Is Default-Risk Negatively Related to Stock Returns?

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Abstract

In contrast to theoretical arguments suggesting a positive risk-return relation, financially distressed stocks have delivered anomalously low returns during the post-1980 period. We argue that detecting the true default-risk-return relation using realized returns as a proxy for expected returns is a challenging task in small samples. Using implied cost of capital computed from analysts forecasts as a measure of ex-ante expected returns, we find an economically and statistically significant *positive* relation between default-risk and expected returns. Extending the sample period back to 1953, we show that there is *no* anomalous negative relation between default-risk and realized returns during the pre-1980 period. Our evidence suggests that investors expected positive returns for bearing default-risk, but in the post-1980 period, especially in the decade of 1980, they were negatively surprised.

JEL Codes: G11, G12, G13, G14.

Keywords: Default-risk, bankruptcy, expected return, realized return, implied cost of capital.

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1 Introduction

Recently, there has been a considerable interest in understanding the relation between default-risk and stock returns. If distress-risk is systematic, then investors should demand a positive risk-premium for bearing this risk as postulated by the classical asset pricing theory. Standard implementation of Capital Asset Pricing Model might fail to completely capture the distress-risk premium if corporate failures are correlated with deterioration in investment opportunities (Merton (1973)) or unmeasured components of wealth such as human capital (Fama and French (1996)) and debt securities (Ferguson and Shockley (2003)). In contrast to the theoretical prediction, recent empirical studies (Dichev (1998) and Campbell, Hilscher and Szilagyi (2007) among others) document an anomalous negative relation between various measures of default-risk and realized stock returns. This finding has important implications for our understanding of the risk-reward relation in the financial markets. Further, the evidence suggests that the cost of equity capital decreases with default-risk, which has important implications for several corporate financing theories.

At first glance, the negative relation between default-risk and equity returns documented in the literature can be taken as evidence in support of market inefficiency. However, it remains unclear why some rational investors are not able to arbitrage away the distress anomaly. We argue that in small samples it is difficult to uncover the true risk-return relation using realized return as a proxy for the expected return (Elton (1999)), especially for the portfolio of high distress-risk stocks given their high volatility. As an alternative to realized returns, we use the implied cost of capital computed using analyst forecasts as a measure of the market's ex-ante expectations (see Pastor, Sinha and Swaminathan (2007)) and find a strong *positive* relation between default-risk and expected stock return. Additionally, we extend the sample period back to 1953 and show that the distress-risk anomaly is absent during the pre-1980 period, even using realized return as a proxy for expected return. Finally, a closer investigation of the post-1980 period shows that the under-performance is mainly concentrated in the decade of 1980.

Consider a portfolio of high default-risk stocks based on a measure of default-risk such as the hazard-model-based probability of distress (Shumway (2001) and Chava and Jarrow (2004)). The key issue from the financial economics perspective is whether the investors of these distressed stocks expect to earn positive risk-premium or not. Equivalently, the key issue is whether they discount the expected future cash-flows sufficiently to account for the risk of these stocks or not. If they expected to earn *negative* risk-premium as in line with the low realized return result in the post-1980 period, then we need to focus more closely on market frictions or investor preferences and enrich our current theoretical models to reconcile the empirical evidence with theoretical predictions. On the other hand, if they expected to earn positive risk-premium, but were negatively surprised in the post-1980 period, then the evidence of low returns on high distress-risk portfolio does not represent an anomaly. In that case, low returns in the post-1980 period can be attributed to a statistical chance and to the difficulty in using realized returns as a proxy for expected returns, which makes the evidence consistent with the theoretical models that we already have.

Elton (1999) argues that realized return is a very poor measure of expected return and uncovering true risk-return relation using a few years of realized returns can be a very challenging empirical task. He provides examples to demonstrate that even for reasonably long time-periods the relation between realized return and risk can be anomalously negative. For example, for a ten year period (1973-1984) the average realized return on market was less than the risk-free rate in the US, and for more than fifty years (1927-1981) risky long-term bonds on average under-performed risk-free rate. He argues that significant information events such as large earnings surprises might not cancel each other out in small periods of study, which in turn makes realized return a poor proxy for the expected return. Further, if large information shocks affect many stocks in a portfolio in similar ways, then even the portfolio-level returns is unlikely to solve this problem. Earlier contributions by Blume and Friend (1973) and Sharpe (1978) also highlight the fact that realized returns maybe very noisy. Merton (1980) shows that estimating the first moment of returns is a difficult empirical task in small samples. Using simulations, Lundblad (2006) shows that a very long sample of realized returns is needed to establish a positive relation between risk and return. He finds that the higher the volatility of return process, the longer the sample period needed to detect the true relation between risk and return inherent in the underlying data generating process.

By construction, the average stock in high default-risk portfolio is more likely to default in future, which contributes negatively to the average portfolio return. The positive portfolio return must, therefore, come from some stocks that perform really well. This in turn implies that the return volatility of such a portfolio is likely to be very high, an assertion that is strongly supported by the data. Further, if a stock performs very well in the first year after portfolio formation, it is likely to be classified out of high default group in the next portfolio re-balancing year. For such a strategy, typically used in the extant literature, the distressed-stock investor must earn large positive returns on some of his holdings within a year itself. Such re-balancing further adds to the volatility of high default-risk portfolio. Further, stocks in this portfolio are all likely to be affected by common shocks or information surprises that affect marginal firms of the economy in general. This implies that even at a portfolio level, the information surprises might not cancel each other out in small samples (Elton (1999)). Motivated by these arguments, in this paper we seek to understand the risk-return relationship for the portfolios of high distress-risk stocks by (a) focussing on other measures of expected returns rather than realized returns, and (b) by using longer sample periods of realized returns.

Pastor, Sinha and Swaminathan (2007) develop the argument on expected vs. realized returns further and propose a solution based on a different proxy of expected return. As an alternative to the realized return, they advocate the use of the implied cost of capital as a proxy for expected return and provide some theoretical underpinnings for the usefulness of this measure in uncovering inter-temporal risk-return relation. In particular, they show that under reasonable assumptions about the dividend growth and expected return processes, implied cost of capital can be a very good proxy for expected returns. Similar to Gebhardt, Lee, and Swaminathan (2001), they compute the implied cost of capital as the internal rate of return that equates current market price to the discounted value of future cash-flows based on the analyst forecasts. Brav, Lehavy, and Michaely (2003) use a measure of expected return from Value Line database to uncover the relation between market beta and expected return.[1]

In our first test we use the implied cost of capital as a measure of expected return to test the distress-risk-return trade-off. As predicted by theory, we find a significant *positive* relation between default-risk and expected returns using this measure. We find that the stocks in top 1% of distress likelihood are expected to earn about 1.30-1.60% more annual risk-premium than the median stock in our sample after controlling for firm characteristics such as size and book-to-market ratio. Our analysis reveals that investors sufficiently discounted the future earnings of high distress-risk firms to reflect its high risk. Thus, consistent with theoretical arguments, they did expect to earn positive risk-premium for bearing default-risk. An immediate concern with the use of implied cost of capital is the assumptions required by such a model with respect to growth rates and dividend forecasts. We use several robustness checks to ensure that our results are not driven by any specific set of model assumptions, parameter selection, analysts biases in forecasts, or stale earnings forecasts.

In our second test, using simple measures of default-risk we extend the sample period

[1]Other researchers have estimated similar proxies of expected return in different contexts. Friend, Westerfield, and Granito (1978), Kaplan and Ruback (1995), and Lee, Ng, and Swaminathan (2007) compute the implied cost of capital for a cross section of firms. Claus and Thomas (2001) use a similar approach to measure the ex-ante equity premium. Fama and French (2002) and Chen, Petkova and Zhang (2007) use dividend growth models to estimate the ex-ante expected returns at the market and portfolio levels, respectively.

back to 1953 based on the availability of COMPUSTAT and CRSP data and show that the realized portfolio return of distressed stocks is explained well by market factor and other well-known empirically motivated factors of asset pricing tests for 1953-1980 period. In the post-1980 period, we are able to very closely replicate the findings of anomalously negative return reported by Campbell, Hilscher and Szilagyi (2007). Thus, while we do find negative relation between default-risk and equity return in the last 25 years of our sample, it disappears in the earlier period. When we combine the two periods together (i.e., for the 1953-2006 period), as expected we find that the economic magnitude of anomalous negative return drops considerably for the entire period. A closer look at the post-1980 under-performance reveals that most of the under-performance in the post-1980 period comes from the decade of 1980.

