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# In Search of Distress Risk

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**ABSTRACT**

This paper explores the determinants of corporate failure and the pricing of financially distressed stocks whose failure probability, estimated from a dynamic logit model using accounting and market variables, is high. Since 1981, financially distressed stocks have delivered anomalously low returns. They have lower returns but much higher standard deviations, market betas, and loadings on value and small-cap risk factors than stocks with low failure risk. These patterns are more pronounced for stocks with possible informational or arbitrage-related frictions. They are inconsistent with the conjecture that the value and size effects are compensation for the risk of financial distress.

THE CONCEPT OF FINANCIAL DISTRESS has been invoked in the asset pricing literature to explain otherwise anomalous patterns in the cross-section of stock returns (Chan and Chen (1991) and Fama and French (1996)). The idea is that certain companies have an elevated probability that they will fail to meet their financial obligations; the stocks of these financially distressed companies tend to move together, so their risk cannot be diversified away; and investors charge a premium for bearing such risk.[1] The premium for distress risk may not be captured by the standard Capital Asset Pricing Model (CAPM) if corporate failures

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[1] Chan and Chen (1991, p. 1468), for example, attribute the size premium to the prevalence of "marginal firms" in small-stock portfolios, and describe marginal 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." Fama and French (1996) use the term "relative distress" in a similar fashion.

are correlated with deteriorating investment opportunities (Merton (1973)) or declines in unmeasured components of wealth such as human capital (Fama and French (1996)) or debt securities (Ferguson and Shockley (2003)).[2] In this case distress risk may help to explain patterns such as the size and value effects that are anomalies in the standard CAPM.

While this idea has a certain plausibility, it leaves some basic empirical questions unanswered. How should we measure the failure to meet financial obligations and the probability that a firm will fail in the future? Given an empirical measure of financial distress, do the stock prices of financially distressed companies move together, and what returns have they generated historically? Is there any evidence that financial distress risk carries a premium?

We address these questions in two steps. In the first step, we construct an empirical measure of financial distress; and in the second step, we calculate the average returns on distressed stocks. We start by considering two alternative ways in which a firm may fail to meet its financial obligations. First, we look at bankruptcy filings under either Chapter 7 or Chapter 11 of the bankruptcy code. Second, we look at failures, defined more broadly to include bankruptcies, financially driven delistings, or D ("default" ) ratings issued by a leading credit rating agency. The broader definition of failure allows us to capture at least some cases in which firms avoid bankruptcy by negotiating with creditors out of court (Gilson, John, and Lang (1990) and Gilson (1997)). It also captures firms that perform so poorly that their stocks are delisted from the exchange, an event that sometimes precedes bankruptcy or formal default.

To measure the probability that a firm enters either bankruptcy or failure, we adopt a relatively atheoretical econometric approach. We estimate a dynamic panel model using a logit specification, following Shumway (2001), Chava and Jarrow (2004), and others. We extend the previous literature by considering a wide range of explanatory variables, including both accounting and equity market variables, and by explicitly considering how the optimal specification varies with the horizon of the forecast. Although like Chava and Jarrow (2004), we use monthly data, we do not try to predict only the event that a bankruptcy will occur during the next month. Over such a short horizon, it should not be surprising that the recent return on a firm's equity is a powerful predictor, but this may not be very useful information if it is relevant only in the extremely short run, just as it would not be useful to predict a heart attack by observing a person dropping to the floor clutching his chest. We also explore time-series

[2] Fama and French (1996) explain the point as follows: "Why is relative distress a state variable of special hedging concern to investors? One possible explanation is linked to human capital, an important asset for most investors. Consider an investor with specialized human capital tied to a growth firm (or industry or technology). A negative shock to the firm's prospects probably does not reduce the value of the investor's human capital; it may just mean that employment in the firm will grow less rapidly. In contrast, a negative shock to a distressed firm more likely implies a negative shock to the value of human capital since employment in the firm is more likely to contract. Thus, workers with specialized human capital in distressed firms have an incentive to avoid holding their firms' stocks. If variation in distress is correlated across firms, workers in distressed firms have an incentive to avoid the stocks of all distressed firms. The result can be a state-variable risk premium in the expected returns of distressed stocks." (p.77).

variation in the number of bankruptcies and ask how much of this variation is explained by changes over time in the variables that predict bankruptcy at the firm level.

Our empirical work begins with monthly bankruptcy and failure indicators provided by Kamakura Risk Information Services (KRIS). The bankruptcy indicator was used by Chava and Jarrow (2004) and covers the period from January 1963 through December 1998. The failure indicator runs from January 1963 through December 2003. We merge these data sets with firm-level accounting data from COMPUSTAT as well as monthly and daily equity price data from CRSP. This gives us about 800 bankruptcies, 1,600 failures, and predictor variables for 1.7 million firm months.

We start by estimating a basic specification used by Shumway (2001) and similar to that of Chava and Jarrow (2004). The model includes both equity market and accounting data. From the equity market, we measure the excess stock return of each company over the past month, the volatility of daily stock returns over the past 3 months, and the market capitalization of each company. From accounting data, we measure net income as a ratio to assets, and total leverage as a ratio to assets. We obtain similar coefficient estimates regardless of whether we are predicting bankruptcies through 1998, failures through 1998, or failures through 2003.

From this starting point, we make a number of contributions to the prediction of corporate bankruptcies and failures. First, we explore some sensible modifications to the variables listed above. Specifically, we show that scaling net income and leverage by the market value of assets rather than the book value and adding further lags of stock returns and net income can improve the explanatory power of the benchmark regression.

Second, we explore some additional variables and find that corporate cash holdings, the market-to-book ratio, and a firm's price per share contribute explanatory power. In a related exercise, we construct a measure of distance to default based on the practitioner model of Moody's KMV (Crosbie and Bohn (2001)) and ultimately on the structural default model of Merton (1974). We find that this measure adds relatively little explanatory power to the reduced-form variables already included in our model.[3]

Third, we examine what happens to our specification as we increase the horizon at which we are trying to predict failure. Consistent with our expectations, we find that our most persistent forecasting variable, market capitalization, becomes relatively more important as we predict further into the future. Volatility and the market-to-book ratio also become more important at long horizons relative to net income, leverage, and recent equity returns.

Fourth, we study time-variation in the number of failures. We compare the realized frequency of failure to the predicted frequency over time. Although the model underpredicts the frequency of failure in the 1980s and overpredicts it in the 1990s, the model fits the general time pattern quite well.

[3] This finding is consistent with recent results of Bharath and Shumway (2008), circulated after the first version of this paper.

In the second part of this paper, we use our fitted probability of failure as a measure of financial distress and calculate the risks and average returns on portfolios of stocks sorted by this fitted probability. We find that financially distressed firms have high market betas and high loadings on the *HML* and *SMB* factors proposed by Fama and French (1993, 1996) to capture the value and size effects. However, they have low, not high, average returns, suggesting that the equity market has not properly priced distress risk.

We find that returns to distressed stocks are particularly low when the implied volatility of the S&P 500 index, measured by the VIX, increases. This implies that distressed stocks are vulnerable to increases in marketwide risk or risk aversion, but it does not help explain the low returns to these stocks as increases in the VIX are normally taken to be negative events, and stocks that do poorly at such times typically have high average returns (Ang et al. (2006)).

We explore the relation between firm characteristics and the distress anomaly in some detail. We find that the distress anomaly is stronger among small stocks, but this fact is entirely explained by the larger spread in financial distress among these stocks; per unit of log failure probability, the distress effect is roughly constant across the size distribution. Controlling for size, we find that the distress anomaly is stronger for stocks with low analyst coverage, institutional ownership, price per share, and liquidity. Thus, like many other anomalies (Hong, Lim, and Stein (2000) and Nagel (2005)), the distress anomaly is concentrated in stocks that are likely to be expensive for institutional investors to arbitrage. This fact is a further challenge to a rational equilibrium explanation of the relation between financial distress and average stock returns.

We also present some evidence bearing on behavioral explanations of the distress anomaly. We show that the low returns to distressed stocks are not concentrated around earnings announcements, suggesting that the anomaly does not result from overoptimistic investor expectations about future earnings. We also show that almost all the variables in our failure prediction model contribute to these low returns, so that the anomaly does not simply reflect momentum in small loser stocks (Hong, Lim, and Stein (2000)), low returns to volatile stocks (Ang et al. (2006)), or other phenomena already documented in the asset pricing literature.

A large related literature studies the prediction of corporate bankruptcy. The literature varies in the choice of variables to predict bankruptcy and the methodology used to estimate the likelihood of bankruptcy. Beaver (1966), Altman (1968), Ohlson (1980), and Zmijewski (1984) use accounting variables to estimate the probability of bankruptcy in a static model. Altman's *Z*-score and Ohlson's *O*-score have become popular and widely accepted measures of financial distress. They are used, for example, by Dichev (1998), Griffin and Lemmon (2002), and Ferguson and Shockley (2003) to explore the risks and average returns for distressed firms. A parallel literature uses accounting variables to predict credit ratings, which can be interpreted as subjective default probabilities provided by credit rating agencies (Kaplan and Urwitz (1979), Blume, Lim, and MacKinlay (1998), and Molina (2005)). The relation between credit ratings and stock returns has recently been explored by Avramov et al. (2006, 2007).

Shumway (2001) estimates a dynamic logit or hazard model at an annual frequency and adds equity market variables to the set of scaled accounting measures used in the earlier literature. He points out that estimating the probability of bankruptcy in a static setting introduces biases and overestimates the impact of the predictor variables. This is because the static model does not take into account that a firm could have had unfavorable indicators several periods before going into bankruptcy. Other recent papers using Shumway's approach include Chava and Jarrow (2004), who work with monthly data and explore industry effects, and Beaver, McNichols, and Rhie (2005), who explore the stability of the coefficients over time.

Duffie, Saita, and Wang (2007) emphasize that the probability of failure depends on the horizon one is considering. They estimate mean-reverting time series processes for macroeconomic and firm-specific predictors of failure and combine these with a short-horizon failure model to find the marginal probabilities of failure at different horizons. We conduct a similar exercise using a reduced-form econometric approach; we do not model the time-series evolution of the predictor variables but instead directly estimate longer-term failure probabilities.

The remainder of the paper is organized as follows. Section I describes the construction of the data set, outlier analysis, and summary statistics. Section II discusses our basic monthly panel model, extensions to it, and the effects of estimating the model at longer horizons. This section also considers the ability of the model to fit the aggregate time series of failures. Section III studies the return properties of equity portfolios formed on the fitted value from our failure prediction model. We ask whether stocks with high failure probability have unusually high or low returns relative to the predictions of standard cross-sectional asset pricing models such as the CAPM or the three-factor Fama–French model. Section IV concludes.

## I. Data Description

In order to estimate a dynamic logit model, we need an indicator of financial distress and a set of explanatory variables. The bankruptcy indicator we use is taken from Chava and Jarrow (2004); it includes all bankruptcy filings in the *Wall Street Journal* Index, the SDC database, SEC filings, and the CCH Capital Changes Reporter. The indicator equals one in a month in which a firm filed for bankruptcy under Chapter 7 or Chapter 11, and zero otherwise; in particular, the indicator is zero if the firm disappears from the data set for some reason other than bankruptcy such as acquisition or delisting. The data span the months from January 1963 through December 1998. We also consider a broader failure indicator, which equals one if a firm files for bankruptcy, is delisted for financial reasons, or receives a D rating, over the period January 1963 through December 2003.[4]

[4] Typical financial reasons to delist a stock include failures to maintain minimum market capitalization or stock price, file financial statements, or pay exchange fees. Nonfinancial reasons to delist a stock include mergers and minor delays in filing financial statements.

**Table I**

**Number of Bankruptcies and Failures per Year**

This table lists the total number of active firms, bankruptcies, and failures for every year of our sample period. The number of active firms is computed by averaging over the numbers of active firms across all months of the year.

| Year | Active Firms | Bankruptcies | (%) | Failures | (%) |
|---|---|---|---|---|---|
| 1963 | 1,281 | 0 | 0.00 | 0 | 0.00 |
| 1964 | 1,357 | 2 | 0.15 | 2 | 0.15 |
| 1965 | 1,436 | 2 | 0.14 | 2 | 0.14 |
| 1966 | 1,513 | 1 | 0.07 | 1 | 0.07 |
| 1967 | 1,598 | 0 | 0.00 | 0 | 0.00 |
| 1968 | 1,723 | 0 | 0.00 | 0 | 0.00 |
| 1969 | 1,885 | 0 | 0.00 | 0 | 0.00 |
| 1970 | 2,067 | 5 | 0.24 | 5 | 0.24 |
| 1971 | 2,199 | 4 | 0.18 | 4 | 0.18 |
| 1972 | 2,650 | 8 | 0.30 | 8 | 0.30 |
| 1973 | 3,964 | 6 | 0.15 | 6 | 0.15 |
| 1974 | 4,002 | 18 | 0.45 | 18 | 0.45 |
| 1975 | 4,038 | 5 | 0.12 | 5 | 0.12 |
| 1976 | 4,101 | 14 | 0.34 | 14 | 0.34 |
| 1977 | 4,157 | 12 | 0.29 | 12 | 0.29 |
| 1978 | 4,183 | 14 | 0.33 | 15 | 0.36 |
| 1979 | 4,222 | 14 | 0.33 | 14 | 0.33 |
| 1980 | 4,342 | 26 | 0.60 | 26 | 0.60 |
| 1981 | 4,743 | 23 | 0.48 | 23 | 0.48 |
| 1982 | 4,995 | 29 | 0.58 | 29 | 0.58 |
| 1983 | 5,380 | 50 | 0.93 | 50 | 0.93 |
| 1984 | 5,801 | 73 | 1.26 | 74 | 1.28 |
| 1985 | 5,912 | 76 | 1.29 | 77 | 1.30 |
| 1986 | 6,208 | 95 | 1.53 | 95 | 1.53 |
| 1987 | 6,615 | 54 | 0.82 | 54 | 0.82 |
| 1988 | 6,686 | 84 | 1.26 | 85 | 1.27 |
| 1989 | 6,603 | 74 | 1.12 | 78 | 1.18 |
| 1990 | 6,515 | 80 | 1.23 | 82 | 1.26 |
| 1991 | 6,571 | 70 | 1.07 | 73 | 1.11 |
| 1992 | 6,914 | 45 | 0.65 | 50 | 0.72 |
| 1993 | 7,469 | 36 | 0.48 | 39 | 0.52 |
| 1994 | 8,067 | 30 | 0.37 | 33 | 0.41 |
| 1995 | 8,374 | 43 | 0.51 | 45 | 0.54 |
| 1996 | 8,782 | 32 | 0.36 | 34 | 0.39 |
| 1997 | 9,544 | 44 | 0.46 | 61 | 0.64 |
| 1998 | 9,844 | 49 | 0.50 | 150 | 1.52 |
| 1999 | 9,675 | – | – | 209 | 2.16 |
| 2000 | 9,426 | – | – | 167 | 1.77 |
| 2001 | 8,817 | – | – | 324 | 3.67 |
| 2002 | 8,242 | – | – | 221 | 2.68 |
| 2003 | 7,833 | – | – | 167 | 2.13 |

Table I summarizes the properties of our bankruptcy and failure indicators. The first column shows the number of active firms in the CRSP database in each year. The second column shows the number of bankruptcies, and the third column the corresponding percentage of active firms that went bankrupt in each year. The fourth and fifth columns repeat this information for our failure series.

