Distressed Stocks in Distressed Times

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Abstract

This paper shows that the well-documented distress anomaly does not hold in market downturns. The asset beta and financial leverage of distressed stocks rise significantly during bear markets, resulting in a dramatic increase in their equity beta. Hence, a long/short healthy-minus-distressed trading strategy leads to significant losses when the market rebounds. Managing this risk mitigates the severe losses of financial-distress strategies and significantly improves their Sharpe ratios. Our results remain strongly significant controlling for the momentum effect and are robust to various estimation procedures.

Keywords: Anomalies, Financial distress, Time-varying risk

JEL Classification: G11, G12

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1. Introduction

Financially distressed stocks earn lower average returns than healthy stocks. This result, known as the "financial-distress puzzle", proves to be a challenge to rational asset pricing. While Fama and French (1992) consider financial distress to be the main reason behind the high expected returns of value stocks, other studies that sort stocks on distress proxies directly, such as Dichev (1998), Griffin and Lemmon (2002), and Campbell, Hilscher, and Szilagyi (2008), find that distressed stocks severely underperform healthy stocks. Deepening the puzzle, distressed firms have higher market betas than healthy firms. Hence, risk and return do not go hand in hand in the financial-distress cross-section.

While a few potential explanations have been proposed, there is still no consensus in the literature about what drives this anomaly. Garlappi, Shu, and Yan (2008), for example, propose a model in which distressed stocks become safer due to violations of the absolute priority rule. George and Hwang (2010) argue that firms with high exposure to systematic distress costs will choose lower leverage levels, whilst having higher expected returns. Opp (2015) develops a dynamic model illustrating that investor learning process on firms' solvency by active investors can generate underperformance of highly distressed stocks. Chava and Purnanandam (2010) argue that the observed anomaly may actually be just an in-sample phenomenon, resulting from a streak of surprisingly low realized returns on distressed stocks in the U.S. in the 1980s.[1]

In this paper we do not attempt to resolve the distress puzzle, but analyze the risk and return patterns of financial-distress portfolios across market states. Investors typically define a bear (bull)

[1] For more studies on the distress puzzle see Avramov et al. (2009), Da and Gao (2010), Garlappi and Yan (2011), Johnson et al. (2011), Friewald, Wagner, and Zechner (2014), Hackbarth, Haselmann, and Schoenherr (2015), Hou, Xue, and Zhang (2015), and Eisdorfer, Goyal, and Zhdanov (2016).

market condition if the cumulative market return during the past two years before portfolio formation is negative (positive). We find that the well-documented underperformance of distressed stocks relative to healthy stocks occurs *only* in bull markets. In bear markets, distressed stocks earn higher average returns than healthy stocks, although the outperformance is insignificant in statistical terms. The latter result stems mainly from the large positive returns of distressed stocks during market rebounds. Hence, the otherwise profitable long/short healthy-minus-distressed (HMD) strategy can be unattractive to investors in a bear market, and even "crash" when the market turns positive.

This paper explains why the returns of distressed/healthy stocks depend on market states by studying the determinants of their market betas. In addition, we suggest a risk-management strategy that mitigates the potential severe losses of the HMD portfolio in bear markets and improves its Sharpe ratio.

We analyze the market exposures of distress-sorted portfolios following the theoretical framework in Choi (2013). The framework is based on a simple decomposition of the equity (market) beta of an individual stock: the equity beta equals the asset beta times the equity elasticity. The derivation of this result is standard in the capital structure literature. For example, building on Merton (1974), who views the firm's equity as a call option on the firm's assets, Galai and Masulis (1976) show that the beta of this call option (the equity beta) equals the beta of the underlying asset (the asset beta) times the option's omega (the equity elasticity, which compares the percentage change in equity value to the percentage change in asset value).

Financial leverage is the key determinant of the equity elasticity. Choi shows that the asset beta is determined by, and increases with, operating leverage, default risk, and the fraction of growth options in firm value. He also allows the equity beta and its components to vary with the business cycle. For example, the equity elasticity is a decreasing function of the demand state variable. In addition, an increase in financial leverage or asset beta components over the business cycle makes the firm riskier, and leads to an increase in the equity beta.[2]

Choi (2013) applies this framework to the value anomaly and computes the financial leverage and asset betas of book-to-market portfolios to justify the pattern of their equity betas. He also tests the implications of his framework empirically using conditional CAPM regressions. In this study we use Choi's theoretical model and empirical procedures to rationalize the increased market exposure of distressed stocks in panic states.

We investigate how the equity beta components vary with market conditions across portfolios that represent different levels of financial distress. We use the failure probability measure of Campbell et al. (2008) to classify stocks into ten distress-based portfolios. As stated above, the equity beta can be expressed as the product of equity elasticity and the asset beta, which are determined by four components: financial leverage (for equity elasticity), operating leverage, default risk, and the fraction of growth options in firm value (for asset beta).

Our analysis shows that all components of the equity beta contribute to a larger gap between the betas of distressed and healthy stocks after bear markets. We find that distressed stocks are out-of-the-money growth option firms with high operating leverage and default risk. Operating leverage and default risk rise in bear markets, elevating the asset beta of distressed stocks. Financial leverage of distressed stocks also rises in bear markets and magnifies their equity risk (market exposure).

[2] Several other papers also study the importance of firm characteristics such as operating leverage, financial leverage, and growth option intensity in determining firm risk (see, for example, Carlson, Fisher, and Giammarino (2004), Gomes and Schmid (2010), and Novy-Marx (2010)).

Healthy stocks, on the other hand, behave like near-the-money growth option firms. Their asset betas increase in bull markets because growth options become more valuable and constitute a higher fraction of firm value. The variation in the asset beta fully captures the variation in the equity beta for such firms because financial leverage is typically low for healthy stocks and does not change much over time.

These patterns in the equity beta components are consistent with the observed time-varying market exposures of distressed/healthy stocks. We find first that the difference between the equity betas of distressed and healthy firms is larger after bear markets than after bull markets. We then show that the financial leverage (as a measure for equity elasticity) and asset beta both explain the differences in time-varying equity betas of financially distressed and healthy stocks. The asset beta and leverage of distressed stocks rise significantly after a two-year market downturn; this results in dramatic increases in the equity beta. In contrast, healthy stocks have procyclical market exposures because their asset risk rises in bull markets while their leverage remains stable over time. Collectively, these results imply that the long/short HMD strategy becomes highly sensitive to market news following bear markets.

We find that the HMD trading strategy essentially crashes in times of market stress. While this strategy yields an average return of 1.69% per month after bull markets (which is consistent with the distress anomaly), it yields a negative profit of −1.62% per month after bear markets. Considering the ten largest market downturns, the HMD portfolio earns less than −10% on average. This reversal in the distress effect is driven jointly by the relatively high equity beta after bear markets and the tendency of the market to bounce back after such periods. That is, shorting distressed stocks with high beta will generate large losses if the market turns positive. Time-series regressions support this proposition; the low profit of the HMD trading strategy after bear markets is further decreased when the markets bounce back.

We also study the impact and potential predictability of these HMD crashes. Noting that bear markets are typically accompanied by high levels of expected market volatility, we suggest risk-management strategies based on ex-ante measures of market volatility. Our main risk-management strategy scales the HMD portfolio by the volatility of daily market returns during the previous year, targeting a strategy that puts less (more) weight on the HMD portfolios during volatile (calm) periods. The Sharpe ratio improves from 0.44 for the standard static HMD to 0.72 for its dynamic risk-managed version. But the most important benefit is the reduction in crash risk. The kurtosis of the HMD returns drops from 10.49 to 6.15, and the left skew improves from −1.56 to −0.82. The minimum one-month return for raw HMD is −60.37%, while the risk-managed HMD declines at most by 33.96%.

Risk-management succeeds as well when we scale HMD by the implied volatility of the option market (VXO) or conditional volatility of the EGARCH model, and when using alternative distress measures to form the HMD portfolio. Market crashes, therefore, seem to be an important and robust feature of financial-distress strategies, and scaling by ex-ante market volatility measures helps investors avoid the big losses of HMD in volatile periods while materializing its upside in calm periods.

We note that the idea that the equity beta of financially distressed firms change over time is not new. Garlappi and Yan (2011), for example, introduce a model in which betas of distressed stocks vary with financial leverage and the potential for shareholder recovery in default. Opp (2015) suggests an alternative model analyzing the cyclical variation of risk in two different aggregate states (good or bad, liquid or illiquid, downturn or boom). An important theoretical result in the latter paper is that distressed firms have lower exposures to systematic risk in downturns. Opp further argues that the empirical findings in O'Doherty (2012) support the predictions of his model.

Our analysis however is based on a detailed decomposition of the equity beta into four components whose time variation is directly related to the extent of financial distress. And, more importantly, our analysis generates a new prediction for the time-varying beta of distressed stocks – *higher* betas of distressed stocks during bear markets – which is consistent with the empirical evidence of the absence of the distress anomaly in downturn markets, as well as with the crashes of the HMD trading strategy when the market rebounds.

Our paper is closely related to two recent papers on the momentum anomaly; Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) study momentum crashes and recommend risk-management solutions for the static winner-minus-loser (WML) momentum strategy. Interestingly, momentum crashes overlap with financial-distress crashes. Both HMD and WML fail when the stock market rebounds following a two-year downturn. These papers suggest scaling the raw WML strategy by ex-ante measures of WML volatility. These alternative risk-management strategies also yield a significant reduction in crash risk and a superior performance relative to raw WML.

Our paper follows a different path from Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). First, we study the crashes of a different anomaly. Campbell et al. (2008) show that while financial-distress and momentum long/short strategies are positively correlated, neither strategy subsumes the other. We show that the negative market exposure of HMD in bear markets emerges even when we control for momentum. In addition, spanning tests show that our risk-managed HMD strategies add to the investment opportunity set of an investor who trades the standard HMD and the risk-managed WML strategies. Most importantly, we analyze in detail the cyclical variation of the firm characteristics that determine equity beta and provide a risk-based explanation for the negative market exposure of the HMD portfolio in bear markets.