Overall, we show that in the post-1980 period and especially in the decade of 1980, high default-risk stocks had realized returns that were on average lower than their expected values, i.e., investors were negatively surprised. In terms of *ex-ante* expectation, which is what matters for the risk-return trade-off, we do find a positive relation between default-risk and expected returns. The results from realized returns suggest that in the longer sample, where *ex-ante* expected returns should be close to the *ex-post* realized returns, the magnitude of the default-risk anomaly drops considerably and the anomaly even gets explained completely for several model specifications.

Though it remains a challenging task to empirically establish the source of this negative surprise, we draw upon the findings of some of the recent papers to shed some light on this. Avramov, Chordia, Jostova, and Philipov (2006) show that among the universe of rated firms, firms with poor credit rating earned low abnormal returns in the post-1984 period, which is consistent with studies on default risk and stock returns for all CRSP-COMPUSTAT firms. More important, they show that the under-performance is predominantly concentrated around rating downgrades. In the context of Elton's argument, rating downgrades can be the negative information events that makes realized returns a poor proxy. Avramov, Chordia, Jostova, and Philipov (2006) also show that firms with poor credit rating have much larger negative earnings surprises around rating downgrades as compared to the safer firms. These findings suggest that investors were negatively surprised by the cash-flow news of high default-risk stocks in the post-1980 period. While suggestive in nature, it is possible that the changes in bankruptcy law in the late 1970s or the increased presence of institutional investors who prefer safer stocks might have been responsible for these surprises in the 1980s. In particular, the under-performance in 1980s coincide well with the large number of bankruptcy filings in the mid-1980s as compared to the earlier decades (see Chava and Jarrow (2004) and Campbell, Hilscher and Szilagyi (2007)).

Our study is related to a growing literature on default-risk and equity returns. Lemmon and Griffin (2002) find that the pattern documented by Dichev (1998) is strong in growth firms. Building on the theoretical foundation of Fan and Sundaresan (2000), Garlappi, Shu, and Yan (2005) use the default-risk measure of Moody's KMV and argue that the potential violation of Absolute Priority Rule (APR) can help explain the negative relation between default-risk and stock returns. Vassalou and Xing (2004) find some evidence that distressed stocks, mainly in small value group, earn higher returns. George and Hwang (2007) argue that the negative relation between returns and leverage drives the negative relation between returns and estimates of default probabilities because default probability estimates are positively related to leverage.

The rest of the paper is organized as follows. Section 2 describes the construction of default-risk measures used in the study. We investigate the link between default-risk measures and expected returns in section 3. In Section 4, we revisit the relation between default-risk and realized returns using data from both post- and pre-1980 period. Section 5 provides a discussion of results and Section 6 concludes the paper.

2 Default-risk measures

We describe the construction of our key default-risk measures in this section before investigating its relation to the implied cost of capital (ICC) and realized returns in the rest of the paper. Analysis involving ICC and default-risk measures are limited to the post-1980 period due to the requirement of I/B/E/S data for this part of the study. For the realized return part, we investigate the relation between default-risk and returns for both pre- and post-1980 period.

There is a large literature on default-risk measures dating back to the seminal contributions by Altman (1968, 1977). In this paper, we use two main measures of default-risk in line with the recent work of Campbell, Hilscher and Szilagyi (2007). First, we estimate a hazard rate model based on the observed bankruptcies among domestic firms. Second, we compute the distance-to-default of every firm based on the option-pricing models. Hazard rate model provides the maximum likelihood estimate of a firm's default probability based on the empirical frequency of default and its correlation with various firm characteristics. Distance-to-default measure is theoretically motivated by the classical option-pricing models (Merton (1974)). In addition to these two measures, we also conduct our analysis with a naive model of default based on simple sorting on firm characteristics that are known to predict default. We restrict our attention to common stocks traded on NYSE, AMEX and NASDAQ stock exchanges (i.e., exchange-codes 1,2, and 3; and share-codes 10 and 11 on CRSP tapes).

2.1 Hazard rate model

The first class of default models we construct are *hazard models* in the spirit of Shumway (2001) and Chava and Jarrow (2004). Campbell, Hilscher and Szilagyi (2007) also focus primarily on hazard models. This measure uses historical default information to obtain a maximum likelihood estimate of default likelihood given firm characteristics at a given point in time. We use a comprehensive database of bankruptcies that includes the majority of bankruptcies (both Chapter 7 and Chapter 11) filed by public firms listed on AMEX, NYSE or NASDAQ during 1963-2005. As in Campbell, Hilscher and Szilagyi (2007), we use Chava and Jarrow (2004) bankruptcy data (extended to 2005). Firm level balance sheet information is from COMPUSTAT and the stock market data is from CRSP.

A limitation of this measure is that it requires historical bankruptcy data to estimate the probability of bankruptcy for future years. Due to this reason, earlier studies that focus on either estimating this measure or using this measure for portfolio formation strategy have concentrated on period after 1980. They consider bankruptcies up to 1980 as the starting point for estimating the hazard rate model and then update their model on a moving basis as more information becomes available for the future years. We follow these conventions and estimate hazard rate models from 1980 onwards.

We provide the methodological and estimation details in the Appendix A.1. Every year starting in 1980, we fit the hazard rate model using data available strictly up to the point of estimation to ensure no look-ahead bias in our analysis. We estimate the model as of the June 30^{th} of a year and sort stocks into different default-risk portfolios as of July 1 of that year. We construct out-of-sample default probabilities each year based on Shumway (2001) model with the following covariates: $\frac{\text{net income}}{\text{total assets}}$, $\frac{\text{total liabilities}}{\text{total assets}}$, idiosyncratic volatility of firm's stock returns over the past 12 months, excess return of the stock over the market, and $log(\frac{\text{market capitalization}}{\text{market capitalization of all NYSE, AMEX, NASDAQ}})$. We label the default measure based on this model as $Hazard_{shumway}$. In addition, as a robustness test for our implied cost of capital section, we also use a reduced-form version of this model by dropping the $log(\frac{\text{market capitalization}}{\text{market capitalization of all NYSE, AMEX, NASDAQ}})$ and excess return variables from the set of covariates - variables that directly depend on price levels. We do so to ensure that our implied cost of capital results are not driven by a mechanical positive correlation between low priced stocks and implied cost of capital. We call these estimates $Hazard_{reduced}$ in the paper.

In the Appendix A.1, we provide one estimation result of the base model that uses information on bankruptcy till year 2005. Default probability increases with leverage and stock return volatility and it decreases significantly with the firm's relative size and past stock returns. These findings are in line with earlier studies.

2.2 Option-pricing based model

The second class of models we employ are the structural models of default based on Merton (1974). In this method, a firm's equity is valued as a call option on firm value. Intuitively, the distance to default measures how many standard deviations away a firm's value is from its debt obligation i.e., the bankruptcy threshold. Based on this measure, we compute an Expected Default Frequency (EDF), which measures the default likelihood of a firm (see Duffie, Saita and Wang (2007)). We provide the estimation details in the Appendix A.2. As explained in detail there, computing EDF requires the estimation of the market value of the firm and volatility of firm's assets, both of which are unobservable. We closely follow Bharath and Shumway (2007) for the construction of the iterated distance to default. Bharath and Shumway (2007) also provide an easier alternative to the distance to default computation that has limited computational requirements. More importantly, they demonstrate that their simple measure does as well as the more complicated model of distance to default. We construct EDF using both approaches and only report results based on the simpler measure since they are very similar to the iterative measure, but easier to replicate.

The estimation of hazard rate model requires data on historical defaults and therefore limits our ability to conduct default-risk related study to post-1980 period only. The distance-to-default models, on the other hand, can be estimated without this knowledge. All the relevant inputs for estimating this model can be obtained from the CRSP and

COMPUSTAT databases, which in turn allows us to estimate this model from 1953 onwards. Thus, we are able to conduct out-of-sample tests for the relation between default-risk and realized return based on this measure. We discuss the COMPUSTAT survivorship bias for pre-1980 period in the robustness section. In particular, we show that our out-of-sample realized return based results are robust to a coarse model of default that can be estimated using CRSP variables only, which allows all CRSP firms to enter our portfolio.