It is immediately apparent that bankruptcies were extremely rare until the late 1960s. In fact, in the 3 years 1967 to 1969, there were no bankruptcies at all in our data set. The bankruptcy rate increased in the early 1970s, and then rose dramatically during the 1980s to a peak of 1.5% in 1986. It remained high through the economic slowdown of the early 1990s, but fell in the late 1990s to levels only slightly above those that prevailed in the 1970s.

Some of these changes through time are probably the result of changes in the law governing corporate bankruptcy in the 1970s, and related financial innovations such as the development of below-investment grade public debt (junk bonds) in the 1980s and the advent of prepackaged bankruptcy filings in the early 1990s (Tashjian, Lease, and McConnell (1996)). Changes in corporate capital structure (Bernanke and Campbell (1988)) and the riskiness of corporate activities (Campbell et al. (2001)) are also likely to have played a role, and one purpose of our investigation is to quantify the time-series effects of these changes.

The broader failure indicator tracks the bankruptcy indicator closely until the early 1980s, but toward the end of the sample it begins to diverge significantly. The number of failures increases dramatically after 1998, reflecting the financial distress of many young firms that were newly listed during the boom of the late 1990s.

In order to construct explanatory variables at the individual firm level, we combine quarterly accounting data from COMPUSTAT with monthly and daily equity market data from CRSP. From COMPUSTAT, we construct a standard measure of profitability: net income relative to total assets. Previous authors have measured total assets at book value, but we measure the equity component of total assets at market value by adding the book value of liabilities to the market value of equities. We call the resulting profitability ratio Net Income to Market-valued Total Assets (*NIMTA*) and the traditional series Net Income to Total Assets (*NITA*). We find that *NIMTA* has stronger explanatory power, perhaps because market prices more rapidly incorporate new information about the firm's prospects or more accurately reflect intangible assets of the firm. We also use COMPUSTAT to construct a measure of leverage: total liabilities relative to total assets. We again find that a market-valued version of this series, defined as total liabilities divided by the sum of market equity and book liabilities, performs better than the traditional book-valued series. We call the two series *TLMTA* and *TLTA*, respectively. To these standard measures of profitability and leverage we add a measure of liquidity, namely, the ratio of a company's cash and short-term assets to the market value of its assets (*CASHMTA*). We also calculate each firm's market-to-book ratio (*MB*).

In constructing these series, we adjust the book value of assets to eliminate outliers, following the procedure suggested by Cohen, Polk, and Vuolteenaho (2003). That is, we add 10% of the difference between market and book equity to the book value of total assets, thereby increasing book values that are extremely small and probably mismeasured, and that create outliers when used as the denominators of financial ratios. We adjust the book value of equity in a similar manner. Just under 2% of firm-months still have negative values for book equity even after this adjustment, and we replace these negative values with small positive values of $1 to ensure that the market-to-book ratios for these firms are in the right tail, not the left tail, of the distribution.

In order to further limit the influence of outliers, including those firms whose book equity has been adjusted as above, we winsorize the market-to-book ratio and all other variables in our model at the 5th and 95th percentiles of their pooled distributions across all firm-months. That is, we replace any observation below the 5th percentile with the 5th percentile, and any observation above the 95th percentile with the 95th percentile.

We align each company's fiscal year appropriately with the calendar year, converting COMPUSTAT fiscal year data to a calendar basis, and then lag accounting data by 2 months. This adjustment ensures that the accounting data are available at the beginning of the month over which bankruptcy is measured. The Appendix to this paper describes the construction of these variables in greater detail.

We add several market-based variables to these two accounting variables. We calculate the monthly log excess return on each firm's equity relative to the S&P 500 index (*EXRET*), the standard deviation of each firm's daily stock return over the past 3 months (*SIGMA*), and the relative size of each firm measured as the log ratio of its market capitalization to that of the S&P 500 index (*RSIZE*). Finally, we calculate each firm's log price per share, truncated above at $15 (*PRICE*). This captures a tendency for distressed firms to trade at low prices per share, without reverse-splitting to bring price per share back into a more normal range.

### A. Summary Statistics

Table II summarizes the properties of our 10 main explanatory variables. Panel A in Table II describes the distributions of the variables in almost 1.7 million firm-months with complete data availability, Panel B describes a much smaller sample of almost 800 bankruptcy months, and Panel C describes just over 1,600 failure months.[5]

In interpreting these distributions, it is important to keep in mind that we weight every firm-month equally. This has two important consequences. First, the distributions are dominated by the behavior of relatively small companies; value-weighted distributions look quite different. Second, the distributions reflect the influence of both cross-sectional and time-series variation. The cross-sectional averages of several variables, in particular, *NIMTA*, *TLMTA*, and *SIGMA*, have experienced significant trends since 1963: *SIGMA* and *TLMTA*

[5] For a firm-month to be included in Table II, we must observe leverage, profitability, excess return, and market capitalization. We do not require a valid measure of volatility, and replace *SIGMA* with its cross-sectional mean when this variable is missing. We do not restrict the cross-section of firms to include only share codes 10 and 11, as Hong, Lim, and Stein (2000) do, but we have checked that all of our results are robust to such a restriction.

**Table II**

## Summary Statistics

This table includes the following variables (various adjustments are described in the data description section): net income over book value of total assets (*NITA*), net income over market value of total assets (*NIMTA*), total liabilities over book value of total assets (*TLTA*), total liabilities over market value of total assets (*TLMTA*), log of gross excess return over value-weighted S&P 500 return (*EXRET*), log of firm's market equity over the total valuation of S&P 500 (*RSIZE*), square root of the sum of squared firm stock returns over a 3-month period (*SIGMA*) annualized, stock of cash and short-term investments over the market value of total assets (*CASHMTA*), market-to-book ratio of the firm (*MB*) and log of price per share winsorized above $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, Panels B and C report summary statistics for the bankruptcy and failure groups. There are a total of 1,695,036 observations, of which 797 are bankruptcy and 1,614 are failure events. Summary statistics are reported for those observations for which values of all variables are available.

| Variable | *NITA* | *NIMTA* | *TLTA* | *TLMTA* | *EXRET* | *RSIZE* | *SIGMA* | *CASHMTA* | *MB* | *PRICE* |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A. Entire Data Set** | | | | | | | | | | |
| Mean | −0.001 | 0.000 | 0.506 | 0.445 | −0.011 | −10.456 | 0.562 | 0.084 | 2.041 | 2.019 |
| Median | 0.007 | 0.006 | 0.511 | 0.427 | −0.009 | −10.570 | 0.471 | 0.045 | 1.557 | 2.474 |
| Std. Dev. | 0.034 | 0.023 | 0.252 | 0.280 | 0.117 | 1.922 | 0.332 | 0.097 | 1.579 | 0.883 |
| Min | −0.102 | −0.069 | 0.083 | 0.036 | −0.243 | −13.568 | 0.153 | 0.002 | 0.358 | −0.065 |
| Max | 0.039 | 0.028 | 0.931 | 0.923 | 0.218 | −6.773 | 1.353 | 0.358 | 6.471 | 2.708 |
| Observations: 1,695,036 | | | | | | | | | | |
| **Panel B. Bankruptcy Group** | | | | | | | | | | |
| Mean | −0.054 | −0.040 | 0.796 | 0.763 | −0.115 | −12.416 | 1.061 | 0.044 | 2.430 | 0.432 |
| Median | −0.054 | −0.047 | 0.872 | 0.861 | −0.171 | −12.876 | 1.255 | 0.021 | 1.018 | −0.065 |
| Std. Dev. | 0.043 | 0.030 | 0.174 | 0.210 | 0.148 | 1.345 | 0.352 | 0.062 | 2.509 | 0.760 |
| Observations: 797 | | | | | | | | | | |
| **Panel C. Failure Group** | | | | | | | | | | |
| Mean | −0.059 | −0.044 | 0.738 | 0.731 | −0.105 | −12.832 | 1.167 | 0.072 | 2.104 | 0.277 |
| Median | −0.066 | −0.062 | 0.821 | 0.842 | −0.179 | −13.568 | 1.353 | 0.029 | 0.751 | −0.065 |
| Std. Dev. | 0.043 | 0.030 | 0.228 | 0.239 | 0.162 | 1.168 | 0.303 | 0.099 | 2.389 | 0.643 |
| Observations: 1,614 | | | | | | | | | | |

have trended up, while *NIMTA* has trended down. The downward trend in *NIMTA* is not just a consequence of the buoyant stock market of the 1990s, because book-based net income, *NITA*, displays a similar trend. These trends reflect increasingly conservative accounting (Basu (1997)) and the tendency for companies to go public earlier in their life cycle when they are still unprofitable.[6]

These facts help to explain several features of Table II. The mean level of *NIMTA*, for example, is almost exactly zero (in fact, very slightly negative). This is lower than the median level of *NIMTA*, which is positive at 0.6% per quarter or 2.4% at an annual rate, because the distribution of profitability is negatively skewed. The gap between mean and median is even larger for *NITA*. All these measures of profitability are strikingly low, reflecting the prevalence of small, unprofitable listed companies in recent years. Value-weighted mean profitability is considerably higher.[7]

The average value of *EXRET* is $-0.011$ or $-1.1\%$ per month. This extremely low number reflects both the underperformance of small stocks during the later part of our sample period (the value-weighted mean is almost exactly zero), and the fact that we are reporting a geometric average excess return rather than an arithmetic average. The difference is substantial because individual stock returns are extremely volatile. The average value of the annualized firm-level volatility *SIGMA* is 56%, again reflecting the strong influence of small firms and recent years in which idiosyncratic volatility has been high (Campbell et al. (2001)).

A comparison of Panels A and B, Table II, reveals that bankrupt firms have intuitive differences from the rest of the sample. In months immediately preceding a bankruptcy filing, firms typically make losses (the mean loss is 4.0% quarterly or 16% of market value of assets at an annual rate, and the median loss is 4.7% quarterly or almost 19% at an annual rate); the value of their debts is extremely high relative to their assets (average leverage is almost 80%, and median leverage exceeds 87%); they have experienced extremely negative returns over the past month (the mean is $-11.5\%$ over a month, while the median is $-17\%$ over a month); and their volatility is extraordinarily high (the mean annualized volatility is 106% and the median is 126%). Bankrupt firms also tend to be relatively small (about 7 times smaller than other firms on average, and 10 times smaller at the median), and they have only about half as much cash and short-term investments, in relation to the market value of assets, as nonbankrupt firms.

[6] The influence of these trends is magnified by the growth in the number of companies and the availability of quarterly accounting data over time, which means that recent years have greater influence on the distribution than earlier years. In particular, there is a scarcity of quarterly COMPUSTAT data before the early 1970s, so years before 1973 have very little influence on our empirical results.

[7] In addition, the distributions of *NIMTA* and *NITA* have large spikes just above zero, a phenomenon noted by Hayn (1995). There is a debate in the accounting literature about this spike. Burgstahler and Dichev (1997) argue that it reflects earnings management to avoid losses, but Dechow, Richardson, and Tuna (2003) and Durtschi and Easton (2005) challenge this interpretation.

The market-to-book ratio of bankrupt firms has a slightly higher mean and a much higher standard deviation than the market-to-book ratio of other firms. Bankrupt firms have often experienced losses that have eroded the book value of their equity, driving up the market-to-book ratio; on the other hand, the stock market often anticipates bankruptcy or future losses, driving down the market value of equity and the market-to-book ratio. Which of these two forces dominates can differ across firms, generating a wide spread in the market-to-book ratio for bankrupt firms.

Finally, firms that go bankrupt typically have low prices per share. The mean price per share is just over \$1.50 for a bankrupt firm, while the median price per share is slightly below \$1.

Panel C of Table II reports the summary statistics for our failure sample through December 2003. The patterns are similar to those in Panel B, but some effects are stronger for failures than for bankruptcies (losses are more extreme, volatility is higher, price per share is lower, and market capitalization is considerably smaller), while other effects are weaker (leverage is less extreme and cash holdings are higher).

## II. A Logit Model of Bankruptcy and Failure

The summary statistics in Table II show that bankrupt and failed firms have a number of unusual characteristics. However, the number of bankruptcies and failures is tiny compared to the number of firm-months in our data set, so it is not at all clear how useful these variables are in predicting bankruptcy. Also, these characteristics are correlated with one another and we would like to know how to weight them optimally. Following Shumway (2001) and Chava and Jarrow (2004), we now estimate the probabilities of bankruptcy and failure over the next period using a logit model.

