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Predicting Financial Distress and the Performance of Distressed Stocks

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Abstract

In this paper we consider the measurement and pricing of distress risk. We present a model of corporate failure in which accounting and market-based measures forecast the likelihood of future financial distress. Our best model is more accurate than leading alternative measures of corporate failure risk. We then use our measure of financial distress to examine the performance of distressed stocks from 1981 to 2008. We find that distressed stocks have highly variable returns and high market betas and that they tend to underperform safe stocks by more at times of high market volatility and risk aversion. However, investors in distressed stocks have not been rewarded for bearing these risks. Instead, distressed stocks have had very low returns, both relative to the market and after adjusting for their high risk. The underperformance of distressed stocks is present in all size and value quintiles. It is lower for stocks with low analyst coverage and institutional holdings, which suggests that information or arbitrage-related frictions may be partly responsible for the underperformance of distressed stocks.

1 Introduction

Interest in the pricing of financially distressed firms is widespread. Chan and Chen (1991) describe marginal and distressed firms as follows: "They have lost market value because of poor performance, they are inefficient producers, and they are likely to have high financial leverage and cash flow problems. They are marginal in the sense that their prices tend to be more sensitive to changes in the economy, and they are less likely to survive adverse economic conditions." Asset pricing theory suggests that investors will demand a premium for holding such stocks. It is an empirical question whether or not investors are indeed rewarded for bearing such risk.

We investigate the pricing of financially distressed stocks in two steps: First, we present a model predicting financial distress. Second, we consider the historical performance of investing in distressed stock portfolios.

Our proposed measure of financial distress is the probability of failure. Following Shumway (2001) we predict failure in a hazard model using explanatory variables constructed from observable accounting and market-based measures. This approach is related to an earlier literature pioneered by Beaver (1966) and Altman (1968) who introduced Z-score as a measure of bankruptcy risk, and has recently been used by Beaver, McNichols, and Rhie (2005).

We classify a firm as more distressed if it is more likely to file for bankruptcy under Chapter 7 or Chapter 11, de-list for performance related reasons, or receive a D rating from a rating agency. This expanded measure of failure (relative to measuring only bankruptcy filings) allows us to capture at least some instances in which firms fail but reach an agreement with creditors before an actual bankruptcy filing (Gilson, John, and Lang 1990, Gilson 1997). Our data set is monthly and includes more than 2 million firm-months and close to 1,750 failure events.

We predict failure over the next month (similar to Chava and Jarrow (2004)). However, in addition we also consider the probability of failure for longer horizons. After all, an investor will certainly care not only about imminent failure, but rather will want to get a sense well in advance which are the firms that are most likely to fail. Although probably quite accurate, it may not be useful to predict a heart attack with a person clutching their hand to their chest.

Firms that are distressed have the characteristics we would expect: they have re-

cently made losses, have high leverage, their stock returns have been low and volatile, and they have low levels of cash holdings. Our best model, which makes several changes relative to Shumway (2001) and Chava and Jarrow (2004), improves forecast accuracy by 16% when compared to these models. It also outperforms another leading alternative – 'distance-to-default' – a measure based on the famous Merton (1974) model of risky corporate debt and popularized by Moody's KMV (see, for example, Crosbie and Bohn(2001)). Relative to distance-to-default our model almost doubles forecast accuracy.

We next investigate the performance of distressed stocks using our best model to measure financial distress. Portfolios of distressed stocks have very high levels of volatility and high market betas, which means that they are risky and should command a high risk premium. However, their returns from 1981 to 2008 have been low: distressed stocks have significantly underperformed the S&P500. A portfolio going long safe stocks and shorting distressed stocks has been a highly profitable strategy and has a significantly higher average return and Sharpe ratio than the S&P500.

The underperformance of distressed stocks is puzzling given that investors seem to realize that distressed stocks are risky: The high market betas of distressed stocks imply that the market perceives distressed stocks as being more sensitive to overall market conditions. Furthermore, we find that distressed stocks underperform more severely at times of increases in market volatility, as measured by the VIX, the implied volatility of S&P500 index options. In the last four months of 2008 a strategy of long safe, short distressed stocks earned a return of 59%, while the return for all of 2008 was 145%.

Even if the average investor does not react, such high performance levels should attract significant arbitrage capital and over time we should see declining profits to this strategy. One reason why we have not observed this could be that it is difficult to obtain information about the health of distressed stocks and that they may be difficult to short sell. Due to these constraints arbitrage activity could be limited. Consistent with this hypothesis we find that the distress effect is more concentrated in stocks with low analyst coverage and in stocks with low levels of institutional holdings, which has been proposed as a proxy for the ability to short such stocks.

The remainder of the paper is organized as follows. After a brief review of the existing literature, Section 2 discusses our data and the construction of our explanatory variables. Section 3 presents our model of failure prediction. We investigate the

ability of our variables to predict failure at different horizons and compare the forecast accuracy of our best model to leading alternatives. We also consider the ability of our model to predict changes in the aggregate failure rate over time. Section 4 focuses on the performance of distressed stock portfolios. We document performance over time and consider performance across size and value quintiles, as well as for firms with higher information and arbitrage-related frictions. Section 5 concludes.

1.1 Related literature

There are several different approaches to predicting bankruptcy. Early studies focused entirely on accounting ratios and often compared financial ratios in a group of non-bankrupt firms to a group of bankrupt firms, e.g. Altman's (1968) Z-score. The subsequent literature introduced market-based variables and adopted more suitable statistical techniques to model probability of bankruptcy. Shumway (2001) discusses this line of research and points out the shortcomings of the early studies. Our paper adds to this line of work by developing the variables used by Shumway (2001) further and adding additional variables that lead to a large increase in the model's explanatory power.

Other studies have instead focused on using Merton (1974) as the basis for modeling and have chosen distance-to-default as the main variable to predict future bankruptcy. Examples include Hillegeist et al. (2004), Vassalou and Xing (2004), and Duffie et al. (2007). We show that using a larger set of explanatory has significantly higher forecasting ability, a fact also pointed out by Bharath and Shumway (2008).

Another possibility is to use credit ratings as a summary measure of the risk of future bankruptcy. Hilscher and Wilson (2009) find that using the model described below has much higher forecast accuracy than credit ratings.

2 Constructing measures of financial distress

Our measure of financial distress is the probability of failure. We define failure to be the first of the following events: chapter 7 or chapter 11 bankruptcy filing, de-listing due to performance related reasons, and a default or selective default rating by a rating agency. We use monthly failure event data that runs from January 1963 to

December 2008. Our data on failures was provided by Kamakura Risk Information Services (KRIS) and represents an updated version of the data in Campbell, Hilscher, and Szilagyi (2008), who use data up to December 2003.

We use accounting and market-based measures to forecast failure. Taking the models used in Shumway (2001) and Chava and Jarrow (2004) as the starting point we construct the following eight measures of financial distress, three accounting-based measures and five market-based measures. We construct all our measures using quarterly and annual accounting data from COMPUSTAT and daily and monthly data from CRSP.

1. We measure profitability as the ratio of net income (losses) over the previous quarter to the market value of total assets ($NIMTA$). We find that the market value of total assets, the sum of book value of total liabilities and market equity, is a more accurate measure of assets than book value of total assets, a measure used to scale income in previous studies. Scaling by market value of assets gives a potentially more timely and accurate picture of the asset value of the firm. Market equity capitalization is available in real time and reflects recent news to the firm. Furthermore, it also allows for a more accurate valuation of assets, e.g. growth opportunities, intangibles, departure from replacement value, and may also reflect the financing capacity of the firm both in terms of equity issuance as well as its ability to secure short-term financing.

2. Our measure of leverage is total liabilities divided by market total assets ($TLMTA$). Similar to profitability, we find that this measure more accurately reflects distress than when scaling by book value of total assets.

3. We measure short-term liquidity using cash holdings scaled by market total assets ($CASHMTA$). If a firm runs out of cash and cannot secure financing it will fail, even if its value of assets is larger than the level of its liabilities.

4. We add the firm's equity return ($EXRET$) which is the stock's excess return relative to the S&P 500 index return. We expect firms close to bankruptcy and failure to have negative returns.

