that the price of distress risk is positive based on the results of this section. It remains possible that distress risk is not priced, but distress risk shocks are correlated with another priced stock characteristic. Therefore, in the next section, we take an alternative approach to estimating the underlying price of distress risk.

4.2 Fama-MacBeth Regressions

In this section, we use Fama and MacBeth (1973) cross-sectional regressions to estimate the relationship between financial distress and subsequent returns. The procedure is an alternative to the sorted portfolio approach examined above and can be interpreted as a robustness test. One advantage of the Fama-MacBeth procedure is that it is easy to simultaneously control for many other characteristics. However, many of the standard controls used in cross-sectional regressions plausibly capture information about distress risk, which is not desirable when examining the distress risk-return relation. In particular, high book-to-market stock may earn a premium because they are in distress (as suggested by Fama and French (1996)). Other characteristics are plausibly related to financial distress as well.[9] For this reason, we report results from a cross-sectional regression with only RD and DD and results from a cross-sectional regression with RD, DD, and controls.

$$R_{i,t+1} = \alpha + \beta_{t,DD} DD_{i,t} + \beta_{t,RD} RD_{i,t} + \gamma_t X_t + \epsilon_{i,t}, \tag{9}$$

where $R_{i,t+1}$ is the excess return for stock i in month $t+1$, X is a vector of controls. This specification allows us to examine the partial RD- and DD-return relations (as do the DDS and RDS hedge portfolios), and can be interpreted as a test for a conditional distress risk-return relation. Our model implies that $\beta_{t,DD} > 0$ and $\beta_{t,RD} < 0$. Our focus on partial RD- and DD-return relations is motivated by our belief that investors may react differently to recent and distant financial distress, perhaps due to underreaction to distress risk innovations.

Note that equation (9) can be rewritten as

$$R_{i,t+1} = \alpha + \delta_{t,DD} DD_{i,t} + \beta_{t,RD}(RD_{i,t} - DD_{i,t}) + \gamma_t X_t + \epsilon_{i,t}, \tag{10}$$

where expected returns depend on the level of distant financial distress and the change in financial distress. This corresponds to equation (4), where expected returns depend on perceived distress risk (measured by DD) and the forecast error (measured by RD-DD).

We perform the Fama-MacBeth procedure using both OLS and WLS (with weights equal to market capitalizations). The OLS and WLS regressions correspond to an equal-weighted and value-weighted approach (respectively). Under the WLS regressions, each observation receives a weight equal to the stock's share of total market capitalization.[10] Stock characteristics included as controls are market capitalization, book-to-market ratio, prior return from month $t-7$ to month $t-2$, prior return over month $t-1$ and illiquidity.[11] We focus on a two-quarter threshold

[9]Suppose distress risk is positively priced. Then small stocks may earn higher returns because small stocks are more likely to be distressed. Illiquid stocks may earn high returns because illiquid stocks are more likely to be distressed.

[10]Under WLS, we minimize $\sum w_i e_i^2$, where w_i is market capitalization and e_i is the difference between the actual and fitted return. Under OLS, $w_i = 1$.

[11]Illiquidity is calculated as the log of the trailing one-year average of daily $|R_{i,t}|/DVOL_{i,t}$, where $R_{i,t}$ is the return of stock i on day t and $DVOL$ is dollar volume. This follows Amihud (2002).

in this section, although results are robust to using other thresholds.[12]

Results are reported in Table 5. Focusing on Panel A, where distress is measured by failure probability, RD is always highly significant and negatively related to subsequent stock returns while DD is always highly significant and positively related to subsequent stock returns. Results are similar when distress is measured by O-score.

Many of the characteristics exhibit a weaker relation with returns when using WLS. In Panel A, book-to-market is an important characteristic both economically and statistically in the OLS regression, although not in the WLS regression (the book-to-market parameter estimate is 0.274 in the equal-weighted regressions (with a t-statistic of 3.11) and 0.159 in the value-weighted regression (with a t-statistic of 1.35)). Similarly, the economic and statistical significance of one-month prior return is attenuated in the value-weighted regressions. In contrast, the DD and RD parameters have similar magnitudes in the equal- and value-weighted regressions. This suggests that the relationship between financial distress and returns is pervasive (i.e. not only found in small stocks). Also, this suggests the the return patterns associated with financial distress are not likely to be explained by return patterns primarily associated with small stocks (e.g. bid-ask bounce or short-term reversals). Overall, these results are consistent with the sorted portfolio results.

4.3 Longer Holding Periods

Under our model of underreaction, prices diverge from rational values. However, the mispricing is temporary. Eventually investors arrive at the correct risk premium. This suggests that one could estimate the underlying price of distress risk by examining distress-sorted hedge portfolios for many months after portfolio formation. Although underreaction may influence the returns of these portfolios for some time after portfolio formation, eventually the effects of underreaction should dissipate, and the mean returns of the portfolios should reflect compensation for risk.

Examining long-run returns will only be useful if distress risk is persistent. If financial

[12] Our results are also robust to using the expected skewness as constructed by Boyer, Mitton, and Vorkink (2010) and historical skewness.

distress is not very persistent, then distress-sorted portfolios formed using year t financial distress will not exhibit much dispersion in financial distress in, say, year $t + 5$. Then, any difference in year $t+5$ mean returns cannot reasonably be attributed to distress risk. However, we find that financial distress is quite persistent. Using predicted default probability as a measure of financial distress, the time series average of the cross-sectional correlation between financial distress and one-, three-, and five-year subsequent financial distress is 0.78, 0.72, and 0.68, respectively. Therefore, our measure of financial distress can be reasonably used to form portfolios with systematically varying distress risk, even if returns are measured long after portfolio formation.

We report the average six-month equal-weighted returns of distress-sorted hedge portfolios for up to five years after portfolio formation in Table 6. First, we note that the return patterns documented in Table 3 are not very persistent. In both panels of Table 6, the negative returns of the distress hedge portfolio persist for about a year after portfolio formation then become positive. This can also be seen in Figure 2, which plots the cumulative returns of distress-sorted hedge portfolio for 60 months after the portfolio formation. The returns of the distress hedge portfolio are negative for about a year after portfolio formation. After a year, the returns are always positive.