Finally, our results have implications for the momentum crashes. Of all long/short WML portfolios, the one holding the most distressed stocks suffers the most in a momentum crash. This evidence represents an important caveat for investors because distressed stocks produce the highest momentum profits (see, e.g., Avramov et al. (2007)). Our risk-management procedure mitigates this problem significantly, generating an alpha of 0.68% per month relative to the standard strategy.

The paper proceeds as follows. The next section presents evidence on the time variation of the distress anomaly. Section 3 applies the theoretical framework of Choi (2013) to justify the highly negative equity beta of the HMD portfolio in bear markets and presents supporting empirical analysis. Section 4 introduces risk-management strategies that mitigate the potential crashes in HMD returns after market downturns. Section 5 shows that the sensitivity of the distress anomaly to the market state is incremental to that of momentum, and Section 6 concludes.

2. Time variation of the distress anomaly

The financial-distress anomaly is one of the patterns most difficult to explain in stock returns. Campbell et al. (2008) show that a trading strategy of buying financially healthy stocks and selling financially distressed stocks produces high raw and risk-adjusted profits. To form the HMD portfolio we classify all stocks each month into ten equal-sized portfolios according to the failure probability measure of Campbell et al. (2008). (The appendix provides details on the distress measures). The HMD portfolio return in the subsequent month is the difference between the value-weighted average returns of the healthiest stocks portfolio and the most distressed stocks portfolio. Panel A of Table 1 highlights the time-series characteristics of this zero-investment financial-distress strategy in comparison to other well-documented long/short anomaly strategies.[3]

Healthy stocks outperform distressed stocks by 1.20% per month, which is significant both economically and statistically (*t*-statistic=2.36) and is comparable with prior literature. The long/short financial-distress strategy ranks first among the ten anomaly strategies reported; moreover, its average profit is more than twice as much as that of size, book-to-market, gross profitability, asset growth, accrual, long-run reversal, short-run reversal, and one-month industry momentum strategies.

The rewards, however, come with high risks. The long/short financial-distress strategy has the highest volatility among all anomaly strategies—which in turn produces a moderate Sharpe ratio. More importantly, the strategy has a very fat left tail: a left skew of −1.56 and a very high kurtosis of 10.49—which indicates that the strategy is highly vulnerable to sudden crashes.

These crashes in the HMD portfolio returns are likely to appear when the entire economy is in distress. Panel B of Table 1 shows that the distress anomaly exists only after bull markets. HMD earns an average return of 1.69% per month after periods of rising markets (with a *t*-statistic of 3.85). Following bear markets, however, the average HMD return is negative at −1.62%, yet it is insignificant in statistical terms. Focusing on the ten largest market upturns and downturns strengthens this result. Distressed stocks earn an average return that is 4.71% lower than healthy

[3] An incomplete list of papers that study the risk and return characteristics of these anomalies includes Fama and French (1993, 1996, 2008, 2015), Jegadeesh and Titman (1993), Sloan (1996), Campbell et al. (2008), Cooper, Gulen, and Schill (2008), Novy-Marx (2013), and Novy-Marx and Velikov (2016).

stocks following the largest ten market upturns, i.e., the distress anomaly is stronger in such periods. But the gap decreases to −10.23% following the largest ten market downturns, thus the distress effect *reverses* after extreme bear markets. In this regard, the HMD strategy is similar to the WML momentum strategy (see Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016)). Figure 1 focuses on the highly turbulent period of January 1998 to December 2010 to illustrate how the potential losses of the HMD portfolio can be even more severe if the market turns positive.

In Table 2 we formally test these qualitative observations using time-series regressions in the manner of Daniel and Moskowitz (2016). The dependent variable is the HMD portfolio monthly return. The independent variables are the cumulative market return in the past two years, a dummy variable indicating past bear market (a bear market is assumed if the cumulative market return during the past two years is negative), mean-adjusted market volatility (realized market volatility divided by its sample mean), the market excess return (in excess of the risk-free rate), a dummy variable indicating an up-market during the holding period, and interaction terms.

Regressions (1) and (2) provide evidence for the negative effect of market conditions on the magnitude of the distress effect: both low past-market performance and high past-market volatility predict low HMD returns. Regressions (3) and (4) show that HMD suffers large losses during market rallies, as reflected by the negative coefficients of the interaction terms involving the up-market dummy variable. This result corroborates the evidence shown in Figure 1.

The remaining regressions in the table explore the market exposures of the HMD portfolio. Regression (5) reveals first that the unconditional beta of HMD is negative (−0.82), suggesting a good performance of the HMD strategy when the market is falling in the holding period. More importantly, regression (6) shows that the beta of HMD depends strongly on market states: the beta after a bull market is −0.57, whereas the beta after a bear market is −1.71 (= −0.57−1.14). This gap in betas lays the foundation for explaining the time-varying risks and returns of the financial-distress anomaly. Regression (7) confirms the results of regression (6) using aggregate volatility as a proxy for market condition. Furthermore, regression (8) shows that the exposure of the HMD portfolio after bear markets is more negative if the markets have bounced back. Following a bear market, the down-market beta is −1.12, and the up-market beta is −2.21. This evidence clearly explains why HMD suffers large losses when the market rebounds after a two-year downturn.

Daniel and Moskowitz (2016) run similar conditional CAPM regressions using the WML momentum portfolio and find similar market betas for WML. They conclude that in a bear market WML acts like a short call option on the market portfolio. The results in Table 2 imply that the HMD portfolio has the same property. Daniel and Moskowitz further show that the optionality of WML comes from its short-leg. They argue that in a bear market, losers are highly levered and face bankruptcy risk. According to Merton's (1974) model, losers' equity is an out-of-the-money call option on the underlying firm value, which makes them highly sensitive to market news.

Our paper presents a more direct test of the latter argument by analyzing financially distressed stocks. Unlike Daniel and Moskowitz (2016) who relates the high equity beta of loser stocks to their past returns, we study the determinants of the market beta in detail to justify the high equity beta of distressed stocks. This exercise gives further insight into why risks and returns vary across different distress-sorted portfolios and different market states.

Given the sensitivity of the distress anomaly to market state reported above, as well as that of the momentum effect reported by Daniel and Moskowitz (2016), one can ask whether this kind of sensitivity is typical of any stock return anomaly. We show in Figure 2 that this is not the case.

Among all the anomaly-based portfolios listed in Table 1, the HMD yields the highest profits (losses) in bull (bear) markets, and is subject to the most severe crashes during market rallies following bear markets. In contrast, most other long/short portfolios, including size, short-run reversal, long-run reversal, book-to-market, and accruals, yield positive returns in bear markets and perform well during market rallies. This evidence strengthens the motivation to explore the time-varying sensitivities of the distress puzzle.

3. The determinants of equity beta and the distress cross-section

Choi (2013) builds a theoretical model in which the systematic risk of equity depends on three factors: (i) the risk of firm assets; (ii) the degree to which these assets are levered; and (iii) the extent to which the asset risk is passed through to shareholders versus debtholders. 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 are captured by the elasticity of equity value with respect to asset value, which is driven primarily by the financial leverage of the firm. Hence, the equity beta (market exposure) equals the product of equity elasticity and the asset beta, and can be expressed as a function of four components:

$$Equity\ beta = \underbrace{f(Financial\ leverage)}_{Equity\ elasticity} \times \underbrace{f(Operating\ leverage, Default\ risk, Growth)}_{Asset\ beta}$$

Choi also allows the equity beta and its components to vary with the business cycle. An increase in financial leverage or asset beta components over the business cycle makes the firm riskier, and leads to an increase in the equity beta.

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. He finds that value firms have low asset betas, but they carry high financial leverage. Growth firms, on the other hand, have high asset betas and low leverage. Due to the inconsistency between asset betas and financial leverage across book-to-market portfolios, Choi argues that equity betas do not display a monotonic pattern.

Choi also studies the time-varying risk of book-to-market portfolios, and finds that during economic downturns the asset betas and financial leverage of value stocks increase, leading to a sharp rise in their equity betas. In contrast, growth stocks' equity betas remain stable over time because they have low leverage and their asset betas are less sensitive to economic conditions.

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 and identify the types of firms in the portfolios. We also analyze the interaction between financial leverage and asset beta over the business cycle and form predictions for the time-varying market exposures of financial-distress portfolios. Last, we compare our paper with related studies in the financial distress literature, and highlight our contribution.

3.1. Full-sample characteristics

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 Merton's (1974) contingent claim model. 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 a 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. Following this method, we can utilize more than 90% of the CRSP/Compustat dataset.[4] 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).

We use two proxies to quantify the fraction of growth opportunities in firm value. In Choi's model, firm size (total value of book assets) proxies for this fraction: growth firms are smaller than assets-in-place firms. A second proxy for growth option intensity is the idiosyncratic volatility beta, i.e., the exposure of stock returns to an increase in idiosyncratic volatility. Ai and Kiku (2016) develop this proxy building on the insight that option payoffs respond positively to an increase in idiosyncratic volatility. We follow the procedure of Ai and Kiku to estimate idiosyncratic volatility betas for our sample firms.

Table 3 presents the equity beta and its components for the ten distress-sorted portfolios. The sample period is March 1982 to December 2013. Distressed firms are more levered than healthy firms. The median firm in the top distressed stocks portfolio has an average financial leverage of 2.01, and the leverage declines monotonically from distressed stocks to healthy stocks. Operating

[4] Choi (2013) uses a unique dataset to generate the asset returns of individual stocks, but this causes a significant drop in sample size.

leverage exhibits a similar pattern across the portfolios. The default risk is, by construction, increasing with the distress level.

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. Ai and Kiku (2016) further show that idiosyncratic volatility beta is informative for the moneyness of the growth options, and it is the highest for out-of-the-money growth options. Thus, the distressed stocks portfolio represents mainly out-of-the-money growth option firms, whereas the growth firms in the healthy stocks portfolio are closer to their investment thresholds than those in the distressed stocks portfolio.

The distribution of two additional firm characteristics across the distress-sorted portfolios lends further support for the latter argument. Recent stock returns are typically high for near-the-money growth options and low for out-of-the-money growth options. In addition, as implied by Choi's (2013) theoretical framework, growth firms exercise their expansion options if productivity reaches its upper boundary. Table 3 shows that 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 the highest for healthy stocks and declines monotonically from the top healthy stocks portfolio to the top distressed stocks portfolio.