5. Volatility ($SIGMA$) is a measure of the stock's standard deviation over the previous three months. Not surprisingly, distressed firms' stocks returns are highly volatile.

6. Relative size ($RSIZE$) is the firm's equity capitalization relative to the S&P500 index, which we measure by taking the log of the ratio. We expect, ceteris paribus, smaller firms to have less of an ability to secure temporary financing to prevent failure.

7. We calculate the firm's ratio of market equity to book equity (MB). Market-to-book may capture over-valuation of distressed firms that have recently experienced heavy losses. It may also be important in modeling default since it might enter as an adjustment factor to our three accounting measures that are scaled by market equity.

8. We add the log of the stock price, which we cap at \$15 ($PRICE$). Distressed firms often have very low prices, a reflection of their decline in equity value. If firms are slow or reluctant to implement reverse stock splits this measure will be related to failure. Variation above \$15 does not seem to affect failure probability and so the measure is capped at that level.

All of our measures are lagged so that they are observable at the beginning of the month over which we measure whether or not the firm fails. The three accounting measures are based on quarterly data and we assume that it is available two months after the end of the accounting quarter. Market data is measured at the end of the previous month. This way we ensure that the failure prediction we propose can be implemented in real time and that the investment returns that we discuss in Section 4 can be constructed using available data.

To control for outliers we winsorize the variables at the 5th and 95th percentile of their distributions. This means that we replace any value below the 5th percentile with the 5th percentile value and replace values above the 95th percentile with the 95th percentile value. The appendix of the paper describes the variable construction in more detail.

2.1 Summary statistics

Table 1 reports summary statistics for these eight measures. Panel A reports summary statistics for the full sample of firm-months that we use to model failure prediction. Panel B reports statistics for the sample of firms that fail over the following month. The table also reports the difference in means in units of standard deviation.

For example the overall firm average of leverage is 44% while firms that are about to fail have an average leverage of 73.7%. This higher level is 1.05 standard deviations higher than the overall mean.

When interpreting the statistics, it is important to remember a few things about the sample and the construction of the variables. First, the summary statistics place equal weight on all observations, which means that, when compared to value-weighted statistics, small firms dominate. This fact is reflected in the summary statistics for relative size, which we report in basis points. Relative to the market capitalization of the S&P500 the average size of a firm in our data set is equal to 1.46 basis points (0.0146%). This fact explains the very low levels of average profitability (-0.01%) and the high levels of annualized volatility (54.2%). Second, excess return is measured in logs, which means that we are reporting a geometric average. This fact is the reason for very low average excess return of -1%. This low number also reflects the very low returns of small firms.

Firms that are about to fail differ from the overall population of firms in ways that we might expect: Distressed firms have experienced losses, they have higher leverage and their cash holdings are low. They have recently had very negative returns and tend to be small, about one tenth of the size of the average firm. They have high volatility, an average of 100% (annualized), and at under $2 their average price per share is less than one sixth the median price per share of the overall population. For one half of the variables, firms that are about to fail differ by more than 1 standard deviation from the population ($NIMTA$, $TLMTA$, $SIGMA$, and $PRICE$), and the difference is large for three more variables. The only variable for which there is not a clear difference is the market-to-book ratio. The reason is that firms that are about to fail have more extreme measures of MB, but not clearly lower or higher levels. Some firms that fail have very high levels of market to book, because they are overvalued or because recent losses have resulted in very low levels of book equity. Other failed firms have low levels of market-to-book, a result of the market anticipating further losses and the possibility of very low levels of valuation. We will see which of these effects dominates in the next section.

These variables are all indicators of distress and using each one of them would result in a forecast of future failure. However, combining the indicators will result in a more accurate measure of distress and we would like to know how to best combine the different explanatory variables. In the next section we combine all the measures into a single model that produces the most precise forecast of failure.

3 A model predicting financial distress

We model financial distress using a logit model, as in Shumway (2001), Chava and Jarrow (2004), and Campbell et al. (2008). The probability of the firm failing over the next month is equal to

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

where Y_{it} is equal to 1 if the firm fails and equal to 0 if the firm remains active. $\beta x_{i,t-1}$ represents a linear combination of our explanatory variables.

Before estimating the model we make two adjustments to the measures discussed in the previous section. We construct a measure of average profitability over the previous four quarters ($NIMTAAVG$). We find that firms that are about to fail will likely have made losses not only over the previous quarter, but rather will have been making losses for a more extended period of time. Since losses over the most recent quarter will be more informative than losses four quarters ago, we place more weight on more recent observations. Thus $NIMTAAVG$ is a geometrically weighted average level of profitability where the weight is halved each quarter. In a similar spirit we also construct a measure of average returns over the last 12 months ($EXRETAVG$) which also places relatively more weight on more recent returns. The exact definition of these two variables is in the appendix.

Table 2 reports model estimation results when we combine these two variables with the accounting measures (leverage and cash) and the market measures (volatility, size, market-to-book, and price). All variables are statistically significant and have the expected sign: firms with lower profitability, higher leverage, and lower cash holdings, with lower and more volatile past returns, and with lower share prices are more likely to fail. The one exception is the coefficient on size which has a counterintuitive positive sign, though this is most likely due to the high correlation of price and size.

We also consider two measures of model fit that are common in the context of bankruptcy prediction: the model delivers an overall pseudo R^2 of 31.6% and an accuracy ratio of 95.5%. The pseudo R^2 (McFadden's R^2) measures the performance of the model relative to a model that only fits the overall average default rate. A completely uninformative model would have a pseudo R^2 equal to 0. The accuracy ratio is a summary measure that compares the number of correct predictions (pairs of high predicted probabilities and subsequent failures, and pairs of low predicted

probabilities and no subsequent failures) to the number of incorrect predictions. An uninformative model would deliver an accuracy ratio of 50%.

Since investors will care not only about modeling financial distress over the next month but will also be interested in the determinants of failure in the future, we consider different prediction horizons. We estimate the probability of failure 12 months in the future, given that the firm has not failed over the next 12 months and we do the same for 36 months. We report estimation results in the second and third columns of Table 2.

When predicting failure in 1 year and in 3 years, all the variables remain statistically significant and come in with the expected signs, with the only exception again being the coefficients on price. At the 1-year horizon the coefficient loses significance and at the 3-year horizon, price comes in with a positive sign. Meanwhile, size comes in with the expected sign – larger firms are less likely to fail. This means that the variables have flipped signs relative to the 1 month prediction horizon. This effect is again likely driven by their high level of correlation and the possibility of unmodeled nonlinearities in the effects of these two variables. We also find that at longer horizons the more persistent characteristics of the firm such as volatility and the market-to-book ratio become relatively more important.

Not surprisingly, it is much more difficult to forecast financial distress farther into the future. Both measures of accuracy drop significantly as the prediction horizon is lengthened. At 1 year the Pseudo R^2 is equal to 11.8% and at 3 years it is 4.1%, while the accuracy ratio drops to 86.2% and 73.7% respectively. Nevertheless, even at longer horizons, our model has a very high level of predictive ability.

We next compare our model, which we will refer to as our 'best model' to leading alternatives. Our model takes as a starting point the model proposed by Shumway (2001) and used by Chava and Jarrow (2004), and five of our eight explanatory variables are closely related to variables used in these models. It is, therefore, natural to consider our model's performance relative to the Shumway (2001) model. We also compare our model's performance to a common alternative, one used especially by practitioners: distance-to-default. The model, popularized by Moody's KMV, takes the insights from option pricing used in the Merton (1974) model of risky debt and applies them to the task of bankruptcy prediction. It assumes that a firm enters bankruptcy if in one year's time the market value of assets lies below the face value of debt. Distance-to-default has been shown to be a predictor of future default (e.g. Vassalou and Xing (2004) and Hillegeist et al (2004)). We compare its performance

to our model and we also ask how much the explanatory power increases if we add distance-to-default (DD) as an additional explanatory variable to our best model. Please see the appendix for a detailed discussion of the construction of DD.