We find that, for each measure of financial distress, the returns of the distress-sorted portfolios are always positive starting one year after portfolio formation (although these returns are not always significantly positive). This is consistent with the notion that distressed stocks are likely riskier than non-distressed stocks, and distress risk should carry a positive premium. Indeed, compensation for risk seems a particularly appealing explanation for the long-run positive returns of Table 6, as most types of mispricing are likely corrected within five years. Overall, these results are consistent with our underreaction framework.

The results of this section can be used to distinguish among explanations of the distress risk-return relation. For example, authors have attempted to explain the negative distress risk-return relation documented by Dichev (1998) and CHS (2008) by appealing to firm's endogenous choice of leverage (George and Hwang, 2010), violations of shareholder priority in bankruptcy

(Garlappi and Yan, 2011), and investors' preference for skewness (Conrad, Kapadia, and Xing, 2014). These explanations may explain the negative relation between recent distress and returns but are then inconsistent with the long-run positive relation. The evidence presented in this paper suggests that a satisfactory explanation of the distress risk-return relation must address both short-run negative and long-run positive returns.

5 Distress Risk and the Size and Value Premiums

The previous section shows that the distress risk-return relation is dynamic. In this section we examine whether financial distress risk, expunged of the effects of underreaction, can explain the size or value premium as suggested by Chan and Chen (1991) and Fama and French (1996). To do this, we examine the ability of traded market and distress factors to explain the nonzero returns of size- and value-sorted portfolios.

In this application, we use CHS (2008) failure probability as a measure of distress. The distress factor (FD) is the equal-weighted DDS hedge portfolio return, using a two-quarter RD-DD threshold.[13] Panel A of Table 7 reports summary statistics for FD, the Fama-French factors (MKT, SMB, and HML), and the momentum factor (WML). The average return of FD is 0.805% monthly. Panel B reports factor correlation coefficients. FD is not highly correlated with any of the other factors, although most of the correlations are statistically significant.[14]

Panel C reports time-series regressions of the SMB, HML, and WML factors on MKT and FD. FD may explain a substantial portion of SMB returns. Adding the distress factor attenuates the SMB alpha from 0.191% to -0.019%, although neither alpha is significant (this is likely a result of our short time series, 1977-2014). However, the SMB hedge portfolio has a highly significant and positive FD loading.

In contrast to the SMB hedge portfolio, we find no evidence that HML is related to distress. Adding FD to the HML regression slightly increases the alpha. Also, HML does not load

[13] We obtain qualitatively similar results if we use value-weighted returns.

[14] We also examined the correlation between FD and the default yield, defined as the return difference between BAA and AAA-rated corporate bonds. The correlation is -0.05, which suggests that the default spread and distress factor share little information.

significantly on FD. Therefore, we find no evidence that financial distress can explain the value premium.

Table 8 reports results when we use GMM to simultaneously examine all of the size- or book-to-market-sorted portfolios, rather than a hedge portfolio formed from the extreme quintile portfolios. The p-value associated with testing overidentifying restrictions is reported. Panel A of Table 8 provides additional evidence that distress risk explains the anomalous returns of the size-sorted portfolio. The intercepts are generally not significant and we fail to reject the null hypothesis that the intercepts are jointly zero (p-value $= 0.271$). The loadings on the distress factor monotonically decrease as size increases. Small firms (quintile 1) have positive and significant loadings on the distress factor while large firms (quintile 5) have negative and significant loadings. Overall, this result is consistent with the suggestion of Chan and Chen (1991); the size premium appears to be related to financial distress.

Panel B of Table 8 reports results for the book-to-market-sorted portfolios. We find a non-monotonic relation between book-to-market and FD loading, consistent with Dichev (1998) and Griffin and Lemmon (2002). If the source of the value premium is distress risk, then firms with high book-to-market should have greater loadings on the distress factor than firms with low book-to-market. However, we find that the loadings on the distress factor for low and high book-to-market firms have similar magnitudes: 0.277 for the low book-to-market quintile and 0.286 for the high book-to-market quintile. The middle quintiles (2, 3, and 4) have the lowest FD loading. The non-monotonic loading pattern of Panel B suggests that market-to-book portfolios are related to distress, although the relation appears to be more complicated than a simple linear relation between market-to-book and financial distress.[15]

[15]Kapadia (2011) finds that stock's covariation with an aggregate firm failure index can be used to construct a distress factor that is related to the value premium. Kapadia (2011) does not address the relation between predicted default probability and subsequent returns.

6 Conclusion

In this paper, we document a short-lived negative relation between distress risk *innovations* and subsequent returns and a persistently positive relation between distress risk levels and future returns. These relations are consistent with a positive price of distress risk and temporary price underreaction to distress risk innovations. Because risk levels and innovations are correlated, the relation between distress risk and future returns may reflect both risk premia and underreaction and yield misleading inference regarding the price of risk.

To explain the return pattern of distress-sorted portfolio, we derive the empirical implications of an investor underreaction model for the distress risk-return relation. We calibrate the model and simulate the long-run expected return response to a positive distress risk shock. The return pattern suggests that expected returns are negative for a few months after the shock, with the most negative return in month one. However, returns become positive over time as the shock gradually decays. This is consistent with investor temporary underreaction to risk innovations and a long-run positive price of distress risk. We empirically confirm these predictions using portfolio analysis and cross-sectional regressions. This allows us to reconcile our findings, and those of Dichev (1998), and Campbell, Hilscher, and Szilagyi (2008), with a positive distress risk premium suggested by Fama and French (1996).

Our inability to measure investors' estimates of distress risk prevents us from directly testing our underreaction framework. To address this, we rule out many alternative explanations of our results. Although it remains possible that some omitted stock characteristic, correlated with financial distress, may explain our findings, such an explanation would need to address the dynamic nature of the distress risk-return relation. Overall, we find investor underreaction to distress risk innovations to be a compelling explanation of these returns patterns.

We explore the relation between distress risk and the size and book-to-market anomalies. We find that distress risk is a plausible explanation of the anomalous returns of the SMB portfolio. However, we find no evidence that distress risk can explain the anomalous returns of the HML portfolio. Therefore, researchers may need to look elsewhere when attempting to explain the value premium.