As discussed above, the asset beta increases with operating leverage, default risk, and the growth option intensity. Choi (2013) further shows that the fraction of growth options in firm value, and thereby the risk of the firm, increases as growth options get closer to their exercise threshold. We find that in the failure probability cross-section, healthy firm portfolio contains near-the-money growth option firms with low operating leverage and default risk, whereas the top distressed firm portfolio contains out-of-the-money growth option firms with high operating leverage and default risk. Collectively, all these observations imply that asset betas should have a U-shaped pattern along the distress-sorted portfolios, and the estimates in Table 3 confirm this prediction.

The CAPM betas display a monotonic pattern in the failure probability cross-section. Healthy firms have the lowest equity beta, and equity risk rises as we move closer to the top distressed stocks portfolio. In addition, 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.

3.2. Equity beta components in bull vs bear markets

An important feature of Choi's (2013) model is that it allows for time-varying risk. The two major components of equity beta, namely the equity elasticity and the asset beta, vary with the demand (productivity) state variable. For example, elasticity is a decreasing function of demand so, in bad times, the impact of an increase in operating leverage or default risk on equity beta amplifies. In addition, growth option intensity is an increasing function of demand, so in good times, near-the-money growth option firms have higher asset betas and thus higher equity betas than in bad times. Our analysis builds on the time variation in the beta components, and specifically assesses how this time variation affects distressed versus healthy firms, so that we can justify the absence of the distress anomaly after poor market performance.

The market performance over the previous one to three years is a good indicator of the state of the economy. Following Cooper, Gutierrez, and Hameed (2004) and Daniel and Moskowitz (2016), we assume a bull (bear) market if the two-year market performance prior to portfolio formation is positive (negative). This classification helps us observe the cyclical variations in each equity beta component and develop rational predictions for the time-varying risks of distress-sorted portfolios.

Table 4 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 the same financial leverage in both states of the market, distressed firms become more levered in bear markets. Financial leverage is a key determinant of elasticity, so it amplifies the equity risk of the distressed stocks portfolio in bear markets.

Healthy firms observe an improvement in their operating leverage in bear markets, which reduces their asset risk. Distressed firms, on the other hand, become more levered in bear markets compared to their positions in bull markets. 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 (healthy) firms should have higher (lower) asset risk in bear markets than in bull markets.

The patterns of firm size and idiosyncratic volatility beta indicate that the composition of financial-distress portfolios does not vary across market states, so distressed and healthy stocks portfolios represent relatively more growth option firms than other decile portfolios. Yet, the market condition affects the moneyness of growth options. For instance, healthy firms get closer to their investment threshold in bull markets. Such firms observe significant improvements in their recent returns and productivity level, which in turn, increases the value of their growth options and elevates their asset risk. Distressed firms' growth options are out-of-the-money in both market states, which degrades the growth option channel; as a result, the cyclical variations of operating leverage and default risk determine the cyclical variation of their asset risk. Consistent with these effects, the top distressed stocks portfolio has the highest asset beta in bear markets, and the top healthy stocks portfolio has the highest asset beta in bull markets.

The equity of a healthy firm acts like a deep-in-the-money call option on its asset. As shown in Table 4, healthy firms have the same financial leverage in both market states. Hence, the asset beta and the equity beta of the healthy stocks portfolio should be close to one another in both bull and bear markets. Distressed firms, on the other hand, experience a sharp increase in their financial leverage in bear markets compared to bull markets; this suggests that their equity betas should increase significantly in bear markets as well.

Table 4 confirms these predictions for the equity beta. Healthy stocks have the lowest market exposure in both states of the market, and they are riskier in good times. The healthy stocks portfolio has a bull-market beta of 0.90 and a bear-market beta of 0.73. These beta estimates are very close to the conditional asset betas; hence, the market exposures of healthy stocks are entirely determined by their asset risk. Market risk increases in bull markets because the growth options of healthy stocks get closer to their investment threshold and increase their fraction of firm value.

Distressed stocks, however, have the highest market exposure in both market states, and they are riskier in bad times. The top distressed stocks portfolio has a bull-market beta of 1.47 and a bear-market beta of 2.44. These beta estimates deviate significantly from conditional asset betas because financial leverage plays a significant role in determining the market exposure of distressed stocks. Market risk increases in bear markets because both financial leverage and asset risk increase. Distressed firms become more levered in bear markets, increasing the elasticity of their equity with respect to firm value.

Distressed firms also observe increases in their operating leverage and default risk in bear markets; hence their asset risk rises. The growth option effect is less important for distressed firms because these options are out-of-the-money in both market states and constitute a low fraction of firm value. The combined effect of high financial leverage and asset risk in bear markets suggests that distressed stocks become highly exposed to market news. This result is an important caveat for investors using distress signals for portfolio construction.

3.3. 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 4). 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 5.[5]

[5] 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

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 0.84 (1.81) in recessions and is 0.95 (1.35) in expansions. Using rolling betas yields similar results; the average rolling beta of the healthy (distressed) stock portfolio is 0.88 (1.83) in recessions and is 0.98 (1.49) in expansions. In all cases, the difference between the point estimates is statistically significant. This evidence strengthens our argument that distressed stocks become riskier in bad times.

3.4. Time-series regressions of HMD portfolios

The relatively high beta of distressed stocks especially after bear markets implies that the long/short HMD distress strategy is subject to significant losses when the market rebounds. As discussed in Section 2, this is consistent with the regression results in Table 2, where the coefficient of the triple interaction term between the market return in the holding period, the bear-market dummy variable, and the up-market, is negative and significant. To confirm that this effect is driven by distressed stocks, we run this regression separately on decile portfolios that hold the healthiest stocks and the most distressed stocks.

Panel A of Table 6 displays regressions (3) and (8) from Table 2 for the HMD portfolio and adds the results of the same regressions for the top healthy and top distressed stocks portfolios. As

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'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 re riskier in trough than in peak.

discussed in Section 2, the regression coefficient of the interaction variable (Bear x Up) shows that the HMD strategy performs very poorly when the market rebounds following a bear market. This effect is consistent with the time-varying beta of the HMD portfolio. Specifically, during a bear market, the market exposure of HMD is −1.12 (=−0.58−0.54) when the market return in the holding period is negative, while the market exposure equals −2.21 (=−0.58−0.54−1.09) when the market return is positive. Following Daniel and Moskowitz's (2016) analogy, we can liken the HMD portfolio to a short call option on the market portfolio.

The main source of this optionality comes from the distressed stocks portfolio. When the market rebounds, distressed stocks earn an average return of 12.25% (=−0.81%−11.41%+24.47%), compared to only 1.83% (=−0.88%−4.32%+7.03%) for healthy stocks. Distressed firms also have strong up-market betas in bear markets. Its down-market beta following bear markets equals 1.87 (=1.49+0.38) and the estimate of the up-market beta is 2.94 (=1.87+1.07). The up-market beta of the healthy stocks portfolio after bear markets is not significantly different from its down-market beta, thus in contrast to distressed stocks, the direction of the market movement in the holding period has no significant effect on the market exposures of healthy stocks.

To show the robustness of the results to the financial-distress measure, we report the results of the same regressions in Panels B and C using two alternative distress models: Ohlson's (1980) O-score and KMV's (2002) distance-to-default, which is based on Merton's (1974) capital structure model (see also Ronn and Verma (1986) and Vassalou and Xing (2004)). The results under both models are similar to those reported in Panel A, but the results based on the O-score are somewhat weaker.

The sensitivity of the HMD portfolios to the market states is similar in pattern to that of the momentum WML portfolio studied in Daniel and Moskowitz (2016). In Section 5 we show that financial-distress and momentum signals convey independent information about the crashes of both anomalies, and that the financial health of the stocks is important for momentum investing.

In sum, HMD strategies have significantly negative market exposures when the market rallies after a two-year downturn. As a result, similar to momentum-based trading strategies, HMD strategies become highly vulnerable to sudden crashes. In Section 4 we show that managing this risk mitigates the severe losses of HMD strategies and increases their Sharpe ratios.

3.5. Relation to prior studies that analyze time-varying betas of distressed stocks

We acknowledge that the idea that the equity betas of financially distressed firms change over time is not new. In this section, we outline the innovative aspects and contribution of our study on this matter. O'Doherty (2012) examines theoretically and empirically the impact of information uncertainty on market risk exposures. He shows that increased information uncertainty lowers the risk of levered firms. He argues that because financially distressed firms are highly levered firms, their market beta should decline when information uncertainty rises. Moreover, he notes that information uncertainty rises in bad times, which would make distressed stocks less risky. Conditional CAPM would then imply that distressed stocks should earn low expected returns thereby rationalizing the distress puzzle.

Our work differs from O'Doherty's (2012) in several aspects. First, O'Doherty's model does not allow for time variation in information uncertainty, market risk premium, and market volatility; hence, it does not provide a direct prediction about co-variation between conditional betas and market fluctuations. Our empirical analysis, however, is based on a solid time-varying risk model that allows a straightforward CCAPM estimation. Second, while O'Doherty focuses on leverage as the primary source of market exposure, we highlight the importance of asset risk. In fact, we show that most distressed stocks do not only have high leverage, but are also subject to substantial asset risk, which contributes significantly to the cyclical variation of their market betas. Asset risk also matters for financially healthy firms, and elevates their market exposure in good times. We also use monthly returns to estimate market betas, as opposed to daily returns in O'Doherty (2012). Our tests indicate that CCAPM *fails* in solving the distress puzzle, but the evidence on time-varying betas, i.e. *higher* betas of distressed stocks in down markets, helps explain the absence of the distress anomaly in such states as well as the crash of the HMD strategy during market rebounds.

Opp (2015) suggests an alternative theoretical framework analyzing the risk variation in two different aggregate states (downturn vs boom). A crucial theoretical result in his paper is that most distressed firms have lower exposures to business-cycle frequency risks in downturns. As market risk premiums tend to be high in recessions, his model can rationalize a negative correlation between market risk premiums and portfolio betas.

Opp argues that the empirical findings in O'Doherty (2012) confirm the predictions of his model. Yet, O'Doherty's empirical tests use high-frequency data, whereas to test Opp's theory, time-varying low-frequency risk exposure estimates are needed. Our empirical framework uses monthly data and a business cycle instrumental variable (two-year cumulative market return prior to portfolio formation), which splits the aggregate economy into a good state and a bad state. Moreover, we show that the market betas of most distressed stocks are actually higher in market downturns.