We assume that the marginal probability of bankruptcy or failure over the next period follows a logistic distribution and is given by

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

where $Y_{it}$ is an indicator that equals one if the firm goes bankrupt or fails in month $t$, and $x_{i,t-1}$ is a vector of explanatory variables known at the end of the previous month. A higher level of $\alpha + \beta x_{i,t-1}$ implies a higher probability of bankruptcy or failure.

Table III reports logit regression results for various alternative specifications. In the first three columns, we follow Shumway (2001) and Chava and Jarrow (2004), and estimate a model (model 1) with five standard variables: *NITA*, *TLTA*, *EXRET*, *SIGMA*, and *RSIZE*. Model 1 measures assets in the conventional way, using book values from COMPUSTAT. It excludes firm age, a variable that Shumway (2001) considers but finds to be insignificant in predicting bankruptcy. Column 1 estimates the model for bankruptcy over the period 1963 to 1998, column 2 estimates it for failure over the

**Table III**

**Logit Regressions of Bankruptcy/Failure Indicator on Predictor Variables**

This table reports results from logit regressions of the bankruptcy and failure indicators on predictor variables. The data are constructed such that all of the predictor variables are observable at the beginning of the month over which bankruptcy or failure is measured. The absolute value of $z$-statistics is reported in parentheses. *denotes significant at 5%, **denotes significant at 1%.

| | Model 1 | | | Model 2 | | |
|---|---|---|---|---|---|---|
| Dependent variable: | Bankruptcy | Failure | Failure | Bankruptcy | Failure | Failure |
| Sample period: | 1963–1998 | 1963–1998 | 1963–2003 | 1963–1998 | 1963–1998 | 1963–2003 |
| *NITA* | −14.05 | −13.79 | −12.78 | | | |
| | (16.03)** | (17.06)** | (21.26)** | | | |
| *NIMTAAVG* | | | | −32.52 | −32.46 | −29.67 |
| | | | | (17.65)** | (19.01)** | (23.37)** |
| *TLTA* | 5.38 | 4.62 | 3.74 | | | |
| | (25.91)** | (26.28)** | (32.32)** | | | |
| *TLMTA* | | | | 4.32 | 3.87 | 3.36 |
| | | | | (22.82)** | (23.39)** | (27.80)** |
| *EXRET* | −3.30 | −2.90 | −2.32 | | | |
| | (12.12)** | (11.81)** | (13.57)** | | | |
| *EXRETAVG* | | | | −9.51 | −8.82 | −7.35 |
| | | | | (12.05)** | (12.08)** | (14.03)** |
| *SIGMA* | 2.15 | 2.28 | 2.76 | 0.920 | 1.15 | 1.48 |
| | (16.40)** | (18.34)** | (26.63)** | (6.66)** | (8.79)** | (13.54)** |
| *RSIZE* | −0.188 | −0.253 | −0.374 | 0.246 | 0.169 | 0.082 |
| | (5.56)** | (7.60)** | (13.26)** | (6.18)** | (4.32)** | (2.62)** |
| *CASHMTA* | | | | −4.89 | −3.22 | −2.40 |
| | | | | (7.96)** | (6.59)** | (8.64)** |
| *MB* | | | | 0.099 | 0.095 | 0.054 |
| | | | | (6.72)** | (6.76)** | (4.87)** |
| *PRICE* | | | | −0.882 | −0.807 | −0.937 |
| | | | | (10.39)** | (10.09)** | (14.77)** |
| Constant | −15.21 | −15.41 | −16.58 | −7.65 | −8.45 | −9.08 |
| | (39.45)** | (40.87)** | (50.92)** | (13.66)** | (15.63)** | (20.84)** |
| Observations | 1,282,853 | 1,302,564 | 1,695,036 | 1,282,853 | 1,302,564 | 1,695,036 |
| Failures | 797 | 911 | 1,614 | 797 | 911 | 1,614 |
| Pseudo-$R^2$ | 0.260 | 0.258 | 0.270 | 0.299 | 0.296 | 0.312 |

same period, and column 3 looks at failure over the entire 1963 to 2003 period.

All five of the included variables in the Shumway (2001) bankruptcy model enter significantly and with the expected sign. As we broaden the definition of financial distress to failure, and as we include more recent data, the effects of market capitalization and volatility become stronger, while the effects of losses, leverage, and recent past returns become slightly weaker.

In columns 4, 5, and 6, we report results for an alternative model (model 2) that modifies the Shumway specification in several ways. First, we replace the traditional accounting ratios *NITA* and *TLTA*, which use the book value of assets, with our ratios *NIMTA* and *TLMTA*, which use the market value of assets. These measures are more sensitive to new information about firm prospects since equity values are measured using monthly market data rather than quarterly accounting data.

Second, we add lagged information about profitability and excess stock returns. One might expect that a long history of losses or a sustained decline in stock market value would be a better predictor of bankruptcy than one large quarterly loss or a sudden stock price decline in a single month. Exploratory regressions with lagged values confirm that lags of *NIMTA* and *EXRET* enter significantly, while lags of the other variables do not. As a reasonable summary, we impose geometrically declining weights on these lags. We construct

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}\left(NIMTA_{t-1,t-3} + \cdots + \phi^9 NIMTA_{t-10,t-12}\right), \quad (2)$$

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

where $\phi = 2^{-\frac{1}{3}}$, implying that the weight is halved each quarter. When lagged excess returns or profitability are missing, we replace them with their cross-sectional means in order to avoid losing observations. The data suggest that this parsimonious specification captures almost all the predictability obtainable from lagged profitability and stock returns.

Third, we add the ratio of cash and short-term investments to the market value of total assets, *CASHMTA*, in order to capture the liquidity position of the firm. A firm with a high *CASHMTA* ratio has liquid assets available to make interest payments, and thus may be able to postpone bankruptcy with the possibility of avoiding it altogether if circumstances improve.[8]

Fourth, the market-to-book ratio, *MB*, captures the relative value placed on the firm's equity by stockholders and by accountants. Our profitability and leverage ratios use market value; if book value is also relevant, then *MB* may enter the regression as a correction factor, increasing the probability of bankruptcy when market value is unusually high relative to book value. Recall from Table II that the average market-to-book ratio is slightly higher for bankrupt firms, so there may also be a modest direct effect of overvaluation on failure probability.[9]

Finally, we add the log price per share of the firm, *PRICE*. We expect this variable to be relevant for low prices per share, particularly since both the NYSE and the Nasdaq have a minimum price per share of \$1 and commonly delist stocks that fail to meet this minimum (Macey, O'Hara, and Pompilio (2008)). Reverse stock splits are sometimes used to keep stock prices away from the

[8] We also considered more traditional measures of working capital, the current ratio of current assets to current liabilities, and the acid test ratio of cash, short-term investments, and receivables to current liabilities. These variables are slightly less effective predictors than *CASHMTA*, perhaps because our ratio uses the market value of assets in the denominator.

[9] Chacko, Hecht, and Hilscher (2004) discuss the measurement of credit risk when the market-to-book ratio is influenced both by cash flow expectations and discount rates.

$1 minimum level, but these often have negative effects on returns and therefore on market capitalization, suggesting that investors interpret reverse stock splits as a negative signal about company prospects (Woolridge and Chambers (1983) and Hwang (1995)). Exploratory analysis suggests that price per share is relevant below $15, and so we winsorize price per share at this level before taking the log.

All the new variables in model 2 enter the logit regression with the expected sign and are highly statistically significant. After accounting for differences in the scaling of the variables, there is little effect on the coefficients of the variables already included in the Shumway model, with the important exception of market capitalization. This variable is strongly correlated with log price per share; once price per share is included, market capitalization enters with a weak positive coefficient, probably as an ad hoc correction to the negative effect of price per share.

To get some idea of the relative impact of changes in the different variables, we compute the proportional impact on the failure probability of a one-standard-deviation increase in each predictor variable for a firm that initially has sample mean values of the predictor variables. Such an increase in profitability reduces the probability of failure by 44% of its initial value; the corresponding effects are a 156% increase for leverage, a 28% reduction for past excess return, a 64% increase for volatility, a 17% increase for market capitalization, a 21% reduction for cash holdings, a 9% increase for the market-to-book ratio, and a 56% reduction for price per share. Thus, variations in leverage, volatility, price per share, and profitability are more important for failure risk than movements in market capitalization, cash, or the market-to-book ratio. These magnitudes roughly line up with the $t$-statistics reported in Table III.

Our proposed model 2 delivers a noticeable improvement in explanatory power over the Shumway model 1. We report McFadden's pseudo-$R^2$ coefficient for each specification, calculated as $1 - L_1/L_0$, where $L_1$ is the log likelihood of the estimated model and $L_0$ is the log likelihood of a null model that includes only a constant term. The pseudo-$R^2$ coefficient increases from 0.26 to 0.30 in predicting bankruptcies or failures over 1963 to 1998, and from 0.27 to 0.31 in predicting failures over 1963 to 2003.

### *A. Forecasting at Long Horizons*

At the 1-month horizon our best specification, model 2, captures about 30% of the variation in bankruptcy risk. We now ask what happens as we try to predict bankruptcies further into the future. In Table IV, we estimate the conditional probability of bankruptcy in 6 months and 1, 2, and 3 years. We again assume a logit specification but allow the coefficients on the variables to vary with the horizon of the prediction. In particular, we assume that the probability of bankruptcy in $j$ months, conditional on survival in the data set for $j - 1$ months, is given by

$$P_{t-1}(Y_{i,t-1+j} = 1 \mid Y_{i,t-2+j} = 0) = \frac{1}{1 + \exp(-\alpha_j - \beta_j x_{i,t-1})}. \tag{4}$$

**Table IV**

**Logit Regressions of Failure Indicator on Lagged Variables**

This table takes our best-model variables (model 2 in Table III) and reports their predictive power for lags of 6, 12, 24, and 36 months. The dependent variable is failure and the sample period is 1963 to 2003. The absolute value of $z$-statistics is reported in parentheses. *denotes significant at 5%, **denotes significant at 1%.

| Lag (Months) | 0 | 6 | 12 | 24 | 36 |
|---|---|---|---|---|---|
| *NIMTAAVG* | −29.67 | −23.92 | −20.26 | −13.23 | −14.06 |
| | (23.37)** | (21.82)** | (18.09)** | (10.50)** | (9.77)** |
| *TLMTA* | 3.36 | 2.06 | 1.42 | 0.917 | 0.643 |
| | (27.80)** | (22.63)** | (16.23)** | (9.85)** | (6.25)** |
| *EXRETAVG* | −7.35 | −7.79 | −7.13 | −5.61 | −2.56 |
| | (14.03)** | (15.97)** | (14.15)** | (10.14)** | (4.14)** |
| *SIGMA* | 1.48 | 1.27 | 1.41 | 1.52 | 1.33 |
| | (13.54)** | (14.57)** | (16.49)** | (16.92)** | (13.54)** |
| *RSIZE* | 0.082 | 0.047 | −0.045 | −0.132 | −0.180 |
| | (2.62)** | (2.02)* | (2.09)* | (6.19)** | (8.03)** |
| *CASHMTA* | −2.40 | −2.40 | −2.13 | −1.37 | −1.41 |
| | (8.64)** | (9.77)** | (8.53)** | (5.09)** | (4.61)** |
| *MB* | 0.054 | 0.047 | 0.075 | 0.108 | 0.125 |
| | (4.87)** | (4.22)** | (6.33)** | (7.92)** | (8.17)** |
| *PRICE* | −0.937 | −0.468 | −0.058 | 0.212 | 0.279 |
| | (14.77)** | (10.36)** | (1.40) | (4.96)** | (6.00)** |
| Constant | −9.08 | −8.07 | −9.16 | −10.23 | −10.53 |
| | (20.84)** | (25.00)** | (30.89)** | (34.48)** | (33.53)** |
| Observations | 1,695,036 | 1,642,006 | 1,565,634 | 1,384,951 | 1,208,610 |
| Failures | 1,614 | 2,008 | 1,968 | 1,730 | 1,467 |
| Pseudo-$R^2$ | 0.312 | 0.188 | 0.114 | 0.061 | 0.044 |

Note that this assumption does not imply a cumulative probability of bankruptcy that is logit. If the probability of bankruptcy in $j$ months did not change with the horizon $j$, that is, if $\alpha_j = \alpha$ and $\beta_j = \beta$, and if firms exited the data set only through bankruptcy, then the cumulative probability of bankruptcy over the next $j$ periods would be given by $1 - (\exp(-\alpha - \beta x_i)/(1 + \exp(-\alpha - \beta x_i)))^j$, which no longer has the logit form. Variation in the parameters with the horizon $j$, and exit from the data set through mergers and acquisitions, only make this problem worse. In principle, we could compute the cumulative probability of bankruptcy by estimating models for each horizon $j$ and integrating appropriately; or by using our one-period model and making auxiliary assumptions about the time-series evolution of the predictor variables in the manner of Duffie, Saita, and Wang (2007). We do not pursue these possibilities here, concentrating instead on the conditional probabilities of default at particular dates in the future.

As the horizon increases in Table IV, the coefficients, significance levels, and overall fit of the logit regression decline as one would expect. Even at 3 years, however, almost all the variables remain statistically significant.

Three predictor variables are particularly important at long horizons: the coefficient and $t$-statistic on volatility *SIGMA* are almost unchanged as the horizon increases; the coefficient and $t$-statistic on the market-to-book ratio $MB$ increase with the horizon; and the coefficient on relative market capitalization $RSIZE$ switches sign, becoming increasingly significant with the expected negative sign as the horizon increases. These variables, market capitalization, market-to-book ratio, and volatility, are persistent attributes of a firm that become increasingly important measures of financial distress at long horizons. Log price per share also switches sign, presumably as a result of the previously noted correlation between this variable and market capitalization.

