Distressed Stocks in Distressed Times: Online Appendix

Online Appendix A: Distress measures

A.1 Campbell, Hilscher, and Szilagyi (2008)

We calculate the distress-risk measure of Campbell, Hilscher, and Szilagyi (2008, Table IV, Column 3), which combines quarterly accounting data from COMPUSTAT with monthly and daily equity market data from CRSP:

$$CHS_t = -9.164 - 20.264 NIMTAAVG_t + 1.416 TLMTA_t - 7.129 EXRETAVG_t + 1.411 SIGMA_t - 0.045 RSIZE_t - 2.132 CASHMTA_t + 0.075 MB_t - 0.058 PRICE_t \quad \text{(A1)}$$

where NIMTA is the net income divided by the market value of total assets (the sum of market value of equity and book value of total liabilities), TLMTA is the book value of total liabilities divided by market value of total assets, EXRET is the log of the ratio of the gross returns on the firm's stock and on the S&P500 index, SIGMA is the standard deviation of the firm's daily stock return over the past three months, RSIZE is ratio of the log of firm's equity market capitalization to that of the S&P500 index, CASHMTA is the ratio of the firm's cash and short-term investments to the market value of total assets, MB is the market-to-book ratio of the firm's equity, and PRICE is the log price per share. NIMTAAVG and EXRETAVG are moving averages of NIMTA and EXRET, respectively, constructed as (with $\varphi = 2^{-1/3}$):

$$NIMTAAVG_{t-1,t-12} = \frac{1-\emptyset^3}{1-\emptyset^{12}}\left(NIMTA_{t-1,t-3} + \cdots + \emptyset^9 NIMTA_{t-10,t-12}\right)$$
$$EXRETAVG_{t-1,t-12} = \frac{1-\emptyset}{1-\emptyset^{12}}\left(EXRET_{t-1} + \cdots + \emptyset^{11} EXRET_{t-12}\right) \quad \text{(A2)}$$

All accounting data are taken with a lag of three months for quarterly data and a lag of six months for annual data. All market data are the most current data. Following Campbell et al. (2008), we winsorize all inputs at the 5th and 95th percentiles of their pooled distributions across all firm-months, where PRICE is truncated above at \$15. Further details on the data construction are provided by Campbell et al. (2008) and we refer the interested reader to their paper.

A.2 Moody's KMV distance to default

Moody's KMV approach to measuring a firm's distance-to-default is based on the two-equation contingent-claim method of Ronn and Verma (1986). The first equation, based on Merton (1974), expresses the value of the firm's equity as the value of a call option written on the firm's assets, using the Black and Scholes (1973) formula:

$$V_E = V_A N(d_1) - F e^{-rT} N(d_2), \quad \text{(A3)}$$

where V_E is the equity value, V_A is the total asset value, $N(\cdot)$ is the cumulative function of a standard normal distribution, $d_1 = \left[\ln\left(\frac{V_A}{F}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T\right]/\sigma_A\sqrt{T}$, $d_2 = d_1 - \sigma_A\sqrt{T}$, σ_A is asset volatility,

F is the face value of debt, r is the risk-free rate, and T is debt maturity. The second equation, which is derived from Ito's lemma, represents the relation between equity volatility, σ_E, and asset volatility, σ_A:

$$\sigma_E = [V_A N(d_1)\sigma_A]/V_E \tag{A4}$$

The unobservable variables V_A and σ_A are then calculated using observable inputs. V_E is the market capitalization, F is measured by the total book value of debt, the short-term risk-free rate r is proxied by the yield on one-year Treasuries, T is assumed to be one year for all firms (see, for example, Crosbie and Bohn (2002) and Hillegeist et al. (2004)), and σ_E is approximated by the annualized standard deviation of monthly returns in the past year.

For each month, we solve the two equations simultaneously for each firm in our sample. Because there are no closed-form solutions for V_A and σ_A we use a numerical algorithm with $V_E + F$ and σ_E as initial values. The risk-neutral probability of bankruptcy is then defined as the probability that the face value of debt exceeds the asset value at maturity, and is given by $1 - N(d_2)$. The distance-to-default is thus denoted as d_2.

Online Appendix B: Conditional beta estimates from an alternative classification of good versus bad times

Our classification of bear/bull markets, which is based on the cumulative returns during the past two years, shows clearly that distressed stocks are exposed to higher systematic risk during market downturns (as shown in Table 3 in the main text and appendix Table A4). To corroborate this result, we estimate equity betas using an alternative classification of the state of the economy. We adopt the conditional CAPM (CCAPM) framework of Petkova and Zhang (2005) who analyze the cyclical variation of betas in the book-to-market cross-section, conditioning on expected market risk premium. We estimate the fitted betas and the rolling betas of financially healthy and distressed stock portfolios, and summarize their average patterns in recessions versus expansions in Table A1.[1]

Consistent with the results under the two-year cumulative return classification (summarized in Panel A of the table), the results under the market risk premium-CCAPM classification show that the healthy stock portfolio has a procyclical pattern of risk whereas the distressed stock portfolio has a countercyclical pattern (as shown in Panel B). The average fitted beta of the healthy (distressed) stock portfolio is 0.83 (1.80) in recessions and is 0.94 (1.35) in expansions. Using rolling betas yields similar results; the average rolling beta of the healthy (distressed) stock portfolio is 0.86 (1.90) in recessions and is 0.97 (1.50) in expansions. In all cases, the difference between the point estimates is statistically significant. This evidence strengthens our argument that

[1] In their CCAPM analysis, Petkova and Zhang (2005) divide recessions and expansions into two subperiods and define four states of the economy. State 'peak' represents the lowest 10% of observations of the expected market risk premium, and state 'expansion' represents the remaining months with the premium below its average. Similarly, state 'recession' represents the months with the premium above its average but not including the 10% highest, and state 'trough' represents the months with the highest 10% of observations of the expected market risk premium. Using this finer classification of bad versus good times, we find that healthy stocks are risker in peak than in trough, whereas distressed stocks are riskier in trough than in peak.

the HMD portfolio becomes riskier in bad times, and is consistent with the conditional CAPM results reported in Table 2.

Online Appendix C: Alternative conditional asset pricing models

We test the performance of conditional versions of mainstream asset pricing models for the distress anomaly. Following Shanken (1990) and Ferson and Harvey (1999), we assume the following general model for the conditional expected returns:

$$E_t\left[r_{i,t+1}\right] = \alpha_{i,t} + \beta'_{i,t} E_t\left[r_{p,t+1}\right]$$

$$\alpha_{i,t} = \alpha_{0,i} + \alpha_{1,i} Z_t$$

$$\beta_{i,t} = \beta_{0,i} + \beta_{1,i} Z_t$$

where $r_{i,t+1}$ is the return on financial distress portfolio i, net of the return to a one-month Treasury bill, $r_{p,t+1}$ is the vector of risk factors (factor mimicking portfolios) of mainstream asset pricing models, $\beta_{i,t}$ is the vector of conditional betas on the factors, and $\alpha_{i,t}$ is the conditional alpha of the asset pricing model. The conditional betas and alphas have a constant component and a time-varying component that depends on the instrument Z_t, which is available to investors in portfolio formation month *t*.