Garlappi and Yan (2011) develop a theoretical model based on the time-varying risk literature, and evaluate its predictions using CCAPM. Since the traditional approach in this literature predicts high risks for distressed stocks, Garlappi and Yan impose a new structure (shareholder recovery) which lowers the betas of the most distressed stocks and produces a hump-shaped market risk pattern in the financial distress cross-section. Using portfolios sorted on expected default frequency (EDF), they report empirical evidence supporting these predictions.

The important firm level variables in Garlappi and Yan's model are book-to-market (or operating leverage), financial leverage, and shareholder recovery. The growth option channel however is turned off in their model. As presented above, our evidence suggests that the growth option is a key factor in determining the cyclical variation of the market beta of financially healthy stocks.

In terms of empirical implementation, our work differs significantly from Garlappi and Yan along several dimensions. First, they measure distress by EDF, while we use Campbell et al.'s (2008) failure probability. The EDF signal does not produce a significant return spread on its zero-cost investment strategy, while Campbell et al.'s signal does, thereby providing a higher potential in studying the risk and return characteristics across distress-based portfolios.

Second, Garlappi and Yan estimate conditional betas using daily stock returns in the portfolio formation month. Portfolio formation betas, however, might be less informative than holding period betas as investors are subject to market risk only during their investment period. We estimate portfolio risks and returns in the holding period using a large number of monthly return observations.[6]

[6] Garlappi and Yan (2011) use Dimson (1979) style CAPM regressions with one lead and one lag of the market factor. O'Doherty (2012) uses five lags of market returns to lessen the infrequent trading bias. This problem is particularly harmful for distressed and healthy stocks because they are smaller on average than the rest of the stocks in the financial distress cross-section. Our estimation is immune to this bias because we employ monthly returns in our regressions.

Most important, we use the instrumental variable approach to categorize the aggregate economy into two different states and analyze the cyclical variation of market beta. This procedure also helps us explain why the distress anomaly does not exist in bear markets and why the HMD strategy crashes when the market rebounds. Our goal is to explain these crashes via a time-varying risk framework, and to identify an investment strategy that manages this risk, rather than rationalizing the unconditional return pattern of the financial distress anomaly. To accomplish the latter goal via CCAPM, the empiricist must show that stocks that earn low expected returns, namely financially distressed stocks, are less risky in bad times. Our paper refutes this claim, and the return pattern of the HMD strategy in bear markets supports our view.[7]

4. Risk management for financial-distress trading strategies

Identifying the dependence of the distress anomaly on the state of the economy provides an opportunity to improve the performance of the HMD portfolio. To manage the risk coming from this dependence, we use market volatility as the primary scaling variable. First, market volatility is relatively high in bear markets. Using market volatility as a state variable in conditional CAPM regressions reproduces the negative market exposure of the HMD portfolio in bad times. In addition, high market volatility forecasts low returns for the HMD portfolio (as shown in Table 2). For robustness, we also scale the HMD portfolio by alternative volatility measures as well as past market return.

The fact that distressed firms are more exposed to market risk than healthy firms at times of high market volatility is also consistent with the evidence that the distressed stocks portfolio

[7] In an unreported robustness test, we use EDF-style (KMV) portfolios as well. We find that distressed stocks become riskier in bear markets.

represents out-of-the-money growth options firms, while the healthy stocks portfolio represents near-the-money growth options firms. According to the conventional wisdom in growth option literature, option value is increasing in the volatility of the underlying cash flows. Since cash flow volatility rises with market volatility, one could expect that both healthy and distressed firms should have high market exposure in high aggregate volatility states.

Yet, an increase in aggregate volatility elevates discount rates as well. Since growth options are levered positions on assets-in-place, their values decline more on positive aggregate volatility news than do assets-in-place. Ai and Kiku (2016) address these two conflicting effects of aggregate volatility and show that the cumulative effect on growth option value depends on the moneyness of the option. Discount rate effects outweigh (fall behind) conventional volatility effects for near-the-money (out-of-the-money) growth options; as a result, such options become less (more) valuable in high aggregate volatility states. Because asset risk rises with the fraction of growth options in firm value, these results lend further support for the negative conditional beta of the HMD portfolio at times of high market volatility.

Our main proxy for market volatility is the realized volatility estimated with 252 daily return observations prior to the portfolio formation month. Since HMD is a zero-cost self-financing strategy, we can scale it without constraints. We use the volatility estimate to scale HMD returns:

$$HMD^{*}_{t+1} = \frac{\sigma_{target}}{\hat{\sigma}_t} \times HMD_{t+1} \tag{1}$$

where HMD* is the scaled or risk-managed HMD strategy, $\hat{\sigma}_t$ is the estimate of realized volatility at the end of portfolio formation month *t*, and σ_{target} is a constant corresponding to the target level of market volatility. Following Barroso and Santa-Clara (2015), we choose a target value that corresponds to annualized market volatility of 12%. Our results are robust to alternative volatility targets; in addition, relative performance evaluation metrics such as Sharpe ratio or information ratio are unaffected by the choice of the target value. Unlike Barroso and Santa-Clara, we apply risk management to the HMD trading strategy instead of a momentum strategy, and we pick realized market volatility as our scaling variable instead of the realized volatility of the long/short trading strategy.[8]

Table 7 summarizes the economic performance of the risk-managed HMD* portfolio. The risk-managed strategy achieves a higher average return with a lower standard deviation than the standard HMD strategy; hence, the Sharpe ratio (in annualized terms) increases by 64% (from 0.44 to 0.72). Similarly, the information ratio of HMD* compared to HMD has a very high value of 0.86.[9] The left panel of Figure 3 illustrates the long-run benefits of the risk-managed strategy: From March 1982 to December 2013, an investment in HMD* yields a value that is eight times as high as the value resulting from an equivalent investment in standard HMD.

The most important benefits of risk management come from improvements in higher order moments. Scaling HMD by realized volatility lowers the kurtosis from 10.49 to 6.15 and elevates the negative skewness from −1.56 to −0.82. These improvements help investors mitigate the crashes of HMD following bear markets. We illustrate this result in the right panel of Figure 3 using market crashes in recent history. Over the period of January 1998 to December 2010 the

[8] In an unreported robustness check, we find that scaling by realized market volatility produces a higher Sharpe ratio and a higher information ratio than scaling by HMD volatility, and that the former risk-management strategy spans the investment opportunities of the latter strategy. Moreover, the evidence in Table 2 and Section 3.2 suggests conditioning the HMD strategy on prior market returns or market volatility. In this section, we evaluate these suggestions, and observe that our market-volatility based strategy becomes the most successful strategy among various alternatives. Hence, we opt to scale HMD by realized market volatility instead of realized HMD volatility.

[9] The benefits of risk-management are comparable to that of momentum reported by Barroso and Santa-Clara (2015): conducting a similar test for standard and risk-managed WML momentum strategies, Barroso and Santa-Clara estimate an information ratio of 0.78.

HMD strategy loses half of its value. The risk-managed HMD* strategy becomes quite successful over the same period, generating more than 100% return, because it weathers these crashes and gains positive profits in bull markets.

Spanning tests evaluate more formally the performance of the risk-managed strategy relative to standard financial distress and other closely related trading strategies. Using monthly observations, we regress HMD* returns on standard HMD returns and also control for risk-managed WML* momentum returns. Controlling for WML* can be desirable as both strategies crash during market recoveries. The spanning tests (reported in Table 7) produce significant alphas around 0.60% per month, indicating that the risk-managed portfolio adds to the opportunity set of an investor trading the standard HMD and the risk-managed WML* strategies. We elaborate on the relation between financial-distress and momentum effects further in the next section.

Next, we compare the performance of our volatility-based risk-management strategy with an alternative one based on prior market returns. Specifically, at the end of each month t, we compute two-year cumulative market returns prior to portfolio formation ($R_{M,t-23,t-1}$) and use it as our conditioning variable. Thus we construct our new strategy (HMD**) as follows:

$$HMD_{t+1}^{**} = \frac{R_{M,t-23,t-1}}{R_{M,\,target}} \times HMD_{t+1} \tag{2}$$

where we choose $R_{M,target}$ such that the new HMD** strategy has the same standard deviation as the volatility-based HMD* strategy from equation (1). Unlike its volatility-based alternative, this new HMD** strategy invests on healthy-minus-distressed (distressed-minus-healthy) portfolios with positive weights whenever prior market returns turn out to be positive (negative).

Panel A of Table 8 shows that the new risk-managed HMD** strategy offers improvements with respect to volatility, skewness, and the kurtosis compared to the standard HMD strategy. Yet, the volatility-based strategy from equation (1) offers a higher annualized Sharpe ratio and a higher information ratio relative to the standard HMD benchmark than the market-return based strategy from equation (2). As a result, the investors of Campbell et al.'s (2008) financial distress signal become better off if they condition their long/short HMD strategy on realized market volatility than prior market returns.

Table 8 provides additional robustness checks using two different scaling volatility variables and financial distress measures. In Panels B and C we scale HMD by two forward-looking measures of market volatility. The first is the implied volatility from the options market (VXO), and the second is the conditional standard deviation derived from an expanding window EGARCH(1,1) model of monthly market returns. The resulting risk-management strategies mitigate HMD's losses, generate high information ratios, and are not captured by standard distress and risk-managed momentum strategies.

Panels D and E quantify the benefits of risk management on HMD strategies that use Ohlson's (1980) O-score and KMV's distance-to-default measures. Scaling these alternative HMD strategies by realized market volatility makes them profitable and reduces their downside risk. In our sample period of March 1982 to December 2013, the average returns on these alternative long/short HMD portfolios are positive, albeit insignificant. The profits on risk-managed HMD* portfolios, however, are significant both economically and statistically. HMD* strategies based on the O-score and KMV earn average monthly returns of 0.58% and 0.64%, respectively, with *t*-statistics of 2.70 and 1.90.

5. Financial distress and momentum

The long/short HMD strategy of Campbell et al. (2008) and the WML momentum strategy of Jegadeesh and Titman (1993) have some common characteristics. Both strategies perform well in the recent past and generate significant profits in the holding period. Also, both strategies crash when the market rebounds following a bear market because they short high-beta securities in an up-market.