Leverage and past excess stock returns have coefficients that decay particularly rapidly with the horizon, suggesting that these are primarily short-term signals of financial distress. Profitability and cash holdings are intermediate, with effects that decay more slowly. Overall, market-based variables become more important relative to accounting variables as we increase the forecast horizon. This pattern is not just due to our use of quarterly accounting data, as we find very similar results if we estimate our model using annual accounting data.

In Table IV the number of observations and number of failures vary with the horizon, because increasing the horizon forces us to drop observations at both the beginning and end of the data set. Failures that occur within the first $j$ months of the sample cannot be related to the condition of the firm $j$ months previously, and the last $j$ months of the sample cannot be used to predict failures that may occur after the end of the sample. Also, many firms exit the data set for other reasons between dates $t-1$ and $t-1+j$. On the other hand, as we lengthen the horizon we can include failures that are immediately preceded by missing data. We have run the same regressions for a subset of firms for which data are available at all the different horizons. This allows us to compare $R^2$ statistics directly across horizons. We obtain very similar results to those reported in Table IV, telling us that variation in the available data is not responsible for our findings.

### *B. Comparison with Distance to Default*

A leading alternative to the reduced-form econometric approach we have implemented in this paper is the structural approach of Moody's KMV (Crosbie and Bohn (2001)), based on the structural default model of Merton (1974). This approach uses the Merton model to construct "distance to default," $DD$, a measure of the difference between the asset value of the firm and the face value of its debt, scaled by the standard deviation of the firm's asset value. Taken literally, the Merton model implies a deterministic relationship between $DD$ and the probability of default, but in practice this relationship is estimated by a nonparametric regression of a bankruptcy or failure indicator on $DD$. That is, the historical frequency of bankruptcy is calculated for firms with different levels of $DD$, and this historical frequency is used as an estimate of the probability of bankruptcy going forward.

To implement the structural approach, we calculate $DD$ in the manner of Hillegeist et al. (2004) by solving a system of two nonlinear equations. The details of the calculation are described in the Appendix. Table V compares the predictive power of the structural model with that of our best reduced-form model. The top panel reports the coefficients on *DD* in a simple regression of our failure indicator on *DD*, and in a multiple regression on *DD* and the variables included in our reduced-form model. *DD* enters with the expected negative sign and is highly significant in the simple regression. In the multiple regression, however, it enters with a *positive* sign at a short horizon, presumably because the reduced-form model already includes volatility and leverage, which are the two main inputs to the calculation of *DD*. The coefficient on *DD* only becomes negative and significant when the horizon is extended to 1 or 3 years.

The bottom panel of Table V reports the pseudo-$R^2$ statistics for these regressions. While the structural model achieves a respectable $R^2$ of 16% for short-term failure prediction, our reduced-form model almost doubles this number. Adding *DD* to the reduced-form model has very little effect on the $R^2$, which is to be expected given the presence of volatility and leverage in the reduced-form model. These results hold both when we calculate $R^2$ in-sample, using coefficients estimated over the entire period 1963 to 2003, and when we calculate it out-of-sample, using coefficients each year from 1981 onwards that were estimated over the period up to but not including that year. The two sets of $R^2$ are very similar because most failures occur toward the end of the data set, when the full-sample model and the rolling model have very similar coefficients.

The structural approach is designed to forecast default at a horizon of 1 year. This suggests that it might perform relatively better as we forecast failure further into the future. It is true that *DD* enters our model significantly with the correct sign at longer horizons, but Table V shows that the relative performance of *DD* and our econometric model is relatively constant across forecast horizons.

We conclude that the structural approach captures important aspects of the process determining corporate failure. The predictive power of *DD* is quite impressive given the tight restrictions on functional form imposed by the Merton model. If one's goal is to predict failures, however, it is clearly better to use a reduced-form econometric approach that allows volatility and leverage to enter with free coefficients and that includes other relevant variables. Bharath and Shumway (2008), in independent recent work, reach a similar conclusion.

### *C. Other Time-Series and Cross-sectional Effects*

As we noted in our discussion of Table I, there is considerable variation in the failure rate over time. We now ask how well our model fits this pattern. We first calculate the fitted probability of failure for each company in our data set using the coefficients from our best reduced-form model. We then average over all the predicted probabilities to obtain a prediction of the aggregate failure rate among companies with data available for failure prediction.

**Table V**

**Distance to Default and Our Best Model**

We report the coefficients on the "distance to default" (DD) variable in a logit regression by itself as well as when included in our best model (model 2 in Table III). The dependent variable is failure and the sample period is 1963 to 2003. Regression results are reported for various horizons: 0, 12, and 36 months. Panel A reports regregression coefficients and the corresponding $z$-statistics (in parentheses). *denotes significant at 5%, **denotes significant at 1%. Panel B reports the in-sample and out-of-sample pseudo-$R^2$ statistics for the regressions from Panel A.

| Lag (Months) | 0 | 12 | 36 |
|---|---|---|---|
| | Panel A. Coefficients | | |
| *DD* only | −0.883 | −0.345 | −0.165 |
| | (39.73)** | (33.73)** | (20.88)** |
| *DD* in best model | 0.048 | −0.0910 | −0.090 |
| | (2.62)** | (7.52)** | (8.09)** |
| Observations | 1,695,036 | 1,565,634 | 1,208,610 |
| Failures | 1,614 | 1,968 | 1,467 |
| | Panel B. $R^2$ | | |
| In-sample (1963 to 2003) | | | |
| *DD* only | 0.159 | 0.066 | 0.026 |
| Best model | 0.312 | 0.114 | 0.044 |
| *DD* in Best model | 0.312 | 0.117 | 0.045 |
| Out-of-sample (1981 to 2003) | | | |
| *DD* only | 0.156 | 0.064 | 0.025 |
| Best model | 0.310 | 0.108 | 0.039 |

Figure 1 shows annual averages of predicted and realized failures, expressed as a fraction of the companies with available data.[10] Our model captures much of the broad variation in corporate failures over time, including the strong and long-lasting increase in the 1980s and cyclical spikes in the early 1990s and early 2000s. However, it somewhat overpredicts failures in 1974 to 1975, underpredicts for much of the 1980s, and then overpredicts in the early 1990s.

Deviations of the aggregate failure rate from the predictions of a model like ours can be caused by shocks that are correlated across firms, and possibly over time. The effect of correlated shocks is sometimes referred to as frailty (Das et al. (2007) and Duffie et al. (2008)). Correlated shocks could result from structural changes in corporate finance such as the creation of the junk bond market, from macroeconomic events such as recessions whose influence is not fully captured by the explanatory variables in our model, or from direct effects of one corporate failure on other distressed corporations. To examine the importance of such shocks, we consider year dummies that shift the baseline probability of bankruptcy from one year to the next. We run bankruptcy prediction regressions on a set of year dummies only, and on both year dummies and our explanatory

[10] The realized failure rate among these companies is slightly different from the failure rate reported in Table I, which includes all failures and all active companies, not just those with data available for failure prediction.

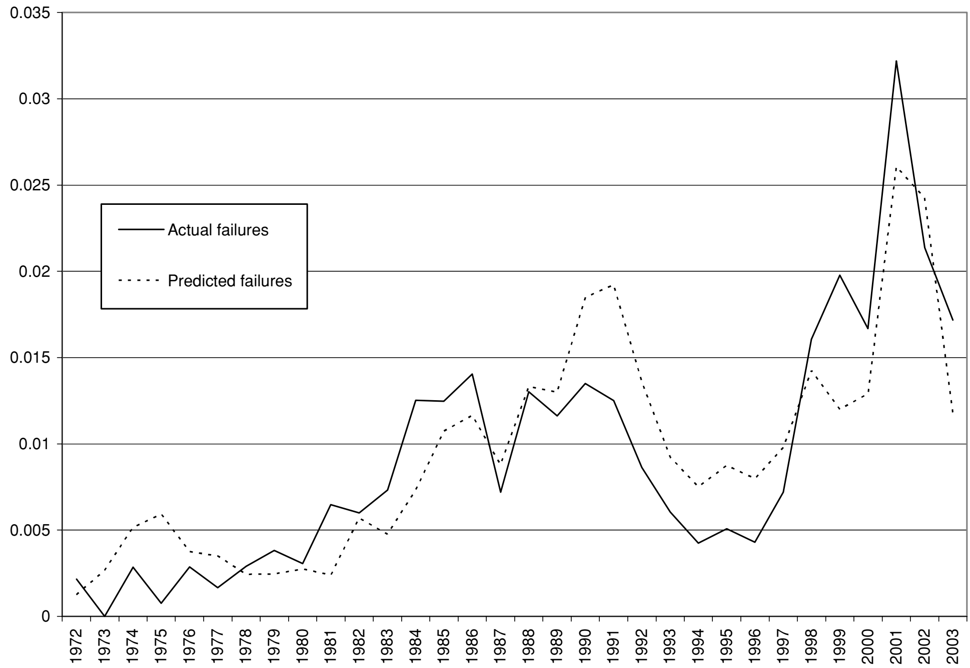


**Figure 1. Predicted versus actual failure rates.** The figure plots the actual and predicted failure rates from 1972 to 2003 for all firms with available data. Failure is defined as a firm filing for bankruptcy under Chapter 7 or Chapter 11, a delisting for financial reasons, or receiving a D rating. Predicted failures are calculated using fitted values of our best model (model 2) from Table III.

variables. We reject the hypothesis that time effects can be omitted from our model, but find that the model captures a large share of the time-variation in bankruptcies.[11] Given our focus on differences in distress risk across firms and the pricing of distressed stocks, we do not pursue this issue further here.

We explore the possibility that there are industry effects on bankruptcy and failure risk. The Shumway (2001) and Chava-Jarrow (2004) specification appears to behave somewhat differently in the finance, insurance, and real estate (FIRE) sector. That sector has a lower intercept and a more negative coefficient on profitability. However, there is no strong evidence of sector effects in our best model, which relies more heavily on equity market data. We also use market capitalization and leverage as interaction variables, to test the hypotheses that other firm-specific explanatory variables enter differently for small or highly indebted firms than for other firms. We find no clear evidence that such interactions are important.

[11] We also consider interacting macroeconomic variables with firm-specific variables. We find that the AAA-BAA credit spread and the Treasury term spread interact with firms' size and leverage to predict bankruptcy. A more complex model including such terms further reduces the importance of time effects.

## III. Risks and Average Returns on Distressed Stocks

We now turn our attention to the asset pricing implications of our failure model. Recent work on the distress premium has tended to use either traditional risk indices such as the Altman *Z*-score or Ohlson *O*-score (Dichev (1998), Griffin and Lemmon (2002) and Ferguson and Shockley (2003)) or the distance to default measure of KMV (Vassalou and Xing (2004) and Da and Gao (2008)). To the extent that our reduced-form model more accurately measures the risk of failure at short and long horizons, we can more accurately measure the premium that investors receive for holding distressed stocks.

We measure the premium for financial distress by sorting stocks according to their failure probabilities, estimated using the 12-month-ahead model of Table IV. Each January from 1981 through 2003, the model is re-estimated using only historically available data to eliminate look-ahead bias. We then form 10 value-weighted portfolios of stocks that fall in different regions of the failure risk distribution. We minimize turnover costs and the effects of bid-ask bounce by eliminating stocks with prices less than \$1 at the portfolio construction date, and by holding the portfolios for a year, allowing the weights to drift with returns within the year rather than rebalancing monthly in response to updated failure probabilities.[12] Our portfolios contain stocks in percentiles 0 to 5, 5 to 10, 10 to 20, 20 to 40, 40 to 60, 60 to 80, 80 to 90, 90 to 95, 95 to 99, and 99 to 100 of the failure risk distribution. This portfolio construction procedure pays greater attention to the tails of the distribution, where the distress premium is likely to be more relevant, and particularly to the most distressed firms. We also construct long-short portfolios that go long the 10% or 20% of stocks with the lowest failure risk, and short the 10% or 20% of stocks with the highest failure risk.

Because we are studying the returns to distressed stocks, it is important to handle carefully the returns to stocks that are delisted and thus disappear from the CRSP database. In many cases, CRSP reports a delisting return for the final month of the firm's life; we have 6,481 such delisting returns in our sample and we use them where they are available. Otherwise, we use the last available full-month return in CRSP. In some cases, this effectively assumes that our portfolios sell distressed stocks at the end of the month before delisting, which imparts an upward bias to the returns on distressed-stock portfolios (Shumway (1997) and Shumway and Warther (1999)).[13] We assume that the proceeds from sales of delisted stocks are reinvested in each portfolio in proportion to the weights of the remaining stocks in the portfolio. In a few cases, stocks are delisted and then re-enter the database, but we do not include these stocks in the sample after the first delisting. We treat firms that fail as equivalent to delisted firms, even if CRSP continues to report returns for these firms. That is,

[12] When we calculate returns on portfolios rebalanced monthly, as in the first version of this paper, we obtain similar results to those reported here.

[13] In the first version of this paper, we do not use CRSP delisting returns and obtain portfolio results similar to those reported here. Our results are also very similar, and slightly stronger, if we use Shumway's median delisting return to proxy for missing CRSP delisting returns.

our portfolios sell stocks of companies that fail and we use the latest available CRSP data to calculate a final return on such stocks.

Table VI reports the results. Each portfolio corresponds to one column of the table. Panel A reports average simple returns in excess of the market, in annualized percentage points, with $t$-statistics below in parentheses, and then alphas with respect to the CAPM, the three-factor model of Fama and French (1993), and a four-factor model proposed by Carhart (1997) that also includes a momentum factor. We estimate these models using the standard factor-mimicking portfolios available on Professor Ken French's website. Panel B reports estimated factor loadings for excess returns on the three Fama–French factors, again with $t$-statistics. Panel C reports some relevant characteristics for the portfolios: the annualized standard deviation and skewness of each portfolio's excess return; the value-weighted mean standard deviation and skewness of the individual stock returns in each portfolio; and value-weighted means of *RSIZE*, market-to-book, and estimated failure probability for each portfolio. Figures 2 and 3 graphically summarize the behavior of factor loadings and alphas.