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Table 1. Financial Distress-Sorted Portfolio Mean Returns

This table reports mean excess return of stock portfolios formed by sequentially sorting on distant financial distress then recent financial distress (and the reverse). Financial distress is measured by CHS (2008) failure probability in Panel A and O-score as in Ohlson (1980) in Panel B. Recent financial distress (RD) is defined as the predicted default probability in the current quarter t. Distant financial distress (DD) is defined as the predicted default probability in quarter $t-2$. Each month, firms whose most recent public earnings announcement date fall into this month are obtained and portfolios are formed at the beginning of month t+1. Portfolios are held for one month and rebalanced monthly. Portfolio returns are equal-weighted, monthly, and span 1977-2014.

Panel A: Distress measured by failure probability

A1: First sort on DD then RD

	DD1	DD2	DD3	DD4	DD5	Row Mean
RDS1	1.08	1.42	1.57	1.41	1.70	1.44
RDS2	0.90	0.89	1.20	0.98	1.00	0.99
RDS3	0.64	0.82	0.69	0.78	0.75	0.73
RDS4	0.50	0.47	0.55	0.48	0.41	0.48
RDS5	0.45	0.50	0.36	0.27	-0.46	0.22
Column Mean	0.72	0.82	0.87	0.78	0.68	

A2: First sort on RD then DD

	DDS1	DDS2	DDS3	DDS4	DDS5	Row Mean
RD1	0.89	0.81	0.95	1.18	1.80	1.13
RD2	0.57	0.73	0.79	1.16	1.48	0.94
RD3	0.61	0.54	0.68	0.81	1.37	0.80
RD4	0.53	0.58	0.56	0.75	1.17	0.72
RD5	-0.09	0.38	0.53	0.40	0.74	0.39
Column Mean	0.50	0.61	0.70	0.86	1.31	

Panel B: Distress measured by O-score

B1: First sort on DD then RD

	DD1	DD2	DD3	DD4	DD5	Row Mean
RDS1	0.75	1.48	1.68	1.75	1.38	1.41
RDS2	1.04	1.21	1.37	1.16	0.96	1.15
RDS3	0.92	0.95	0.76	0.54	1.07	0.85
RDS4	0.56	0.63	0.52	0.67	0.66	0.61
RDS5	0.40	-0.01	-0.36	-0.15	0.00	-0.02
Column Mean	0.73	0.85	0.79	0.79	0.81	

B2: First sort on RD then DD

	DDS1	DDS2	DDS3	DDS4	DDS5	Row Mean
RD1	0.64	0.72	0.99	1.18	1.53	1.01
RD2	0.63	0.99	1.12	1.44	1.80	1.20
RD3	0.43	0.67	0.84	0.92	1.49	0.87
RD4	-0.05	0.37	0.57	1.01	1.03	0.59
RD5	-0.52	0.23	0.63	0.63	0.85	0.36
Column Mean	0.23	0.60	0.83	1.04	1.34	

Table 2. Financial Distress-Sorted Portfolio Descriptive Statistics

This table reports time series averages of sorted stock portfolio mean characteristics. Characteristics are mean excess returns (RET), standard deviation (SD) and skewness (SKEW), distant financial distress (DD), recent financial distress (RD), the portfolio share of firms delisted from CRSP due to bankruptcy, liquidation or performance within 12 months of portfolio formation (DELIST), log of the market value of equity (ME), book-to-market ratio (BM), 6-month prior returns (PRET6), the average of the absolute value of the daily return divided by dollar vol over the last year (ILLIQ, see Amihud (2002)), and the share of the aggregate market capitalization. Financial distress is the annualized 12-month failure probability following CHS (2008). We use a two-quarter RD-DD threshold. DD and RD quintile portfolios are formed by sorting stocks by DD and RD (respectively). DDS quintile portfolios are formed by sequentially sorting stocks into RD then DD quintiles. Corresponding DD quintile portfolios are then aggregated to form DDS portfolios. The RDS hedge portfolio is formed similarly. Data spans 1977-2014.

Sort	RET (%)	SD	SKEW	DD (%)	RD (%)	DELIST (%)	ME	BM	PRET6 (%)	ILLIQ	Cap. Share
DD1	0.72	11.74	0.84	0.01	0.03	2.97	5.74	0.67	7.87	0.83	0.24
DD2	0.82	13.22	1.44	0.03	0.07	4.75	5.53	0.76	6.73	1.21	0.23
DD3	0.87	15.35	1.76	0.05	0.14	10.30	4.95	0.86	5.87	2.23	0.21
DD4	0.78	18.48	3.18	0.12	0.30	22.22	4.29	0.90	6.59	4.35	0.18
DD5	0.68	22.96	5.71	0.81	0.85	59.76	3.41	0.70	11.52	11.27	0.14
RD1	1.13	11.42	1.10	0.03	0.01	2.27	5.71	0.65	16.56	0.69	0.24
RD2	0.94	12.61	1.51	0.05	0.03	2.14	5.58	0.72	13.30	1.02	0.23
RD3	0.80	14.87	2.40	0.09	0.05	4.79	4.99	0.84	9.58	2.01	0.21
RD4	0.72	18.10	2.73	0.21	0.15	13.41	4.32	0.91	5.48	4.14	0.18
RD5	0.39	24.44	5.10	0.63	1.14	77.40	3.32	0.78	-6.51	12.05	0.14
DDS1	0.50	6.17	-0.54	0.03	0.19	14.67	4.82	0.85	-2.54	2.79	0.21
DDS2	0.61	5.90	-0.58	0.05	0.20	16.43	4.87	0.87	1.55	3.28	0.21
DDS3	0.70	5.85	-0.56	0.09	0.23	18.66	4.77	0.87	5.53	3.84	0.21
DDS4	0.86	6.06	-0.77	0.17	0.23	21.17	4.51	0.84	11.29	5.01	0.20
DDS5	1.31	6.92	-0.49	0.60	0.37	29.08	3.99	0.74	24.96	7.29	0.17
RDS1	1.44	5.60	-0.86	0.14	0.03	3.94	4.82	0.76	24.91	1.96	0.21
RDS2	0.99	5.57	-1.07	0.14	0.06	6.12	4.95	0.82	15.39	2.60	0.22
RDS3	0.73	5.88	-0.67	0.17	0.11	10.46	4.82	0.86	8.91	3.54	0.21
RDS4	0.48	6.41	-0.49	0.21	0.22	20.27	4.52	0.90	2.24	5.18	0.20
RDS5	0.22	8.04	0.05	0.29	0.86	59.21	3.87	0.84	-10.70	9.00	0.17