Therefore, it is worth analyzing whether financial distress and past-returns convey incremental information in bear markets. We address this issue by looking at the intersection of financial distress and momentum and test whether distress-sorted portfolios differ in bear-market betas when controlling for the momentum effect. In addition, we run market-timing regressions of WML portfolio returns within different distress quintiles to examine whether the distress level has any implication for the cyclical behavior of momentum strategies.

5.1. The intersection of financial distress and momentum

Each month we sort all stocks independently by distress and by momentum into five equal-sized quintiles, resulting in 25 distress-momentum portfolios. We calculate the value-weighted returns of the portfolios in the subsequent month and estimate their bull- and bear-market betas using conditional CAPM regressions. It is important to note that even though the level of distress and past-return are not independent, the distress-momentum portfolios are sufficiently populated; the time-series average number of stocks in the portfolios ranges between 60 and 348.

Table 9 reports the time-varying betas of these 25 portfolios and those of the self-financing HMD and WML portfolios. The market betas exhibit several interesting patterns. First, within each momentum quintile, distressed firms have higher betas than healthy firms in both market states, and the difference is bigger in bear markets. This evidence is important because it shows that the high market exposure of the HMD portfolio in bear markets emerges even in the presence of the momentum effect.

Second, among distressed stocks, the bear-market beta is greater than the bull-market beta in four momentum quintiles (except for the winner quintile), and the difference is the biggest within the loser quintile. By construction, within a given momentum quintile, each distress-sorted portfolio contains stocks that have experienced similar ranking period returns. The distressed-winner portfolio contains countercyclical stocks in bear markets, thus its bear-market beta is not significantly different from its bull-market beta. However, other distressed stocks portfolios, in particular the distressed-loser portfolio, appear to be highly procyclical. The bull-market beta of distressed-loser portfolios is 1.38, while their bear-market beta is 2.48; and the difference in beta is highly significant (*t*-statistic=4.04). Increasing leverage and probability of default in bear markets are likely to be the main reasons for the spike in market beta. The results in Table 8 therefore indicate that the sensitivity of the distress anomaly to the market state is incremental to that of momentum.

5.2. The effect of financial distress on the optionality of momentum portfolios

Daniel and Moskowitz (2016) find that the WML momentum portfolio acts like a short call option on the market portfolio in bear markets, and that this optionality stems from shorting loser stocks, which are likely to be more levered in bad times. We, however, show that firms' financial health also plays a significant role in determining their market exposure. Hence, we classify WML strategies with respect to failure probability and show that the momentum optionality argument in Daniel and Moskowitz applies more directly to distressed stocks.

The test assets are 25 value-weighted portfolios sorted conditionally on momentum and financial distress. We first rank all stocks according to past returns into five equal-sized quintiles. Then, within each momentum quintile we rank all stocks by distress level into five equal-sized quintiles. Panel A of Table 10 confirms that the momentum effect is mostly concentrated in distressed stocks. The WML momentum strategy produces its highest profits within the quintile containing the most distressed stocks, and the profits are the lowest and statistically insignificant within the quintile containing the healthiest stocks. This evidence echoes the finding in Avramov et al. (2007) showing that momentum profits exist only among stocks with a low credit rating.

More important, in Panel B we estimate the market-timing regressions of WML strategies for different financial-distress quintiles. We find that the optionality of WML is strongest in the most distressed quintile. First, while the distressed-WML strategy earns the highest profits among all momentum strategies (1.62% per month), it also experiences severe crashes when the market rebounds following a bear market, with an average return of −7.56% (=2.26%+3.73%−13.55%) per month. Second, following bear markets, the beta of the distressed-WML portfolio is −0.62 (=0.08−0.70) if the market keeps falling in the holding period, whereas the beta equals −2.33 (=0.08−0.70−1.71) if the market turns positive. Hence, due to its highly negative market exposure, the otherwise profitable distressed-WML strategy can hurt its investors badly when the market rallies at the end of a bear market.

In unreported results we find that risk management also improves the performance of the distressed-WML (D-WML) portfolio. Scaling this strategy by realized market volatility succeeds in mitigating its downside risk. Regressing the risk-managed D-WML* portfolio returns on the standard D-WML returns produces an alpha of 0.68% per month (with a *t*-statistic of 4.18); hence, D-WML* enhances the opportunity set of an investor who trades the static D-WML strategy.

6. Conclusions

Financial distress is a robust anomaly in asset pricing, allowing a self-financing healthy-minus-distressed (HMD) trading strategy to produce high average returns to investors. In this paper we first show that this anomaly does not hold in market downturns, and that the profitable long/short strategy is subject to sudden crashes during market recoveries. Second, we uncover the reasons behind these crashes by studying the firm characteristics of the stocks held in the long-leg and the short-leg of the HMD strategy.

We argue that the negative contemporaneous relation between market recovery and the HMD portfolio return stems from the fact that in a bear market the distressed stocks portfolio contains high-beta stocks. Following the theoretical framework of Choi (2013) we decompose the equity beta into two components: equity elasticity, which is primarily affected by financial leverage, and asset beta, which is determined by operating leverage, default risk, and the fraction of growth options in firm value. Exploring the cyclical variation of the equity beta components suggests a large gap between the betas of distressed and healthy stocks after bear markets, which explains the sensitivity of the HMD portfolio to market state.

Last, to weather the crashes in HMD returns, we suggest a risk-management method that scales HMD by market volatility. This method puts less weight on the HMD portfolio in high volatility periods thereby decreasing the vulnerability of this zero-cost strategy to sudden crashes. The risk-management method also improves the Sharpe ratio of the standard HMD strategy by more than

60%. Using alternative proxies for financial distress and market volatility produces similar results. We show that the crashes of distress-based portfolio strategies emerge in the presence of the momentum effect.

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Table 1. Time-series properties of the distress anomaly

Each month we sort all stocks into ten equal-sized portfolios based on the financial-distress measure of Campbell et al. (2008). We construct a zero-investment value-weighted portfolio (HMD) of buying the most healthy stocks portfolio and selling the most distressed stocks portfolio, and we hold this portfolio for one month. Panel A shows the properties of the HMD portfolio return, in comparison to other well-documented long/short anomaly strategies. Panel B shows the average returns of the ten distress-sorted portfolios and the performance of the HMD strategy when applied only after bull markets 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 March 1982 to December 2013.

Panel A: Time-series properties of long/short portfolios

Anomaly-based strategy	mean	stdev	skewness	kurtosis	min	max	Sharpe
Size	0.06%	4.62%	1.05	10.58	-20.55%	31.93%	0.04
Book-to-market	0.42%	4.62%	0.60	5.97	-13.51%	26.73%	0.31
Momentum	1.12%	7.57%	-1.59	11.57	-45.89%	26.18%	0.51
Net issuance	0.62%	3.57%	0.32	6.80	-13.67%	18.28%	0.60
Gross profitability	0.49%	3.19%	0.17	4.13	-11.77%	13.37%	0.53
Asset growth	0.35%	3.73%	0.36	4.62	-12.57%	16.95%	0.33
Accrual	0.24%	3.07%	0.17	4.72	-11.22%	14.23%	0.27
Long-run reversal	0.28%	4.88%	1.13	7.59	-15.82%	28.92%	0.20
Short-run reversal	0.19%	5.76%	0.02	6.27	-24.96%	21.61%	0.12
Industry momentum	0.47%	6.30%	-0.01	5.73	-24.70%	27.20%	0.26
Financial distress	1.20%	9.39%	-1.56	10.49	-60.37%	28.02%	0.44

Panel B: Average returns of ten value-weighted distress-sorted portfolios (in percent)

	#months	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD	t-statistic
Full Sample	382	1.21	1.15	0.99	1.14	1.06	0.96	0.93	0.49	0.58	0.02	1.20	2.36
Bull Market	325	1.28	1.25	1.07	1.17	1.06	0.97	0.89	0.46	0.39	-0.42	1.69	3.85
Bear Market	57	0.85	0.60	0.58	1.02	1.06	0.88	1.13	0.71	1.66	2.47	-1.62	-0.76
Top 10 Bull	10	-4.20	-4.23	-3.21	-2.95	-3.79	-5.34	-5.84	-5.88	-6.21	-8.91	4.71	2.33
Top 10 Bear	10	1.15	1.46	1.68	2.52	2.66	4.00	3.72	5.72	9.89	11.38	-10.23	-2.21

Table 2. Time-series regression of HMD portfolio monthly return on market fluctuations

The dependent variable in each regression is the HMD 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, a dummy variable (Up) that equals 1 if RmRf is positive, and interaction terms. The table reports regression coefficients and Newey-West (1987) corrected *t*-statistics with three-month lags. The sample period is March 1982 to December 2013.

	Intercept	Rm[t-24,t-1]			Adj R2
(1) Estimate	-0.21%	5.61%			0.02
t-stat	-0.22	2.06			
	Intercept	AVol			Adj R2
(2) Estimate	4.35%	-3.16%			0.02
t-stat	3.81	-2.47			
	Intercept	Bear	Bear x Up		Adj R2
(3) Estimate	1.69%	7.09%	-17.44%		0.14
t-stat	3.84	4.04	-6.53		
	Intercept	AVol	AVol x Up		Adj R2
(4) Estimate	4.03%	1.32%	-6.74%		0.16
t-stat	4.67	1.30	-6.58		
	Intercept	RmRf			Adj R2
(5) Estimate	1.77%	-0.82			0.15
t-stat	4.19	-6.36			
	Intercept	RmRf	RmRf x Bear		Adj R2
(6) Estimate	1.69%	-0.57	-1.14		0.20
t-stat	3.97	-4.54	-3.65		
	Intercept	RmRf	AVol	RmRf x AVol	Adj R2
(7) Estimate	3.72%	0.16	-2.04%	-0.85	0.21
t-stat	4.02	0.68	-2.16	-3.87	
	Intercept	RmRf	RmRf x Bear	RmRf x Bear x Up	Adj R2
(8) Estimate	2.08%	-0.58	-0.54	-1.09	0.22
t-stat	5.14	-4.70	-2.18	-2.08	

Table 3. Equity beta components for distress-sorted portfolios

The table shows the characteristics of the median firm held in financial-distress decile portfolios at the end of portfolio formation. 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. Asset beta is estimated by regressing the firm's monthly asset return on market return, where the market value of assets is derived from 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 March 1982 to December 2013.