The asset pricing models that we evaluate are the conditional CAPM ($r_p = RmRf$), the conditional versions of the Fama-French (1993) three factor model ($r_p = \{RmRf, SMB, HML\}$), the Carhart (1997) four factor model ($r_p = \{RmRf, SMB, HML, UMD\}$), and the Fama-French (2015) five factor model ($r_p = \{RmRf, SMB, HML, RMW, CMA\}$).

Following Shanken (1990), we test the null hypothesis that $\alpha_{0,i}$ and $\alpha_{1,i}$ are zero for every distress portfolio *i*, when we evaluate the pricing ability of a conditional asset pricing model. If a candidate asset pricing model helps explain the dynamic patterns of the returns on financial distress portfolios, the alphas from that model should all be zero. We also let the alphas vary with the instrument (Z_t) in order to collect information about their dependence on market state variables. The conditioning variables that we use as instruments (Z_t) include a bear-market dummy, cumulative two-year past returns prior to portfolio formation period (Rm[t-24,t-1]), and the ratio of realized market volatility to its sample mean (AVol). We also demean Rm[t-24,t-1] and AVol before we estimate conditional betas and alphas.

Table A2 estimates the above-mentioned conditional asset pricing models, and report the alphas for the HMD portfolio. The table also reports the *p*-values of the Wald tests that question the joint significance of each alpha component ($\alpha_{0,i}$ and $\alpha_{1,i}$) across ten portfolios sorted on Campbell et al.'s (2008) financial distress measure.

In Panel A, we consider the conditional CAPM, and reproduce the results in Table 2 of the main text. The HMD strategy provides abnormal profits to investors in bull markets, yet these profits decline significantly in bear markets. Similarly, the abnormal profits increase (decline) with two-year cumulative market returns (realized market volatility). Wald tests further show that we reject the null hypotheses that $\alpha_{0,i}$ and $\alpha_{1,i}$ are zero for ten distress portfolios. Hence, conditional CAPM does not explain the distress puzzle.

Panels B through D show the results for conditional multifactor models. The regressions of the HMD portfolio and the Wald tests reveal that the conditional Fama-French (1993) three-factor model and the conditional Carhart (1997) four-factor model capture the information in the time-varying component of the alpha. The *t*-statistics for $\alpha_{1,HMD}$ are insignificant at 5% level for all three instruments (Z_t), and the Wald tests do not reject the null hypotheses that $\alpha_{1,i}$ are zero for ten distress portfolios. Nevertheless, the constant component of alpha ($\alpha_{0,i}$) is significantly different from zero in all specifications that we consider. Hence, we conclude that conditional versions of mainstream multifactor models do not explain the distress puzzle, either.

Online Appendix D: Choi's (2013) model

We analyze the market exposures of distress-sorted portfolios across market states following the theoretical framework in Choi (2013). This appendix discusses in detail Choi's framework and its implications for our study.

D.1 A theoretical framework for equity beta decomposition

Choi (2013) models a firm i with a production function of $\Pi = X_t K_i^{\alpha}$ where X_t represents the firm's technology having one idiosyncratic and one systematic (market) shock component, α is a parameter ($0 < \alpha < 1$) and K_i is the capital stock having two values ($K_0 < K_1$). The firm i is a growth option (assets-in-place) firm if $K_i = K_0$ ($K_i = K_1$). The growth option firm can transform itself into an assets-in-place firm by undertaking an irreversible investment I_1 ($=K_1 - K_0$) when the technology level X_t reaches an investment boundary (threshold) $X_t = X_I$. The growth option firm finances investment with equities and bonds, and determine the coupon streams of bonds at the time of financing. Both the growth option firm and the assets-in-place firm can declare bankruptcy when the technology level X_t reaches a default boundary (threshold) $X_t = X_D$.

Choi (2013) uses the standard methods in growth option literature (see, for example, Carlson, Fisher, and Giammarino (2004) and Gomes and Schmid (2010), among others) to estimate firm value. The value of an asset-in-place firm is determined by the discounted value of future cash flows—which is positively related to the capital stock level. The value of the growth option firm, however, has both a cash flow component and an expansion option component.

The model has the following expression for the systematic risk of firm equity:

$$\beta^E = \beta^A \, \frac{A}{E} \frac{\partial E}{\partial A} \tag{D1}$$

The systematic risk of firm equity (β^E) depends on three factors: (i) the risk of firm assets(β^A), (ii) the degree to which these assets are levered $\left(\frac{A}{E}\right)$, and (iii) the extent to which the asset risk is passed through to shareholders versus debtholders $\left(\frac{\partial E}{\partial A}\right)$.

The asset beta (β_1^A) of an assets-in-place firm ($i = 1$) measures the sensitivity of firm's asset to the systematic component of the technology process (market factor), and equals:

$$\beta_1^A = \left(1 + \frac{OPEX_1}{A_1(X_t)} + DR_1(X_t)\right)\sigma_M \tag{D2}$$

where $\frac{OPEX_1}{A_1(X_t)}$ is the ratio of operating expense to the market value of the firm, $DR_1(X_t)$ is the default risk of the firm, and σ_M is the volatility of the systematic shock.

The asset beta (β_0^A) of a growth option firm ($i = 0$) has one additional risk component due to its option to expand:

$$\beta_0^A = \left(1 + \frac{OPEX_0}{A_0(X_t)} + DR_0(X_t) + \frac{\mathrm{GO}(X_t)}{A_0(X_t)}\right)\sigma_M \quad \text{(D3)}$$

where $\frac{\mathrm{GO}(X_t)}{A_0(X_t)}$ is the fraction of growth options in firm value (there is a constant term attached to this fraction, but it does not affect the results).

Asset risk is determined by, and increases with, operating leverage, default risk, and the fraction of growth options in firm value. The other two factors in equation (D1) are captured by the elasticity of equity value with respect to asset value $\left(\eta = \frac{A}{E}\frac{\partial E}{\partial A}\right)$, which is driven primarily by the financial leverage of the firm. Choi (2013) also allows the equity beta and its components to vary with the business cycle, i.e., the market (aggregate) component of the technology level X_t. An increase in asset beta components or financial leverage over the business cycle makes the firm riskier, and leads to an increase in the equity beta.

For example, a market downturn, which lowers X_t and creates a bear-market condition, could increase the operating leverage and the default risk of an assets-in-place firm, thereby elevating its asset risk. A lower value of X_t could also increase the financial leverage and thereby the equity elasticity.[2] As a result, an assets-in-place firm would have higher equity risk in bear markets than in bull markets.

The same prediction about equity risk could hold also for an out-of-the-money growth option firm. The technology level of the latter firm is far from the investment threshold (X_I), and the growth option constitutes a low fraction of the firm value. As the growth option component is less effective, the cyclical variations in operating leverage, default risk, and financial leverage collectively determine the cyclical variation in equity beta.

A near-the-money growth option firm, however, could show a different cyclical pattern for equity risk. In Choi's (2013) model, the fraction of growth options is an increasing function of the technology level X_t. A lower value of X_t would decrease the value of the expansion option relative to assets-in-place, thereby reducing the asset risk of a near-the-money growth option firm. If the firm also has little debt on its balance sheet, it could have *lower* equity risk in bad times (e.g., bear markets) than in good times (e.g., bull markets).