Table 3. Financial Distress-Sorted Hedge Portfolio Returns

This table reports the monthly hedge portfolio excess returns for stocks sorted by financial distress, measured by CHS (2008) failure probability in Panel A and O-score as in Ohlson (1980) in Panel B. Table reports mean returns of DD, RD, DDS, RDS hedge portfolios using various sample thresholds. DD and RD quintile portfolios are formed by sorting stocks by DD and RD (respectively). RD is the recent financial distress calculated using data up to the current quarter t. DD is the distant financial distress estimated using data up to quarter $t - s$, where s is the threshold that partitions recent and distant distress. DDS quintile portfolios are formed by sequentially sorting stocks into RD then DD quintiles. Corresponding DD quintile portfolios are then aggregated to form DDS portfolios. The RDS hedge portfolio is formed similarly. For each portfolio, the return is reported above the estimated standard error. ***, **, * indicates significance at the 1%, 5%, and 10% level, respectively. Data spans 1977 to 2014.

Panel A: Distress measured by failure probability

Equal-Weighted				Value-Weighted			
DD	RD	DDS	RDS	DD	RD	DDS	RDS
Two-Quarter Threshold, $s = 2$							
0.16	-0.71**	0.81***	-1.21***	0.34	-0.79***	0.85***	-1.05***
(0.26)	(0.35)	(0.18)	(0.26)	(0.34)	(0.43)	(0.25)	(0.37)
Four-Quarter Threshold, $s = 4$							
-0.10	-0.65*	0.45***	-0.90***	0.11	-0.63	0.51**	-0.99***
(0.25)	(0.34)	(0.17)	(0.27)	(0.40)	(0.44)	(0.23)	(0.35)
Six-Quarter Threshold, , $s = 6$							
0.03	-0.56*	0.47***	-0.92***	0.02	-0.58	0.45*	-1.14***
(0.24)	(0.34)	(0.17)	(0.27)	(0.33)	(0.44)	(0.25)	(0.34)

Panel B: Distress measured by O-score

Equal-Weighted				Value-Weighted			
DD	RD	DDS	RDS	DD	RD	DDS	RDS
Two-Quarter Threshold, $s = 2$							
0.11	-0.68***	1.11***	-1.43***	0.26	-0.33	0.92***	-1.07***
(0.18)	(0.21)	(0.15)	(0.17)	(0.23)	(0.28)	(0.21)	(0.22)
Four-Quarter Threshold, $s = 4$							
-0.06	-0.65***	0.46***	-0.87***	0.20	-0.37	0.43**	-0.55**
(0.18)	(0.21)	(0.15)	(0.18)	(0.24)	(0.26)	(0.19)	(0.22)
Six-Quarter Threshold, $s = 6$							
-0.01	-0.63***	0.52***	-1.00***	-0.01	-0.30	0.55***	-0.74***
(0.18)	(0.22)	(0.16)	(0.19)	(0.23)	(0.29)	(0.20)	(0.24)

Table 4. Financial Distress-Sorted Hedge Portfolio Returns Regressed on Factor Returns

This table reports the intercepts and coefficients when DDS and RDS hedge portfolios are regressed on contemporaneous Fama-French factors. Financial distress is measured by CHS (2008) failure probability in Panel A and O-score as in Ohlson (1980) in Panel B. DDS quintile portfolios are formed by sequentially sorting stocks into RD then DD quintiles. DDS portfolio returns are the simple average of the five corresponding DD quintile returns (one for each RD quintile). RDS portfolio returns are formed similarly. Hedge portfolio returns is the return difference between the highest and lowest quintile. Newey-West adjusted standard errors are reported in parentheses. Data is monthly and spans 1977-2014. ***, **, * indicates intercepts significant at the 1%, 5%, and 10% level, respectively.

Panel A: Distress measured by failure probability

DDS Hedge Portfolio

Equal-Weighted					Value-Weighted				
INT	MKT	SMB	HML	WML	INT	MKT	SMB	HML	WML
Two-Quarter Threshold, $s = 2$									
0.69***	0.03	0.37	-0.03		0.75***	-0.02	0.44	-0.06	
(0.17)	(0.04)	(0.06)	(0.06)		(0.25)	(0.06)	(0.08)	(0.09)	
0.50***	0.07	0.35	0.04	0.21	0.41*	0.05	0.41	0.07	0.37
(0.17)	(0.04)	(0.05)	(0.06)	(0.04)	(0.24)	(0.05)	(0.08)	(0.08)	(0.05)
Four-Quarter Threshold, $s = 4$									
0.37*	0.06	0.30	-0.09		0.40*	-0.04	0.54	-0.08	
(0.17)	(0.04)	(0.06)	(0.06)		(0.22)	(0.05)	(0.07)	(0.08)	
0.16	0.10	0.28	-0.01	0.23	0.05	0.03	0.50	0.06	0.39
(0.16)	(0.04)	(0.05)	(0.06)	(0.03)	(0.20)	(0.05)	(0.07)	(0.07)	(0.04)
Six-Quarter Threshold, $s = 6$									
0.45***	-0.01	0.32	-0.19		0.43*	-0.06	0.53	-0.29	
(0.16)	(0.04)	(0.05)	(0.06)		(0.23)	(0.05)	(0.08)	(0.08)	
0.20	0.04	0.30	-0.10	0.27	0.02	0.03	0.49	-0.13	0.44
(0.15)	(0.03)	(0.05)	(0.05)	(0.03)	(0.21)	(0.05)	(0.07)	(0.07)	(0.05)