	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Equity beta	0.86	0.91	0.95	0.97	1.06	1.20	1.27	1.55	1.60	1.69	-0.82
Financial leverage	1.20	1.28	1.37	1.47	1.57	1.68	1.77	1.88	1.97	2.01	-0.81
Asset beta	0.82	0.79	0.79	0.76	0.73	0.70	0.65	0.62	0.70	0.91	-0.09
Operating leverage	0.51	0.48	0.49	0.51	0.55	0.59	0.64	0.69	0.72	0.80	-0.29
Default risk (Failure probability)	0.15%	0.22%	0.29%	0.37%	0.49%	0.65%	0.92%	1.47%	3.22%	13.70%	-13.55%
Firm size ($ million)	434.49	654.69	758.31	757.12	702.85	647.98	531.85	388.17	244.61	74.66	359.83
Idiosyncratic volatility beta (in percent)	1.72	1.55	1.51	1.58	1.71	1.93	2.08	2.30	2.77	3.12	-1.40
Two-year cumulative past returns	58.95%	54.85%	47.58%	41.62%	38.45%	37.37%	31.87%	22.52%	8.42%	-17.56%	76.51%
Productivity (Asset turnover)	1.04	1.05	1.03	0.97	0.93	0.90	0.90	0.90	0.91	0.85	0.19

Table 4. Equity beta components for distress-sorted portfolios separately for bull and bear markets

The table shows the same characteristics as in Table 3, 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 March 1982 to December 2013.

	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Equity beta											
Bull Market	0.90	0.95	0.95	0.96	1.03	1.13	1.18	1.36	1.41	1.47	-0.57
Bear Market	0.73	0.79	0.97	1.01	1.19	1.45	1.60	2.24	2.27	2.44	-1.71
Difference	-0.17	-0.15	0.02	0.06	0.16	0.31	0.42	0.88	0.86	0.96	-1.14
t-statistic	-3.29	-3.73	0.72	1.06	2.22	2.89	3.00	4.41	4.33	3.49	-3.65
Financial leverage											
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Bull Market	1.20	1.26	1.35	1.44	1.53	1.64	1.73	1.83	1.92	1.92	-0.72
Bear Market	1.21	1.31	1.42	1.52	1.65	1.76	1.88	1.99	2.08	2.23	-1.02
Difference	0.01	0.05	0.07	0.08	0.12	0.12	0.15	0.16	0.16	0.31	-0.30
t-statistic	0.69	2.79	3.02	2.58	3.06	2.70	2.75	3.26	2.36	2.27	-2.24
Asset beta											
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Bull Market	0.86	0.81	0.81	0.77	0.72	0.71	0.63	0.61	0.64	0.83	0.03
Bear Market	0.66	0.69	0.72	0.72	0.79	0.66	0.70	0.67	0.90	1.18	-0.52
Difference	-0.20	-0.12	-0.09	-0.05	0.07	-0.05	0.07	0.07	0.27	0.35	-0.55
t-statistic	-3.22	-2.79	-2.74	-0.94	1.45	-1.08	1.53	1.13	2.63	2.12	-2.79
Operating leverage											
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Bull Market	0.52	0.49	0.50	0.51	0.55	0.60	0.64	0.70	0.71	0.78	-0.26
Bear Market	0.44	0.43	0.46	0.48	0.52	0.55	0.62	0.68	0.73	0.94	-0.50
Difference	-0.08	-0.06	-0.04	-0.03	-0.04	-0.05	-0.02	-0.02	0.01	0.16	-0.25
t-statistic	-2.25	-1.99	-1.43	-1.10	-1.21	-1.28	-0.54	-0.37	0.20	2.86	-4.82
Default risk (Failure probability)											
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Bull Market	0.15%	0.22%	0.28%	0.35%	0.46%	0.61%	0.84%	1.30%	2.71%	11.69%	-11.54%
Bear Market	0.16%	0.25%	0.34%	0.46%	0.64%	0.87%	1.34%	2.46%	6.11%	25.18%	-25.02%
Difference	0.01%	0.03%	0.06%	0.11%	0.18%	0.26%	0.50%	1.16%	3.40%	13.49%	-13.48%
t-statistic	1.33	2.14	2.71	3.04	2.61	2.19	2.27	3.09	4.37	3.96	-3.96
Firm Size ($ million)											
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Bull Market	443.04	656.40	749.09	742.92	702.88	656.71	533.12	399.30	250.79	73.67	369.37
Bear Market	410.46	649.88	784.24	797.07	702.78	623.42	528.26	356.87	227.24	77.44	333.02
Difference	-32.58	-6.52	35.15	54.15	-0.10	-33.30	-4.87	-42.43	-23.56	3.77	-36.35

t-statistic	-0.59	-0.10	0.56	0.75	0.00	-0.43	-0.07	-0.90	-0.73	0.48	-0.74
Idiosyncratic volatility beta (in percent)											
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Bull Market	1.71	1.55	1.52	1.58	1.77	1.99	2.12	2.30	2.75	2.95	-1.24
Bear Market	1.75	1.55	1.49	1.58	1.51	1.73	1.98	2.31	2.83	3.62	-1.87
Difference	0.04	0.00	-0.03	0.00	-0.26	-0.26	-0.14	0.01	0.08	0.66	-0.62
t-statistic	0.12	0.00	-0.13	0.01	-1.02	-1.10	-0.62	0.03	0.20	1.02	-1.20
Two-year cumulative past returns											
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Bull Market	67.00%	63.91%	56.49%	50.01%	46.56%	45.92%	40.66%	31.13%	16.62%	-10.70%	77.70%
Bear Market	17.23%	7.97%	1.47%	-1.84%	-3.56%	-6.92%	-13.62%	-22.07%	-34.05%	-53.07%	70.30%
Difference	-49.77%	-55.94%	-55.01%	-51.86%	-50.13%	-52.85%	-54.28%	-53.20%	-50.67%	-42.37%	-7.40%
t-statistic	-5.49	-7.44	-9.18	-8.13	-7.61	-6.92	-7.36	-6.51	-6.60	-6.58	-0.69
Productivity (Asset turnover)											
	Healthy	2	3	4	5	6	7	8	9	Distressed	HMD
Bull Market	1.06	1.07	1.05	0.99	0.95	0.92	0.92	0.92	0.93	0.89	0.18
Bear Market	0.93	0.94	0.92	0.85	0.84	0.81	0.79	0.77	0.81	0.68	0.25
Difference	-0.13	-0.13	-0.13	-0.14	-0.12	-0.10	-0.13	-0.15	-0.11	-0.20	0.07
t-statistic	-3.35	-4.53	-5.67	-7.29	-5.68	-4.41	-4.90	-4.75	-5.00	-6.01	1.31

Table 5. 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 4) 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 March 1982 to December 2013.

	Panel A: Equity betas by prior market returns							
	Conditional market regression				Rolling window beta estimation			
	Bear	Bull	difference	t-stat	Bear	Bull	difference	t-stat
HMD portfolio	-1.71	-0.57	-1.14	-3.65	-1.59	-0.58	-1.01	-7.15
Healthy stocks portfolio	0.73	0.90	-0.17	-3.29	0.72	0.97	-0.25	-3.28
Distressed stocks portfolio	2.44	1.47	0.96	3.49	2.31	1.55	0.76	6.84
	Panel B: Equity betas by expected market risk premium							
	Conditional market regression – fitted beta				Rolling window beta estimation			
	Recession	Expansion	difference	t-stat	Recession	Expansion	difference	t-stat
HMD portfolio	-0.97	-0.40	-0.57	-4.39	-0.95	-0.51	-0.44	-4.35
Healthy stocks portfolio	0.84	0.95	-0.11	-5.09	0.88	0.98	-0.10	-2.59
Distressed stocks portfolio	1.81	1.35	0.46	4.20	1.83	1.49	0.35	4.08

Table 6. Time-series regression of HMD, healthy, and distressed stocks portfolios' monthly returns on market fluctuations

Each panel 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 1 if RmRf is positive, a dummy variable indicating a bear market, and interaction terms. In Panel A, the failure probability of Campbell et al. (2008) measures financial distress. Panel B uses Ohlson's (1980) O-score model as a distress proxy, and Panel C uses Merton (1974)-KMV's distance-to-default model. The table reports regression coefficients and Newey-West corrected *t*-statistics with three-month lags. The sample period is March 1982 to December 2013.

		Intercept	Bear	Bear x Up	Intercept	RmRf	RmRf x Bear	RmRf x Bear x Up
Panel A: Distress by Campbell et al.								
HMD portfolio	Estimate	1.69%	7.09%	-17.44%	2.08%	-0.58	-0.54	-1.09
	t-stat	3.84	4.04	-6.53	5.14	-4.70	-2.18	-2.08
Healthy stocks portfolio	Estimate	0.88%	-4.32%	7.03%	0.25%	0.90	-0.16	-0.03
	t-stat	3.63	-6.03	9.03	2.58	27.12	-2.71	-0.36
Distressed stocks portfolio	Estimate	-0.81%	-11.41%	24.47%	-1.83%	1.49	0.38	1.07
	t-stat	-1.42	-6.31	8.86	-4.59	14.63	1.73	2.22
Panel B: Distress by O-score								
		Intercept	Bear	Bear x Up	Intercept	RmRf	RmRf x Bear	RmRf x Bear x Up
HMD portfolio	Estimate	0.70%	2.91%	-7.45%	0.89%	-0.30	-0.11	-0.50
	t-stat	2.62	2.89	-5.85	3.65	-4.87	-0.71	-1.97
Healthy stocks portfolio	Estimate	0.79%	-5.71%	9.07%	0.05%	1.00	-0.04	-0.01
	t-stat	3.06	-8.01	9.80	0.55	47.27	-0.58	-0.05
Distressed stocks portfolio	Estimate	0.08%	-8.62%	16.52%	-0.84%	1.30	0.07	0.49
	t-stat	0.20	-7.09	11.70	-3.94	21.5	0.39	2.21
Panel C: Distress by Merton-KMV								
		Intercept	Bear	Bear x Up	Intercept	RmRf	RmRf x Bear	RmRf x Bear x Up
HMD portfolio	Estimate	0.92%	6.96%	-15.70%	1.35%	-0.66	-0.65	-0.71
	t-stat	2.27	4.68	-6.51	3.93	-7.07	-3.84	-1.87
Healthy stocks portfolio	Estimate	0.73%	-4.01%	6.13%	0.13%	0.84	-0.16	-0.08
	t-stat	3.24	-6.07	7.74	1.49	34.57	-2.54	-1.08
Distressed stocks portfolio	Estimate	-0.19%	-10.98%	21.83%	-1.22%	1.50	0.49	0.64
	t-stat	-0.38	-5.87	7.83	-4.23	18.78	3.50	1.90