In the asset pricing literature on growth options, the theoretical models assume a single systematic shock to the state variable (X_t), so the systematic risk factor represents an aggregate productivity (technology) shock. The empirical work that tests these models, however, uses stock market returns to proxy for the innovations in the systematic component of X_t. As a result, the theoretical models suggest a conditional CAPM for empirical analysis. Several important papers

[2] Choi (2013) shows that a lower value of X_t increases leverage $\left(\frac{A}{E}\right)$ directly, but it also decreases the derivative term $\left(\frac{\partial E}{\partial A}\right)$ because debt becomes riskier. He shows that when the absolute priority rule holds, the effect through leverage dominates and elasticity (η) is also a decreasing function of X_t.

in this literature include Petkova and Zhang (2005), Zhang (2005), Ozdagli (2012), and Choi (2013), among others.

Choi applies this framework to the value anomaly and estimates the financial leverage ratios and asset betas of book-to-market portfolios to justify the pattern of their equity betas. Our paper, however, focuses on the financial-distress anomaly, and uses Choi's (2013) model to rationalize the time-varying risks of distress-based portfolios. Unlike Choi, we estimate the asset beta components of our test portfolios and investigate how these components vary with market states. These exercises reveal the sources of asset risk for firms in the distress-sorted portfolios.

D.2 Implication of Choi's model to financial distress

We build on Choi's model to analyze how the components of equity betas differ between healthy and distressed stocks across markets states, which shapes the time variation of the HMD portfolio return.

The first major component of the equity beta according to Choi's model is the financial leverage, which is naturally related to the extent of financial distress. Conventional wisdom and empirical evidence suggest that distressed firms have higher leverage ratios than healthy firms (leverage ratio also serves as an input in bankruptcy prediction models). This gap in leverage ratios should further increase in market downturns due to the decrease in market values. The financial leverage thus should contribute to a bigger difference between the equity betas of distressed and healthy stocks in bear markets.

The second major component of the equity beta, the asset beta, is a function of three variables: operating leverage, default risk, and the fraction of growth options in firm value. The arguments for operating leverage and default risk are similar to that for financial leverage. Operating leverage and default risk are usually higher for distressed companies, and are therefore likely to experience more meaningful increases in downturn economies. These effects also should contribute to a larger gap between the equity betas of distressed and healthy stocks in bear markets.

The effect of the fraction of growth options is less meaningful for distressed stocks. The growth options of distressed firms are typically out-of-the-money across market states, which is consistent with the lower level of investment by these firms, and should thus constitute a relatively low fraction of firm value. For financially healthy firms, on the other hand, growth options are likely to be near-the-money, which is consistent with accelerated investment that indicates the exercise of these options. Because the growth options become more valuable in bull markets, they likely constitute a higher fraction in the market value of a healthy firm. Hence, while growth options do not affect much the asset beta of distressed firms across market states, they expect to elevate the asset beta of healthy stocks in bull markets. This effect thus further widens the gap between the equity betas of distressed and healthy stocks in bear markets.

Collectively, all components of equity beta shape our prediction that while distressed stocks have higher market risk in bear markets, healthy stocks have procyclical market exposures. This implies that the long/short HMD strategy becomes highly sensitive to market news during bear markets, which is consistent with our findings. In the following subsections we provide empirical evidence that supports our predictions for the time variation of equity beta and its components for healthy and distressed stocks.

D.3 The measurement of equity beta components

We estimate the equity beta and its components as follows. The equity beta is measured by the standard market model regression using monthly returns as in Table 2. Financial leverage is the market value of assets divided by market value of equity, where the market value of assets is measured at the quarterly frequency and equals the sum of market value of equity and book value of debt. To measure the asset beta we use the Merton's (1974) contingent claim model (see online Appendix A above). We first estimate the asset value using the KMV's distance-to-default procedure (see Crosbie and Bohn (2002)), and calculate the asset returns of individual securities at monthly frequency. We then compute value-weighted asset returns for the distress-sorted portfolios, and regress the asset returns on market returns to estimate portfolio asset betas.

Next, we turn to the measurement of the components that determine the asset beta. Operating leverage is the ratio of operating expense to the market value of assets; operating expense equals the sum of the cost of goods sold and selling, and general and administrative expenses over the past four quarters. Default risk is measured by the failure probability model of Campbell et al. (2008).

To estimate whether growth options constitute a high fraction of firm value, we look at three factors: growth option intensity (growth opportunities), the moneyness of growth options, and the exercise of the growth options. We use two proxies for growth option intensity. The first is firm size; according to Choi's (2013) model and other empirical growth option studies (e.g., Grullon et al. (2012)), smaller firms tend to have more growth opportunities. The second proxy is the idiosyncratic volatility beta, which builds on the insight of Ai and Kiku (2016) that option payoffs respond positively to idiosyncratic volatility shocks.

Two other variables convey information about the moneyness of the growth options. The first variable is the productivity. In Choi's (2013) model, a growth option firm exercises its expansion option when the productivity level reaches an investment threshold. In addition, both the growth option firm and the assets-in-place firm can declare bankruptcy when the productivity level reaches a default boundary. Hence, near-the-money growth option firms with little debt on their balance sheet (financially distressed out-the-money growth option firms) are likely to be more (less) productive than other firms in the economy. We measure productivity by asset turnover (the sales-to-assets ratio).

The second variable is the two-year past returns prior to portfolio formation. Grullon et al. (2012) find that positive returns in the recent past (1-2 years) precede growth option exercises (abnormal investment growth). In addition, negative (positive) returns in the recent past increase (decrease) the likelihood of default (see, for example, Campbell et al. (2008)). Hence, financially healthy near-the-money growth option firms (financially distressed out-the-money growth option firms) would likely appear as the winner (loser) stocks of the recent past.

Finally, to identify the exercise of growth options, we analyze the evolution of abnormal investment growth around the formation of the distress-sorted portfolios. Similar to Anderson and Garcia-Feijoo (2006), we measure the abnormal investment growth in quarter k as the ratio of the capital expenditures in the annual period $[k-4Q,k]$ over the simple average of capital expenditures in three previous annual periods $([k-8Q,k-4Q],[k-12Q,k-8Q],[k-16Q,k-12Q])$. We use a six-year event-window $[t-12Q,t+12Q]$ relative to portfolio formation quarter t. We would expect that near-the-money (out-of-the-money) growth option firms experience significant increases (decreases) in their abnormal investment growth prior to portfolio formation period, and that investment growth peaks (bottoms) during the holding period.

D.4 Equity beta components over the full-sample period

We calculate the median values of the variables that determine the equity beta for each of the ten distress-sorted portfolios, and average them over the period January 1975-December 2017. Table A3 presents the results. The CAPM betas display a monotonic pattern in the failure probability cross-section. The istressed stocks portfolio has the highest equity beta, and it decreases as we move closer to the healthy stocks portfolio. The decomposition of equity beta into equity elasticity (financial leverage) and the asset beta helps explain this cross-sectional risk pattern.

Distressed firms are more levered than healthy firms, as expected. The median firm in the top distressed stocks portfolio has an average financial leverage of 1.92, and the leverage declines monotonically from distressed stocks to healthy stocks. Asset beta, on the other hand, has a U-shaped pattern in the financial distress cross-section, which is driven by the dispersion of asset beta components. The high asset beta of the most distressed stocks is driven primarily by their high operating leverage and default risk.