The average excess returns reported in the first row of Table VI are strongly and almost monotonically declining in failure risk. The average excess returns for the lowest-risk 5% of stocks are positive at 3.3% per year, and the average excess returns for the highest-risk 1% of stocks are significantly negative at −16.1% per year. A long-short portfolio holding the safest decile of stocks and shorting the most distressed decile has an average return of 9.7% per year and a standard deviation of 26%, so its Sharpe ratio is comparable to that of the aggregate stock market.

There is striking variation in factor loadings across the portfolios in Table VI. The low failure risk portfolios have negative market betas for their excess returns (i.e., betas less than one for their raw returns), negative loadings on the value factor *HML*, and negative loadings on the small-firm factor *SMB*. The high failure risk portfolios have positive market betas for their excess returns, positive loadings on *HML*, and extremely high loadings on *SMB*, reflecting the prevalence of small firms among distressed stocks.

These factor loadings imply that when we correct for risk using either the CAPM or the Fama–French three-factor model, we worsen the anomalous poor performance of distressed stocks rather than correcting it. A long-short portfolio that holds the safest decile of stocks and shorts the decile with the highest failure risk has an average excess return of 9.7% with a $t$-statistic of 1.8; it has a CAPM alpha of 12.1% with a $t$-statistic of 2.2; and it has a Fama–French three-factor alpha of 22.7% with a $t$-statistic of 6.0. When we use the Fama–French model to correct for risk, all portfolios beyond the 60th percentile of the failure risk distribution have statistically significant negative alphas.

One of the variables that predicts failure in our model is recent past return. This suggests that distressed stocks have negative momentum, which might explain their low average returns. To control for this, Table VI also reports alphas from the Carhart (1997) four-factor model including a momentum factor. This adjustment cuts the alpha for the long-short decile portfolio roughly in half, from 22.7% to 12.1%, but it remains strongly statistically significant.

**Table VI**

**Returns on Distress Risk-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 99th to 100th percentile (9900). In this table, we show results from regressions of value-weighted excess returns over the market on a constant, market return (*RM*), as well as three (*RM, HML, SMB*) and four (*RM, HML, SMB, UMD*) Fama-French factor regressions. The sample period is 1981 to 2003. Panel A shows monthly alphas (in annualized percent units) from these regressions and the corresponding absolute values of $t$-statistics (in parentheses). Panel B shows loadings on the three factors and the corresponding $t$-statistics (in parentheses) from the three-factor regression. Panel C reports annualized standard deviation and skewness of individual and portfolio returns, mean relative size (*RSIZE*), market-to-book (*MB*), and probability of failure ($\hat{P}$) values for each portfolio. $^{*}$denotes significant at 5%, $^{**}$denotes significant at 1%.

| Portfolios | 0005 | 0510 | 1020 | 2040 | 4060 | 6080 | 8090 | 9095 | 9599 | 9900 | LS1090 | LS2080 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A. Portfolio Alphas** | | | | | | | | | | | | |
| Mean excess return | 3.30 | 1.48 | 0.97 | 0.93 | 0.58 | −0.23 | −4.41 | −7.97 | −6.80 | −16.14 | 9.66 | 6.30 |
| | (1.35) | (0.62) | (0.80) | (1.04) | (0.39) | (0.10) | (1.25) | (1.70) | (1.27) | (1.96) | (1.76) | (1.41) |
| CAPM alpha | 2.70 | 1.22 | 1.16 | 1.51 | 0.55 | −1.64 | −6.64 | −10.86 | −9.54 | −18.56 | 12.05 | 8.58 |
| | (1.10) | (0.50) | (0.95) | (1.74) | (0.37) | (0.72) | (1.95) | (2.38)$^{*}$ | (1.80) | (2.25)$^{*}$ | (2.21)$^{*}$ | (1.95) |
| 3-factor alpha | 5.91 | 4.76 | 2.56 | 0.90 | −1.91 | −5.79 | −12.63 | −18.03 | −16.30 | −24.15 | 22.65 | 17.27 |
| | (2.89)$^{**}$ | (2.27)$^{*}$ | (2.24)$^{*}$ | (1.16) | (1.51) | (3.21)$^{**}$ | (4.60)$^{**}$ | (5.71)$^{**}$ | (3.99)$^{**}$ | (3.33)$^{**}$ | (6.04)$^{**}$ | (5.34)$^{**}$ |
| 4-factor alpha | 2.51 | 2.52 | 1.48 | 2.06 | 0.95 | −1.17 | −5.74 | −9.81 | −8.40 | −20.24 | 12.07 | 8.10 |
| | (1.19) | (1.14) | (1.23) | (2.56)$^{*}$ | (0.76) | (0.67) | (2.14)$^{*}$ | (3.20)$^{**}$ | (2.02)$^{*}$ | (2.62)$^{**}$ | (3.37)$^{**}$ | (2.63)$^{**}$ |
| **Panel B. Three-Factor Regression Coefficients** | | | | | | | | | | | | |
| *RM* | −0.094 | −0.121 | −0.064 | −0.032 | 0.100 | 0.337 | 0.478 | 0.475 | 0.422 | 0.255 | −0.565 | −0.559 |
| | (2.39)$^{*}$ | (2.98)$^{**}$ | (2.92)$^{**}$ | (2.11)$^{*}$ | (4.11)$^{**}$ | (9.68)$^{**}$ | (9.02)$^{**}$ | (7.78)$^{**}$ | (5.34)$^{**}$ | (1.82) | (7.80)$^{**}$ | (8.95)$^{**}$ |
| *HML* | −0.507 | −0.532 | −0.194 | 0.106 | 0.361 | 0.600 | 0.841 | 0.915 | 0.842 | 0.615 | −1.435 | −1.215 |
| | (9.79)$^{**}$ | (10.03)$^{**}$ | (6.73)$^{**}$ | (5.43)$^{**}$ | (11.34)$^{**}$ | (13.15)$^{**}$ | (12.11)$^{**}$ | (11.45)$^{**}$ | (8.15)$^{**}$ | (3.35)$^{**}$ | (15.13)$^{**}$ | (14.85)$^{**}$ |
| *SMB* | 0.170 | −0.034 | −0.154 | −0.115 | 0.099 | 0.252 | 0.579 | 1.464 | 1.551 | 1.981 | −1.462 | −0.871 |
| | (2.95)$^{**}$ | (0.58) | (4.80)$^{**}$ | (5.29)$^{**}$ | (2.79)$^{**}$ | (4.97)$^{**}$ | (7.50)$^{**}$ | (16.48)$^{**}$ | (13.50)$^{**}$ | (9.71)$^{**}$ | (13.85)$^{**}$ | (9.57)$^{**}$ |
| **Panel C. Portfolio Characteristics** | | | | | | | | | | | | |
| Portfolio *SD* | 0.117 | 0.115 | 0.058 | 0.043 | 0.071 | 0.112 | 0.168 | 0.225 | 0.257 | 0.395 | 0.264 | 0.214 |
| Portfolio skewness | 1.166 | 0.413 | 0.169 | −0.470 | −0.299 | −0.455 | 0.981 | 1.760 | 2.401 | 1.848 | | |
| Individual *SD* | 0.352 | 0.343 | 0.298 | 0.283 | 0.302 | 0.369 | 0.507 | 0.683 | 0.778 | 0.943 | | |
| Individual skewness | 0.674 | 0.723 | 0.553 | 0.923 | 1.030 | 0.839 | 1.553 | 3.752 | 1.753 | 2.495 | | |
| Mean *RSIZE* | −7.677 | −7.398 | −7.172 | −7.134 | −7.341 | −7.779 | −8.733 | −9.992 | −10.600 | −11.283 | | |
| Mean *MB* | 2.639 | 3.148 | 2.962 | 2.522 | 2.126 | 2.000 | 2.246 | 2.602 | 3.097 | 3.752 | | |
| Mean $\hat{P}$ | 0.011% | 0.014% | 0.018% | 0.024% | 0.036% | 0.057% | 0.109% | 0.192% | 0.340% | 0.803% | | |

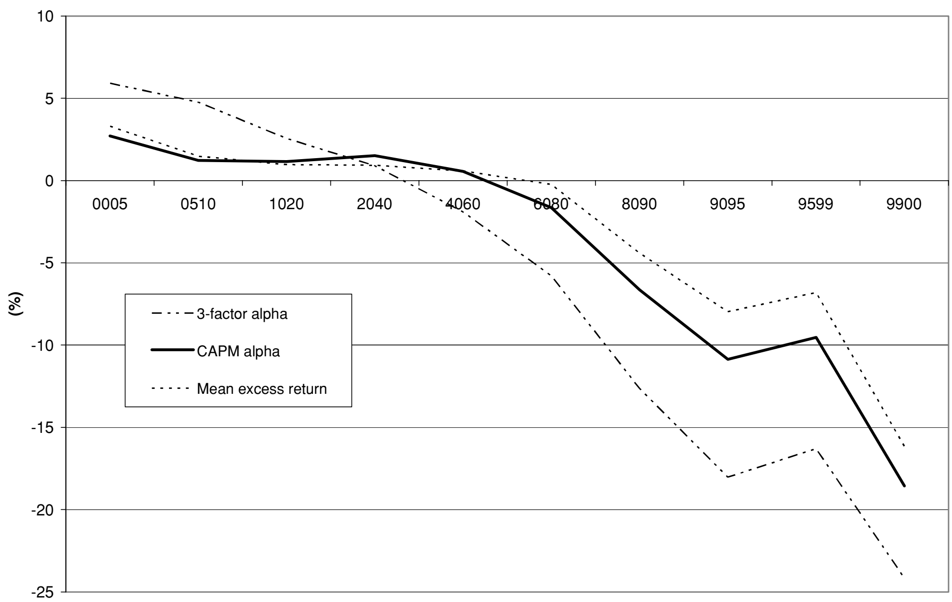


**Figure 2. Alphas of distressed stock portfolios.** The figure plots the annualized mean excess return over the market, CAPM alpha, and Fama–French three-factor alpha for the 10 distress risk-sorted portfolios from 1981 to 2003. Portfolios are formed at the beginning of January every year using the model-predicted probability of failure.

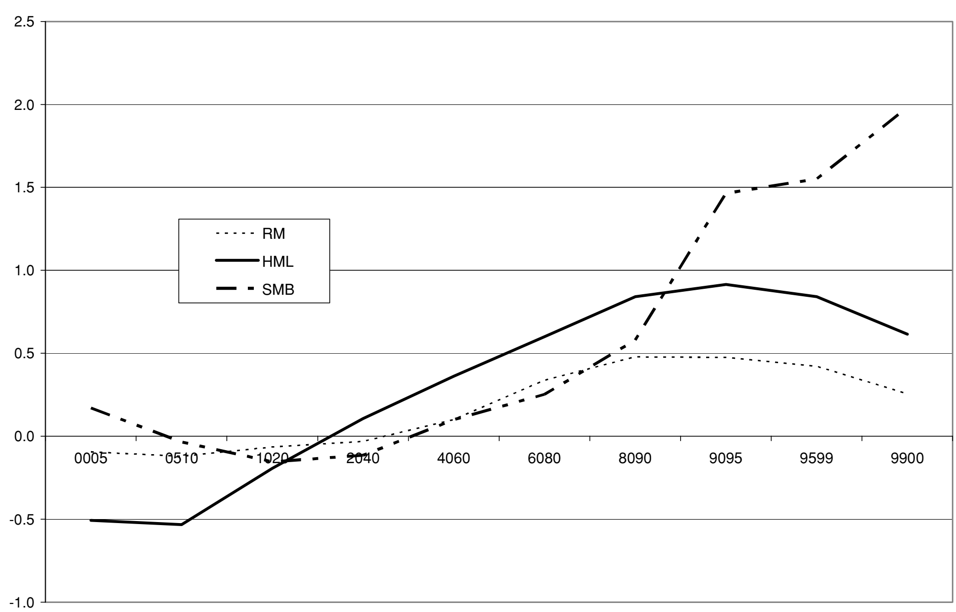


**Figure 3. Factor loadings of distressed stock portfolios.** The figure plots loadings on the excess market return (*RM*), the value factor (*HML*), and the size factor (*SMB*) for the 10 distress risk-sorted portfolios from 1981 to 2003. Portfolios are formed at the beginning of January every year using the model-predicted probability of failure.

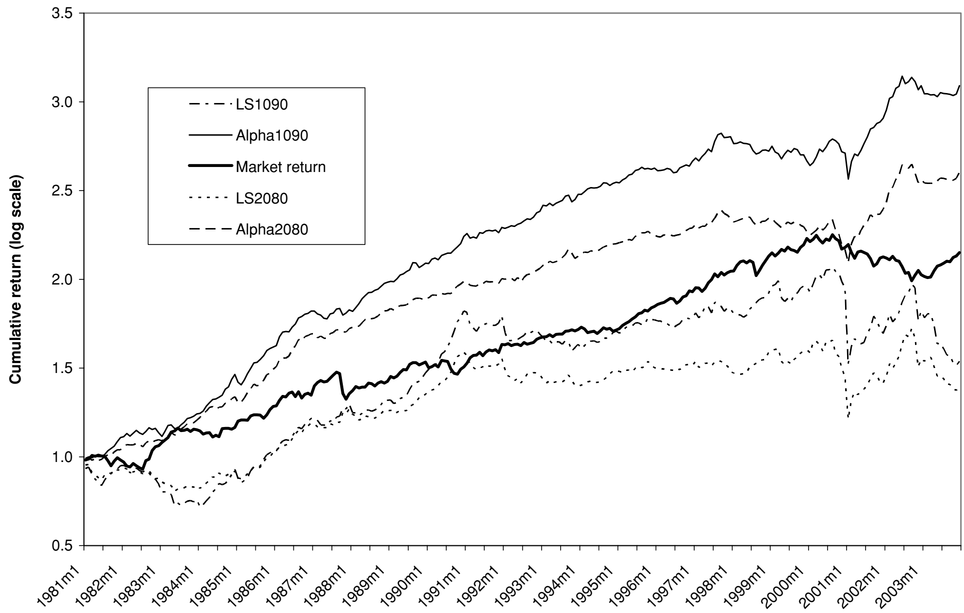


**Figure 4. Returns on long-short distressed stock portfolios.** The figure plots cumulative excess returns and Fama-French three-factor alphas from 1981 to 2003 for long-short portfolios LS1090 and LS2080 going long the 10% (20%) safest stocks and short the 10% (20%) most distressed stocks, respectively. The figure also plots the cumulative market return (S&P500) over the period.