Table 7. Risk-managed HMD portfolio

The table compares the performance of the long/short HMD strategy with the performance of its risk-managed counterpart (HMD*). The risk-management scales HMD by market volatility over the 252 days prior to a portfolio formation month. Reported statistics for both long/short distress strategies include average monthly returns, standard deviations, higher moment statistics (skewness and kurtosis), minimum and maximum one-month strategy returns observed in the sample, (annualized) Sharpe ratio, and an information ratio (IR) relative to HMD. The table also reports the output of regressions where HMD* return is the dependent variable, and returns of standard HMD and risk-managed WML* momentum strategy are the independent variables. The *t*-statistics are corrected by Newey-West with three-month lags. The sample period is March 1982 to December 2013.

	mean	stdev	skewness	kurtosis	min	max	SR (annualized)	IR
HMD	1.20%	9.39%	-1.56	10.49	-60.37%	28.02%	0.44	n.a.
HMD*	1.38%	6.62%	-0.82	6.15	-33.96%	20.01%	0.72	0.86
			Spanning tests: Regression of HMD*					
	alpha	HMD	Adj R2			alpha	HMD	WML*	Adj R2
Estimate	0.60%	0.66	87%		Estimate	0.58%	0.65	0.01	87%
t-stat	3.88	16.31			t-stat	3.62	16.91	0.34	

Table 8. Risk-managed HMD portfolio by different scaling variables and distress measures

The table replicates the tests reported in Table 7 using alternative state variables for hedging HMD strategy, and alterative distress signals for portfolio construction. Alternative state variables include prior market returns (computed over a two-year period before portfolio formation), the implied volatility from the option market (VXO), and the forecasted market volatility from the EGARCH(1,1) model. Alternative distress measures are Ohlson's (1980) O-score and Merton (1974)-KMV's distance-to-default models. The sample period is March 1982 to December 2013, except for the VXO which starts at July 1986.

Panel A: Scaling by prior market returns									
	mean	stdev	skewness	kurtosis	min	max		SR (annualized)	IR
HMD	1.20%	9.39%	-1.56	10.49	-60.37%	28.02%		0.44	n.a.
HMD**	1.25%	6.62%	0.77	7.67	-28.34%	34.28%		0.65	0.53
Spanning tests: Regression of HMD**									
	alpha	HMD	Adj R2			alpha	HMD	WML*	Adj R2
Estimate	0.96	0.24	12%		Estimate	0.65	0.27	0.22	19%
t-stat	2.45	2.56			t-stat	1.99	3.18	2.27	
Panel B: Scaling by VXO									
	mean	stdev	skewness	kurtosis	min	max		SR (annualized)	IR
HMD	1.08%	9.84%	-1.53	9.97	-60.37%	28.02%		0.38	n.a.
HMD*	1.40%	8.89%	-0.92	6.07	-42.15%	22.75%		0.55	0.61
Spanning tests: Regression of HMD*									
	alpha	HMD	Adj R2			alpha	HMD	WML*	Adj R2
Estimate	0.47%	0.86	91%		Estimate	0.51%	0.87	-0.03	91%
t-stat	2.68	19.92			t-stat	2.74	21.54	-1.08	
Panel C: Scaling by EGARCH(1,1) volatility									
	mean	stdev	skewness	kurtosis	min	max		SR (annualized)	IR
HMD	1.20%	9.39%	-1.56	10.49	-60.37%	28.02%		0.44	n.a.
HMD*	1.51%	8.78%	-0.86	6.13	-46.91%	25.62%		0.60	0.58
Spanning tests: Regression of HMD*									
	alpha	HMD	Adj R2			alpha	HMD	WML*	Adj R2
Estimate	0.44%	0.89	91%		Estimate	0.45%	0.89	0.00	91%
t-stat	2.71	23.12			t-stat	2.62	24.40	-0.18	

Panel D: Distress by O-Score								
	mean	stdev	skewness	kurtosis	min	max	SR (annualized)	IR
HMD	0.47%	4.61%	-0.64	6.55	-22.16%	16.28%	0.36	n.a.
HMD*	0.58%	3.46%	-0.01	4.20	-12.17%	14.21%	0.58	0.66

Spanning tests: Regression of HMD*

	alpha	HMD	Adj R2		alpha	HMD	WML*	Adj R2
Estimate	0.25%	0.69	86%	Estimate	0.26%	0.70	-0.01	86%
t-stat	3.02	16.89		t-stat	2.96	17.93	-0.69	

Panel E: Distress by Merton-KMV								
	mean	stdev	skewness	kurtosis	min	max	SR (annualized)	IR
HMD	0.56%	7.69%	-0.75	6.05	-37.06%	20.15%	0.25	n.a.
HMD*	0.64%	5.70%	-0.35	4.40	-25.39%	20.34%	0.39	0.39

Spanning tests: Regression of HMD*

	alpha	HMD	Adj R2		alpha	HMD	WML*	Adj R2
Estimate	0.26%	0.68	84%	Estimate	0.28%	0.68	-0.02	84%
t-stat	1.71	13.59		t-stat	1.78	14.45	-0.73	

Table 9. Bear- vs bull-market betas of 25 portfolios sorted on distress and momentum

Each month we sort all stocks independently by distress (based on Campbell et al. (2008)) and by momentum (return in the past twelve months) into five equal-sized quintiles, resulting in 25 distress-momentum portfolios. We hold the portfolios for one month and use value-weights. The table reports the market beta of the portfolios (estimated from market model regression) separately for periods after bull markets 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). We also report the differences and *t*-statistics between the two extreme distress and momentum quintiles. The sample period is March 1982 to December 2013.

Bull-market beta								Bear-market beta							
Portfolio	Loser	2	3	4	Winner	WML	t-statistic	Portfolio	Loser	2	3	4	Winner	WML	t-statistic
Healthy	1.08	0.82	0.83	0.85	1.05	-0.03	-0.35	Healthy	1.26	1.05	0.80	0.68	0.69	-0.57	-3.14
2	0.98	0.86	0.88	0.89	1.15	0.17	1.65	2	1.37	1.12	0.97	0.75	0.82	-0.55	-2.50
3	1.09	1.00	1.04	1.01	1.25	0.17	1.83	3	1.68	1.40	0.98	0.93	1.04	-0.63	-2.11
4	1.31	1.15	1.02	1.09	1.35	0.05	0.42	4	2.11	1.48	1.59	1.36	1.14	-0.97	-3.68
Distressed	1.38	1.28	1.31	1.27	1.54	0.16	1.45	Distressed	2.48	1.72	1.90	1.76	1.44	-1.04	-2.69
HMD	-0.30	-0.46	-0.47	-0.42	-0.49			HMD	-1.22	-0.67	-1.10	-1.08	-0.74		
t-statistic	-3.13	-4.42	-3.87	-3.13	-4.75			t-statistic	-4.36	-3.98	-6.31	-4.97	-3.54		

Table 10. Effect of distress on time variation of momentum

Each month we sort all stocks first by momentum (return in the past twelve months) into five equal-sized quintiles, and within each quintile, we sort all stocks by distress (based on Campbell et al. (2008)) into five equal-sized quintiles. We hold the portfolios for one month and use value-weights. Panel A shows the average returns of the portfolios. Panel B shows the regression of the WML portfolio return (the difference between the top and bottom momentum portfolio returns) in a given distress quintile. The independent variables are the market excess return (RmRf) during the holding period month, a dummy variable (Up) that equals 1 if RmRf is positive, a dummy variable indicating a bear market (if the cumulative market return during the past two years prior to portfolio formation is negative), and interaction terms. The regression *t*-statistics are corrected by Newey-West with three-month lags. The sample period is March 1982 to December 2013.

Panel A: Average returns of 25 portfolios sorted conditionally on momentum and distress

	Loser	2	3	4	Winner	WML	t-statistic
Healthy	1.09%	1.10%	1.11%	1.26%	1.46%	0.37%	1.27
2	0.74%	1.06%	0.99%	1.04%	1.33%	0.59%	1.66
3	0.08%	0.94%	1.11%	1.24%	1.23%	1.15%	2.85
4	0.07%	1.15%	0.90%	1.09%	1.25%	1.18%	2.70
Distressed	-0.32%	0.68%	1.00%	1.26%	1.30%	1.62%	3.38

Panel B: Market-timing regression of WML portfolio return for different distress quintiles

		intercept	Bear	Bear x Up	intercept	RmRf	RmRf x Bear	RmRf x Bear x Up
Healthy	Estimate	0.53%	2.48%	-5.99%	0.60%	0.03	-0.58	-0.52
	t-stat	1.83	2.45	-3.50	2.01	0.28	-2.91	-1.37
2	Estimate	0.86%	3.68%	-9.18%	1.06%	-0.13	-0.58	-0.84
	t-stat	2.49	2.77	-4.05	2.99	-1.16	-2.53	-1.63
3	Estimate	1.48%	7.31%	-15.98%	1.64%	-0.18	-1.15	-0.69
	t-stat	4.11	4.02	-5.94	4.52	-1.74	-3.78	-1.33
4	Estimate	1.57%	5.37%	-13.39%	1.81%	-0.11	-0.61	-1.28
	t-stat	3.98	2.25	-4.10	4.58	-0.94	-1.38	-1.96
Distressed	Estimate	2.26%	3.73%	-13.55%	2.29%	0.08	-0.70	-1.71
	t-stat	5.11	1.90	-4.27	5.24	0.74	-1.74	-2.72

Figure 1. HMD portfolio performance: January 1998–December 2010

The figure plots the value of a $1 investment in the HMD portfolio (dashed line) and in the market portfolio in excess of the risk-free asset (solid line) from January 1998 to December 2010.