The high asset beta of the most healthy stocks is driven by the fraction of growth options in firm value. As shown in the table, firm size has a hump-shaped pattern across the ten portfolios, and the idiosyncratic volatility beta exhibits a U-shaped pattern. Hence, the top distressed stocks portfolio and the top healthy stocks portfolio represent relatively more growth option firms than other portfolios. Yet, the moneyness of the growth options is different for healthy and distressed stocks. Distressed stocks have negative cumulative returns over a two-year preformation period, while healthy stocks experience the highest returns among all portfolios. Similarly, productivity (measured by asset turnover) is high for healthy stocks and declines almost monotonically from the top healthy stocks portfolio to the top distressed stocks portfolio. These observations suggest that the growth options of healthy firms are closer-to-the-money than those of distressed stocks, implying a higher fraction of growth options in a healthy firm value.

This assessment of growth option moneyness is further supported by the investment behavior analysis. Figure A1 shows the average abnormal capital expenditure growth rate in each of the 12 preformation quarters and 12 postformation quarters. Distressed stocks have higher investment growth than healthy stocks during the preformation quarters $[t-12Q, t-8Q]$. Their investment growth peaks at 30% in quarter $t-7Q$; afterwards, it experiences a significant drop till it reaches its trough at -22% in quarter $t+4Q$. Their investment behavior indicates that in the portfolio formation quarter *t*, distressed firms act like growth firms that lost their expansion opportunities, namely out-of-the-money growth option firms.

Healthy stocks, on the other hand, accelerate their investment growth during the period $[t-8Q, t+3Q]$. Their investment growth peaks at 64% in quarter $t+3Q$; afterwards, it experiences a gradual decline, i.e., healthy stocks exercise their expansion options during the first year of the holding period. Their investment behavior indicates that in the portfolio formation quarter *t*, healthy firms act like growth firms with valuable expansion opportunities, namely near-of-the-money growth option firms.

Table A3 further reveals that the equity betas of healthy firms are slightly higher than their asset betas. This result is not surprising because the equity of a healthy firm is a deep-in-the-money call option on its underlying asset, the beta of a call option is the product of the elasticity and the beta of the underlying asset, and the elasticity of a deep-in-the-money call option is slightly higher than one. The impact of elasticity on equity beta, however, is evident for distressed stocks. Distressed firms have the highest financial leverage and the highest asset beta; as a result, they have the highest CAPM beta.

D.5 Equity beta components in bull vs bear markets

Table A4 presents the equity beta and its components for the distress-sorted portfolios in bull versus bear markets. The important observation is that all components contribute to a larger gap between the betas of distressed and healthy stocks in bear markets. While healthy firms have similar financial leverage in both states of the market, distressed firms become more levered in bear markets. Financial leverage is a key determinant of equity elasticity, so it amplifies the equity risk of the distressed stocks portfolio in bear markets.

Healthy firms have stable operating leverage in both market states. Distressed firms, on the other hand, become more levered in bear markets compared to their positions in bull markets. Similarly, default risk rises significantly for distressed firms in bear markets, while it remains unchanged for healthy firms. Putting growth option effects aside, these results imply that distressed firms should have higher asset risk in bear markets than in bull markets, whereas healthy firms should have the same asset risk in both market states.

The patterns of firm size and idiosyncratic volatility beta indicate that the composition of financial-distress portfolios does not vary across market states, where distressed and healthy stocks portfolios represent relatively more growth option firms than other decile portfolios. Yet, the market condition affects differently the moneyness and thereby the exercising of growth options of healthy and distressed firms. As discussed in the previous section, both measures of growth option moneyness (recent return and productivity) suggest that growth options of healthy firms are more likely to be near-the-money, and those of distressed firms out-of-the-money.

We further argue that healthy firms get closer to their investment threshold in bull markets. First, as shown in Table A4, in bull markets healthy firms show higher productivity and higher past return, thus their growth option moneyness is higher, which likely puts them closer to their investment threshold. (as outlined above, Choi shows that firms with valuable growth opportunities exercise their growth options when the productivity level reaches an investment threshold.). Second, we provide evidence that healthy firms accelerate their investment growth during bull market conditions, with a peak in the first year (see Figure A1), which indicates the exercise of growth options. This suggests that bull markets carry healthy firms closer to their investment threshold. In contrast, distressed firms reduce investment growth in both market states, providing further indication that their growth options are out-of-the-money.

These differences suggest therefore that for healthy firms, growth options become more valuable and constitute a higher fraction of firm value in bull markets, whereas for distressed firms, the fraction of growth options is low and does not change much across market states. This time variation in the fractions of growth options, together with the other two components of asset beta (operating leverage and default risk), explains the time variation in asset beta, as summarized in the following table:

	Asset beta components	From bear to bull market
Healthy firms	Fraction of growth options	Increase
	Operating leverage	No significant change
	Default risk	No significant change
	➔ **Asset beta**	**Increase**
Distressed firms	Fraction of growth options	No significant change
	Operating leverage	Decrease
	Default risk	Decrease
	➔ **Asset beta**	**Decrease**

And these time variations in asset beta, together with the other component of equity beta (the financial leverage) explain the time variations in equity beta across market states.

	Equity beta components	From bear to bull market
Healthy firms	Asset beta	Increase
	Financial leverage	No significant change
	➔ **Equity beta**	**Increase**
Distressed firms	Asset beta	Decrease
	Financial leverage	Decrease
	➔ **Equity beta**	**Decrease**

In sum, the time variation in equity beta and its components for healthy and distressed stocks can rationalize why the distress anomaly does not hold in bear markets.

Online Appendix E: Expanding window analysis

The construction of the dynamic hedging strategy (HMD**) in the main text is subject to a potential look-ahead bias. The optimal weight ω_t^* that investors assign to the HMD portfolio at the end of each month t depends on its expected return (μ_t) and volatility (σ_t^2), but the time series models that estimate these conditional moments utilize the full sample period. To overcome this possible bias, we construct an alternative HMD** portfolio by employing historical data that are available to investors at time *t*, and using expanding windows to estimate the empirical models for μ_t and σ_t^2. The first window of each empirical model ends in December 1984. A minimum of ten years of monthly return series ensures that the empirical models produce reliable parameter estimates and optimal weights ω_t^* for the HMD portfolio.

Figure A2 compares alternative HMD strategies over the subperiod January 1985-December 2017. The dynamic hedging strategy outperforms the other strategies. HMD* ranks second and tracks HMD** portfolio quite well. The difference between the performances of HMD* and HMD** strategies in this subperiod are not as pronounced as their difference over the full sample. Moreover, spanning tests where one risk-managed HMD strategy is regressed on the other risk-managed HMD strategy produces insignificant alphas. Hence, scaling HMD by market volatility seems to be a simple and highly productive way of managing the downside risks of the standard HMD portfolio.

Online Appendix F: An alternative HMD strategy that controls for past returns

In Section 4, we construct five distress portfolios controlled for the momentum effect (CHS-MOM) from a 5x5 conditional double sort. Table 8 shows that the healthy-minus-distressed (HMD) portfolio of the CHS-MOM cross-section has a higher market beta in bear markets than in bull markets; as a result, we argue that the sensitivity of the distress anomaly to the market state is incremental to that of momentum.

Next, we confirm the robustness of this argument to employing the two alternative market state variables: the two-year cumulative market return (Rm[t-24,t-1]) and the realized market volatility (AVol). In Table 2, we use these state variables as independent variables of the predictive regressions and the conditional CAPM regressions in which the standard decile-based HMD portfolio is the dependent variable. To calculate how much the momentum effect captures the time variation in average returns and market betas, we should also form an HMD portfolio from decile portfolios that control for past returns. Then we can check whether the earlier HMD results in Table 2 are robust to controlling for momentum.