Figure 1 reports the results. We compare our model, the Shumway model, DD by itself, and DD in our best model. We consider seven prediction horizons, ranging from predicting failure over the next month to predicting it in three years. At all horizons our best model is more accurate than the Shumway model and than DD only. The levels of outperformance vary: Our model is between 12% and 16% more accurate than the Shumway model and between 49% and 94% more accurate than DD only. When we add DD to our best model there is a very slight improvement in fit, which is natural given that we have allowed for an additional degree of freedom. However, the incremental explanatory power is less than 5% at horizons up 18 months, reaching 8% at 3 years. Given that DD is one single measure, it performs quite well, and some may view it as 'unfair' to compare a model with eight variables to one with only one variable. However, when predicting financial distress there is no restriction that says that the model can use only one variable. A richer empirical model seems to have clear and measurable benefits relative to using only one variable.

We also consider the ability of our measure to explain variation in the aggregate failure rate over time. Changes in the bankruptcy rate over time may be related to changes in capital structure (Bernanke and Campbell (1988)), to the riskiness of corporate activities (Campbell et al. (2001)) and to default correlation (Das et al (2007), Duffie et al. (2009)). We compare the realized failure rate and the predicted failure rate in Figure 2. The predicted failure rate is the average probability of failure using our best model. The failure rate is quite volatile over time and our model captures the broad variation in the failure rate well, including the high failure rates in the 1980s and early 1990s, the high levels of failures as a result of the bursting of the technology bubble, the subsequent low failure rates from 2004 to 2007, and the increase in the failure rate in 2008. The strong relationship which is apparent in the graph is also reflected in a correlation of actual and predicted failures of 84%.

4 Returns to investing in distressed stocks

We now consider the historical rates of return earned by financially distressed stocks. We use our model of financial distress to sort stocks into portfolios and examine their

returns from 1981 to 2008. The pronounced variation in the failure rate reflected in Figure 2 suggests that variations in the failure rate are not idiosyncratic and cannot be diversified away. This means that investors should demand a premium for holding them.

Every January we sort firms into 10 portfolios using the 12-month ahead probability of failure from Table 3. In choosing the composition of the portfolios we pay special attention to portfolios containing stocks with very low and very high failure probabilities. The first portfolio contains those stocks with the lowest five percent of the failure probability distribution (0005), the second portfolio contains the next five percent of stocks, those with failure probabilities between the 5th and 10th percentile of the distribution (0510). We construct the next eight portfolios similarly so that we cover the entire spectrum of distress risk: 1020, 2040, 4060, 6080, 8090, 9095, 9599, and 9900, which invests in the firms with the top 1% of the failure probabilities. We also consider a portfolio that goes long the safest 10% of stocks and short the most distressed 10% ($LS1090$).

To avoid look-ahead bias we re-estimate the model coefficients every year. For example, we use data up to December 1990 to estimate the coefficients on the eight variables in our model, calculate failure probabilities, and then sort stocks into portfolios in January 1991. We hold stocks for one year and calculate value-weighted returns. To reduce turnover, we do not rebalance portfolios during the year, but instead use weights that drift with the performance of the stocks.

Table 3 reports average returns (Panel A) and characteristics (Panel B) for the 11 portfolios. We find an almost monotonic relationship between distress and returns, though not in the direction one might expect: safe stocks have earned high returns, while distressed stocks have had very low returns. Average excess returns relative to S&P500 index returns are negative starting with portfolio 4060; they are statistically significant at the 5% level for portfolio 8090, and significant at the 1% level for the three most distressed portfolios. The 1% most distressed stocks have underperformed the S&P500 index by 26% (annualized monthly return). Table 3 Panel A also reports CAPM alphas as well as alphas from the Fama and French (1993) three factor model and the four factor model proposed by Carhart (1997). We use returns for the factors from Ken French's website to estimate these alphas. Figure 3 graphically summarizes the pattern in returns across different levels of distress.

Panel B reports characteristics of the portfolios' constituent stocks. As expected, distressed stocks are more risky than safe stocks. The three most distressed stock

portfolios have market betas of close to 1.5. The constituent stocks are highly volatile (between 64% and 92%) and this high volatility is also reflected in the portfolio standard deviations of between 23% and 39%. The fact that distressed stocks are more risky means that when we correct for risk using the CAPM, the mispricing of distressed stocks will become more pronounced. Indeed we find that CAPM alphas and Fama French 3-factor alphas follow the same pattern as mean excess returns: distressed stocks significantly underperform safe stocks. For CAPM alphas there is statistically significant underperformance starting with portfolios 8090 while for 3-factor alphas there is significant underperformance even for the 4060 portfolio, as well as significant outperformance for the two portfolios containing the safest stocks. One of the variables in the failure prediction model is the weighted average of recent past returns which means that distressed stocks may have negative momentum. We indeed find that when we correct for the momentum factor the underperformance of distressed stocks is less pronounced, though still large and significant.

Distressed stocks are much smaller than safe stocks: the average stock in the safest 80% of the distress risk distribution has a size of between 7 and 9 basis points of the overall S&P500 market capitalization, while the 1% most distressed stocks have a size of 0.36 basis points, close to 1/20th of that.[2] The market-to-book ratio follows a U-shaped pattern. Both safe and distressed firms have higher levels of market-to-book than firms towards the middle of the distribution. This pattern may reflect the fact that young firms with low levels of leverage are safe growth stocks. At the same time, distressed firms may be overvalued or have low levels of book equity due to recent losses and high levels of market-to-book. We also report annualized 12-month failure probabilities, which are much higher for distressed stocks.

Our findings are related to previous studies that have used Ohlson's (1980) O-Score and Altman's (1968) Z-Score to explore pricing of financially distressed firms. Examples include Dichev (1998), Griffin and Lemmon (2002) and Ferguson and Shockley (2003). Avramov et al. (2007) and Avramov et al. (2009) consider equity returns using credit ratings. We use an updated and improved measure of distress risk that we find to be significantly more accurate than previous measures. By using this measure we are able to show a more accurate picture of the characteristics and relative underperformance of distressed stocks.

[2]Since the portfolios are value-weighted, the characteristics reported in Panel B are also value weighted. This explains the difference in average size when compared to the equally-weighted statistics reported in Table 1.

4.1 Performance of distressed stocks across characteristics and over time

The pronounced pattern of size and value across the distress-risk sorted portfolios suggests that the underperformance of distressed stocks may be related to their characteristics. We therefore now consider the performance of distressed stocks across portfolios sorted on size and value. For both characteristics we sort first on size and value, then on distress. We use the NYSE breakpoints from Ken French's website to do the sorting. We then calculate 3-factor alphas on portfolios long the safest quintile, short the most distressed quintile.

Figure 4 reports the results. We find a clear pattern across size-sorted portfolios with annualized alphas of 16.3% for small firms, compared to 10.2% for large firms. Though the outperformance is larger for small firms, this may be driven by a larger spread in distress risk between safe and risky small stocks. This is likely given that distressed firms are much smaller. We correct for the higher spread in distress for smaller stocks by calculating 3-factor alphas scaled by the difference in failure probability ('$\hat{P}$-adjusted 3-factor alpha') and find that the difference in performance is driven entirely by the higher spread in distress risk for small firms.

We also compare the relative performance of safe and distressed stocks across portfolios sorted on value. The underperformance of distressed stocks is more pronounced for extreme growth and value stocks. The 3-factor alphas for the highest and the lowest quintile of the book-to-market distribution are almost twice as large as the alphas for the three middle groups. We again adjust for the dispersion in failure probability and find that the large performance gap for the extreme portfolios is partly driven by the larger spread in the failure probability $\hat{P}$. The 3-factor alpha and the $\hat{P}$-adjusted 3-factor alpha are all statistically significant (18 of 20 coefficients at the 1% level, and 2 coefficients at the 5% level). We conclude that the underperformance of financially distressed stocks is present across the entire spectrum of the size and value distributions and is not concentrated only in a particular group of firms.

One possibility for the underperformance of distressed stocks might be that investors are unaware of some companies' level of financial distress or that it is difficult for investors to easily borrow stocks of distressed firms that they can short sell. In other words, it is possible that the underperformance of distressed stocks is concentrated in firms that have informational or arbitrage related frictions.