Option pricing models upon which our EDF measure is based came into existence almost after two decades of the beginning of our sample period. We emphasize that we are not using the option pricing model to estimate the exact price of a firm's equity in our analysis. Our goal is to be able to rank and sort stocks into portfolio in such a way so that it is able to mimic any heuristic or model investors might have used for default-risk even before the advent of the option pricing models. Indeed there is some evidence in the literature suggesting that long before the discovery of Black-Scholes formula, investors had an intuitive grasp of the key determinants of derivative pricing (see Moore and Juh (2006)).

2.3 Leverage-sigma model

In addition to the more standard hazard rate and EDF measures, we use a simple sorting strategy that does not require the knowledge of either historical defaults or option-pricing model. Rather than estimating a model of default, as of July 1 of every year, we sort stocks based on their *leverage* and *equity return volatility* to assess their default likelihood. *Leverage* is the ratio of total debt of the firm (sum of long-term debt and short-term debt) to the market value of asset (sum of long-term debt, short-term debt and market value of equity). *volatility* is the standard deviation of the stock return computed using daily returns over the past one year. Theoretically, a firm's operating and financial risks are the key drivers of its bankruptcy risk. A firm with high volatility in operating business and with high leverage has higher likelihood of bankruptcy. We sort stocks into ten groups based on these two measures and classify stocks into top 1% of distress if a firm obtains a rank of 10 on each dimension.[2] Though coarse, the advantage of this model is that it doesn't require any assumptions on bankruptcy likelihood function (as in hazard rate model) or the model of default.

Table 1 presents the summary statistics for various default-risk measures over the time period 1980-2006. These numbers are in line with the earlier studies. In untabulated results, we find that the EDF and hazard rate model based estimates have about 77% rank correlation.[3] The correlation is high, but they do have some independent information in them. As we'll show later, we are able to closely replicate the negative abnormal realized returns for the post-1980 period using both these measures of default, which gives confidence in our use of both of these measures. This also ensures that our realized return result from the pre-1980 period, that uses EDF as a measure of default-risk, is not an artifact of a different model of default. We defer the discussion on default-risk and realized discussion to Section 4.

3 Expected Returns

We start our formal tests by investigating the relation between default-risk and implied cost of equity capital - our measure of ex-ante expected return based on analysts forecasts. We follow Pastor, Sinha and Swaminathan (2007) to compute this measure.

[2] Our simple sorting technique based on leverage and volatility is reasonably consistent with the more sophisticated sorting techniques based on hazard rate model or option pricing methodology. For example, over 85% of stocks sorted into top decile of each leverage and volatility measure are classified into top 10% of distress likelihood using the EDF measure. About 74% of firms that fall in top two deciles of both leverage and volatility dimension are classified into top 10% of EDF measure. And about 60% of firms that fall in top three deciles on both dimensions fall into top 10% of EDF.

[3] We compute the rank correlation between these measures on yearly basis from 1980 to 2005. The mean (median) correlation across these years works out to 76%(77%).

3.1 Estimation of implied cost of capital

We compute the implied cost of capital using a discounted cash-flow model of equity valuation. In this approach, the expected return on a stock is the internal rate of return that equates the present value of discounted free cash flows to equity to current stock price. The stock price of a firm i at time t can be represented as the following:

$$P_{i,t} = \sum_{k=1}^{k=\infty} \frac{E_t(FCFE_{i,t+k})}{(1 + r_{i,e})^k} \tag{1}$$

where $P_{i,t}$ is the time t stock price of firm i. $FCFE_{i,t+k}$ is the free cash flow to equity of the shareholders of firm i in year t+k. E_t is the expectation operator conditional on information available as of time t. In this equation, $r_{i,e}$ is the expected return on firm i's equity capital. We are interested in computing $r_{i,e}$ for every firm-year observation in our sample.

This method of computing expected return has two immediate advantages. First, it is a forward looking measure and thus a suitable proxy for expected returns. And second, it is free from any specific functional form of asset pricing model. Market price of a stock is obviously easily observable. So the key step in the implementation of this model is to come up with economically reasonable estimates of the free cash-flow to equity-holders of the firm. We follow earlier papers to do so in this paper.

Equation 1 represents the current stock price as a discounted sum of all future cash-flows extending up to infinite time horizon. The first step in the implementation of this model is to assume a terminal date (T) for the model and explicitly forecast cash-flows up to that date (i.e., $t + T$). The present value of cash-flows beyond terminal year is captured by a terminal value estimation. We estimate the free cash-flow to equity of firm i in year $t + k$ by using the following formula:

$$E_t(FCFE_{i,t+k}) = FE_{i,t+k} * (1 - b_{t+k}) \tag{2}$$

where $FE_{i,t+k}$ is the earnings estimate of firm i in year $t+k$ and b_{t+k} is its plowback rate. $FE_{i,t+k}$ is estimated using earnings forecast available from I/B/E/S database. Due to this requirement, our analysis in this part of the paper is limited to the set of I/B/E/S firms for which we are able to obtain all the relevant data to compute ICC. This sample covers an overwhelming majority of publicly traded firms in the US. More important for our exercise, in unreported analysis we find that we are able to reproduce the result of negative realized returns to high default-risk portfolio in post-1980 period even for the subset of these firms. In other words, we do not suffer from any material sample selection bias due to the requirement of I/B/E/S coverage.

Using analyst consensus estimates, we get the explicit forecast of $FE_{i,t+k}$ for years $t+1$ and $t+2$. Analysts provide one-year and two-year ahead forecast of earnings per share for each I/B/E/S firm. We take the consensus earnings forecast for the first two years. Year $t+3$ earnings is estimated by multiplying year $t+2$ estimates with the consensus long-term growth forecast of the firm. I/B/E/S provides the long-term consensus growth forecast for most of the firms. In case of missing data on growth rate, we compute the growth rate implicit in the forecasts of earnings estimate of years $t+1$ and $t+2$. We assign a value of 100% to firms with growth rate above 100% and 2% to firms with growth rate below this number to avoid outlier problems.

We forecast earnings from year $t+4$ to year $t+T+1$ implicitly by mean-reverting the year $t+3$ earnings growth rate to a steady long-run value by year $t+T+2$. The steady state growth rate of a firm's earnings is assumed to be the GDP growth rate (g) as of the previous year. The growth rate for year $t+k$ is assumed to follow the following functional form:

$$g_{i,t+k} = g_{i,t+k-1} * exp^{\frac{ln(g/g_{i,t+3})}{T-1}} \tag{3}$$

This specification assumes an exponential decline in the earnings growth rate to the GDP of the country as in Pastor, Sinha and Swaminathan (2007). Using these growth rates, the earnings in year $t+k$ is estimated as the following:

$$FE_{i,t+k} = FE_{i,t+k-1} * (1 + g_{i,t+k}) \tag{4}$$

After forecasting the earnings, our next step involves an estimation of the plowback rate. For the first year, we estimate the plowback rate from actual historical data. For every firm, we compute the plowback rate (i.e., one minus the payout ratio) from the most recent fiscal year of the firm. The payout is defined as the sum of dividends and share repurchase minus any issuance of new equity. Dividend is taken from COMPUSTAT annual data item 21. Share repurchase is taken from item 115, which represents the amount of common and preferred stock purchased by the firm in year t. Issuance of new equity is taken from item 108. If any of the data item has a missing value code of 'I' or 'M' on the COMPUSTAT tapes, then we set it to zero. After computing the net payout, for firms with positive net income, we divide it by the firm's net income (item 18) to compute the payout ratio. One minus payout ratio is the plowback rate that we use for the first year of estimation.

For those firms for which the plowback ratio could not be computed using the above method, we set their first-year plowback rate to the median payout ratio of their two-digit SIC-code industry for that year. To minimize outlier problems, if the payout ratio of a firm is above 1 or below -0.5, we set it to the industry median payout ratio as well.