Hence, we form a 3x10 conditional double sort on momentum and distress. We sort all stocks first by momentum, and allocate them into three equal-sized portfolios. Next, within each momentum tercile, we sort stocks by distress, and distribute them into ten equal-sized portfolios. Last, we average the distress portfolio returns over momentum terciles to construct ten distress portfolios controlled for the momentum effect. Finally, we form a healthy-minus-distressed long/short portfolio (HMD-MOM) and use its monthly return as a dependent variable in the predictive regressions and the conditional CAPM regressions.

Table A5 present the results. In Panel A, the bear-market dummy, Rm[t-24,t-1], and AVol are able to predict future HMD-MOM returns, yet the regression coefficients are smaller in absolute value than their counterparts in Table 2. Similarly, the market betas of HMD-MOM portfolio vary significantly with the bear-market dummy, Rm[t-24,t-1], and AVol. The signs of the regression coefficients for the interaction variables are consistent with the poor performance of HMD-MOM portfolio during market downturns. Comparing the coefficients in Table 2 with those in Table A5 indicates that momentum captures a significant portion of the time variation in market beta, but it does not eliminate it. We argue that financial distress captures incremental information about time varying risk and return beyond the momentum effect.

Online Appendix G: Distress by KMV and alternative definition of bear market

We conduct several robustness tests using a KMV-based healthy-minus-distressed (HMD) portfolio and an alternative definition of bear† markets. As in Section 2.3, we assume that investors experience a bear† (bull†) market if the cumulative return relative to most recent peak (Rm[Peak,t-1]) is less than or equal to (greater than) -20%.

Table A6 provides corroborating evidence about the negative effect of market conditions on the magnitude of the distress effect. Panel A shows that average HMD return is lower in bear† markets than in bull† markets. Similarly, low performance relative to most recent peak and high past-market volatility predict low HMD returns. These results are quite similar to the ones that we obtain with Campbell et al.'s distress measure and report in Table 4 of the main text.

Table A6 also echoes the conditional CAPM results in Table 4 by showing that the beta of HMD depends strongly on market states: The beta in a bull† market is −0.73, whereas the beta in a bear† market is −1.75 (=−0.73−1.02). Using $R_m[Peak, t-1]$ and AVol as conditioning variables also produces similar results for the KMV-based HMD portfolio.

The highly negative beta of HMD portfolio in bear† markets suggests that the long/short KMV-based distress strategy can incur big losses when the market rebounds. The regressions in Table A7 confirm this claim. The coefficient of the interaction variable (Bear x Up) is negative (−17.16%) and highly significant (t-statistic=−7.33). In a bear† market, HMD loses 8.90% (1.29%+6.97%−17.16%) per month if the market rallies.

The time-varying beta of HMD portfolio supports this return pattern. HMD has a beta of −2.38 (=−0.73−0.74−0.91) when the market rallies in bear markets. Analyzing the long- and short-leg of the strategy indicates that the exposures of distressed stocks portfolio to market fluctuations mainly determine these results. In sum, the time variation in average returns and market betas of the KMV-based HMD portfolio is very similar to that of the HMD portfolio that we construct using Campbell et al.'s (2008) distress signal.

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Table A1: Equity betas by prior market return and expected market risk premium

The table reports the time varying betas of HMD, healthy, and distressed stocks portfolios in different states of the economy. The failure probability of Campbell et al. (2008) measures financial distress. In Panel A, the state of the economy is determined by two-year cumulative market returns. Investors observe a bear-market (bull-market) state if cumulative returns are negative (positive). The left subpanel presents the time-varying betas from conditional market regressions (see Table 2 of the main text) and serves as a benchmark. The estimation procedure of the right subpanel interacts rolling betas of distress portfolios with bear- and bull-market dummy variables. We estimate rolling betas at the firm-level using 36-month rolling-window CAPM regressions, and subsequently value-weight them to obtain portfolio-level beta estimates. In Panel B, we adopt the empirical procedure in Petkova and Zhang (2005). The state of the economy is determined by the expected market risk premium. To estimate this premium, we regress market excess returns on four conditioning variables, namely dividend yield, term premium, default premium, and the risk-free rate. Investors observe a recession (expansion) state if the expected market risk premium is above (below) average. The estimation procedure in the left subpanel is based on conditional market regressions that employ the four conditioning variables above and produce the fitted betas of distress portfolios. The estimation procedure of the right subpanel is based on rolling beta estimation. We interact the betas of distress portfolios with recession and expansion dummy variables. The sample period is January 1975 to December 2017.

Panel A: Equity betas by prior market return

	Conditional market regression					Rolling window beta estimation			
	Bear	Bull	difference	t-statistic		Bear	Bull	difference	t-statistic
HMD	-1.56	-0.57	-0.99	-3.33	HMD	-1.79	-0.61	-1.18	-6.15
Healthy	0.69	0.91	-0.22	-3.54	Healthy	0.69	0.95	-0.27	-2.81
Distressed	2.25	1.48	0.78	2.90	Distressed	2.48	1.56	0.91	5.87

Panel B: Equity betas by expected market risk premium

	Conditional market regression – fitted beta					Rolling window beta estimation			
	Recession	Expansion	difference	t-statistic		Recession	Expansion	difference	t-statistic
HMD	-0.97	-0.41	-0.55	-3.45	HMD	-1.03	-0.54	-0.50	-3.56
Healthy	0.83	0.94	-0.11	-3.99	Healthy	0.86	0.97	-0.10	-2.15
Distressed	1.80	1.35	0.45	3.32	Distressed	1.90	1.50	0.39	3.36

Table A2: Time varying alphas of financial distress portfolios for alternative conditional asset pricing models

Conditioning variables are a bear market dummy (if cumulative market return in the past two years, Rm[t-24,t-1], is negative), demeaned Rm[t-24,t-1], and demeaned market volatility (AVol). We interact market excess return (RmRf), Fama-French (1993, 2015), and Carhart (1997) factors with these state variables to estimate the conditional betas and alphas of the HMD portfolio. The table reports the intercept terms (the constant components of alphas) and the coefficients for state variables (the time varying components of alphas) and Newey-West (1987) corrected *t*-statistics with 24 lags. In addition, we repeat these conditional regressions using ten value-weighted distress portfolios, and perform Wald tests for the joint significance of the constant components (as well as the time-varying components) of portfolio alphas. The table reports the *p*-values of the Wald tests in parentheses. The sample period is January 1975 to December 2017.