We consider this hypothesis by comparing performance across stocks with different levels of analyst coverage. If firms have high analyst coverage it is likely that information is more easily available and that news about firms' prospects reaches market participants more quickly. Since there is a strong relationship between size and analyst coverage – large stocks tend to have higher analyst coverage than small stocks – we correct for the effect of size on analyst coverage by calculating residual analyst coverage (following Hong, Lim, and Stein (2001)). This way we include both large and small stocks that have lower analyst coverage than other stocks of comparable size. We then sort first on the top and bottom third of the distribution of residual analyst coverage, then on distress.

Table 4 reports the results. We find that the relative underperformance of distressed stocks, measured by their 3-factor alphas, is about twice as large for firms with low analyst coverage. The difference in $\hat{P}$-adjusted 3-factor alphas is smaller which means that the effect is partly driven by a higher dispersion in distress for lower analyst coverage stocks.

We also consider whether or not there is a relationship between the level of institutional holdings and the performance of distressed stocks. Higher institutional holding may be viewed as a proxy for the relative availability of stocks that can be borrowed for short-selling purposes and that can be arbitraged by institutional investors (see, for example, Nagel (2005)). Similar to analyst coverage, institutional holdings also have a strong pattern across size so we calculate residual institutional holdings before sorting stocks into the top and bottom third of the distribution. We find that the underperformance of distressed stocks is again about twice as large for low institutional holding stocks. The relative magnitude is similar for $\hat{P}$-adjusted 3-factor alphas.

It is also possible that the underperformance of distressed stocks is very concentrated. It may also have been reduced over time as investors have become more aware of the pattern. We consider this hypothesis and next examine the relative performance of distressed stocks over time. Figure 5 reports the cumulative performance of the portfolio long the safest 10% of stocks and short the most distressed 10% ($LS1090$ in Table 3), from 1981 to 2008. The figure plots cumulative excess returns, CAPM alphas and 3-factor alphas. For comparison we also report the cumulative excess return of the S&P500 relative to the risk-free rate. (We use monthly risk free returns from Ken French's data library.)

The graph illustrates the performance of the long-short portfolio relative to the

market portfolio. Over the entire period the long-short portfolio has outperformed the market, which reflects the significant excess return we report in Table 3. Once we adjust for risk the outperformance of the long safe, short distressed strategy widens, again consistent with the results reported in Table 3. A long-short strategy with initial size of $1 and invested in from January 1981 to December 2008 resulted in $3.41 (market return relative to the risk-free rate), $18.33 (long safe-short distressed), $38.60 (CAPM alpha) and $220.92 (3-factor alpha). The Sharpe ratios of the four strategies over the period are equal to 37% (market), 55% (long safe-short distressed), 67% (CAPM alpha) and 97% (3-factor alpha).

Figure 5 also illustrates that there are risks associated with the long-short strategy and that returns have not been uniformly high. Excess returns and CAPM alphas are somewhat concentrated in the period from 1984 to 1991 as well as from 2003 to 2008. Also, cumulative returns of the long-short strategy over the period from 2000 to the second quarter of 2008 have been close to zero (though, not surprisingly, they were very high from September to December 2008). The performance for risk-adjusted returns (CAPM alpha and 3-factor alpha) is much more consistent over time. In addition, especially since 2000, the long safe-short distressed portfolio has tended to have high returns during times of low market returns. Table 3 reports that the CAPM beta of the long-short portfolio is equal to -0.47 and this negative beta is reflected in the graph: The market downturns of 2001/2002 and 2008 are both associated with strong performance of the long-short portfolio, while the market rally of 2003 is associated with low returns of the long-short strategy.

It is possible that investors do not perceive distressed stocks as risky and therefore do not demand compensation for taking on risk. However, if instead distressed stocks are viewed by investors as risky and if they are viewed as marginal, then we might expect distressed stocks to do particularly poorly at times of heightened market uncertainty and at times during which investors are reluctant to hold risky assets. As a proxy for such times we use the VIX index, the implied volatility of the S&P500. During times of high market volatility, we might expect a 'flight to quality effect,' which leads investors to bid up the prices of safe stocks relative to those that are distressed. We would also expect such a pattern given the evidence of a positive correlation between credit spreads and the VIX index (see, for example, Berndt et al. (2005), and Schaefer and Strebulaev (2008)).

Figure 6 plots the cumulative return on the long safe-short distressed portfolio (the same as in Figure 5) and the VIX index from 1990 to 2008 (the time during with the

VIX is available). The graph illustrates the pattern that we might expect: distressed stocks do relatively more poorly during times of heightened market volatility and risk aversion. The graph also reflects the correlation of long safe-short distressed and contemporaneous changes in the VIX of 24% (monthly frequency) and 42% (quarterly frequency).

5 Conclusion

In this paper we consider the measurement and pricing of stocks in financial distress. We first present a model of financial distress that predicts corporate failure using accounting and market-based variables. The model's predictions are intuitive: distressed firms are those that have recently made losses, have high leverage, low and volatile recent returns, have levels of market-to-book and low share prices. Our best model outperforms leading alternatives such as the model proposed by Shumway (2001) as well as distance-to-default, an approach popular in industry and one use by Vassalou and Xing (2004) as well as Hillegeist et al. (2004).

In the second part of the paper we consider the performance of distressed stocks from 1981 to 2008. We find that distressed stocks have significantly underperformed the S&P500 and that they are risky – they have high levels of volatility and high market betas. This means that once we adjust for risk using the CAPM and Fama French 3-factor model, the apparent mispricing of distressed stocks worsens.

The strong underperformance of distressed stocks is a puzzle. We examine it further by considering three hypotheses: is the underperformance concentrated in firms with particular characteristics, is it more pronounced for firms with lower levels of available information, or is it concentrated at particular points in time?

We find that the underperformance of distressed relative to safe stocks is present across all size and value quintiles, though it is more pronounced for portfolios that have a larger spread in failure probability, a fact that explains the more extreme underperformance of distressed stocks for small firms. Furthermore, we find that the low performance of distressed stocks is concentrated in stocks with lower analyst coverage and lower institutional holdings. We interpret this fact as suggesting that for some distressed firms it may be difficult to easily gain information about their financial health and it may not be possible to short-sell severely distressed stocks.

The potential barriers to arbitrage may be one reason why there have continued to be times of strong underperformance throughout our sample period.

What does all of this mean in practice? Our results suggest that investors should stay away from investing in distressed stocks. Furthermore, it should be quite possible for investors to collect information about firms' health using the measures in our model. Investing more heavily in safe stocks will reduce a diversified portfolio's volatility and its beta while increasing its returns. When possible, investors should also short sell firms in distress.

It seems unlikely that investors are not informed well enough to realize the opportunities that they seem to be missing. We present a measure that is straight forward to construct and that investors could easily get access to. A more plausible explanation is that for some stocks short selling is constrained. This constraint may cause prices of distressed stocks to stay too high for too long. However, we find that the underperformance of distressed stocks is still present for large firms, for firms with higher than average analyst coverage and with high levels of institutional holdings. For those stocks we might expect profits to decline in the future.

In many areas of quantitative equity investing, profits have declined over time due to increased entry into the market and the resulting increase in competition (Khandani and Lo (2007)). The return to a strategy investing in safe stocks and shorting distressed stocks does not seem to be an obvious exception to this pattern. There are clear risks associated with a long-short strategy, profits have not been uniformly high, and over the last decade a simple long short strategy has only marginally outperformed the market. However, a strategy long safe, short distressed stocks has a very appealing quality in that returns seem to be concentrated in down markets. Furthermore, once adjusting for risk, the returns have been more stable and there has been less evidence of a decline in profits.

Appendix

In this appendix we discuss issues related to the construction of our data set and restrictions for the inclusion in our estimation sample. All variables are constructed using COMPUSTAT and CRSP data.