From year $t+2$ onwards, we mean-revert the plowback rate to a steady-state value by year $t+T+1$. We use a linear decline in plowback ratio to the sustainable growth rate formula. A linear decline in plowback rate captures the intuition that plowback rates mean-revert slower than earnings growth rate. The steady state formula assumes that, in the steady state, the product of the steady-state return on new investments, ROI, and the steady-state plowback rate is equal to the steady-state growth rates in earnings. Thus, we impose the condition that $g = ROI * b$ in steady-state. Further, we set ROI

for new investments to r_e under the assumption that competition drives returns on new investments to the cost of equity. With these assumptions, the plowback rate for year $t+k$ $(k = 2, 3, ...T)$ is given by the following:

$$b_{i,t+k} = b_{i,t+k-1} - \frac{b_{i,t+1} - b_i}{T} \tag{5}$$

$$b_i = \frac{g}{r_{i,e}} \tag{6}$$

Finally, we compute terminal value as the following perpetuity:

$$TV_{i,t+T} = \frac{FE_{i,t+T+1}}{r_{i,e}} \tag{7}$$

This specification of terminal value assumes that beyond the terminal year, any growth in the firm's earnings is value-irrelevant. Collecting all the terms above, our final expression is the following:

$$P_{i,t} = \sum_{k=1}^{k=T} \frac{FE_{i,t+k} * (1 - b_{i,t+k})}{(1 + r_{i,e})^k} + \frac{FE_{i,t+T+1}}{r_{i,e}(1 + r_{i,e}^T)} \tag{8}$$

We set $T = 15$ following the earlier literature. We solve the above equation for $r_{i,e}$ to get our measure of market's expectation about returns on a firm's stock. We use several robustness checks by changing the key assumptions of the model to ensure the validity of our key results for a wide range of plausible model selection criteria. In our robustness tests, we experiment with a shorter terminal date of ten years to examine the sensitivity with respect to terminal date assumption. Further, instead of using the consensus earnings forecast, we use lowest as well as highest estimates of earnings forecast in alternative models. We also allow a model with exponential decline in the plowback rate against the linear decline in the base model. As we discuss later, these changes do not change any of our key results in the paper.

3.2 Default-risk and implied cost of capital

We estimate this model for every firm covered in the intersection of CRSP, COMPUSTAT and I/B/E/S databases as of June 30 of every year starting from 1980 and ending in 2005. We start in 1980 mainly because of the better coverage of firms on I/B/E/S database after that year. After computing the implied cost of capital using equation 8, we subtract the prevailing risk-free rate based on one year treasury yield to get a measure of expected excess return on the stock.

3.2.1 Descriptive statistics

We provide descriptive statistics of the key variables used for this part of the study in Table 2. Panel A provides the distribution of key inputs to the model. The median firm's earnings per share is \$1.11 for the next fiscal year and \$1.42 two years hence. The long-term growth forecast for the median firm is 16%. Since we cover all US firms in the intersection of CRSP-COMPUSTAT-I/B/E/S databases starting from 1980, these numbers are representative of the entire sample typical for studies with analyst's forecast data.

Panel B provides the distribution of implied risk-premium (i.e., expected return in excess of risk-free rate) estimated by solving the equation 8. To ensure that our results are not driven by outliers, we winsorize the implied cost of capital at 1% from both tails. For our base model, the excess expected return is 4.11% for the median stock in the sample. For the average stock in our sample, market expects to earn 4.66% in excess of the risk-free rate.[4] In Panel B we also provide the distribution of excess expected return for four alternative models. We discuss these models and the results in detail in the robustness section.

[4] These are pooled estimates with observations from over 25 years. In our formal regression analysis, we estimate regression in a Fama-McBeth framework to account for yearly variations in these numbers and other economic characteristics.

We analyze whether market expects to earn positive risk-premium for holding high distress-risk stocks or not. The default-risk measures are also estimated as of June 30 of every year. We use hazard model and EDF measure of distress-risk to analyze the risk-return tradeoff. The hazard rate estimation includes a firm's relative size defined as the logarithm of firm's market capitalization to market capitalization of all NYSE/AMEX/NASDAQ stocks as a covariate to explain default probability. One concern with the use of implied risk-premium as a measure of expected return is the mechanical positive correlation between risk-premium and default-risk for stocks with lower price or market capitalization.

In the hazard rate model, the relative size is the only variable that is constructed using the price level of the firm. To avoid such mechanical relation, in our base hazard rate model we measure the relative size of the firm as of December 31 of the prior year, rather than as of June 30 of the year, the date at which we estimate the implied risk-premium.[5] In addition, we modify the hazard rate model further by dropping the relative size and excess return from the Shumway (2001) model. Obviously, this model labeled the reduced hazard-rate model has lower predictive power for the default prediction, but it removes any concern about mechanical correlation. Finally, in our regression analysis we also control for the firm's price to directly address this issue.

We start with a univariate analysis in Table 3. Every year in the sample, we break all available stocks into different distress-risk percentiles and compute the average expected risk-premium for the year. We average these yearly averages and report them in Table 3. For all three measures of default-risk, we find an almost monotonic relation between default risk and expected risk-premium. For the base hazard rate measure of default, we find that market expects to earn 5.80% risk-premium for holding top 20% distress-risk stocks as compared to 3.55% for the bottom 20% group. Based on the EDF measure, the expected risk-premium is 6.15% for top 20% default likelihood stocks as against 3.24%

[5]Results get marginally stronger if we include relative size as of June 30 in the hazard rate model.

for the bottom 20% stocks. For the inferior model of default-risk as well, namely for the reduced hazard-rate model, we find a positive relation between risk and expected return.

When we analyze the stocks in top 10% or 5% of distress-risk, we again find a monotonic increase in the expected risk-premium. To save space, we present the relation between ICC and the entire spectrum of default-risk in a graphical manner. In Figures 1 and 2, we plot the expected risk-premium against various 5^{th} percentiles of the default risk-measure. First we sort stocks into 20 groups every year and then compute the average ICC for each group. Then we take the average across all years and plot them against the default-group in these figures. In figure 1, the average expected return r_e^{base} is plotted against the default group ranking based on hazard rate as well as distance-to-default model. In figure 2, we take the average of all expected return measures (r_e^{base}, r_e^{10year}, r_e^{loweps}, $r_e^{higheps}$ and, $r_e^{expplow}$) as ICC and plot it against the default group rankings. These alternative measures compute ICC by altering assumptions on the terminal date (r_e^{10year}), measure of earnings forecast (r_e^{loweps}, $r_e^{higheps}$), and plowback rate ($r_e^{expplow}$), discussed in detail in the robustness section. In both cases, there is a remarkable, almost monotonic positive risk-return relation across the entire spectrum of distress-risk. These are point estimates of the mean expected returns across distress-risk portfolios. Some of the differences across these portfolios can be explained by differences in their size or other characteristics. We conduct formal statistical tests in the remainder of this section to control for these effects.

3.2.2 Fama-MacBeth regression results

High distress-risk stocks are characterized by smaller size, high book-to-market ratio, high leverage and high return volatility. Gebhardt, Lee, and Swaminathan (2001) find robust relation between cost of capital and book-to-market ratio and several other firm attributes. Pastor, Sinha and Swaminathan (2007) provide evidence in support of a positive relation between expected market return and volatility. In our multivariate tests, we control for these well known drivers of implied risk-premium to understand the effect of distress-risk on expected risk-premium over and above these characteristics.

We estimate Fama-MacBeth regression model with annual cross-sectional regressions on June 30 of every year and report the time-series means in Table 4. Since implied cost of capital makes use of analyst's forecast of next two years, we correct for autocorrelations up to two lags in computing the standard errors. We regress implied risk-premium on a firm's default-risk along with several firm-level control variables. For every default-risk measure, we compute the percentile ranking of a firm based on the distribution of default-risk in that year. We call this the Default Likelihood Percentile (DLP) variable. This transformation removes outlier problems and makes the interpretation of the estimated coefficient easier.

The coefficient on DLP variable indicates the increase in expected risk-premium as an investor moves from the safest to riskiest stock. We control for the well-known drivers of expected return such as firm size and market-to-book ratio. In addition, we control for the firm's leverage and stock return volatility in stepwise manner. It is worth pointing out that DLP is a non-linear combination of these variables. In linear regressions some of the effect of DLP maybe explained away by these factors, but the measure is expected to retain some explanatory power as by construction it is the maximum likelihood estimate of a firm's default probability.

Panels A to C of Table 4 present the results for three different measures of default-risk. In Panel A, we use the base hazard rate ($Hazard_{shumway}$) model. Model 1 controls for size and market-to-book ratio. All covariates are winsorized at 1% to minimize outlier problems. We find that as we move from the safest to riskiest stocks on the distress-risk dimension, market's expectation of risk-premium increases by 1.57% per annum. Smaller firms and firms with low market-to-book ratio command higher risk-premium as well. In Models 2 and 3, we introduce leverage and stock return volatility as additional regressors. We find that DLP remains positive and significant at 1.31-1.62% per annum. Return volatility has positive and significant coefficient - firms with higher return volatility are expected to earn higher risk-premium.