Panel A: Conditional CAPM

	HMD Portfolio			Wald test (p-value)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
intercept	2.04%	1.79%	1.61%	(<0.01)	(<0.01)	(<0.01)
t-statistic	7.22	6.16	5.18			
Bear	-2.82%			(<0.01)		
t-statistic	-2.52					
Rm[t-24,t-1]		4.28%			(0.03)	
t-statistic		3.12				
AVol			-1.89%			(0.04)
t-statistic			-2.54			

Panel B: Conditional Fama-French (1993) model

	HMD Portfolio			Wald test (p-value)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
intercept	2.18%	2.04%	1.98%	(<0.01)	(<0.01)	(<0.01)
t-statistic	9.65	8.26	9.19			
Bear	-2.13%			(<0.01)		
t-statistic	-1.95					
Rm[t-24,t-1]		1.79%			(0.28)	
t-statistic		1.10				
AVol			-1.04%			(0.21)
t-statistic			-1.62			

Panel C: Conditional Carhart (1997) model

	HMD Portfolio			Wald test (p-value)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
intercept	1.42%	1.30%	1.36%	(<0.01)	(<0.01)	(<0.01)
t-statistic	5.12	5.78	5.33			
Bear	-1.41%			(0.03)		
t-statistic	-1.33					
Rm[t-24,t-1]		0.35%			(0.41)	
t-statistic		0.22				
AVol			-0.18%			(0.23)
t-statistic			-0.29			

Panel D: Conditional Fama-French (2015) model

	HMD Portfolio			Wald test (p-value)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
intercept	1.60%	1.11%	1.32%	(<0.01)	(<0.01)	(<0.01)
t-statistic	6.53	3.75	6.27			
Bear	-3.79%			(<0.01)		
t-statistic	-5.00					
Rm[t-24,t-1]		4.09%			(0.01)	
t-statistic		2.98				
AVol			-2.84%			(<0.01)
t-statistic			-3.89			

Table A3: Equity beta components for distress-sorted portfolios

The table shows the equity (CAPM) beta and its components for decile portfolios sorted on Campbell et al.'s (2008) financial distress measure. Equity beta is measured by the standard market model regression as in Table 2. Financial leverage is ratio of market value of assets to market value of equity. The asset beta is estimated by regressing portfolio asset return on market return, where the asset return calculation is based on Merton's (1974) contingent claim model. Operating leverage is operating expense divided by market value of assets. Default risk is the failure probability of Campbell et al. (2008). Firm size is the book value of assets. Idiosyncratic volatility beta is the sensitivity of the stock return to an unexpected increase in idiosyncratic volatility (estimated by the procedure outlined in Ai and Kiku (2016)). Cumulative return is estimated during the two years prior to the portfolio formation month. Productivity is measured by the asset turnover ratio (sales to total assets). The sample period is January 1975 to December 2017.

	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Equity Beta	0.86	0.92	0.97	1.01	1.06	1.16	1.23	1.45	1.53	1.65	-0.79	-4.64
Financial leverage	1.21	1.28	1.37	1.46	1.55	1.64	1.73	1.81	1.89	1.92	-0.71	-10.13
Asset Beta	0.82	0.78	0.75	0.71	0.66	0.65	0.67	0.80	0.83	0.95	-0.13	-1.81
Operating leverage	0.51	0.48	0.48	0.48	0.50	0.52	0.56	0.60	0.65	0.75	-0.24	-8.01
Default Risk (Failure probability)	0.14%	0.21%	0.27%	0.35%	0.45%	0.60%	0.82%	1.30%	2.85%	12.83%	-12.68%	-8.87
Firm Size ($ million)	541.29	773.09	814.29	787.31	721.49	636.34	537.90	423.39	304.67	121.66	419.63	11.10
Idio. volatility beta (in percent)	2.11	1.78	1.46	1.31	1.48	1.74	1.91	2.12	2.63	3.46	-1.35	-5.85
Two-year cumulative past returns	58.23%	53.89%	47.88%	43.39%	40.61%	36.30%	30.03%	21.05%	7.47%	-22.02%	80.25%	11.39
Productivity (Asset turnover)	1.12	1.13	1.12	1.07	1.03	0.98	0.97	0.97	0.97	0.88	0.23	9.51

Table A4: Equity beta components for distress-sorted portfolios separately for bull and bear markets

The table shows the same characteristics as in Table A3, separately for bull and bear markets. A bull (bear) market is assumed if the cumulative market return during the past two years prior to portfolio formation is positive (negative). The sample period is January 1975 to December 2017.

	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Panel A: Equity Beta												
Bull Market	0.91	0.95	0.97	1.00	1.02	1.10	1.12	1.27	1.36	1.48	-0.57	-4.12
Bear Market	0.69	0.81	0.98	1.03	1.21	1.40	1.60	2.08	2.16	2.25	-1.56	-6.02
Difference	-0.22	-0.14	0.00	0.03	0.19	0.30	0.47	0.81	0.80	0.78	-0.99	-3.33
t-statistic	-3.54	-3.29	0.11	0.68	2.52	3.27	4.83	3.95	4.82	2.90		
Panel B: Financial Leverage												
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Bull Market	1.21	1.28	1.36	1.44	1.53	1.62	1.71	1.79	1.87	1.88	-0.67	-9.71
Bear Market	1.22	1.33	1.44	1.55	1.66	1.78	1.89	1.94	2.07	2.15	-0.92	-7.13
Difference	0.02	0.05	0.08	0.10	0.12	0.15	0.18	0.15	0.21	0.27	-0.25	-2.35
t-statistic	1.44	3.48	3.79	4.03	4.16	3.79	3.83	2.99	3.09	2.45		
Panel C: Asset Beta												
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Bull Market	0.85	0.82	0.78	0.73	0.65	0.65	0.64	0.73	0.77	0.87	-0.02	-0.24
Bear Market	0.67	0.66	0.65	0.63	0.66	0.67	0.81	1.04	1.06	1.23	-0.56	-3.21
Difference	-0.18	-0.16	-0.13	-0.10	0.00	0.03	0.18	0.31	0.29	0.36	-0.54	-2.88
t-statistic	-3.36	-3.03	-2.45	-1.61	0.05	0.42	1.59	2.36	1.96	2.06		
Panel D: Operating leverage												
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Bull Market	0.52	0.48	0.48	0.48	0.50	0.52	0.56	0.59	0.65	0.73	-0.21	-7.22
Bear Market	0.48	0.48	0.49	0.50	0.52	0.54	0.57	0.62	0.71	0.85	-0.37	-7.73
Difference	-0.04	0.00	0.01	0.01	0.02	0.02	0.01	0.03	0.06	0.12	-0.16	-3.57
t-statistic	-1.27	-0.01	0.44	0.70	0.83	0.75	0.33	0.95	1.68	2.80		
Panel E: Default risk (Failure probability)												
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Bull Market	0.14%	0.20%	0.26%	0.33%	0.43%	0.56%	0.76%	1.16%	2.45%	11.27%	-0.11	-9.96
Bear Market	0.17%	0.26%	0.35%	0.46%	0.60%	0.81%	1.20%	2.16%	5.37%	22.62%	-0.22	-4.36
Difference	0.02%	0.06%	0.09%	0.13%	0.18%	0.24%	0.43%	1.00%	2.92%	11.35%	-0.11	-2.20
t-statistic	2.42	2.91	3.78	4.02	2.97	2.22	2.05	2.37	2.62	2.21		
Panel F: Firm size ($ million)												
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Bull Market	545.07	777.21	806.57	790.59	719.84	640.79	543.37	425.30	303.97	122.88	422.19	9.47
Bear Market	517.58	747.23	862.64	766.76	731.81	608.49	503.58	411.42	309.07	113.96	403.62	5.66
Difference	-27.49	-29.99	56.07	-23.83	11.97	-32.30	-39.79	-13.88	5.10	-8.92	-18.57	-0.28
t-statistic	-0.38	-0.37	0.67	-0.33	0.19	-0.53	-0.71	-0.32	0.13	-0.70		