Figure 4 illustrates the performance over time of the long-short portfolios that hold the safest decile (quintile) of stocks and short the most distressed decile (quintile). Performance is measured both by cumulative return, and by cumulative alpha or risk-adjusted return from the Fama–French three-factor model. For comparison, we also plot the cumulative return on the market portfolio. Raw returns to these portfolios are concentrated in the late 1980s and late 1990s, with negative returns in the last few years; however, the alphas for these portfolios are much more consistent over time.

The bottom panel of Table VI reports characteristics of these portfolios. There is a wide spread in failure risk across the portfolios. Stocks in the safest 5% have an average failure probability of about 1 basis point, while stocks in the riskiest 5% have a failure probability of 34 basis points and the 1% of riskiest stocks have a failure probability of 80 basis points.

Stocks with a high risk of failure are highly volatile, with average standard deviations of almost 80% in the 5% most distressed stocks and 94% in the 1% most distressed stocks. This volatility does not fully diversify at the portfolio level.[14] The excess return on the portfolio containing the 5% of stocks with the

[14] On average there are slightly under 500 stocks for each 10% of the failure risk distribution, so purely idiosyncratic firm-level risk should diversify well, leaving portfolio risk to be determined primarily by common variation in distressed stock returns.

lowest failure risk has an annual standard deviation of 12%, while the excess return for the portfolio containing the 5% of stocks with the highest failure risk has a standard deviation of 26%, and the concentrated portfolio containing the 1% most distressed stocks has a standard deviation of 40%. The returns on distressed stocks are also positively skewed, both at the portfolio level and particularly at the individual stock level.

Distressed stocks are much smaller than safe stocks. The value-weighted average size of the 5% safest stocks, reported in the table, is over 18 times larger than the value-weighted average size of the 5% most distressed stocks, and the equal-weighted size is about 10 times larger. Market-to-book ratios are high at both extremes of the failure risk distribution, and lower in the middle. This implies that distressed stocks have the market-to-book ratios of growth stocks but the factor loadings of value stocks, since they load positively on the Fama–French value factor.

As a further specification check, we sort stocks on our measure of distance to default, but do not report these results in a table. Contrary to the findings of Vassalou and Xing (2004), this sort also generates low returns for distressed stocks, particularly after correction for risk using the Fama–French three-factor model. These results are discouraging for the view that distress risk is positively priced in the U.S. stock market, as we consistently find that stocks with a high risk of failure have low average returns despite their high loadings on market, small-cap, and value risk factors.

### *A. Firm Characteristics and the Distress Anomaly*

The wide spread in firm characteristics across the failure risk distribution suggests the possibility that the apparent underperformance of distressed stocks results from their characteristics rather than from financial distress per se. For example, it could be the case that extremely small stocks, or extreme growth stocks with very low book-to-market ratios, underperform in a manner that is not captured by the Fama–French three-factor model. To explore this possibility, in Table VII we double-sort stocks, first on size or book-to-market using NYSE quintile breakpoints, and then on failure risk. We report the average returns, with and without risk adjustment, and portfolio characteristics for long-short portfolios that hold the least financially distressed quintile of stocks and short the most financially distressed quintile of stocks within each size or book-to-market quintile.

The left side of Table VII shows that long-short portfolios based on estimated financial distress outperform whether they contain small stocks or large stocks. However, the outperformance is considerably stronger among small stocks. In Panel A, the average return on the long-short portfolio is more than five times larger when the stocks are in the smallest quintile as opposed to the largest quintile. If we correct for risk using the Fama–French three-factor model, the average alpha on the long-short portfolio is about 70% larger in the smallest quintile than in the largest quintile. These results imply that equal-weighted portfolios of distressed stocks would underperform even more dramatically than

**Table VII**

**Distress Effect Across Size and Value Quintiles**

We report mean excess returns and three-factor alphas for portfolios sorted on size and value. The portfolios are long safe stocks (0 to 20th percentile of the failure probability distribution) and short distressed stocks (80th to 100th percentile). We first sort on size and value using NYSE quintile breakpoints, then on distress. We report value-weighted returns for long-short portfolios for all quintiles. Panel A shows monthly excess returns and alphas (in annualized percent units) and the corresponding $t$-statistics (in parentheses). Panel B reports the average spread in log probability of failure ($\hat{P}$) across safe and distressed stocks and the average relative size (*RSIZE*) of the stocks in the long-short (LS) portfolios. Panel C reports annualized percentage returns per unit of log $\hat{P}$. Specifically, in Panel C we run regressions of LS excess returns and alphas on the spread in log $\hat{P}$. *denotes significant at 5%, **denotes significant at 1%.

| | Size | | | | | Value | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Long-short portfolios | Small | | | | Large | Growth | | | | Value |
| **Panel A. Portfolio Returns** | | | | | | | | | | |
| Mean excess return | 10.81 | 8.46 | 4.30 | 2.93 | 1.73 | 14.35 | 5.29 | 7.16 | 5.92 | 9.24 |
| | (3.05)** | (2.88)** | (1.27) | (0.74) | (0.45) | (2.95)** | (1.03) | (1.84) | (1.19) | (1.61) |
| 3-factor alpha | 17.49 | 15.06 | 12.15 | 11.56 | 10.18 | 25.42 | 14.97 | 15.26 | 14.85 | 20.00 |
| | (5.82)** | (7.06)** | (5.11)** | (4.01)** | (3.58)** | (6.77)** | (3.40)** | (4.61)** | (3.58)** | (4.81)** |
| **Panel B. Portfolio Characteristics** | | | | | | | | | | |
| Spread in log $\hat{P}$ | 2.60 | 1.90 | 1.64 | 1.50 | 1.27 | 2.23 | 1.86 | 1.78 | 1.79 | 2.27 |
| Average *RSIZE* | −10.92 | −9.42 | −8.53 | −7.60 | −6.81 | −8.07 | −7.97 | −8.05 | −8.38 | −9.00 |
| **Panel C. $\hat{P}$-Adjusted Returns** | | | | | | | | | | |
| Mean excess return | 3.41 | 3.58 | 1.80 | 0.70 | −0.44 | 5.80 | 1.92 | 3.41 | 2.65 | 3.38 |
| | (2.58)* | (2.42)* | (0.93) | (0.29) | (0.16) | (2.78)** | (0.74) | (1.65) | (1.00) | (1.40) |
| 3-factor alpha | 6.30 | 7.49 | 7.03 | 6.83 | 6.76 | 10.98 | 7.56 | 8.40 | 7.73 | 8.68 |
| | (5.83)** | (7.20)** | (5.34)** | (3.94)** | (3.41)** | (7.05)** | (3.49)** | (4.93)** | (3.60)** | (5.12)** |

the value-weighted portfolios reported in Table VI, a pattern that has been documented for many other cross-sectional anomalies (Fama (1998), Fama and French (2008), and Loughran (1997)).

One reason for the greater underperformance of the most distressed small stocks may be that these stocks are in more severe financial distress than the most distressed large stocks. Panel B reports the spread in the value-weighted average log of our estimated failure probability between the long side and the short side of each long-short portfolio, as well as the average value of *RSIZE* for each portfolio. The spread in financial distress is more than two times greater for small stocks than for large stocks.

To correct for this difference in the distress spread, in Panel C of Table VII we regress the return on each long-short portfolio onto the distress spread, including no intercept in the regression, and report the estimated coefficient and its $t$-statistic. This is a measure of the return per unit of log failure probability. The results in Table VI suggest that average return is roughly linear in log failure probability, and Panel C of Table VII confirms this finding by showing that there is relatively little difference across size quintiles in the return per unit of log failure probability, once we correct for risk using the Fama–French three-factor model.

The right side of Table VII shows that long-short portfolios based on estimated financial distress outperform whether they contain growth stocks or value stocks. The raw underperformance is more extreme and statistically significant among growth stocks, but this difference largely disappears when we correct for risk using the Fama–French three-factor model. The spread in financial distress is somewhat more extreme for stocks at either end of the growth-value spectrum, but correcting for this makes little difference to the pattern of outperformance.

We can extend this analysis to consider other characteristics of firms. In Table VIII, we look at characteristics that measure the availability of information about stocks, the tendency of sophisticated investors to hold them, and the ease of trading them. Many anomalies in stock prices are more pronounced for stocks with relatively poor dissemination of information, an unsophisticated investor base, and poor liquidity.[15] We find that the financial distress anomaly is no exception to this pattern.

The first column of Table VIII, for reference, reports results for the long-short portfolio that holds the least financially distressed quintile of stocks and shorts the most financially distressed quintile. Panel A reports the mean return and three-factor alpha for this portfolio (repeated from the last column of Table VI), Panel B reports the spread in log failure probability and the average relative size of the stocks in the portfolio, and Panel C reports the mean return and three-factor alpha per unit of log failure probability, estimated in the same way as in Table VII.

[15] See, for example, Hong, Lim, and Stein (2000) and Nagel (2005). Nagel emphasizes that institutional ownership is a proxy for the ease of shorting a stock, as institutions are more likely to make their shares available to short sellers.

**Table VIII**

**Distress Effect for Different Characteristics**

We report mean excess returns and three-factor alphas by characteristic for portfolios long safe stocks (0 to 20th percentile of the failure probability distribution) and short distressed stocks (80th to 100th percentile). We first sort on the characteristic, then on distress. We report value-weighted excess returns for all stocks (Overall) and for stocks in the top third (H) and bottom third (L) of each characteristic's distribution. We sort on previous year's residual analyst coverage (from I/B/E/S), the percentage of shares outstanding held by institutions (from Spectrum), beginning-of-year price per share, contemporaneous monthly turnover, and contemporaneous change in institutional holdings, where residuals are calculated from a regression of the characteristic on relative size (*RSIZE*) with time fixed effects. Panel A shows monthly excess returns and alphas (annualized) and the corresponding $t$-statistics (in parentheses). Panel B reports the average spread in log failure probability ($\hat{P}$) across safe/distressed stocks and average relative size (*RSIZE*) of stocks in long-short (LS) portfolios. Panel C reports annualized percentage returns per unit of log $\hat{P}$ calculated by running regressions of LS excess returns and alphas on the spread in log $\hat{P}$. $^{*}$denotes significant at 5%, $^{**}$denotes significant at 1%.

| Characteristics | | Analyst Coverage | | Institutional Holdings | | Price | | Turnover | | Change in Holdings | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Long-short portfolios | Overall | H | L | H | L | H | L | H | L | H | L |
| | | | | Panel A. Portfolio Returns | | | | | | | |
| Mean excess return | 6.30 | 0.01 | 10.10 | 2.65 | 12.23 | 7.05 | 12.94 | −17.91 | 26.75 | −2.13 | 10.91 |
| | (1.41) | (0.00) | (2.21)$^{*}$ | (0.57) | (2.27)$^{*}$ | (1.59) | (2.89)$^{**}$ | (3.23)$^{**}$ | (6.40)$^{**}$ | (0.50) | (2.18)$^{*}$ |
| 3-factor alpha | 17.27 | 11.62 | 20.68 | 11.93 | 22.60 | 15.57 | 22.81 | −6.45 | 36.52 | 6.41 | 20.82 |
| | (5.34)$^{**}$ | (3.03)$^{**}$ | (5.94)$^{**}$ | (3.55)$^{**}$ | (5.36)$^{**}$ | (4.22)$^{**}$ | (6.53)$^{**}$ | (1.41) | (11.76)$^{**}$ | (1.89) | (5.12)$^{**}$ |
| | | | | Panel B. Portfolio Characteristics | | | | | | | |
| Spread in log $\hat{P}$ | 2.14 | 1.86 | 2.06 | 1.96 | 2.01 | 1.80 | 2.16 | 2.16 | 2.16 | 1.91 | 2.04 |
| Average *RSIZE* | −8.14 | −7.58 | −8.38 | −7.98 | −8.08 | −7.61 | −8.43 | −8.23 | −8.33 | −8.01 | −7.97 |
| | | | | Panel C. $\hat{P}$-Adjusted Returns | | | | | | | |
| Mean excess return | 1.97 | −0.64 | 3.54 | 0.03 | 4.31 | 1.82 | 4.78 | −8.91 | 10.73 | −2.50 | 4.54 |
| | (1.00) | (0.25) | (1.67) | (0.01) | (1.67) | (0.80) | (2.41)$^{*}$ | (3.73)$^{**}$ | (5.73)$^{**}$ | (1.18) | (1.96) |
| 3-factor alpha | 7.66 | 6.39 | 9.47 | 5.73 | 10.79 | 7.15 | 9.68 | −2.96 | 15.85 | 3.27 | 10.34 |
| | (5.56)$^{**}$ | (3.42)$^{**}$ | (6.05)$^{**}$ | (3.66)$^{**}$ | (5.49)$^{**}$ | (3.85)$^{**}$ | (6.43)$^{**}$ | (1.54) | (11.79)$^{**}$ | (2.03)$^{*}$ | (5.74)$^{**}$ |

The second pair of columns repeats this exercise for stocks with high and low residual analyst coverage. Following Hong, Lim, and Stein (2000), we regress the log of one plus the number of analysts covering each firm, as reported by I/B/E/S, on the firm's relative size and time dummies, and take the residual to avoid sorting stocks by a characteristic that is highly correlated with size. Stocks whose residual analyst coverage is in the top third of the distribution are defined as having high coverage, while stocks whose coverage is in the bottom third of the distribution are defined as having low coverage. We sort stocks within each group by financial distress, and find that the long-short portfolio holding the safest quintile and shorting the most distressed quintile outperforms in both groups, but more strongly among low-analyst-coverage stocks. The stocks with low analyst coverage do have a somewhat greater spread in failure probability, but even after correcting for this in Panel C, the distress anomaly is still stronger for these stocks.