The accounting ratios, relative size, excess return, and market-to-book are defined as follows:

$$\begin{aligned}
NIMTA_{it} &= \frac{Net\ Income_{it}}{(ME_{it} + Total\ Liabilities_{it})} \\
TLMTA_{it} &= \frac{Total\ Liabilities_{it}}{(ME_{it} + Total\ Liabilities_{it})} \\
CASHMTA_{it} &= \frac{Cash\ and\ Short\ Term\ Investments_{it}}{(ME_{it} + Total\ Liabilities_{it})} \\
RSIZE_{it} &= \log\left(\frac{ME_{it}}{Total\ S\&P500\ Market\ Value_t}\right) \\
EXRET_{it} &= \log(1 + R_{it}) - \log(1 + R_{S\&P500,t}) \\
MB_{it} &= \frac{ME_{it}}{BE_{adjusted,i,t}}
\end{aligned}$$

where ME is the market value of equity and book equity (BE) is constructed as in Davis, Fama and French (2000) and outlined in detail in Cohen, Polk and Vuolteenaho (2003). We adjust BE by the difference between market equity (ME) and BE:

$$BE_{adjusted,i,t} = BE_{it} + 0.1(ME_{it} - BE_{it}).$$

This transformation helps with the values of BE that are very small, probably mismeasured and lead to very large values of MB. To adjust for negative levels of BE we replace those observations with \$1 before calculating the market-to-book ratio. We use the following COMPUSTAT quarterly data items for the construction of the accounting measures: LTQ and MIBQ for total liabilities. Note that as a result of recent COMPUSTAT reporting changes LTQ no longer includes minority interest. To account for this change we measure $Total\ Liabilities_{it}$ as LTQ plus MIBQ. We use NIQ for net income, and CHEQ for cash and short-term investments. Each of the seven explanatory variables is winsorized using a 5/95 percentile interval in order to eliminate outliers.

Our measure of equity return volatility is the annualized 3-month return standard

deviation centered around zero:

$$SIGMA_{i,t-1,t-3} = \left(252 * \frac{1}{N-1} \sum_{k \in \{t-1,t-2,t-3\}} r_{i,k}^2 \right)^{\frac{1}{2}}$$

We eliminate cases where too few observations are available to construct a valid measure of volatility and set $SIGMA$ to missing if there are fewer than five non-zero return observations over the three months window. We also construct

$$\begin{aligned} NIMTAAVG_{t-1,t-12} &= \frac{1-\phi^3}{1-\phi^{12}} \left(NIMTA_{t-1,t-3} + ... + \ \phi^9 NIMTA_{t-10,t-12} \right) \\ EXRETAVG_{t-1,t-12} &= \frac{1-\phi}{1-\phi^{12}} \left(EXRET_{t-1} + ... + \ \phi^{11} EXRET_{t-12} \right) \end{aligned}$$

where the coefficient $\phi = 2^{-\frac{1}{3}}$, which implies that the weight is halved each quarter.

For a firm-month observation to be included in the estimation sample (Table 2) we must observe leverage, profitability, excess return, and market capitalization. We do not require a valid measure of $SIGMA$ and replace it with its cross-sectional mean when this variable is missing. We use a similar procedure for missing lags of $NIMTA$ and $EXRET$ in constructing the weighted average measures $NIMTAAVG$ and $EXRETAVG$. We also replace missing values of cash and market-to-book with the respective cross-sectional means. We do not restrict our sample of firms to include only those with share codes 10 and 11, as Hong, Lim, and Stein (2000) do, though our results are robust to such a restriction.

In order to calculate distance-to-default we construct measures of asset value and asset volatility by solving two equations simultaneously: First, in the Merton model equity is valued as a European call option on the value of the firm's assets:

$$\begin{aligned} ME &= TA_{DD} N(d_1) - BD \exp(-R_{BILL} T) N(d_2) \\ d_1 &= \frac{\log\left(\frac{TA_{DD}}{BD}\right) + \left(R_{BILL} + \frac{1}{2} SIGMA_{DD}^2\right) T}{SIGMA_{DD}\sqrt{T}} \\ d_2 &= d_1 - SIGMA_{DD}\sqrt{T}, \end{aligned}$$

where TA_{DD} and $SIGMA_{DD}$ denote asset value and volatility, BD is the face value of debt maturing at time T, and R_{BILL} is the Treasury bill rate. Following the convention for the distance-to-default calculation (Crosbie and Bohn (2001), Vassalou

and Xing (2004)), we assume $T = 1$, and use short term plus one half long term book debt to proxy for BD.

The second equation is a relation between equity volatility and asset volatility:

$$SIGMA = N(d_1)\frac{TA_{DD}}{ME}SIGMA_{DD}.$$

We solve the two equations numerically to find values for TA_{DD} and $SIGMA_{DD}$ that are consistent with the inputs. Before calculating asset value and volatility, we adjust BD so that $BD/(ME + BD)$ is winsorized at the 0.5 and 99.5 percentiles of the cross-sectional distribution and winsorize $SIGMA$ at the same percentline levels. We do this to reduce cases for which the numerical algorithm does not converge. We then compute distance to default as

$$DD = \frac{-\log(BD/TA_{DD}) + 0.06 + R_{BILL} - \frac{1}{2}SIGMA_{DD}^2}{SIGMA_{DD}}.$$

The number 0.06 appears in the formula as an empirical proxy for the equity premium. We view using this measure as less noisy than using e.g. the average stock return over the previous year, an approach employed in previous studies.

References

Altman, Edward I., 1968, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance* 23, 589–609.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2009, Credit ratings and the cross-section of stock returns, *Journal of Financial Markets* 12, 469–499.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2007, Momentum and credit rating, *Journal of Finance* 62, 2503–2520.

Beaver, William H., 1966, Financial ratios as predictors of failure, *Journal of Accounting Research* 4, 71–111.

Beaver, William H., Maureen F. McNichols, and Jung-Wu Rhie, 2005, Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy, *Review of Accounting Studies*.

Bernanke, Ben S. and John Y. Campbell, 1988, Is there a corporate debt crisis?, *Brookings Papers on Economic Activity* 1, 83–139.

Berndt, Antje, Rohan Douglas, Darrell Duffie, Mark Ferguson, and David Schranz, 2005, Measuring default-risk premia from default swap rates and EDFs, working paper, Stanford University.

Bharath, Sreedhar and Tyler Shumway, 2004, Forecasting default with the Merton distance to default model, *Review of Financial Studies* 21, 1339–1369.

Campbell John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance*, 63, 2899–2939.

Campbell, John Y., Martin Lettau, Burton Malkiel, and Yexiao Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance* 56, 1–43.

Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Chan, K.C. and Nai-fu Chen, 1991, Structural and return characteristics of small and large firms, *Journal of Finance* 46, 1467–1484.

Chava, Sudheer and Robert A. Jarrow, 2004, Bankruptcy prediction with industry effects, *Review of Finance* 8, 537–569.

Cohen, Randolph B., Christopher Polk and Tuomo Vuolteenaho, 2003, The value spread, *Journal of Finance* 58, 609–641.

Crosbie, Peter J. and Jeffrey R. Bohn, 2001, *Modeling Default Risk*, KMV, LLC, San Francisco, CA.

Das, Sanjiv R., Darrell Duffie, Nikunj Kapadia, and Leandro Saita, 2007, Common failings: How corporate defaults are correlated, *Journal of Finance* 57, 93–117.

Davis, James L., Eugene F. Fama and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389–406.

Dichev, Ilia, 1998, Is the risk of bankruptcy a systematic risk?, *Journal of Finance* 53, 1141–1148.

Duffie, Darrell, Leandro Saita, and Ke Wang, 2007, Multi-period corporate default prediction with stochastic covariates, *Journal of Financial Economics* 83, 635–665.

Duffie, Darrell, Andreas Eckner, Guillaume Horel, and Leandro Saita, 2006, Frailty correlated default, *Journal of Finance* 66, 2089-2123.

Fama, Eugene F. and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics 33, 3–56.*

Ferguson, Michael F. and Richard L. Shockley, 2003, Equilibrium "anomalies", *Journal of Finance* 58, 2549–2580.

Gilson, Stuart C., Kose John, and Larry Lang, 1990, Troubled debt restructurings: An empirical study of private reorganization of firms in default, *Journal of Financial Economics* 27, 315–353.