Panel G: Idiosyncratic volatility beta (in percent)												
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Bull Market	2.12	1.79	1.46	1.31	1.49	1.75	1.92	2.14	2.60	3.41	-1.29	-5.61
Bear Market	2.05	1.71	1.47	1.32	1.44	1.68	1.88	2.03	2.80	3.74	-1.69	-4.57
Difference	-0.07	-0.08	0.01	0.01	-0.05	-0.07	-0.04	-0.11	0.20	0.33	-0.40	-1.11
t-statistic	-0.23	-0.30	0.04	0.04	-0.20	-0.30	-0.18	-0.33	0.50	0.71		

Panel H: Two-year cumulative past returns												
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Bull Market	65.29%	61.43%	55.23%	50.46%	47.65%	43.70%	37.24%	28.03%	14.51%	-17.49%	82.78%	11.38
Bear Market	14.01%	6.64%	1.84%	-0.89%	-3.49%	-10.07%	-15.10%	-22.70%	-36.67%	-50.42%	64.43%	3.88
Difference	-51.28%	-54.79%	-53.39%	-51.35%	-51.14%	-53.77%	-52.34%	-50.72%	-51.17%	-32.93%	-18.35%	-1.06
t-statistic	-5.35	-6.75	-7.86	-7.62	-6.12	-7.00	-6.30	-5.72	-5.20	-2.83		

Panel I: Productivity (Asset turnover)												
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Bull Market	1.14	1.15	1.14	1.09	1.05	1.01	1.00	1.00	1.00	0.92	0.22	10.18
Bear Market	0.98	1.00	0.97	0.92	0.88	0.84	0.80	0.80	0.77	0.67	0.31	4.04
Difference	-0.16	-0.15	-0.17	-0.17	-0.17	-0.16	-0.20	-0.20	-0.23	-0.25	0.09	1.21
t-statistic	-2.39	-3.18	-5.07	-4.83	-4.95	-4.44	-4.69	-4.58	-5.78	-4.95		

Table A5: Time-series regression of HMD-MOM portfolio monthly return on market state variables

We sort all stocks first by momentum (return in the past twelve months) into three equal-sized terciles, and within each tercile, we sort all stocks by distress (based on Campbell, Hilscher and Szilagyi (CHS, 2008)) into ten equal-sized deciles. We then construct ten financial distress portfolios controlled for the momentum effect (CHS-MOM). Next, we form a healthy-minus-distressed long/short strategy (HMD-MOM) from the latter decile portfolios to assess the impact of momentum on time-varying HMD returns and betas. Finally, we repeat the predictive regressions and conditional CAPM regressions in Table 2 with HMD-MOM portfolio. The dependent variable in each regression is the HMD-MOM portfolio monthly return. Independent variables are the cumulative market return in the past two years (Rm[t-24,t-1]), a dummy variable indicating a bear market (if the cumulative market return during the past two years prior to portfolio formation is negative), realized daily market volatility estimated with 252 days prior to portfolio formation (AVol = realized market volatility divided by its sample mean), the market excess return (RmRf) during the holding period month, and interaction terms. We demean Rm[t-24,t-1] and AVol before we run the regressions. The table reports regression coefficients and Newey-West corrected *t*-statistics with 24 lags. The sample period is January 1975 to December 2017.

Panel A: Predictive Regressions

		Intercept	Bear	Rm[t-24,t-1]	AVol	Adj R²
(1)	Estimate	1.06%	-1.98%			0.01
	t-statistic	4.09	-1.98			
(2)	Estimate	0.78%		3.42%		0.02
	t-statistic	2.71		3.05		
(3)	Estimate	0.78%			-1.43%	0.01
	t-statistic	2.67			-2.07	
(4)	Estimate	0.80%	-0.09%	2.83%	-0.57%	0.01
	t-statistic	2.57	-0.07	2.10	-0.71	

Panel B: CAPM Regressions

		Intercept	Bear	Rm[t-24,t-1]	AVol	RmRf	RmRf x Bear	RmRf x Rm[t-24,t-1]	RmRf x AVol	Adj R²
(5)	Estimate	1.20%				-0.60				0.18
	t-statistic	4.69				-4.84				
(6)	Estimate	1.38%	-1.33%			-0.49	-0.51			0.20
	t-statistic	5.62	-1.74			-4.41	-2.24			
(7)	Estimate	1.27%		1.92%		-0.58		0.70		0.21
	t-statistic	5.18		1.84		-5.78		3.08		
(8)	Estimate	1.17%			-0.66%	-0.52			-0.54	0.22
	t-statistic	4.83			-1.27	-6.00			-3.11	
(9)	Estimate	1.29%	-0.63%	1.05%	-0.08%	-0.53	-0.02	0.30	-0.42	0.22
	t-statistic	5.29	-0.53	0.76	-0.14	-5.26	-0.05	1.37	-1.74	

Table A6: Time-series regression of KMV-based HMD portfolio monthly return on an alternative set of market state variables

The dependent variable in each regression is the HMD portfolio monthly return. We construct healthy stocks portfolio and distressed stocks portfolio using default probabilities from Merton (1974)-KMV's distance-to-default model. Independent variables are the market return relative to the most recent peak (Rm[Peak,t-1]), an alternative dummy variable indicating a bear† market (if the market return relative to the most recent peak is less than or equal to -20%), realized daily market volatility estimated with 252 days prior to portfolio formation (AVol = realized market volatility divided by its sample mean), the market excess return (RmRf) during the holding period month, and interaction terms. We demean Rm[Peak,t-1] and AVol before we run the regressions. The table reports regression coefficients and Newey-West (1987) corrected *t*-statistics with 24 lags. The sample period is April 1970 to December 2017.

Panel A: Predictive Regressions									
	Intercept	Bear†							Adj R^2
Estimate	1.29%	-3.78%							0.03
t-statistic	3.75	-3.63							
	Intercept		Rm[Peak,t-1]						Adj R^2
Estimate	0.69%		16.83%						0.06
t-statistic	1.82		5.17						
	Intercept			AVol					Adj R^2
Estimate	0.69%			-2.81%					0.02
t-statistic	1.72			-3.51					
	Intercept	Bear†	Rm[Peak,t-1]	AVol					Adj R^2
Estimate	0.39%	1.85%	22.68%	0.26%					0.06
t-statistic	0.95	1.04	3.59	0.23					
Panel B: CAPM Regressions									
	Intercept				RmRf				Adj R^2
Estimate	1.24%				-0.99				0.33
t-statistic	3.81				-7.36				
	Intercept	Bear†			RmRf	RmRf x Bear†			Adj R^2
Estimate	1.62%	-2.15%			-0.73	-1.02			0.42
t-statistic	5.30	-2.86			-7.44	-6.69			
	Intercept		Rm[Peak,t-1]		RmRf		RmRf x Rm[Peak,t-1]		Adj R^2
Estimate	1.26%		10.33%		-0.85		3.29		0.44
t-statistic	4.62		5.02		-10.46		9.42		
	Intercept			AVol	RmRf			RmRf x AVol	Adj R^2
Estimate	1.22%			-1.74%	-0.89			-0.71	0.39
t-statistic	3.92			-2.98	-7.87			-5.57	
	Intercept	Bear†	Rm[Peak,t-1]	AVol	RmRf	RmRf x Bear†	RmRf x Rm[Peak,t-1]	RmRf x AVol	Adj R^2
Estimate	0.94%	2.02%	16.85%	0.37%	-0.80	-0.30	2.25	-0.09	0.44
t-statistic	2.86	1.51	3.21	0.50	-9.61	-0.88	2.27	-0.49	

Table A7: Effect of market rebound on the KMV-based HMD portfolio using alternative definition of market state

We construct healthy stocks portfolio and distressed stocks portfolio using default probabilities from Merton (1974)-KMV's distance-to-default model, and construct a healthy-minus-distressed (HMD) zero-cost investment strategy. The table shows two regressions for three dependent variables: the HMD portfolio return, the most healthy stocks portfolio excess return, and the most distressed stocks portfolio excess return. The independent variables are the market excess return (RmRf), a dummy variable (Up) that equals one if RmRf is positive, a dummy variable indicating a bear market, and interaction terms. A bear† market is assumed if the market return relative to the most recent peak is less than or equal to -20%. The table reports regression coefficients and Newey-West corrected *t*-statistics with 24 lags. The sample period is April 1970 to December 2017.