We find similar results in the third pair of columns. Here, we sort stocks by residual institutional holdings, using 13-F filings data processed by Kovtunenko and Sosner (2003) and taking the residual from a regression of the institutional ownership share on relative size. The distress anomaly appears to be stronger when individuals, who are presumably less sophisticated investors, own a large fraction of a company's shares. Nagel (2005) finds similar results for several other anomalies and attributes this to the fact that individual investors are less likely to lend out their shares, so short selling is harder for stocks with low institutional ownership.

The fourth and fifth pair of columns looks at two measures of liquidity, the price per share and the contemporaneous monthly turnover in a stock, again measured using residuals from a regression on size. The distress anomaly is slightly stronger among low-priced stocks, and very much stronger among stocks with low turnover; in fact, distressed stocks with high turnover actually outperform safe stocks with high turnover. Note, however, that this turnover effect cannot be used in a trading rule as turnover is not known in advance. Although there is some persistence in monthly turnover, lagged turnover does not generate the same pattern.

The last pair of columns looks at the contemporaneous change in institutional holdings. The distress anomaly is concentrated among stocks that institutions are selling, and is very much weaker among stocks that institutions are buying. If we split the long-short returns into the excess returns on the longs and the shorts, we find that the distress anomaly results primarily from the underperformance of distressed stocks that institutions are selling.

### *B. What Explains the Low Returns of Distressed Stocks?*

What can explain the anomalous underperformance of distressed stocks? We consider three explanations in turn: unexpected events in our sample period, valuation errors by irrational or imperfectly informed investors, and characteristics of distressed stocks that may induce even rational investors to hold them despite their low average returns.

First, the distress anomaly may result from unexpected developments during our sample period. That is, it may be an in-sample phenomenon that is unlikely to continue in the future. Our sample period generally had strong economic growth, so it is not likely that macroeconomic news was worse than expected, but debtholders may have become more adept at forcing bankruptcy or transferring resources from equityholders to debtholders after default occurs.[16]

Another development that may have been unexpected is the strong shift of equity ownership from individuals to institutions during this period. Kovtunenko and Sosner (2003) document that institutions prefer to hold profitable stocks, and that this preference helped institutional performance during the 1980s and 1990s because profitable stocks outperformed the market. It is possible that the strong performance of profitable stocks in this period was endogenous, the result of demand for these stocks by rapidly growing institutional investors. If institutions more generally prefer stocks with low failure risk, and tend to sell stocks that enter financial distress, then a similar mechanism could drive our results. A piece of circumstantial evidence in favor of this hypothesis is that the outperformance of the portfolio that is long safe stocks and short distressed stocks is concentrated in periods such as the late 1980s, when aggregate institutional ownership was growing rapidly. There is a positive correlation of 0.29 between the excess return on the long-short portfolio and the change in the overall institutional share in the U.S. equity market reported by Binay (2005). The importance of institutional preferences is also suggested by the findings of Table VIII that distressed stocks underperform more strongly when institutions have a low ownership share and particularly when the institutional ownership share is declining.

Second, our predictors of financial distress may be correlated with valuation errors. For example, investors may not have fully understood the relation between our predictive variables and failure risk, and so may not have discounted the prices of high-risk stocks enough to offset their failure probability. Or, more simply, investors may not have understood that the variables in our model predict low future profitability.

One might suppose that valuation errors will disproportionately be resolved by the information revealed in earnings announcements. La Porta (1996) and La Porta et al. (1997) show that a large fraction of the superior returns to value stocks are earned in short periods of time around earnings announcements, and use this observation to argue that the value premium results from mispricing. We conduct a similar analysis for financially distressed stocks, reporting the results in Table IX. Panel A of the table shows the average excess returns on the distressed-stock portfolios of Table VI, using only the returns realized during a 3-day window around earnings announcements. There is no tendency for distressed-stock portfolios to do particularly poorly around earnings announcements; instead, the most distressed stocks actually outperform

[16] We thank Myron Scholes for suggesting this explanation of our results. Garlappi, Shu, and Yan (2006) also emphasize the bargaining between equityholders and debtholders in bankruptcy.

**Table IX**

**Earnings Announcement Returns**

We sort all stocks based on the predicted 12-month probability of failure and divide them into 10 portfolios based on percentile cutoffs (as in Table VI), for example, 0 to 5th percentile (0005) and 99th to 100th percentile (9900). Panel A reports 3-day ($t-1, t+1$) excess returns over the equally weighted market index during earnings announcements. In Panel B, we report earnings-announcement-adjusted mean excess returns over the market, as well as one factor (*RM*), Fama-French three-factor (*RM, HML, SMB*) and four factor (*RM, HML, SMB, UMD*) alphas (in annualized percent units) and the corresponding $t$-statistics below. *denotes significant at 5%, **denotes significant at 1%. Before calculation of the portfolio return we adjust individual stock returns to eliminate any abnormal returns around earnings announcements. Specifically, we replace individual stock returns for the 3-day ($t-1, t+1$) earnings announcement window with the return on a benchmark. The benchmark return is simply the return on factor portfolios during the 3-day earnings announcement window, calculated using the estimated factor loadings from Table VI.

| Portfolios | 0005 | 0510 | 1020 | 2040 | 4060 | 6080 | 8090 | 9095 | 9599 | 9900 | LS1090 | LS2080 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Panel A. Three-Day Earnings Announcement Returns | | | | | | | | | | | | |
| Mean excess return | 0.413 | 0.104 | 0.024 | 0.034 | −0.010 | 0.101 | 0.146 | 0.424 | 0.197 | 0.111 | | |
| | (7.37)** | (1.89) | (0.64) | (1.29) | (0.37) | (3.16)** | (2.61)** | (4.39)** | (1.53) | (0.34) | | |
| Panel B. Earnings-Announcement-Adjusted Portfolio Alphas | | | | | | | | | | | | |
| Mean excess return | 2.40 | 1.55 | 0.38 | 0.38 | −0.52 | −0.34 | −3.49 | −9.18 | −6.40 | −14.81 | 10.02 | 5.24 |
| | (1.05) | (0.70) | (0.32) | (0.42) | (0.37) | (0.15) | (1.01) | (2.05)* | (1.21) | (1.86) | (1.91) | (1.20) |
| CAPM alpha | 1.82 | 1.31 | 0.55 | 0.94 | −0.55 | −1.79 | −5.64 | −12.06 | −9.00 | −16.93 | 12.40 | 7.46 |
| | (0.80) | (0.59) | (0.47) | (1.08) | (0.39) | (0.80) | (1.68) | (2.80)** | (1.73) | (2.14)* | (2.40)* | (1.75) |
| 3-factor alpha | 4.99 | 4.77 | 1.97 | 0.36 | −2.97 | −5.83 | −11.52 | −18.92 | −15.55 | −22.84 | 22.64 | 15.95 |
| | (2.71)** | (2.51)* | (1.85) | (0.46) | (2.62)** | (3.36)** | (4.41)** | (6.31)** | (4.01)** | (3.32)** | (6.44)** | (5.23)** |
| 4-factor alpha | 1.62 | 2.60 | 0.91 | 1.50 | −0.15 | −1.25 | −4.78 | −10.84 | −7.77 | −19.04 | 12.24 | 6.96 |
| | (0.90) | (1.39) | (0.86) | (1.98)* | (0.14) | (0.79) | (1.98)* | (3.94)** | (2.10)* | (2.77)** | (3.86)** | (2.52)* |

at these times, possibly because the ability to announce earnings is itself good news for companies that are in severe financial difficulty. Panel B of Table IX calculates excess returns and alphas to distressed-stock portfolios, taking out the 3-day windows around earnings announcements. That is, we calculate the alphas for an investment strategy that holds distressed stocks most of the time, but replaces them with factor portfolios for 3 days around each stock's earnings announcement. The alphas shown in Panel B of Table IX are almost identical to those reported in Table VI. These results do not support the view that distressed stocks underperform because investors are overoptimistic about their future earnings.

One might also suppose that valuation errors are more likely to be correlated with sophisticated failure predictors, such as those we added to Shumway's (2001) model, than with obvious predictors such as leverage and profitability.[17] The latter variables have always been followed by practitioners, and academics have used them to predict failure at least since the late 1960s (Beaver (1966) and Altman (1968)). To explore the relative importance of obvious and sophisticated variables, in Panel A of Table X, we report disaggregated estimates of the ability of each of our failure predictors to forecast future stock returns. These estimates are based on repeated cross-sectional multiple regressions of returns on the full set of failure predictors; following Fama and MacBeth (1973), we report the time-series means of the cross-sectional coefficients, and standard errors computed from the time-series variability of those coefficients. For comparison, Panel B of Table X also repeats the failure coefficients reported in Table IV.

Column 1 of Table X predicts monthly returns using variables measured at the start of each year, analogous to the sorting procedure we used in Table IX. In this regression, all the explanatory variables enter significantly with the exception of market capitalization. Of the significant variables, five enter with a sign opposite to that in the failure prediction regression—that is, they contribute to the low returns on distressed stocks—and two, leverage and stock price, enter with the same sign that they have in the failure prediction regression. Highly leveraged stocks are more likely to fail, but have delivered high average returns, while stocks with high prices are less likely to fail, but have delivered low average returns. The former pattern may result from the salience of leverage to even unsophisticated investors, while the latter may reflect the value effect, imperfectly captured by the market-to-book ratio, or the size effect, imperfectly captured by our measure of relative market capitalization. Column 2 of Table X repeats the regression using predictor variables measured at the start of each month. Results are similar except that lagged returns no longer enter the regression significantly, perhaps because short-term reversal now offsets medium-term momentum.

Overall, Table X shows that the low returns to distressed stocks result from many of the variables in our failure prediction model. They reflect more than just momentum in stocks with bad news (Hong, Lim, and Stein (2000)) or low

[17] In a similar spirit, Franzoni and Marin (2006) argue that firms with underfunded pension plans underperform because pension plan funding status is not of obvious significance to investors.

**Table X**

## Comparison of Equity Return and Failure Predictors

This table reports coefficients on explanatory variables when predicting failure and equity returns. Panel A reports coefficients from Fama–MacBeth return prediction regressions. We run monthly regressions of returns on characteristics and a constant for the sample of returns included in portfolios in Table VI, that is, for the period 1981 to 2003. We average the individual coefficients over time and report the mean and standard error of the mean in percent. We run regressions both using beginning-of-year and beginning-of-month characteristics. In Panel B, we report coefficients from taking our best-model variables and predicting failure at different horizons. The numbers correspond to those reported in Table IV. The absolute value of $z$-statistics is reported in parentheses. *denotes significant at 5%, **denotes significant at 1%.

| Panel A. Return Prediction | | | Panel B. Failure Prediction | | | |
|---|---|---|---|---|---|---|
| Characteristic Observed: | Beginning of Year | Beginning of Month | Lag (Months) | 0 | 6 | 12 |
| *NIMTAAVG* | 14.55 | 38.99 | | −29.67 | −23.92 | −20.26 |
| | (4.09)** | (11.02)** | | (23.37)** | (21.82)** | (18.09)** |
| *TLMTA* | 0.58 | 0.74 | | 3.36 | 2.06 | 1.42 |
| | (2.76)** | (3.65)** | | (27.80)** | (22.63)** | (16.23)** |
| *EXRETAVG* | 11.50 | 0.88 | | −7.35 | −7.79 | −7.13 |
| | (6.78)** | (0.40) | | (14.03)** | (15.97)** | (14.15)** |
| *SIGMA* | −0.96 | −2.05 | | 1.48 | 1.27 | 1.41 |
| | (2.68)** | (5.85)** | | (13.54)** | (14.57)** | (16.49)** |
| *RSIZE* | 0.02 | −0.02 | | 0.08 | 0.05 | −0.05 |
| | (0.48) | (0.45) | | (2.62)** | (2.02)* | (2.09)* |
| *CASHMTA* | 2.93 | 4.33 | | −2.40 | −2.40 | −2.13 |
| | (8.49)** | (11.42)** | | (8.64)** | (9.77)** | (8.53)** |
| *MB* | −0.19 | −0.05 | | 0.05 | 0.05 | 0.08 |
| | (6.61)** | (1.59) | | (4.87)** | (4.22)** | (6.33)** |
| *PRICE* | −0.62 | −0.80 | | −0.94 | −0.47 | −0.06 |
| | (5.41)** | (6.64)** | | (14.77)** | (10.36)** | (1.40) |

returns to volatile stocks (Ang et al. (2006)). Some of the standard variables we include in our model, such as recent profitability, are significant return predictors, implying that low returns to distressed stocks are not just the result of sophisticated variables identified by our econometric analysis.