Gilson, Stuart C., 1997, Transactions costs and capital structure choice: Evidence from financially distressed firms, *Journal of Finance* 52, 161–196.

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

Hillegeist, Stephen A., Elizabeth Keating, Donald P. Cram and Kyle G. Lunstedt, 2004, Assessing the probability of bankruptcy, *Review of Accounting Studies* 9, 5–34.

Hilscher, Jens, and Mungo Wilson, 2009, Credit ratings and credit risk, unpublished paper, Brandeis University and Oxford University.

Khandani, Amir E., and Andrew W. Lo, 2007, What happened to the Quants in August 2007? *Journal of Investment Management* 5, 29-78.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.

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

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Ohlson, James A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18, 109–131.

Schaefer, Stephen M., and Ilya A. Strebulaev, 2008, Structural models of credit risk are useful: Evidence from hedge ratios on corporate bonds, *Journal of Financial Economics* 90, 1-19.

Shumway, Tyler, 2001, Forecasting bankruptcy more accurately: a simple hazard model, *Journal of Business* 74, 101–124.

Vassalou, Maria and Yuhang Xing, 2004, Default risk in equity returns, *Journal of Finance* 59, 831–868.

Table 1: Summary statistics

This table reports summary statistics for the following variables (for more details see the data description and the appendix): net income over market value of total assets (**NIMTA**), total liabilities over market value of total assets (**TLMTA**), excess return relative to value-weighted S&P 500 return, annualized (**EXRET**), firm's market equity over the total valuation of S&P 500, reported in basis points (**RSIZE**), stock return standard deviation computed as square root of a sum of squared firm stock returns over three-month period, annualized (**SIGMA**), stock of cash and short-term investments over the market value of total assets (**CASHMTA**), market-to-book value of the firm (**MB**) and price per share winsorized above at $15 (**PRICE**). Market value of total assets is calculated by adding the market value of firm equity to its total liabilities. Panel A reports summary statistics for all firm-month observations, Panel B reports summary statistics for the failure group. Summary statistics are reported for those observations for which values of all variables are available. Panel B reports the difference between the full sample mean and the failure group mean in units of full sample standard deviation.

Variable	**NIMTA**	**TLMTA**	**CASHMTA**	**EXRET**	**RSIZE**	**SIGMA**	**MB**	**PRICE**
Panel A: Entire data set								
Mean	-0.01%	44.0%	8.7%	-1.0%	1.46	54.2%	2.08	10.13
Median	0.5%	41.6%	4.7%	-0.8%	0.26	45.4%	1.62	12.63
St. Dev.	2.3%	28.2%	10.0%	11.4%	2.81	32.0%	1.58	5.34
Observations: 2,022,562								
Panel B: Failure group								
Mean	-4.3%	73.7%	7.3%	-10.7%	0.15	113.7%	2.10	1.93
St. Dev. Difference	1.88	1.05	0.14	0.85	0.47	1.86	0.01	1.53
Observations: 1,756								

Table 2: Failure prediction at different horizons

This table reports results from logit regressions of the failure indicator on our set of explanatory variables. The data are constructed such that all of the predictor variables are observable at the beginning of the month over which failure is measured ('0'), as well as when using data lagged 12 and 36 months to predict failure. Failure events are measured from 1963 to 2008. Z-statistics (reported in parentheses) are calculated using standard errors that are robust and clustered by year. ** denotes significant at 1%.

Lag (months)	0	12	36
NIMTAAVG	-29.00	-20.12	-11.93
	(16.65)**	(14.11)**	(5.13)**
TLMTA	3.51	1.60	0.73
	(12.77)**	(8.34)**	(3.84)**
CASHMTA	-2.49	-2.27	-1.85
	(7.07)**	(7.39)**	(5.02)**
EXRETAVG	-8.02	-7.88	-3.50
	(12.40)**	(9.16)**	(3.19)**
SIGMA	1.69	1.55	1.43
	(9.31)**	(5.44)**	(8.58)**
RSIZE	0.138	-0.005	-0.133
	(2.84)**	(0.15)	(3.44)**
MB	0.05	0.07	0.115
	(3.23)**	(5.57)**	(6.41)**
PRICE	-0.974	-0.09	0.219
	(10.26)**	(0.84)	(3.21)**
Constant	-8.63	-8.87	-10.03
	(14.17)**	(17.44)**	(20.93)**
Observations	2,022,562	1,870,481	1,477,749
Failures	1,756	2,159	1,655
Pseudo-R^2	0.316	0.118	0.041
Accuracy ratio	0.955	0.862	0.737

Table 3: Returns on failure probability-sorted stock portfolios

We sort all stocks based on the predicted 12-month probability of failure and divide them into 10 portfolios based on percentile cutoffs, for example, 0 to 5th percentile (0005) and from the 99th to 100th percentile (9900) of the P_hat distribution, as well as a portfolio long the 10% lowest P_hat stocks and short the 10% highest P_hat stocks. We report measures of returns for value-weighted excess returns over the market. We report mean excess returns, CAPM alphas, Fama-French 3-factor alphas and Carhart 4-factor alphas, all annualized, as well as absolute values of t-statistics (in parentheses); * denotes significant at 5%, ** denotes significant at 1%. The sample period is 1981 to 2008. Panel B reports portfolio characteristics: CAPM betas, annualized standard deviation and skewness of individual and portfolio returns, mean market equity over the total valuation of the S&P 500, reported in basis points (RSIZE), market-to-book (MB), and probability of failure (Phat) values for each portfolio, annualized.

Portfolios	**0005**	**0510**	**1020**	**2040**	**4060**	**6080**	**8090**	**9095**	**9599**	**9900**	**LS1090**
Panel A: Portfolio alphas											
Mean excess return	3.7%	1.0%	0.2%	0.9%	-0.5%	-1.5%	-6.5%	-12.6%	-9.4%	-25.7%	14.3%
	(1.55)	(0.45)	(0.18)	(1.31)	(0.37)	(0.74)	(2.05)*	(2.91)**	(1.88)	(3.51)**	(2.92)**
CAPM alpha	3.1%	0.7%	0.1%	1.2%	-0.7%	-2.5%	-8.3%	-15.4%	-12.1%	-28.2%	16.7%
	(1.32)	(0.30)	(0.08)	(1.74)	(0.57)	(1.27)	(2.74)**	(3.79)**	(2.52)*	(3.92)**	(3.53)**
3-factor alpha	5.2%	4.2%	1.4%	0.9%	-2.5%	-5.6%	-12.2%	-17.4%	-16.4%	-31.2%	22.5%
	(2.53)*	(2.07)*	(1.22)	(1.26)	(2.10)*	(3.01)**	(4.23)**	(4.72)**	(3.90)**	(4.81)**	(4.94)**
4-factor alpha	1.0%	0.6%	-0.6%	1.1%	0.1%	-0.6%	-4.7%	-7.9%	-7.5%	-24.2%	9.2%
	(0.55)	(0.31)	(0.51)	(1.57)	(0.05)	(0.38)	(2.00)*	(2.60)**	(2.00)*	(3.75)**	(2.68)**
Panel B: Portfolio characteristics											
CAPM beta	1.07	1.03	0.99	0.91	1.01	1.16	1.31	1.51	1.49	1.46	-0.47
Portfolio SD	12.5%	12.1%	6.5%	3.7%	6.6%	10.7%	16.8%	22.9%	26.6%	38.7%	25.9%
Portfolio skewness	1.20	0.62	0.03	0.07	-0.18	-0.14	0.72	1.27	1.62	1.63	
Individual SD	34.4%	33.8%	29.6%	27.9%	29.1%	34.7%	48.1%	64.4%	76.4%	92.0%	
Individual skewness	0.65	0.74	0.57	0.87	0.85	0.78	1.38	2.94	1.68	2.50	
Mean RSIZE	7.35	8.23	9.00	9.19	8.50	7.21	4.70	2.19	1.16	0.36	
Mean MB	2.70	3.18	3.02	2.62	2.20	1.98	2.27	2.69	3.14	3.79	
Mean Failure Prob.	0.1%	0.2%	0.2%	0.3%	0.5%	0.7%	1.3%	2.2%	3.9%	9.0%	

Table 4: Information and arbitrage related frictions

We report three-factor alphas and P_hat-adjusted alphas for portfolios long safe, short distressed stocks. We sort first on size-adjusted analyst coverage (from I/B/E/S) and size-adjusted institutional holdings (constructed from spectrum data), then on distress. We report returns for stocks in the top third (high) and bottom third (low) of each characteristic's distribution. ** denotes significant at the 1% level.