RDS Hedge Portfolio

Equal-Weighted					Value-Weighted				
INT	MKT	SMB	HML	WML	INT	MKT	SMB	HML	WML
Two-Quarter Threshold, $s = 2$									
-1.49***	0.31	0.31	0.07		-1.41***	0.37	0.61	-0.02	
(0.25)	(0.06)	(0.08)	(0.09)		(0.35)	(0.08)	(0.12)	(0.12)	
-0.93***	0.19	0.37	-0.15	-0.62	-0.58**	0.20	0.69	-0.34	-0.91
(0.21)	(0.05)	(0.07)	(0.07)	(0.05)	(0.29)	(0.07)	(0.09)	(0.10)	(0.06)
Four-Quarter Threshold, $s = 4$									
-1.22***	0.30	0.41	0.09		-1.46***	0.42	0.66	0.20	
(0.25)	(0.06)	(0.08)	(0.09)		(0.33)	(0.08)	(0.11)	(0.12)	
-0.64***	0.17	0.47	-0.13	-0.65	-0.64**	0.25	0.74	-0.12	-0.91
(0.21)	(0.05)	(0.07)	(0.07)	(0.04)	(0.26)	(0.06)	(0.09)	(0.09)	(0.06)
Six-Quarter Threshold, $s = 6$									
-1.25***	0.29	0.43	0.14		-1.63***	0.39	0.64	0.28	
(0.26)	(0.06)	(0.09)	(0.09)		(0.32)	(0.07)	(0.10)	(0.11)	
-0.69***	0.17	0.49	-0.07	-0.61	-0.95***	0.25	0.70	0.02	-0.75
(0.23)	(0.05)	(0.07)	(0.08)	(0.05)	(0.27)	(0.06)	(0.09)	(0.09)	(0.06)

Table 4. (Continued)

Panel B: Distress measured by O-score

DDS Hedge Portfolio

Equal-Weighted					Value-Weighted				
INT	MKT	SMB	HML	WML	INT	MKT	SMB	HML	WML
Two-Quarter Threshold, $s = 2$									
1.16***	-0.12	0.24	-0.15		0.93***	-0.14	0.38	-0.13	
(0.15)	(0.03)	(0.05)	(0.05)		(0.20)	(0.05)	(0.07)	(0.07)	
0.88***	-0.06	0.21	-0.05	0.31	0.49***	-0.05	0.33	0.05	0.49
(0.14)	(0.03)	(0.04)	(0.05)	(0.03)	(0.17)	(0.04)	(0.06)	(0.06)	(0.04)
Four-Quarter Threshold, $s = 4$									
0.47***	-0.08	0.24	-0.11		0.40**	-0.10	0.40	-0.10	
(0.15)	(0.03)	(0.05)	(0.05)		(0.19)	(0.04)	(0.06)	(0.07)	
0.26*	-0.03	0.22	-0.03	0.23	0.10	-0.03	0.37	0.01	0.33
(0.15)	(0.03)	(0.05)	(0.05)	(0.03)	(0.17)	(0.04)	(0.06)	(0.06)	(0.04)
Six-Quarter Threshold, $s = 6$									
0.54***	-0.05	0.23	-0.17		0.55***	-0.07	0.39	-0.22	
(0.15)	(0.03)	(0.05)	(0.05)		(0.19)	(0.04)	(0.06)	(0.07)	
0.30**	0.00	0.21	-0.08	0.26	0.18	0.00	0.35	-0.08	0.40
(0.14)	(0.03)	(0.05)	(0.05)	(0.03)	(0.17)	(0.04)	(0.06)	(0.06)	(0.04)

RDS Hedge Portfolio

Equal-Weighted					Value-Weighted				
INT	MKT	SMB	HML	WML	INT	MKT	SMB	HML	WML
Two-Quarter Threshold, $s = 2$									
-1.60***	0.05	-0.01	0.44		-1.32***	0.12	0.00	0.55	
(0.16)	(0.04)	(0.05)	(0.06)		(0.21)	(0.05)	(0.07)	(0.07)	
-1.27***	-0.02	0.02	0.31	-0.35	-0.81***	0.01	0.05	0.36	-0.56
(0.14)	(0.03)	(0.05)	(0.05)	(0.03)	(0.17)	(0.04)	(0.06)	(0.06)	(0.04)
Four-Quarter Threshold, $s = 4$									
-1.06***	0.04	0.04	0.48		-0.86***	0.09	0.08	0.70	
(0.17)	(0.04)	(0.06)	(0.06)		(0.21)	(0.05)	(0.07)	(0.07)	
-0.74***	-0.02	0.07	0.35	-0.35	-0.43**	0.00	0.12	0.54	-0.47
(0.15)	(0.03)	(0.05)	(0.05)	(0.03)	(0.18)	(0.04)	(0.06)	(0.06)	(0.04)
Six-Quarter Threshold, $s = 6$									
-1.23***	0.05	0.07	0.54		-1.10***	0.10	0.15	0.78	
(0.18)	(0.04)	(0.06)	(0.06)		(0.22)	(0.05)	(0.07)	(0.08)	
-0.92***	-0.01	0.11	0.42	-0.34	-0.61***	0.00	0.20	0.59	-0.54
(0.16)	(0.04)	(0.05)	(0.06)	(0.03)	(0.18)	(0.04)	(0.06)	(0.06)	(0.04)

Table 5. Fama-MacBeth Estimation of the Price of Distress Risk

This table reports the results from Fama-MacBeth regressions of stock returns on stock characteristics. Characteristics are distant financial distress(DD), recent financial distress (RD), the log of the market value of equity (ME), the log of the book-to-market ratio (BM), 1- and 6-month prior returns (PRET1 and PRET6), a measure of illiquidity (ILLIQ) based on Amihud (2002). Financial distress is measured by CHS (2008) failure probability in Panel A and O-score as in Ohlson (1980) in Panel B. Distant financial distress (DD) and recent financial distress (RD) are calculated using two-quarter threshold. For each characteristic, point estimates are reported above standard errors. Data is monthly and spans 1977-2014. ***, **, * indicates significance at the 1%, 5%, and 10% level, respectively.