More generally, the stocks that our model identifies as distressed move with aggregate market conditions in the way that one would expect if investors understand them to be risky. Figure 5 plots the cumulative return to our portfolio long the safest decile of stocks and short the riskiest decile, together with the implied volatility (VIX) on the S&P 500 index, over the period since 1990 for which we have VIX data. The correlation of the monthly portfolio return with the change in the VIX is 0.22. This positive correlation is consistent with the view that investors "flee to quality," selling distressed stocks when market risk or risk aversion increase as measured by the VIX. It is also consistent with the positive correlation between credit spreads and the VIX documented in the literature on corporate bonds and credit default swaps (Berndt et al. (2005), Pan and Singleton (2008), and Schaefer and Strebulaev (2008)). If investors

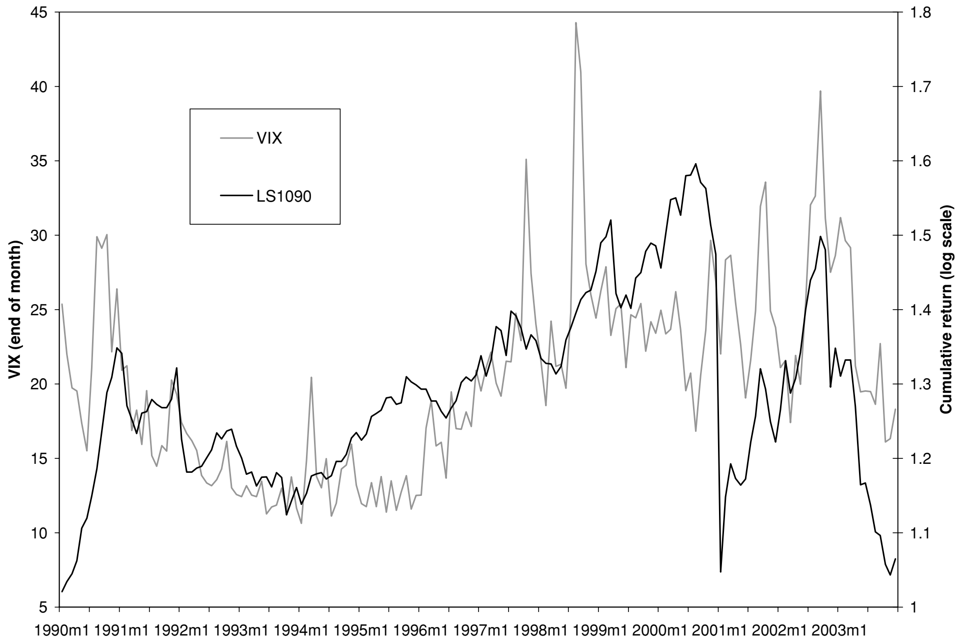


**Figure 5. VIX and returns on long-short distressed stock portfolio.** The figure plots the VIX and the cumulative return on the LS1090 portfolio, which goes long the 10% safest stocks and short the 10% most distressed stocks.

were completely unable to distinguish between stocks with high and low failure probabilities, we would not expect this pattern. Of course, this finding leaves open the possibility that investors perceive cross-sectional differences in failure probabilities but underestimate their importance.

Third, some investors may have motives to hold distressed stocks despite their tendency to underperform. These motives are not captured by standard models of risk and return, since we have shown that risk adjustment for size and value effects worsens the underperformance of distressed stocks, and adjustment for momentum reduces but does not eliminate it. Adjustment for volatility risk (Ang et al. (2006)) would also worsen the underperformance of distressed stocks since these stocks do poorly when the VIX increases, and investors normally require compensation for such a correlation.

Two other motives may be relevant, however. First, Barberis and Huang (2008) model the behavior of investors whose preferences satisfy the cumulative prospect theory of Tversky and Kahneman (1992). Such investors have a strong desire to hold positively skewed portfolios, and may even hold undiversified positions in positively skewed assets. Barberis and Huang argue that this effect can explain the high prices and low average returns on IPOs, whose returns are positively skewed. In a related study, Zhang (2006) finds that industries with a positively skewed cross-sectional return distribution tend to have low average returns. The same effect could be at work here, because Table VI shows that both individual distressed stocks and our portfolios of distressed stocks offer returns with strong positive skewness. Second, von Kalckreuth (2005) argues that majority owners of distressed companies can extract private benefits, for example, by buying the company's output or assets at bargain prices. The incentive to extract such benefits is greater when the company is unlikely to survive and generate future profits for its shareholders. Thus, majority owners may hold distressed stock, rather than selling it, because they earn a greater return than the return we measure to outside shareholders.

These hypotheses have the potential to explain why some investors hold distressed stocks despite their low average returns, but they do not explain why rational outside investors fail to arbitrage the distress anomaly. Although Table VII shows that the distress anomaly is found in both small and large stocks, there is a wider spread in financial distress among small stocks, which are generally harder to arbitrage. Further, controlling for size, Table VIII shows that the distress anomaly is stronger among less liquid stocks that are less favored by analysts and institutional investors. These patterns suggest that sophisticated investors trading on financial distress are likely to face significant arbitrage costs.

## IV. Conclusion

This paper makes two main contributions to the literature on financial distress. First, we carefully implement a reduced-form econometric model to predict corporate bankruptcies and failures at short and long horizons. Our best model has greater explanatory power than the existing state-of-the-art models estimated by Shumway (2001) and Chava and Jarrow (2004), and includes additional variables with sensible economic motivation. We believe that models of the sort estimated here have meaningful empirical advantages over the bankruptcy risk scores proposed by Altman (1968) and Ohlson (1980). While Altman's $Z$-score and Ohlson's $O$-score were seminal early contributions, better measures of bankruptcy risk are available today. We also present evidence that failure risk cannot be adequately summarized by a measure of distance to default inspired by Merton's (1974) pioneering structural model. While our distance to default measure is not exactly the same as those used by Crosbie and Bohn (2001) and Vassalou and Xing (2004), we believe that this result, similar to that reported independently by Bharath and Shumway (2008), is robust to alternative measures of distance to default.

Second, we show that stocks with a high risk of failure tend to deliver anomalously low average returns. We sort stocks by our 12-month-ahead estimate of failure risk, calculated from a model that uses only historically available data at each point in time. We calculate returns and risks on portfolios sorted by failure risk over the period 1981 to 2003. Distressed portfolios have low average returns, but high standard deviations, market betas, and loadings on Fama and French's (1993) small-cap and value risk factors. They also tend to do poorly when marketwide implied volatility increases. Thus, from the perspective of any of the leading empirical asset pricing models, these stocks have negative alphas. This result is a significant challenge to the conjecture that the value and size effects are proxies for a financial distress premium. More generally, it is a challenge to standard models of rational asset pricing in which the structure of the economy is stable and well understood by investors.

Some previous authors report evidence that distressed stocks underperform the market, but results vary with the measure of financial distress that is used. Our results are consistent with the findings of Dichev (1998), who uses Altman's *Z*-score and Ohlson's *O*-score to measure financial distress; Garlappi, Shu, and Yan (2008), who obtain default risk measures from Moody's KMV; and Avramov et al. (2006), who use credit ratings to measure firms' financial status. Vassalou and Xing (2004) calculate distance to default; they find some evidence that distressed stocks with a low distance to default have higher returns, but this evidence comes entirely from small value stocks. Da and Gao (2008) argue that Vassalou and Xing's distressed-stock returns are biased upwards by 1-month reversal and bid-ask bounce. Griffin and Lemmon (2002), using *O*-score to measure distress, find that distressed growth stocks have particularly low returns. Our measure of financial distress generates underperformance among distressed stocks in all quintiles of the size and value distributions. The underperformance is more dramatic among small stocks, but this is due to the fact that these stocks have a wider spread in financial distress; the return scaled by log failure probability is roughly constant across the size distribution.

We discuss a number of possible explanations for the anomalously low returns on distressed stocks. It is possible that unexpected developments during our sample period—such as increased power to debtholders in bankruptcy, or increased equity ownership by institutions with a preference for safe stocks—have driven down the prices of distressed stocks. A second obvious possibility is that investors make valuation errors, overpricing these stocks because they fail to understand their poor prospects. This simple story may be correct, but we do not find that valuation errors are corrected when distressed stocks make earnings announcements, and we do not find any strong tendency for poor returns to be associated with the more subtle and less obvious variables in our failure prediction model. A third possibility is that distressed stocks have characteristics that appeal to certain investors, such as increased opportunities to extract private benefits of control (von Kalckreuth (2005)) or positive skewness of returns (Barberis and Huang (2007) and Zhang (2006)). We have no direct evidence that distressed stocks offer private benefits to majority shareholders, but we do find that these stocks offer positively skewed returns regardless of whether they are held in concentrated or diversified portfolios.

Finally, we show that controlling for firm size, the distress anomaly is stronger among stocks with low analyst coverage, institutional ownership, price per share, and turnover. These findings would be difficult to explain using a fully rational model in which investors have homogeneous beliefs and preferences. Instead, they suggest that the anomaly is driven by behavioral factors but is expensive for sophisticated investors to arbitrage. Information disseminates more slowly when fewer analysts cover a stock (Hong, Lim, and Stein (2000)); short selling a stock is likely to be more difficult when there are few institutional investors ready to lend their shares (Nagel (2005)); and a stock with a low price per share and low turnover is likely to be expensive to trade in any quantity. These limits to arbitrage help us to understand how the distress anomaly has persisted into the 21st century.

## Appendix

In this appendix, we discuss issues related to the construction of our data set. All variables are constructed using COMPUSTAT and CRSP data. Relative size, excess return, and accounting ratios are defined as follows:

$$
\begin{aligned}
RSIZE_{i,t} &= \log\left(\frac{Firm\ Market\ Equity_{i,t}}{Total\ S\&P500\ Market\ Value_t}\right)\\
EXRET_{i,t} &= \log(1+R_{i,t}) - \log(1+R_{S\&P500,t})\\
NITA_{i,t} &= \frac{Net\ Income_{i,t}}{Total\ Assets\ (adjusted)_{i,t}}\\
TLTA_{i,t} &= \frac{Total\ Liabilities_{i,t}}{Total\ Assets(adjusted)_{i,t}}\\
NIMTA_{i,t} &= \frac{Net\ Income_{i,t}}{(Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t})}\\
TLMTA_{i,t} &= \frac{Total\ Liabilities_{i,t}}{(Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t})}\\
CASHMTA_{i,t} &= \frac{Cash\ and\ Short\ Term\ Investments_{i,t}}{(Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t})}.
\end{aligned}
$$

The COMPUSTAT quarterly data items used are Data44 for total assets, Data69 for net income, and Data54 for total liabilities.

To deal with outliers in the data, we correct both *NITA* and *TLTA* using the difference between market equity (*ME*) and book equity (*BE*) to adjust the value of total assets:

$$Total\ Assets\ (adjusted)_{i,t} = TA_{i,t} + 0.1(ME_{i,t} - BE_{i,t}).$$

Book equity is as defined in Davis, Fama, and French (2000) and outlined in detail in Cohen, Polk, and Vuolteenaho (2003). This transformation helps with the values of total assets that are very small and probably mismeasured, and that lead to very large values of *NITA*. After total assets are adjusted, each of the seven explanatory variables is winsorized using a 5/95 percentile interval in order to eliminate outliers.

To measure the volatility of a firm's stock returns, we use a proxy, centered around zero rather than the rolling 3-month mean, for daily variation of returns computed as an annualized 3-month rolling sample standard deviation:

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

To eliminate cases in which few observations are available, *SIGMA* is coded as missing if there are fewer than five nonzero observations over the 3 months used in the rolling window computation. In calculating summary statistics and estimating regressions, we replace missing *SIGMA* observations with the cross-sectional mean of *SIGMA*; this helps us avoid losing some failure observations for infrequently traded companies. A dummy for missing *SIGMA* does not enter our regressions significantly. We use a similar procedure for missing lags of *NIMTA* and *EXRET* in constructing the moving average variables *NIMTAAVG* and *EXRETAVG*.

In order to calculate distance to default, we need to estimate asset value and asset volatility, neither of which are directly observable. We construct measures of these variables 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. Then:

$$ME = TA_{DD} N(d_1) - BD \exp(-R_{BILL} T) N(d_2)$$

$$d_1 = \frac{\log\left(\frac{TA_{DD}}{BD}\right) + \left(R_{BILL} + \frac{1}{2} SIGMA_{DD}^2\right) T}{SIGMA_{DD}\sqrt{T}}$$

$$d_2 = d_1 - SIGMA_{DD}\sqrt{T},$$

where $TA_{DD}$ is the value of assets, $SIGMA_{DD}$ is the volatility of assets, $ME$ is the value of equity, and $BD$ is the face value of debt maturing at time $T$. Following convention in the literature on the Merton model (Crosbie and Bohn (2001) and Vassalou and Xing (2004)), we assume $T = 1$ and use short-term plus one half long-term book debt to proxy for the face value of debt $BD$. This convention is a simple way to take account of the fact that long-term debt may not mature until after the horizon of the distance to default calculation. We measure the risk-free rate $R_{BILL}$ as the Treasury bill rate.

The second equation is a relation between the volatility of equity and the volatility of assets, often referred to as the optimal hedge equation:

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

As starting values for asset value and asset volatility, we use $TA_{DD} = ME + BD$ and $SIGMA_{DD} = SIGMA(ME/(ME + BD))$. We iterate until we find values for $TA_{DD}$ and $SIGMA_{DD}$ that are consistent with the observed values of $ME$, $BD$, and $SIGMA$.

If $BD$ is missing, we use $BD = median(BD/TL) * TL$, where the median is calculated for the entire data set. This captures the fact that empirically, $BD$

tends to be much smaller than $TL$. If $BD = 0$, we use $BD = median(BD/TL) * TL$, where now we calculate the median only for small but nonzero values of $BD$ ($0 < BD < 0.01$). If $SIGMA$ is missing, we replace it with its cross-sectional mean. 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. We also winsorize $SIGMA$ in the same way. This significantly reduces instances in which the search algorithm does not converge.

Finally, we 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. Vassalou and Xing (2004) instead estimate the average return on each stock, while Hillegeist et al. (2004) calculate the drift as the return on assets during the previous year. If the estimated expected return is negative, they replace it with the riskfree interest rate. We believe that it is better to use a common expected return for all stocks than a noisily estimated stock-specific number.

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