	Analyst Coverage		Institutional Holdings	
	high	low	high	low
3-factor alpha	11.6%	20.7%	11.9%	22.6%
	(3.03)**	(5.94)**	(3.55)**	(5.36)**
P_hat-adjusted 3-factor alpha	6.4%	9.5%	5.7%	10.8%
	(3.42)**	(6.05)**	(3.66)**	(5.49)**

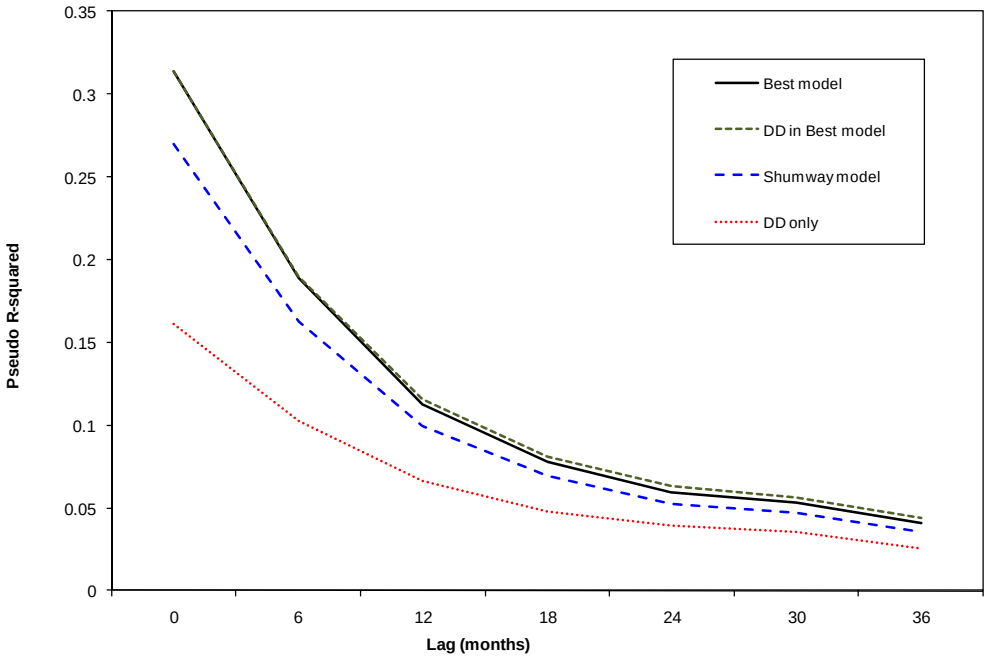

Figure 1: Prediction accuracy for different models: The figure plots the pseudo R-squared for four different models when predicting failures over different horizons.

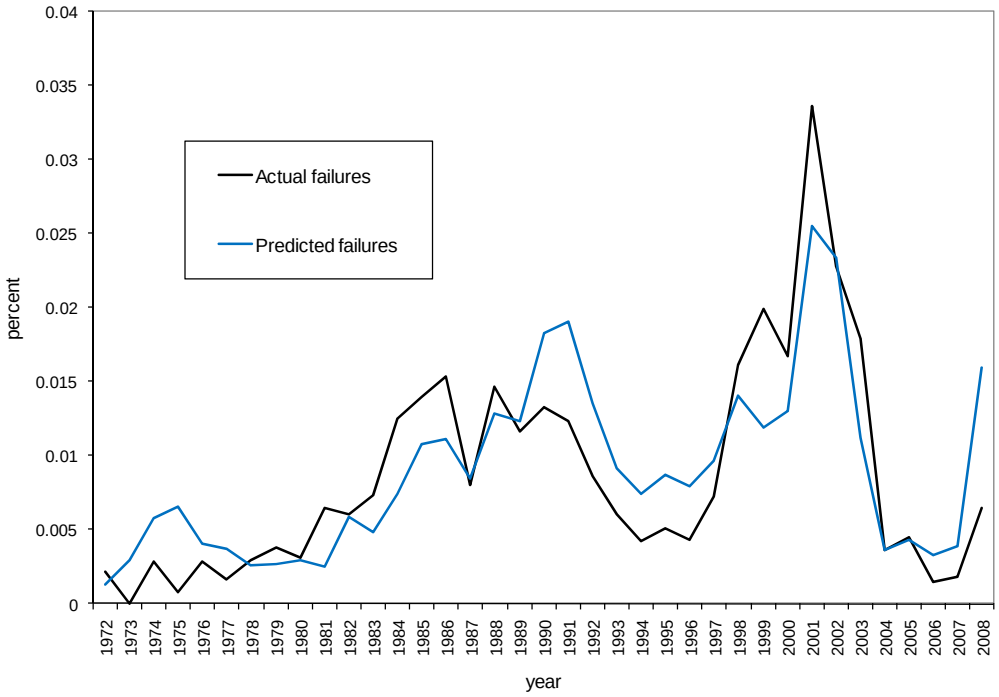

Figure 2: Actual and predicted failures over time: The figure plots the actual frequency of failures and the model-predicted frequency (using our best model).

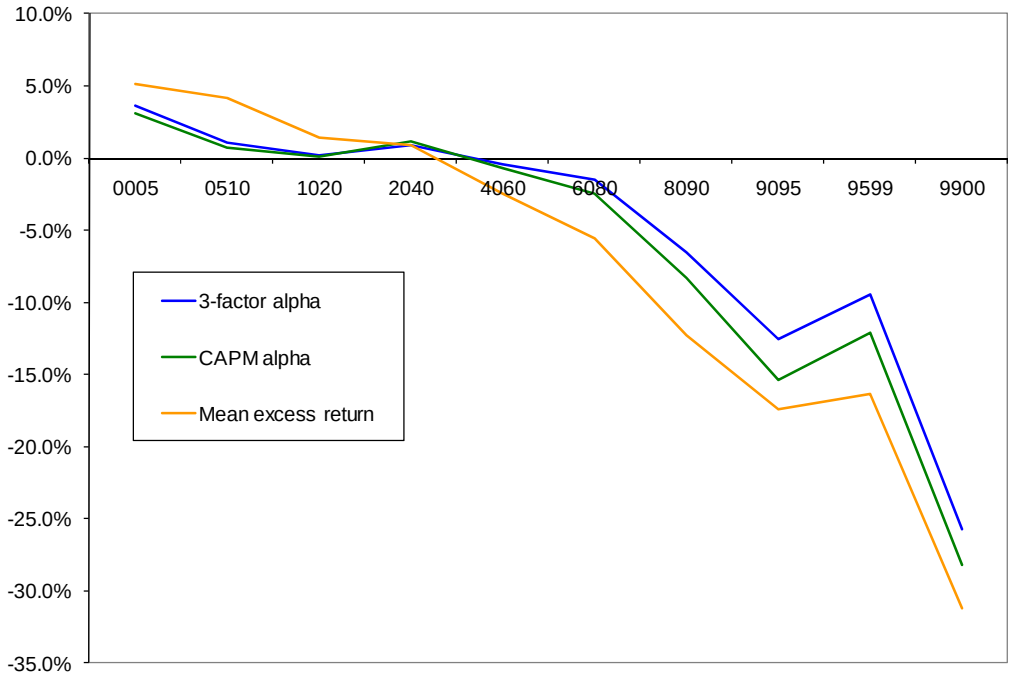

Figure 3: Returns of distress risk-sorted portfolios: The figure plots the annualized mean excess return relative to the market, portfolio CAPM alpha, and Fama-French 3-factor alpha for the 10 distress risk sorted portfolios from 1981 to 2008. Portfolios are formed at the beginning of January every year using the model predicted probability of failure.