Panel A: Distress measured by failure probability

Equal-Weighted Cross-Sectional Regression

DD	RD	ME	BM	PRET6	PRET1	ILLIQ
0.413***	-0.462***					
(0.068)	(0.094)					
0.479***	-0.695***	-0.112	0.274***	0.001	-0.033***	0.025
(0.060)	(0.085)	(0.089)	(0.088)	(0.002)	(0.004)	(0.059)

Value-Weighted Cross-Sectional Regression

DD	RD	ME	BM	PRET6	PRET1	ILLIQ
0.442***	-0.591***					
(0.144)	(0.177)					
0.320**	-0.618***	0.015	0.159	0.001	-0.011*	0.083
(0.124)	(0.146)	(0.106)	(0.118)	(0.003)	(0.007)	(0.073)

Panel B: Distress measured by O-score

Equal-Weighted Cross-Sectional Regression

DD	RD	ME	BM	PRET6	PRET1	ILLIQ
0.679***	-0.613***					
(0.082)	(0.091)					
0.531***	-0.712***	-0.110	0.335***	0.011***	-0.053***	0.106*
(0.068)	(0.076)	(0.096)	(0.089)	(0.002)	(0.005)	(0.056)

Value-Weighted Cross-Sectional Regression

DD	RD	ME	BM	PRET6	PRET1	ILLIQ
0.389***	-0.364**					
(0.139)	(0.159)					
0.215***	-0.279**	-0.037	0.180*	0.007***	-0.036***	0.041
(0.090)	(0.121)	(0.146)	(0.102)	(0.003)	(0.008)	(0.097)

Table 6. Longer Horizon Returns of Distress-Sorted Hedge Portfolios for Five Years after Portfolio Formation

This table reports average monthly returns of equal-weighted distress hedge portfolio for month 1-60 subsequent to portfolio formation. Hedge portfolios are formed by single sorts on recent financial distress (RD) in the current quarter t. Financial distress is measured by CHS (2008) failure probability in Panel A and O-score as in Ohlson (1980) in Panel B. Sample period corresponds to 1977 to 2014. Newey-West standard error are reported below each mean return. ***, **, * indicates intercepts significant at the 1%, 5%, and 10% level, respectively.

Panel A: Distress measured by failure probability

Month 1 to 6	Month 7 to 12	Month 13 to 18	Month 19 to 24	Month 25 to 30	Month 31 to 36	Month 37 to 42	Month 43 to 48	Month 49 to 54	Month 55 to 60
-0.86***	-0.28**	0.19	0.17	0.17	0.09	0.12	0.26**	0.29**	0.26***
(0.17)	(0.12)	(0.18)	(0.17)	(0.15)	(0.14)	(0.11)	(0.11)	(0.14)	(0.10)

Panel B: Distress measured by O-score

Month 1 to 6	Month 7 to 12	Month 13 to 18	Month 19 to 24	Month 25 to 30	Month 31 to 36	Month 37 to 42	Month 43 to 48	Month 49 to 54	Month 55 to 60
-0.54**	0.05	0.09	0.14	0.02	0.05	0.03	0.24**	0.11	0.21**
(0.10)	(0.10)	(0.13)	(0.12)	(0.16)	(0.11)	(0.14)	(0.12)	(0.15)	(0.10)

Table 7. Distress Factor and the Fama-French Factors

This table reports summary statistics of the distress factor (FD). The distress factor is the equal-weighted DDS hedge portfolio return, using a two-quarter RD-DD threshold. MKT, SMB, and HML are the Fama and French (1996) factors; WML is the momentum factor. "Auto" refers to the first-order autocorrelation. In all regressions, standard errors are adjusted for heteroskedasticity and serial correlation. Data is monthly and spans 1977-2014. ***, **, * indicates significance at the 1%, 5%, and 10% level, respectively.

Panel A: Summary Statistics

	Mean (%)	Std (%)	Skew	Kurt	Auto
FD	0.805	3.551	1.216	9.210	0.133
MKT	0.539	4.593	-0.783	5.280	0.093
SMB	0.284	3.139	0.522	10.669	-0.003
HML	0.333	3.078	0.004	5.451	0.155
WML	0.713	4.650	-1.499	14.073	0.086

Panel B: Correlations

	FD	MKT	SMB	HML	WML
FD	1				
MKT	0.130***	1			
SMB	0.344***	0.250***	1		
HML	-0.141***	-0.345***	-0.310***	1	
WML	0.286***	-0.091*	0.087*	-0.187***	1

Panel C: Time-Series Regressions for the Fama-French Factors

Dep. var	α	MKT	FD	Adj. R^2
SMB	0.191	0.171***		6.01%
	(0.146)	(0.035)		
SMB	-0.019	0.143***	0.280***	15.71%
	(0.154)	(0.036)	(0.105)	
HML	0.457**	-0.231***		11.70%
	(0.188)	(0.068)		
HML	0.521***	-0.223***	-0.085	12.43%
	(0.175)	(0.070)	(0.093)	
WML	0.763***	-0.092		0.59%
	(0.223)	(0.110)		
WML	0.465**	-0.132	0.397***	9.41%
	(0.236)	(0.104)	(0.120)	

Table 8. Time-Series Regressions on the Size and Book-to-Market-Sorted Portfolios

This table reports GMM estimates of the intercepts (in % per month) and factor loadings from time-series regressions of size and book-to-market-sorted portfolios on the market (MKT) and distress factor (FD). The distress factor is the equal-weighted DDS hedge portfolio return, using a two-quarter RD-DD threshold. In all regressions, standard errors are adjusted for heteroskedasticity and serial correlation. The p-values to test the joint significance of the intercepts are reported. Sample spans 1977-2014. **, **, * indicates significance at the 1%, 5%, and 10% level, respectively.