Panel B uses EDF measure and reaches similar conclusion about the relation between default-risk and expected return. As we move from the safest to riskiest stocks, investors demand an increase of 2.65-3.25% in the expected risk-premium. Equivalently, investors expect about 1.30-1.60% higher returns from stocks with highest distress-risk as compared to the median stock in the portfolio. The magnitude of risk-premium is stronger for EDF-model than the hazard-rate based model of default. In Panel C we use the inferior model namely the reduced hazard model, but still find positive and significant coefficient estimates in the range of 1.70-2.00% per annum depending on the model specification.

Except for leverage, coefficients on all other covariates in Panels B and C are similar to the ones in Panel A. We find a negative coefficient on firm leverage in all three models, which is insignificant for Panel A, but significant for the other two models. Firms with high leverage are expected to earn lower returns. This is counter-intuitive and what might explain this? We explore this further and find that when we drop DLP from the model, highly levered firms are expected to earn higher risk-premium. Once we control for the default likelihood, the distress effect of leverage is completely subsumed by our refined distress-risk measure. Though beyond the scope of this paper, our results indicate that once we parse out the cost side of leverage, in the regression model we are capturing the benefits associated with leverage financing such as tax-shields and decreased agency costs. A detailed analysis of the effect of leverage on implied risk-premium, after accounting for the costs and benefits more precisely, is an interesting issue that we leave for future research.

Overall, we find a strong *positive* relation between default likelihood and implied risk-premium for all specifications, including the models of default-risk that do not directly include market price of the stock in the computation of default-risk measure. In the remainder of this section, we run a series of robustness tests about the key assumption used in computing the implied cost of capital to alleviate concerns that our results are driven by a particular set of assumptions. Our goal is to first highlight the potential biases and how it might affect our results. After understanding that, we provide robustness tests to show that our main results remain qualitatively similar for alternative assumptions that control for these biases.

To save space, in robustness tests we produce Fama-MacBeth coefficients for a composite measure of default likelihood rather than producing them for all different measures as done before. The composite measure is computed as the average rank based on hazard rate model, EDF and reduced hazard rate model. Results are provided in Table 5. In the first column, for comparison, we produce the result for the base case estimate as well.

3.2.3 Robustness: Different forecasting horizon

The measures of implied risk-premium can be sensitive to the choice of terminal date. We use a 15 year horizon for our forecasting exercise in line with the earlier literature. As a robustness, we take a 10 year horizon and re-estimate implied cost of capital using equation 8. We find an annual distress-risk premium of 3.64% from the safest to the riskiest stocks for the base case estimation of implied cost of capital and using composite DLP measure. For estimation using ten year forecasting horizon, we find very similar results to the base case. The coefficient estimate is slightly higher at 3.81% for the distress-risk premium from the safest to riskiest stock.

In the descriptive statistics, we show that the average expected risk-premium is lower for the ten-year forecasting horizon as compared to fifteen-year case (see Table 2). When we estimate the regression model relating risk-premium to DLP measure, we capture the difference in risk-premium across different groups. Our findings suggest that even though the computation of implied risk-premium comes down for ten year model, the relative expectation across high and low distress group remains the same. Thus, there doesn't seem to be any systematic relation between default-risk and the sensitivity of implied rate of return calculation across different forecasting horizons.

3.2.4 Robustness: Biases in analyst forecasts

Our next two robustness tests are with respect to the analyst forecasts that we use. In the base model, we use consensus one and two year ahead forecast as the proxy for future earnings. There is a large literature that addresses the issue of biases in analyst forecast. If analysts are biased positively in general, then the consensus forecast is upward biased. This bias per se does not create any problem for our analysis unless analysts are systematically biased in favor of stocks with high default-risk. If that were true, then for the high default-risk stocks we will get higher than the unbiased expectation of future cash-flows, which in turn results in higher than unbiased implied cost of capital for a given price. This will help us in finding our results. For the same reason, if analysts are biased in favor of stocks with low default-risk, the bias will be against finding our results. It is likely that most of the bias in analysts forecasts is concentrated in firms with large investment banking businesses which are likely to be low, not high, default-risk stocks. Since we are not aware of any study directly relating distress-risk to analyst biases, we take an empirical approach to address the issue.

In the first test, rather than using the consensus forecast, we take the lowest estimates of earnings forecast from the I/B/E/S database and re-estimate the entire model using this measure. This test, therefore, computes expected returns from the perspective of the most pessimistic analyst. Descriptive statistics presented in Table 2 show that the median implied risk-premium for this model is 3.52% per annum, lower than 4.11% for the base model. When future cash-flows are lower, the discount rate has to be lower to justify the same price. This results in a downward shift in the median risk-premium. Fama-MacBeth regression in Table 5 show that the distress-risk premium is 3.08% and highly significant for this specification as well. As a complement to the *pessimistic* forecast model, in unreported analysis we implement an *optimistic* model where we take the highest earnings estimate for all firms in the sample and find similar results. In sum, we conclude that our key results are unaffected by the choice of specific measure of analyst's forecast of future earnings.

To further address the issue of analyst bias, in our next test we compute the implied cost of capital by taking the most pessimistic earnings forecasts for high default-risk firms and the most optimistic forecast for the low default-risk firms. This procedure assumes that analysts in general are biased in favor of high default risk stocks and we take forecast measures that makes it difficult for us to find our results. In particular, every year we compute the percentile ranking of all sample firms based on their default likelihood and for a firm with percentile ranking d_i, we take the earnings forecast as $EPS_i = LOWEPS_i + [(1-d_i)*(HIGHEPS_i - LOWEPS_i)]$. For the safest firm ($d_i = 0$) this method takes highest earnings forecast; for the riskiest firm it takes the lowest forecasts; and for the remaining firms it linearly weights highest and lowest forecasts based on default probability. Thus, we introduce a bias in our computation of earnings forecasts such that we are unlikely to find our results if it were all driven by analysts bias in favor of high default-risk stocks. Results are provided in Table 5. As expected, the coefficient on DLP comes down to 1.82%, but even in this model it remains positive and significant. Overall, we conclude that our results are unlikely to be explained by analyst biases.

3.2.5 Robustness: Exponential decline in plowback rate

In the base case, we assumed a linear decline in plowback rate to the sustainable growth rate value to capture the intuition that plowback rates mean-revert slower than the earnings growth rate. As an alternative, we allow an exponential decline in the plowback rate, i.e., we assume that plowback rates decline in the same fashion in which the growth rate declines. We provide the distribution of implied risk-premium for this specification in Table 2. With exponential decline in this rate, which means a rapid increase in payout ratio, the implied cost of capital goes up to equate the present value of relatively higher cash-flows now to the same market price. In Table 5, we show that the expected risk-premium increases to 3.94% as investors move from the safest to riskiest stocks.

3.2.6 Robustness: Impact of stock price

Another concern may be that the implied cost of capital used in our analysis is just proxying for the inverse of price. Firms with high default-risk have lower prices and we pick up this effect in our regressions. To address this issue, we repeat the regressions of Panel A of Table 5 by including *invprice* as a regressor. *invprice* is defined as one divided by the stock price of the firm as of previous fiscal year end. Results are provided in Panel B. The coefficient on the composite default-risk variable remains positive and statistically and economically significant for all model specifications.

3.2.7 Robustness: Stale forecasts

If analysts are slow in revising their forecasts of future earnings, then our estimation of implied cost of capital might suffer from a bias. To estimate the implied cost of capital, we compute the rate that equates the discounted value of future estimates of cash-flows to the firm's current stock price. Consider a situation where some adverse firm related event in the recent past leads to negative returns, but the analysts have not yet updated their forecasts. In this situation, we will have a positively biased measure of future earnings. This in turn will result in higher values of implied cost of capital. If this situation is more likely to happen for high default-risk stocks, then our cross-sectional regressions relating distress-risk measures to implied cost of capital is likely to be biased.

In our analysis, we take the most recent analysts forecasts as of the July 1 of every year. We also ensure that the forecast is not older than more than three months as of the estimation date. Thus, the bias is only likely to occur for events that have happened in the very recent past. To directly address this issue, we include the past month's return in the cross-sectional regression.[6] This specification ensures that in estimating the effect of distress-risk on expected returns, we remove the effect of recent changes in stock prices, which is a catch-all proxy for events that might have happened between the analyst forecast dates and the date of estimation of implied cost of capital. Results are provided in Panel C of Table 5. As expected, the addition of past month's return leads to lower coefficient on the DLP variable as compared to the base model. But it remains positive and highly significant. In other words, our results are unlikely to be an artifact of sluggishness in analyst's forecast revisions.