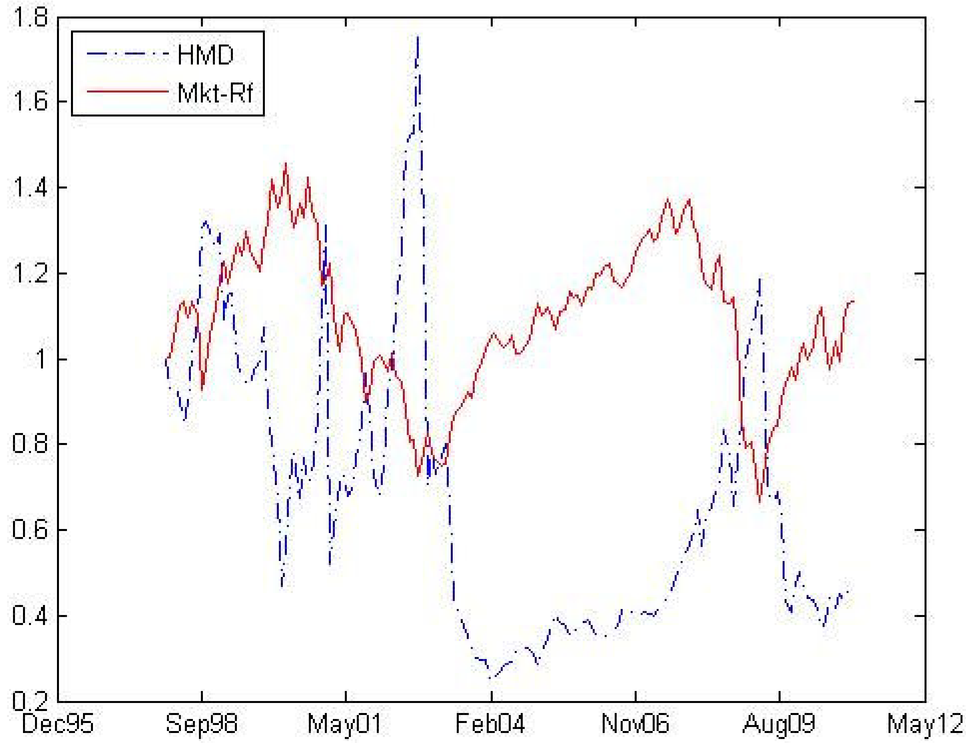
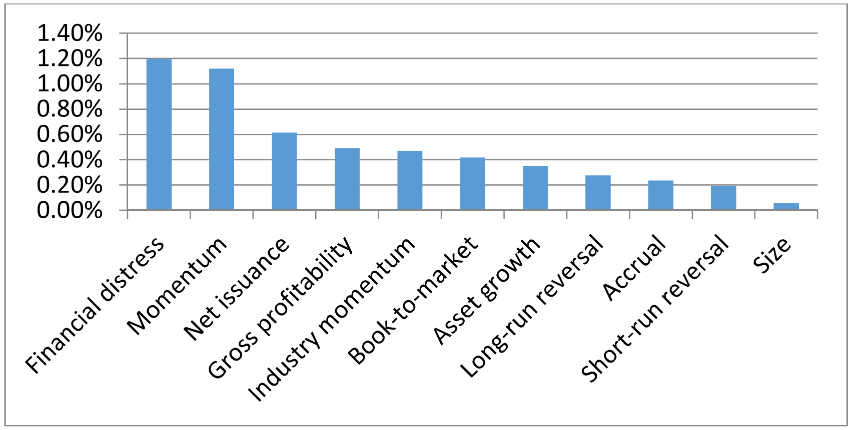
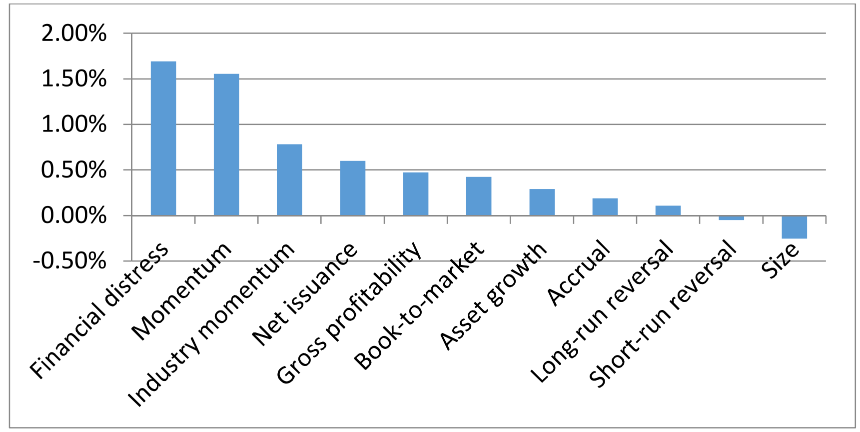


Figure 2. Performance of long/short anomaly portfolios over the full sample and in different market states

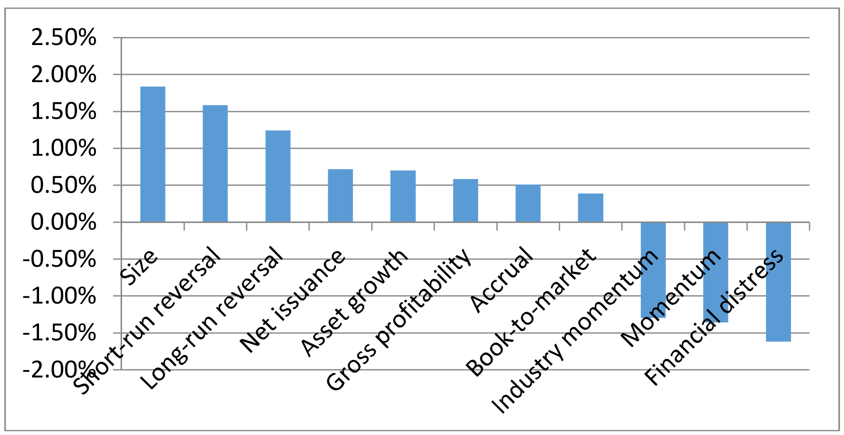
We form zero-cost long/short portfolios for several well-documented anomalies and report their average returns over the full sample and in different states of the market. A bull (bear) market is assumed if the cumulative market return during the past two years prior to portfolio formation is positive (negative). Investors observe an up-market month when the market turns positive following a bear market. The sample period is March 1982 to December 2013.



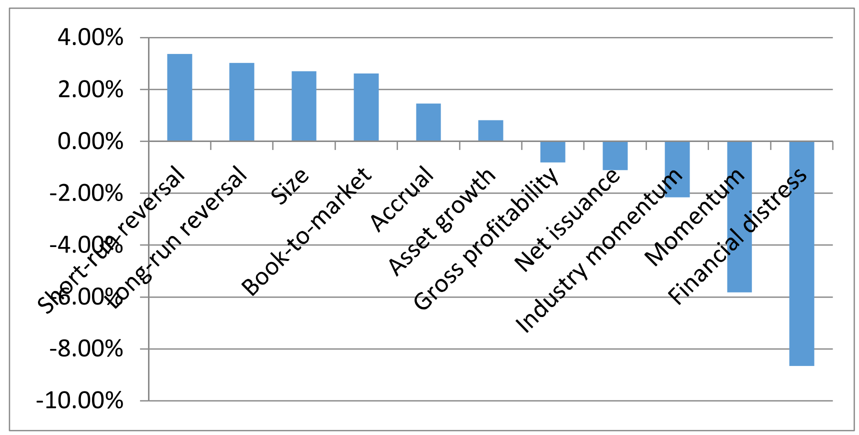
Full sample



Bull market



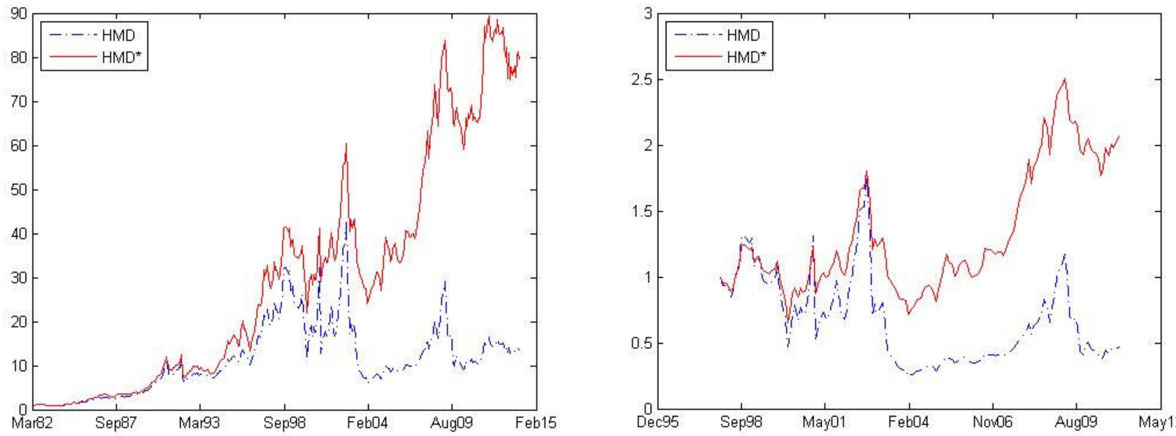
Bear market



Up-market following bear market (market rebound)

Figure 3. Performance of standard HMD and risk-managed HMD* portfolios

The figure plots the value of a $1 investment in the HMD portfolio (dashed line) and the risk-managed HMD* portfolio (solid line) for the entire sample period, March 1982 to December 2013, and for the period of January 1998 to December 2010. The risk management strategy scales HMD by market volatility over the 252 days prior to the portfolio formation month.



Appendix: Distress measure

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:

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

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

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

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. We include all common stocks, although our results are robust to the exclusion of financial stocks. The sample period for our study is 1982 to 2013 as the coverage of quarterly COMPUSTAT data is sparse before this date.