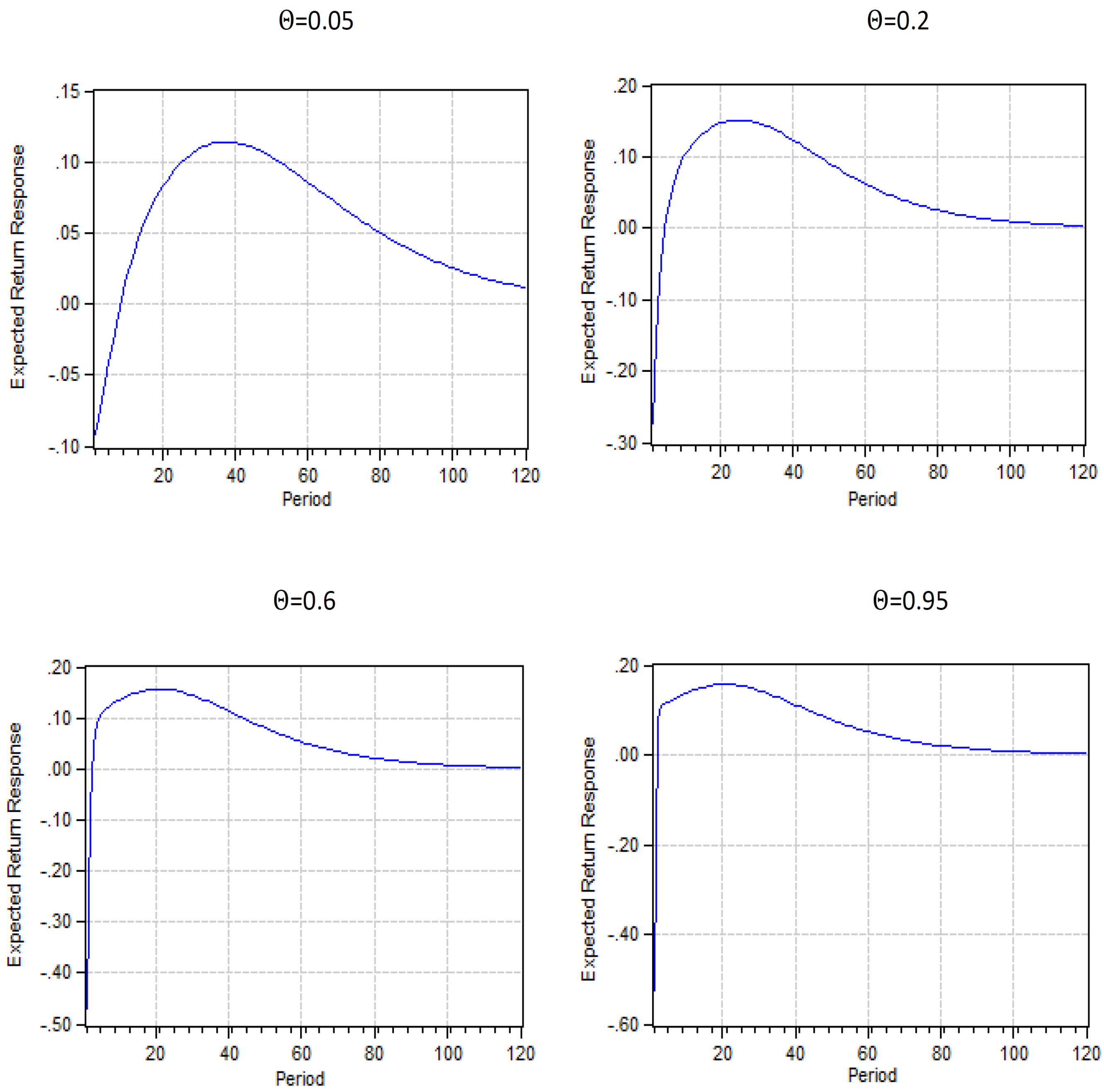
Panel A: Size-Sorted Portfolios

	α	MKT	FD	Adj. R^2
Small	0.126	1.004	0.362***	61.78%
	(0.220)	(0.050)	(0.109)	
2	0.059	1.184	0.095	79.84%
	(0.154)	(0.039)	(0.065)	
3	0.150	1.165	0.002	85.62%
	(0.121)	(0.033)	(0.049)	
4	0.145	1.125	-0.035	91.74%
	(0.089)	(0.021)	(0.026)	
Big	0.120**	1.039	-0.113***	95.36%
	(0.057)	(0.018)	(0.031)	
p-value ($H_0: \alpha = 0$)	0.271			

Panel B: Book-to-Market-Sorted Portfolios

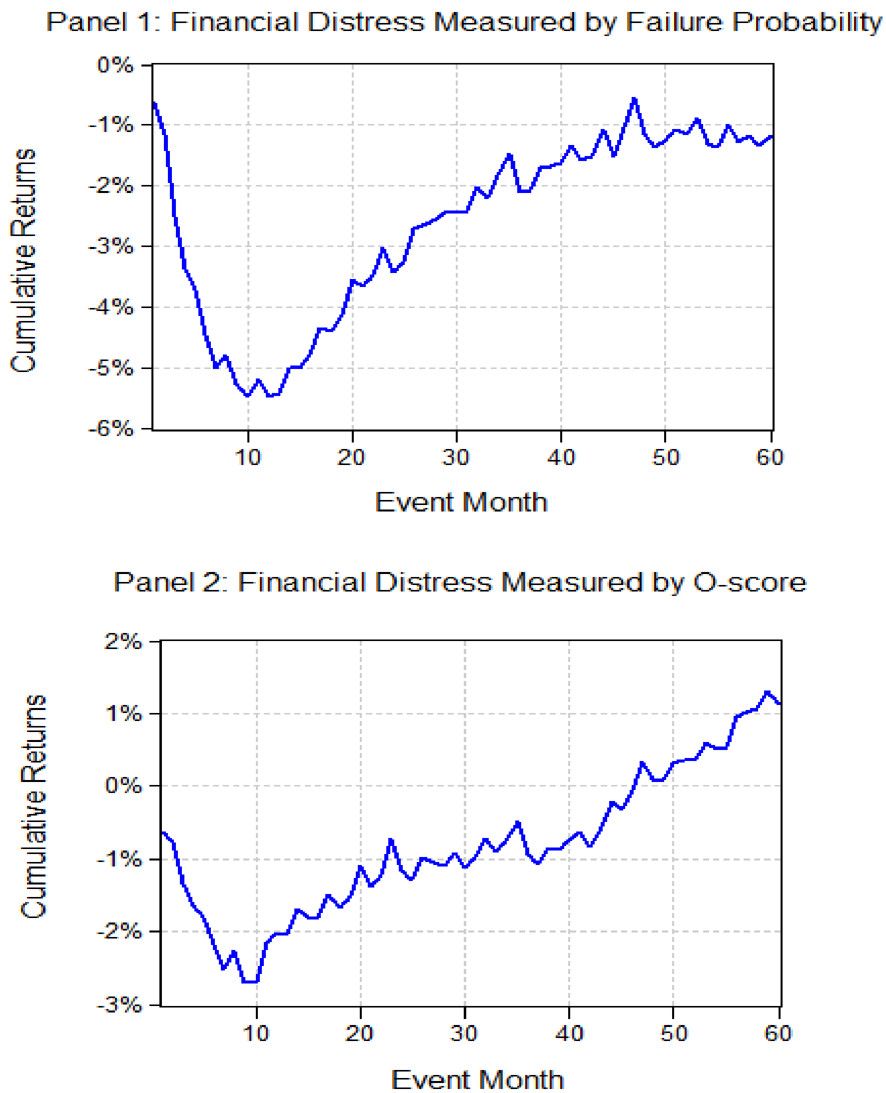
	α	MKT	FD	Adj. R^2
Low B/M	-0.507***	1.286	0.277**	72.80%
	(0.198)	(0.056)	(0.127)	
2	0.173	1.098	0.174***	77.07%
	(0.160)	(0.036)	(0.060)	
3	0.355**	0.987	0.150***	77.59%
	(0.157)	(0.041)	(0.048)	
4	0.438***	0.878	0.174***	72.78%
	(0.157)	(0.044)	(0.056)	
High B/M	0.642***	0.920	0.286***	61.88%
	(0.212)	(0.061)	(0.087)	
p-value ($H_0: \alpha = 0$)	0.000			