3.2.8 Robustness: Simulated bankruptcy time

To estimate the implied cost of capital, we make use of a valuation formula that considers firm as a going concern. Going concern assumption is almost always used in such valuation models under the assumption that financial distress is likely a temporary event for the average firm in the portfolio. When we deal with the set of high default-risk stocks, the possibility of bankruptcy becomes more likely by definition. Note that to the extent analysts incorporate the effect of default-risk in forecasting future cashflows by lowering the mean estimates, we do not suffer from any bias in the estimates of expected future cash-flows. The bias could come in terms of forecasting horizon and computation of the terminal value by ignoring the possibility of bankruptcy explicitly. A bankrupt firm loses all its future cash-flows; by ignoring this we might overstate the future cash-flows of high default-risk group. This in turn can provide a higher estimate of their expected returns.

To address the extent of this bias, we explicitly incorporate the possibility of bankruptcy in the forecasts of future cash-flows (see Damodaran (2006)). For every firm-year observation, we forecast the cash-flows based on the analysts estimates as in the base case till a simulated point of bankruptcy in future, after which the cash-flows are identically

[6] Results are robust to control for the past two or three month's returns.

set to zero. The point of bankruptcy is simulated based on the estimated hazard rate of bankruptcy as of the cash-flow estimation date and assuming a Bernoulli distribution of bankruptcy every year. To illustrate, consider a firm in year t with default probability p_t. Every year we obtain a draw from a Bernoulli distribution with success probability p_t and if the outcome is one, we assume that the firm goes bankrupt in that year. All future cash-flows are then identically set to zero for this firm. We estimate the implied cost of capital based on the same procedure as described earlier based on these estimates of truncated cash-flows. By construction, this model ensures that firms with high default-risk (higher p_t) experience higher bankruptcy rates in future.

Our results remain robust. In Table 6, we reproduce the result of Fama-McBeth regression using this new measure of ICC. We find that the implied cost of capital increases with the default-risk measure as in our earlier estimation and the estimates remain economically and statistically significant. Compared to the base case regression, the coefficient on default-risk variable is marginally lower in the range of 2.1-2.4%. This is expected since high default-risk stocks are more likely to fail, which in turn means that the estimates of future cashflows are set to zero more often for such firms in the computation of this new measure. For a given price, it lowers the required discount rate for such firms. However, the bias is not significant enough to qualitatively, and to a large extent even quantitatively, change our basic results.

4 Realized Returns

We have so far established a positive risk-return trade-off based on ex-ante measure of expected returns and various measures of default risk. As a complement to this exercise, we analyze the relation between realized return and default-risk in a longer time-series in this section. We sort stocks into different distress groups based on the respective distress-risk measures as of the July 1 of every year. We hold a stock in the assigned portfolio till the next re-balancing period or de-listing date, whichever is earlier. We obtain the monthly returns from CRSP tapes. In the month of de-listing, we take the de-listing return whenever available in the CRSP files. If the delisting return is missing, then we take the returns from the monthly CRSP tapes as in the case of regular months. Further, we remove stocks with less than one dollar price as of the portfolio formation date. These filters are in line with Campbell, Hilscher and Szilagyi (2007).

4.1 Evidence from the post-1980 period

We start our analysis by replicating the key results of Campbell, Hilscher and Szilagyi (2007) for 1981-2006 period. We sort stocks into top 1%, 5% or 10% of distress likelihood based on the default probability estimates from the hazard rate model and compute these portfolio's value-weighted returns on a monthly basis. We regress these returns on the four factor returns. In Panel A of Table 7 we provide the results for this model.[7]

The portfolio of top 1% distressed stocks earned significant negative returns during this period. The economic magnitude of under-performance is large at -1.23% per month or about -14.75% per annum. Stocks in the top 5% and 10% of distress-risk underperformed four factor returns by 9.54% and 9.34%, respectively. The economic magnitude of under-performance is large and consistent with the findings of Campbell, Hilscher and Szilagyi (2007). We also provide the annual standard deviation of excess portfolio return, in excess of risk-free rate, in the bottom row of the Table. These numbers are in the range of 27%-41%, which is remarkably higher than the market return volatility of about 15% during this period. As expected, the top 1% portfolio has the highest return volatility of 41.45%, which decreases monotonically to 27.25% for the top 10% portfolio.

We extend Campbell, Hilscher and Szilagyi (2007) study by investigating portfolio

[7]Market model and the three factor model (that omits momentum) results are similar to Campbell, Hilscher and Szilagyi (2007) and hence not presented. In particular, we find that the high default-risk stocks produce significant negative returns in both market and three-factor model.

returns based on two other measures of default-risk. In Panel B of Table 7 we present four-factor regression results for the model based on the expected default frequency (EDF). Based on this measure, stocks in top 1% of distress-risk under-perform the four-factor model by about 17.94% on annual basis. The under-performance remains high at 11.73% and 8.6% for the top 5% and 10% portfolio. In fact the returns are slightly more negative than the estimates based on hazard rate model, implying that the distress-risk anomaly only gets strengthened when we use the EDF measure for the post-1980 period.

In Panel C, we investigate returns to three portfolios that are likely to have high default-risk based on their leverage and stock return volatility. We sort stocks into ten groups based on both dimensions and classify a stock in Top 1% distress group if it achieves a score of 10 on both dimensions. The set of stocks that fall in top two deciles of each dimension are classified as Top 5% group and those that fall in top three deciles of each dimension are classified as Top 10% group.[8] Top 1% stocks under-performed the four-factor benchmark by a significant 17.75% in this period. Top 5% stocks earned negative model-adjusted return of 8.73%, whereas Top 10% group earned negative returns of about 7.09% during this period.

Thus the under-performance of high distress stocks reported by Campbell, Hilscher and Szilagyi (2007) and Dichev (1998) is robust to various methods of classifying stocks into high distress group. This is important for our analysis, since we will be using these measures of default-risk to analyze the portfolio returns during earlier periods.

The other factor loadings indicate that distress stocks have very high market beta: in the range of 1.3 to 1.6 depending on the measure of distress and cut-off percentile considered for the analysis. They have a positive and significant loading on SMB and HML factors. Consistent with the intuition, the return to distressed stock's portfolio mimics returns on small stocks and value stocks i.e., stocks with high book-to-market

[8]Needless to say, there are fewer than 5% and 10% of stocks in these portfolio, but we prefer this classification so as to be consistent with the rest of the presentation in the paper.

value ratio. Finally, the momentum factor explains a large portion of these portfolios' returns. As expected, the portfolio returns of high default-risk stocks exhibit returns close to the recent loser portfolio.

4.2 Evidence from the pre-1980 period

Using the naive EDF measure as well as two-way sort based on leverage and equity return volatility, we investigate the returns of high default-risk stocks during the pre-1980 period.[9] This can be taken as an out-of sample test for the robustness of the distress-risk anomaly. Conrad, Cooper and Kaul (2003) discuss the usefulness of out-of-sample tests in detecting risk-return relationship especially for portfolios sorted on firm characteristics.

As noted earlier, we extend the sample as far back as possible based on the availability of COMPUSTAT and CRSP data. Constrained by the COMPUSTAT data availability, we start our portfolio in 1953 since before that we do not have enough number of firms to form meaningful portfolios, especially for the top 1% group. We ensure that there are at least five stocks in a portfolio in a given month.[10]

We provide results in Table 8. In Panel A we provide a simple market-model estimation results, whereas Panel B provides results from four-factor model. Based on the EDF measure, the portfolio return of stocks in top 1%, 5% and 10% of the distress likelihood is completely explained by the simple market model. The market beta of the portfolio is high in the range of 1.3-1.5, which is comparable to the post-1980 period. The Top 1% portfolio has negative intercept of -0.49% per month, which is not significant. For the Top 5% and 10% portfolios, the market model intercept is insignificant -0.12% and -0.04%, respectively. When we analyze the four-factor model results, the negative re-

[9] For this period, we do not have the estimates of hazard rate model implied default probability. This is mainly due to the lack of data on historical bankruptcies in this period.