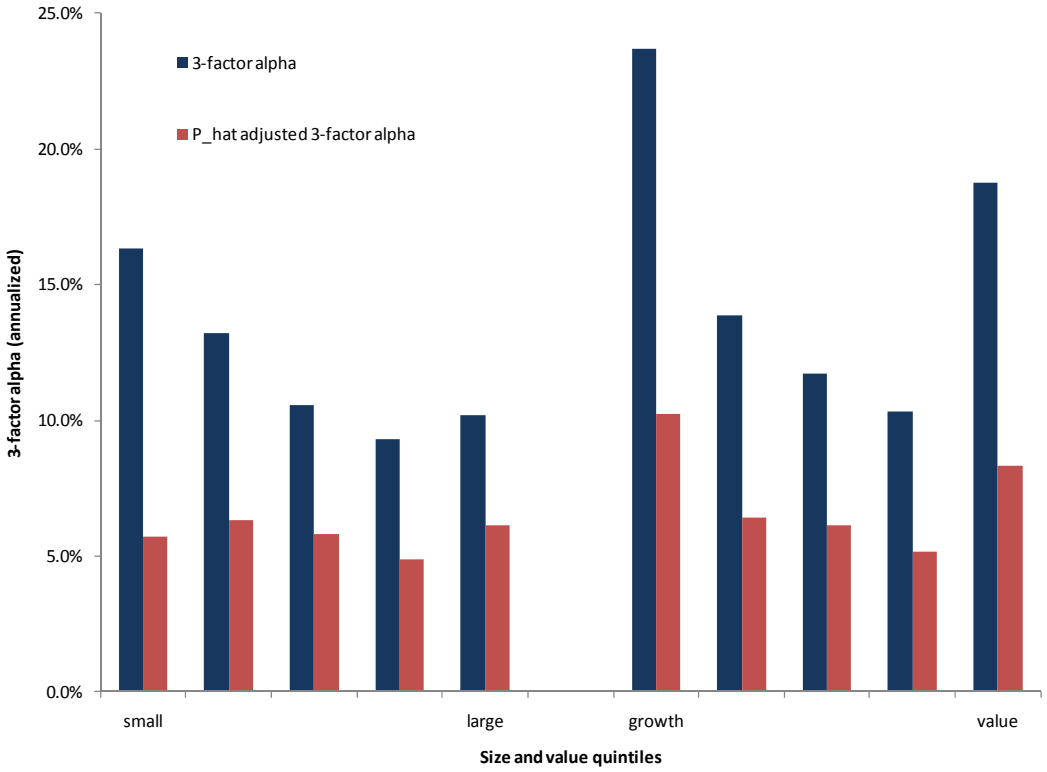

Figure 4: Distress effect across size and value quintiles: The figure plots portfolio alphas for long safe, short distressed stocks across size and value quintiles. P_hat-adjusted returns are average excess returns adjusted for the difference in probability of failure between the high and the low distress components of the long-short portfolios.

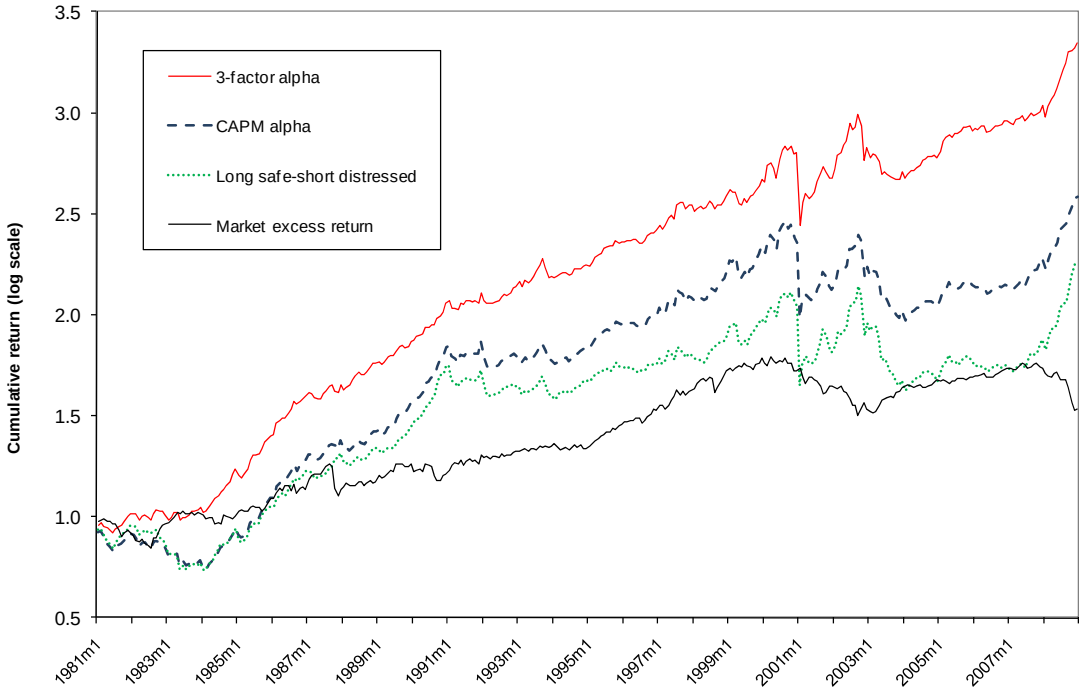

Figure 5: Cumulative returns for different strategies: The figure plots the cumulative returns for the following excess returns series: (1) long safe-short distressed (portfolio LS1090 in Table 3), and that portfolio's (2) CAPM alpha, and (3) 3-factor alpha, as well as a portfolio (4) long the market, short the risk-free asset.

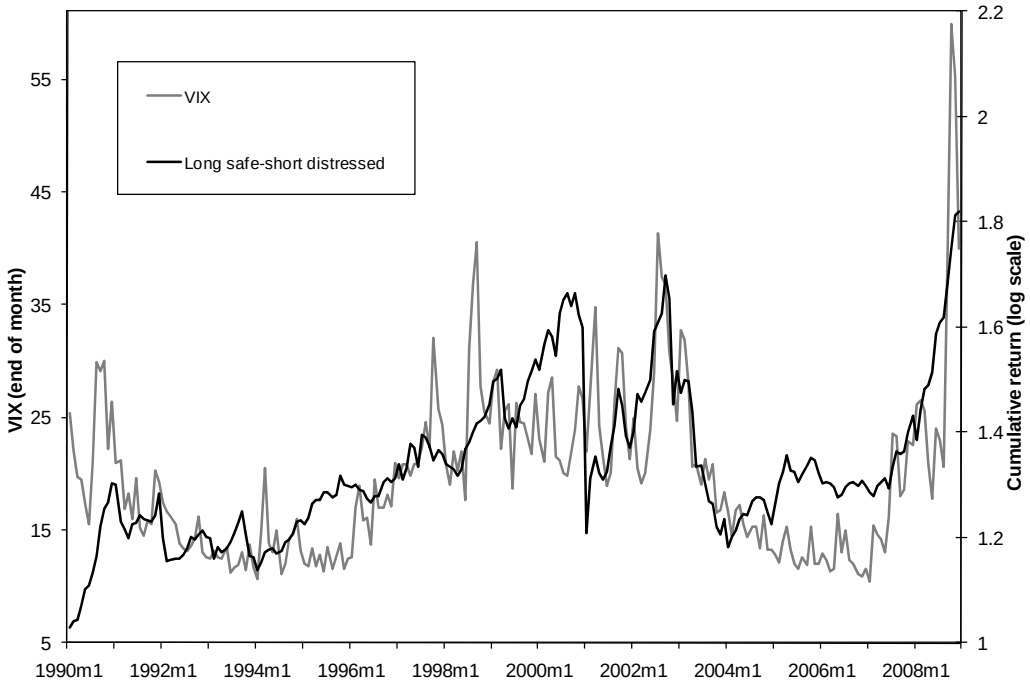

Figure 6: Distressed stock returns and VIX: The figure plots excess returns for portfolios long safe, short distressed stocks (LS1090 in Table 3) and the VIX index.