Figure 1: Expected Return Response to a Positive Distress Shock



Notes - This figure presents the long-run response of expected return to a one-standard-deviation shock to financial distress for different Θ values 0.05, 0.2, 0.6, and 0.95.

Figure 2: Financial Distress Hedge Portfolio Returns



Notes - This figure presents cumulative hedge portfolio returns sorted on financial distress, by months after portfolio formation. The sample period is 1977-2014. Financial distress is measured by CHS (2008) failure probability in Panel 1 and O-score as in Ohlson (1980) in Panel 2.

Appendix: Variable Definitions

The CHS distress index is the predicted failure probability of the firm. This measure tracks realized failure rates (CHS (2008)). The CHS distress index and failure probability are calculated as

$$\begin{aligned} CHS_{i,t} &= -9.164 - 20.264NIMTAAVG_{t-1,t-12} + 1.416TLMTA_{t-1} \\ &\quad -7.129EXRETAVG_{t-1,t-12} + 1.411SIGMA_{t-1,t-3} - 0.045RSIZE_{t-1} \\ &\quad -2.132CASHMTA_{t-1} + 0.075MB_{t-1} - 0.058PRICE_{t-1} \end{aligned}$$

$$P\_CHS = Failure\ Probability = P_{t-1}(Y_{i,t} = 1) = \frac{1}{1 + exp(-CHS_{i,t-1})} \tag{11}$$

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1,t-3} + ... + \phi^9 NIMTA_{t-10,t-12})$$

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(EXRET_{t-1} + ... + \phi^{11} EXRET_{t-12})$$

in which $\phi = 2^{-1/3}$. $NIMTAAVG$ is a geometrically declining average of past values of the ratio of net income to the market value of total assets. Market value of assets equals the book value of assets plus the market value of common stock less the sum of book value of common stock and balance sheet deferred taxes. $NIMTA$ is the ratio of net income to the market value of total assets. $NIMTAAVG$ is calculated as a moving average to capture the intuition that a long history of losses is a better predictor of bankruptcy than one large quarterly loss. $TLMTA$ is the ratio of total liabilities to the market value of total assets. $EXRETAVG$ is a geometrically declining average of monthly log excess return over the S&P 500 index. $EXRET_{i,t} = log(1 + R_{i,t}) - log(1 + R_{S\&P500,t})$ is the monthly log excess return relative to the S&P500 index. $SIGMA_{i,t-1,t-3} = (252 * \frac{1}{N-1} \sum_{k \in \{t-1,t-3\}} r_{i,k}^2)^{\frac{1}{2}}$ is the annualized standard deviation of daily stock returns over the previous three months. This standard deviation is centered around zero rather than the rolling 3-month mean and is coded as missing if there are less than 5 observations. $RSIZE$ is the log of the ratio of market capitalization to the market value of the S&P 500 index. $CASHMTA$ is the ratio of cash holdings and short term investments to the market value of total assets. MB is the market-to-book ratio. Book equity is defined as in

Davis, Fama and French (2000), which equals to the stockholders' equity, plus balance sheet deferred taxes. If this data is unavailable, we measure stockholders'equity as the book value of common equity. Following CHS, we adjust the book value of equity by adding 10% of the difference between market and book equity to the book value of equity. This adjustment increases extremely small (or negative) book values that are likely mismeasured, which can result in outliers when calculating financial ratios. $PRICE$ is the log price per share. To further reduce the influence of outliers, we follow CHS and winsorize all variables at 5th and 95th percentiles of their pooled distribution. P_CHS is the failure probability from the estimated dynamic logit model. The sample is restricted to firm-quarters with complete data for profitability ($NIMTA$) and leverage ($TLMTA$), with no missing monthly stock returns or quarterly accounting items.

We follow Ohlson (1980) to construct the O-score. The O-score is the predicted value from a dynamic logit regression of bankruptcy on financial ratios. High O-score is associated with high financial distress. O-score is calculated as

$$\begin{aligned} O\,score \;=\; & -1.32 - 0.407 * log(\frac{MKTASSET}{CPI}) + 6.03 * TLTA \\ & -1.43 * WCTA + 0.076 * CLCA - 1.72 * OENEG \\ & -1.83 * FUTL + 0.285 * INTWO - 0.521 * CHIN \\ & -2.37 * NITA \end{aligned} \tag{12}$$

where $MKTASSET$ is the total market value of asset, CPI is the consumer price index. $TLTA$ is the leverage ratio, defined as the the book value of debt ($DLCQ$ plus $DLTTQ$) divided by market value of assets. $WCTA$ is the working capital, defined as the difference between current assets ($ACTQ$) and current liabilities ($LCTQ$). $CLCA$ is ratio of current liabilities to current assets. $OENEG$ is a dummy variable that equals to one if total liabilities (LTQ) exceeds total assets (ATQ) and is zero otherwise. $NITA$ is net income (NIQ) divided by market assets. $FUTL$ is the ratio of funds provided by operations (PIQ) to liabilities (LTQ). $INTWO$ is a dummy variable that equals to one if net income (NIQ) is negative for the measurement horizon and zero otherwise. $CHIN = (NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$ is the change in net income over the measurement horizon. All inputs are winsorized at the 5th and 95th percentiles of their pooled distributions.