		Intercept	Bear†	Bear x Up	Intercept	Bear†	RmRf	RmRf x Bear†	RmRf x Bear† x Up
HMD Portfolio	Estimate	1.29%	6.97%	-17.16%	1.62%	-0.80%	-0.73	-0.74	-0.91
	t-statistic	3.75	5.57	-7.33	5.30	-1.20	-7.44	-6.83	-2.95
		Intercept	Bear†	Bear x Up	Intercept	Bear†	RmRf	RmRf x Bear†	RmRf x Bear† x Up
Healthy Stocks Portfolio	Estimate	0.83%	-3.46%	3.91%	0.45%	-1.09%	0.83	-0.44	0.01
	t-statistic	4.29	-5.97	3.91	5.31	-2.79	32.89	-2.31	0.09
		Intercept	Bear†	Bear x Up	Intercept	Bear†	RmRf	RmRf x Bear†	RmRf x Bear† x Up
Distressed Stocks Portfolio	Estimate	-0.45%	-10.42%	21.07%	-1.16%	-0.29%	1.56	0.30	0.93
	t-statistic	-1.11	-9.30	8.84	-4.39	-0.35	17.03	1.94	3.17

Figure A1: Abnormal investment growth of financial distress portfolios in event-time

At the end of each quarter *t* from 1984Q1 through 2017Q4, stocks are ranked according to their probability of default by the Campbell et al. (2008) measure, and distributed into ten financial distress portfolios. For every portfolio, the average abnormal capital expenditure (CAPX) growth rate of the median firm is computed in each of the twelve pre-formation quarters and twelve post-formation quarters. We report event-time abnormal investment growth rates of the healthy stocks portfolio (solid line) and the distressed stocks portfolio (dashed line) over the full sample and in two different states of the market. A bull (bear) market is assumed if the cumulative market return during the past two years prior to portfolio formation is positive (negative).

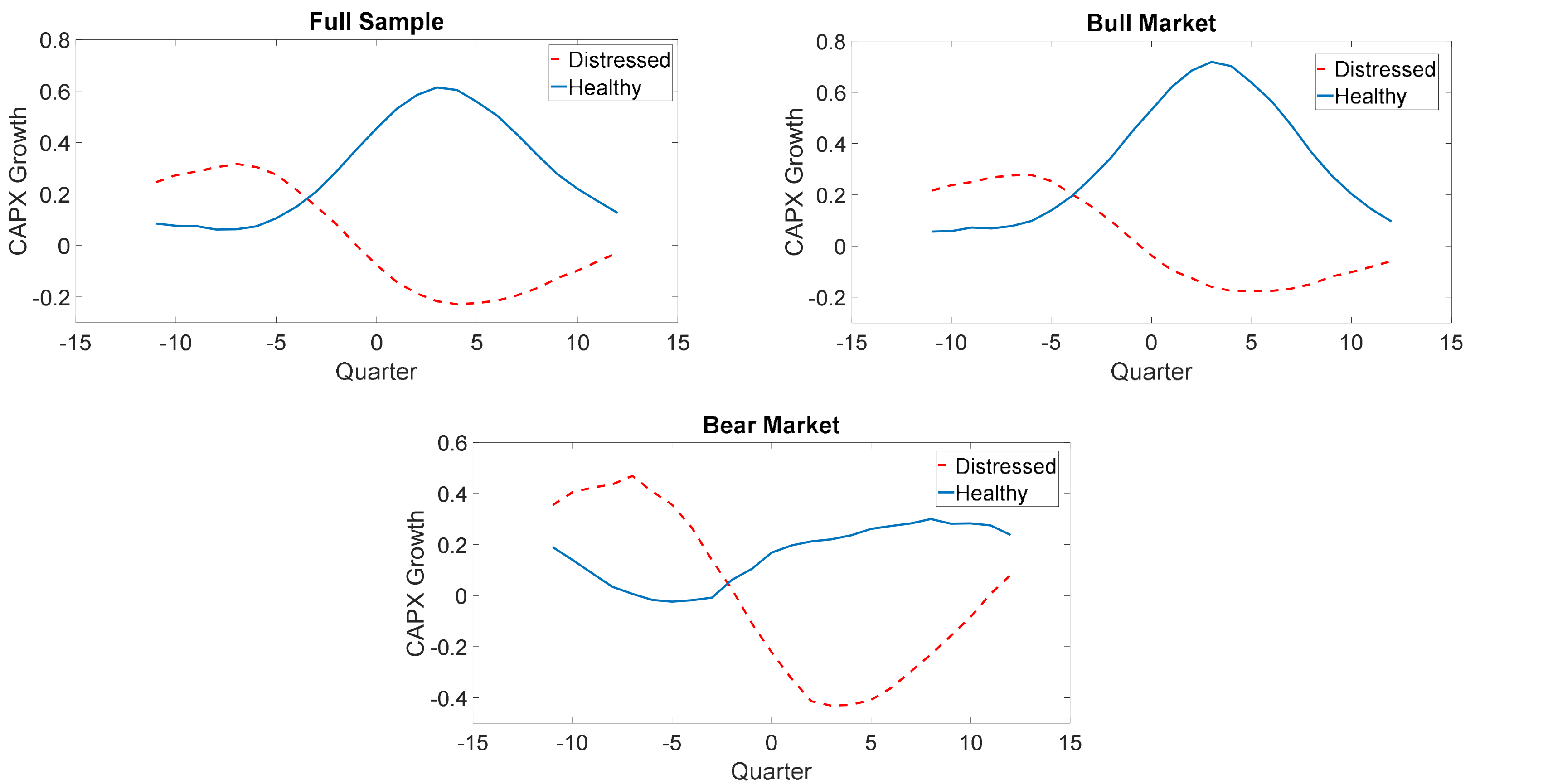

Figure A2: Performance of standard and risk-managed HMD portfolios – Expending window estimation

The figure plots the value of a $1 investment in the market portfolio in excess of the risk-free asset (solid line), the standard HMD portfolio (dashed line), the risk-managed HMD* portfolio scaled by market volatility (dotted line), and the dynamic hedging portfolio HMD** (circled line). We form the HMD** portfolio via an expanding window estimation framework in which the parameters associated with the expected HMD returns and the conditional volatility of HMD returns are estimated using historical information available to investors prior to portfolio formation month. For example, the first window of this estimation framework uses past 120 monthly observations of HMD returns. The second (third) window uses past 121 (122) monthly observations of HMD returns, and so on. The shaded grey areas represent bear markets in our sample. A bear market is assumed if the cumulative market return during the past two years prior to portfolio formation is negative. We evaluate the performance of alternative HMD strategies and the market portfolio over the period January 1985-December 2017.