[10] In unreported analysis, we experiment with a minimum of ten stocks and with no minimum stock requirement rules as well and find similar results.

turns become a little more pronounced especially for the Top 1% group. But it is still insignificant for the Top 5% and 10% default-risk portfolio. Thus, the additional three factors weaken the model's power to explain portfolio return as compared to the simple market model.

For the portfolio returns based on leverage and volatility sorts, we find positive (but insignificant) intercept in the market model regression. The Top 1% portfolio earns a positive per month return of 0.40%, which is not significant. Top 5% and 10% portfolios earn positive but insignificant market-model adjusted returns. The four factor model intercepts are negative, but insignificant in Top 1% and 5% model. As with the EDF measure, the four factor control makes the model perform poorly in explaining the portfolio returns during this period.

Overall, in the pre-1980 period, we find negative intercepts in only two out of 12 specifications that we consider. And these intercepts are also insignificant at a higher hurdle of 1% significance. In a few specifications, we even find weak positive intercepts for the high distress-risk stocks. We experiment with several alternatives such as Top 20% portfolios and alternative measures of distress likelihood such as fitted values of hazard rate implied default likelihood from later period[11] and obtain similar results.

4.3 Evidence from the entire period

We present the full sample period result (1953-2006) in Table 9. The market model intercept is negative and significant for Top 1% default-risk portfolio, but negative and insignificant for Top 5% and 10% group. For two-way sort based on leverage and return volatility, the market-model intercept is insignificant for all three portfolios. When we analyze the four-factor model estimates, we find that the returns are negative and significant, but their economic magnitude has come down considerably as compared to the

[11]Due to the obvious look-ahead bias for this model, we do not present the results for this model.

post-1980 period. This is not surprising given the earlier results, where we find under-performance in one period and no under-performance for the other. Once again, the four-factor model adjustment performs poorly than the market-model in explaining the returns for entire period.

In the post-1980 period, Top 1% distress-risk portfolio earned negative abnormal returns of 17.95% based on the EDF measure. In contrast, the entire period estimation shows under-performance of only 10.71%. The portfolio return for Top 5% and 10% group also comes down by 40-50% for the entire period as compared to the post-1980 period. Similar pattern is obtained for two-way sort on leverage and return volatility.

In sum, we find a significant decline in the under-performance of high distress-risk portfolios for the longer sample period as compared to the post-1980 period. Though it doesn't completely disappear in the four factor model, the magnitude of under-performance drops considerably in the long period. Market model does a better job in explaining the portfolio returns of distressed stocks in 1953-2006. The under-performance is completely explained by the market beta in this model. In contrast, in the post-1980 period, the market model under-performance is significant and large in the range of 6-10% per annum for both the EDF model and leverage-volatility sorting technique. Thus, the default-risk anomaly weakens considerably for the long time-series of data.

4.4 Evidence without the decade of 1980s

So far we have shown that in the post-1980 period, high default risk stocks earned abnormally low return and combined with our earlier results on expected returns we claim that investors were negatively surprised by low returns on their holdings of high default-risk stocks. It is natural to ask why were investors consistently surprised for about 25 years in the post-1980 period. In this section, we show that the significant part of the post-1980 under-performance is concentrated in the first decade of the sample itself, i.e., in the 1980s decade. In Table 10, we provide results from this decade as well as from a sample that excludes this period. We re-estimate the market-model and four-factor model regressions based on EDF measure of default. Results are similar for other measures of default and therefore not reported to save space.

In the post-1989 sample there is no reliable evidence of under-performance. Though negative, the market-model and four-factor intercepts are insignificant. The under-performance is large and significant for the 1980s decade. Thus, the majority of post-1980 period under-performance can be attributed to one decade's poor performance. In a sense, the real surprise extends for a shorter period of less than 10 years and not for a period of about 25 years. When we estimate the model with entire sample period and excluding 1980s decade, i.e., for period 1953-1980 and 1990-2005 we find that there is no significant under-performance by high default-risk stocks (unreported). Thus, the significant portion of negative returns of high default-risk stocks is concentrated in one out of six decades.

4.5 Robustness: CRSP-only model

A concern with pre-1980 period analysis could be the issue of survivorship bias in COMPUSTAT data especially for pre-1970 data (see Davis (1994)). Though Chan, Jegadeesh, and Lakonishok (1995) argue that the survivorship bias in COMPUSTAT data is small, we address this concern in two ways. First, we estimate our pre-1980 model with data from the 1970 decade only. For this smaller period of 120 months, we find that the top 5%(1%) distress-risk portfolio has market-model intercept of +0.22%(-0.12%), which is statistically insignificant. Three and four-factor model intercepts are insignificant as well.

In the second test, we make use of all CRSP-listed stocks by compromising on the accuracy of default-risk measure. For our results so far, we have used two key default-risk-measures i.e., distance-to-default and $Hazard_{Shumway}$. These measures require data on leverage among other variables for estimation purposes. Since leverage data comes from the COMPUSTAT tapes, we limit our analysis to the intersection of CRSP and COMPUSTAT firms in the paper.

However, a closer look at the hazard models of default-risk suggest that market-based measures such as past stock returns, return volatility and market capitalization are able to capture a large portion of cross-sectional variation in default likelihood. Controlling for these variables (which are all available from CRSP), leverage and profitability (obtained from COMPUSTAT) add only little to the explanatory power of default probability. Shumway (2001) and Chava and Jarrow (2004) show that the market-only based models perform reasonably well in the out-of-sample default predictability. Given these results, we perform our analysis on the set of all CRSP-listed stocks without requiring the data to be present in COMPUSTAT. We take all bankruptcies from 1962 onwards as in our base case analysis and augment the set of bankruptcies with delisting from CRSP for the earlier period (identified from CRSP delisting code as being delisted because of liquidation or performance related reasons). Then we estimate the Hazard rate model with only three predictors: past year's stock return, past year's return volatility and market capitalization as of July 1 of every year. We use data from 1926-1952 as the initial period and then estimate default probabilities for every year starting with 1953 using strictly historical data.

An obvious limitation of this approach is that we do not have precise data on bankruptcy for the pre-1962 period and we lack information on leverage and accounting profitability. Though the stock return volatility captures the effect of leverage to a large extent, results based on CRSP-only measure has to be read with this caveat in mind. With this coarse CRSP-only model of default we estimate the returns on portfolios of high default-risk. First, we estimate this model for post-1980 period as a check of the model's validity as well as a check for the generalization of original Campbell et al. (2007) result to CRSP-only firms. To save space, we do not tabulate estimation results for this model.

For post-1980 period, the top 5%(1%) default-risk portfolio has market model monthly intercept of -1.11%(-1.92%), which is significant at 1% and even higher than the estimates we obtain for more refined measures of default. The four factor model intercept is -0.80%(-1.43%) for the top 5%(1%), which is significant at 1% as well. Thus, our coarse CRSP-only model also produces similar result for the post-1980 period. When we use this model for the 1953-1980 period, we do not find any evidence of under-performance for high default-risk portfolio. Top 5%(1%) portfolio has insignificant market-model intercept of +0.30%(-0.12%). Four-factor model intercepts are insignificant as well: -0.18% for the top 5% group and -0.56% for the top 1% portfolio. These results alleviate concerns about COMPUSTAT survivorship bias.

5 Discussion

We show that investors expected to earn positive risk-premium for bearing default-risk, but they were negatively surprised in the post-1980 period. It's natural to ask what precisely might be the reason behind this surprise. More important, could investors remain surprised for a period extending over 20 years? As noted in the introduction, Elton (1999) points out the fact that even at the market level the realized return can be lower than the risk-free rate for a period as high as ten years (1973-1984). Thus, it is not implausible to find that investors were negatively surprised for over 20 years for the portfolio of high default-risk stocks. However, as we show in our analysis the majority of under-performance was concentrated in the decade of 1980s. In other words, the real negative surprise is with respect to the first ten years of post-1980 sample. What might be responsible for this?

Elton (1999) expresses realized returns as $R_t = E_{t-1}(R_t) + I_t + \epsilon_t$, where E(.) is the expectation operator, I_t is the information surprises and ϵ_t random noises. If information events cancel each other out, then we have a good proxy in realized return for expected returns. However, if there are large information events or correlated multiple surprises is smaller samples, then the information surprises might not cancel each other out and the realized return is no longer a good proxy for expected returns. Avramov, Chordia, Jostova, and Philipov (2006) show that the negative returns to high default risk stocks is also present in the subset of rated firms. Firms with poor credit rating underperformed highly rated firms in their sample. They also document that cross-sectionally poorly rated firms have large negative returns around rating downgrades. And if we remove the rating downgrade periods, there is no evidence of under-performance of high default-risk stocks. Their findings are consistent with our evidence if we view large rating downgrades as the significant information events in Elton's model. Avramov, Chordia, Jostova, and Philipov (2006) also document that around the rating downgrades the actual earnings of poorly rated firms have been significantly below their forecasts as compared to those of highly rated firms. Thus, on average investors were surprised by the low realizations of earnings of high default risk portfolios. Overall, these findings provide some support that investors were surprised by the poor cash-flow news of high default-risk stocks.

Though hard to establish a causal link, there are several plausible arguments behind negative cash-flow surprises in the post-1980 period. One possible reason could be the changes in bankruptcy law of 1978 and the consequent increase in bankruptcy filings during the 1980 decade. Campbell, Hilscher and Szilagyi (2007) show that corporate failure which was in the range of 0.30-0.50% of active companies in the 1970s went up considerably in the 1980s reaching a peak of 1.53% in 1986. It is therefore possible that investors experienced too many bankruptcies for the first time in the recent history and that led to the negative surprise in realized cash-flows of high default-risk stocks. Another argument for the negative surprise could be the increasing role of managed money and institutional preferences for safer stocks in the post-1980 period. There is some evidence that institutions prefer safe stocks (see Kovtunenko and Sosner (2003)). Since their holdings increased considerably during the post-1980 period, it is plausible that the other investors were negatively surprised on their holdings of high default-risk stocks because of the endogenous selling (buying) of distressed (safer) stocks by the institutional investors. Establishing a precise channel of investor's surprise is an interesting question that we leave for the future research.

6 Conclusion

Understanding the link between default-risk and expected return is important for our understanding of how asset prices are formed and how efficiently markets incorporate risk-factors into their estimates of returns. This has important implications for asset pricing theories as well as for corporate financial policies. Several recent studies document anomalous *negative* relation between various measures of default-risk and realized stock returns in the post-1980 period. We argue that detecting the true risk-return relation for portfolios of very high default-risk stocks using realized returns as a proxy for expected return requires a much longer time-series of data given the high volatility of these portfolios. Annual re-balancing exacerbates the problem further.

Thus, we expect to find an improvement in our understanding of the true risk-return relation for high distress-risk stocks by focussing on either longer samples or by using other proxies of expected returns (other than realized returns). Building on these arguments, we use a proxy of expected return that is based on the implied cost of equity capital using analysts forecasts and find a significant and *positive* default-risk premium. With respect to the realized returns, we find *no* reliable evidence of under-performance of high distress-risk stocks during 1953-1980 period using market-model or a four-factor model regression analysis.

Overall, we show that in the post-1980 period, high default-risk stocks had realized returns that were on average lower than their expected returns. In other words, investors were negatively surprised by the low returns on their holdings of high default-risk stocks in a relatively short period post-1980 and especially in the decade of 1980. In terms of *ex-ante* expectation, which is what matters for the risk-return trade-off, we do find a positive relation between default-risk and expected returns using the implied cost of capital measure. The results from realized returns suggest that in the longer sample, where *ex-ante* expected returns and *ex-post* realized returns should average out to be the same, the default-risk anomaly either disappears or weakens considerably depending on the model specification.

Appendix: Construction of Default Measures

In this appendix, we describe in detail, the construction of the default-risk measures used in this paper.

A.1 Hazard Models

We follow Shumway (2001) and Chava and Jarrow (2004) for the construction of hazard models. See Shumway (2001) and Chava, Stefanescu and Turnbull (2005) for more details on various bankruptcy estimation procedures. Consider an observation time period $[0, T]$. During this observation period, any particular firm may experience three possible events: it may default, it may leave the sample before time T for reasons other than default (for example a merger or an acquisition), or it may survive in the sample until time T. A firm's lifetime is said to be censored if either default does not occur by the end of the observation period, or if the firm leaves the sample because of a non–default event. Let T_i denote the observed (possibly censored) lifetime of the i-th firm and let N_i be the censoring indicator, where $N_i = 1$ if T_i is a default time and $N_i = 0$ if T_i is a censoring time. For every $t = 1, \ldots, T$, let $\delta_i(t) = 1$ if the ith firm is in the sample at time t, and zero otherwise. For example, if the firm is in the sample at the beginning of the observation period and censoring only occurs at time T, then $\delta_i(t) = 1$, for $t = 1, ..., T$.

Let $X_i(t)$ be a $1 \times K$ vector of covariates at time t. The vector $X_i(t)$ usually includes firm-specific variables and, a constant component representing an intercept term. Information about the firm-specific variables terminates at time T_i. Let $\lambda(t)$ be the default intensity function (the hazard function) or the instantaneous rate of failure.

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{Pr(t \leq T < T + \Delta \mid T > t)}{\Delta t}$$

Let $L(\beta)$ denote the likelihood conditional on the data $\{X_i, N_i\}$. This is given by

$$L(\beta) = \prod_{i=1}^{N} L(\beta \,|\, T_i, N_i, X_i),$$

where

$$L(\beta \,|\, T_i, N_i, X_i) \quad = \quad [\lambda(t_i)]^{\delta_i} e^{-\{\int_0^{T_i} \lambda(u) du\}}$$

Following Shumway (2001) and Chava and Jarrow (2004), we estimate the discrete time hazard model using a program that estimates logistic model. Our data contains one record for each the firm is in existence, from the year of listing to the year the firm is delisted (either because of a default, merger or other reasons). Our key variable indicating default, *defexit*, is coded as zero if the firm hasn't defaulted that year, and one in the year of default. If the firm exits the sample because of non-default reasons, *defexit* is coded as zero. Some firms get delisted from the exchange and may file for bankruptcy or default at a later date. Once the firms are delisted, we won't have any market information for these firms. We follow Shumway (2001) and code the year of delisting as the year of default incase the firm defaults within five years after delisting due to non-merger reasons.

Our definition of default is a bankruptcy filing (either Chapter 7 or Chapter 11 filing). Bankruptcy filings are collected from SDC Database, SEC filings, CCH Capital Changes Reporter and New Generation Research. Our bankruptcy database is comprehensive and includes the majority of defaults of publicly listed firms during 1962–2005. Chava and Jarrow (2004) provide more information on this bankruptcy database. This is the same database that is used in Campbell et al (2007).

The data is constructed as of 1-July of each year with *defexit* indicating default during the next one year (1-July to 30-June of next year). We take latest available accounting date from annual COMPUSTAT files after lagging the data by at least six months after the fiscal year end. That is, say, if a firm's fiscal year ends in Dec 2002, this information is assigned to the firm-year record that starts on July 1, 2003. This is an attempt to ensure that at the time of estimation we use only the accounting and market data that is available to market participants at that time. Similarly, stock market data is also taken as of the firm's fiscal year end.

We construct two hazard models, one with price data and one without. The first hazard model we consider includes the following covariates: $log(\text{total assets})$, $\frac{\text{net income}}{\text{total assets}}$, $\frac{\text{total liabilities}}{\text{total assets}}$ and, idiosyncratic volatility of firm's stock returns over the past 12 months. The second hazard model we consider is the Shumway (2001) model, with the following covariates: $\frac{\text{net income}}{\text{total assets}}$, $\frac{\text{total liabilities}}{\text{total assets}}$, $log(\frac{\text{market capitalization}}{\text{market capitalization of all NYSE, AMEX, NASDAQ}})$, idiosyncratic volatility of firm's stock returns over the past 12 months, excess return of the stock over the market. Idiosyncratic volatility is constructed as the standard deviation of the residual from a regression with the firm's monthly stock returns over the past 12 months as the dependent variable and the value weighted monthly market return over the past 12 months as the explanatory variable. The past 12 months are computed from the fiscal year end for each year. We exclude any firm-year observations with less than 10 monthly returns from the volatility estimation.

The variables $hazard_{shumway}$ and $hazard_{reduced}$ are constructed as out-of-sample default probabilities from these hazard models using rolling regressions. For eg., $hazard_{shumway}$ default probabilities for the year 1980, we estimate a hazard model using default data from 1963-1979 and multiply the estimates from this model with the covariates for the year 1980. For each subsequent year, the model is updated and out-of-sample default probabilities are constructed for the next year (say, for 1981, we use data from 1963-1980 and so on). Below, we present the estimates for the hazard models for the time period $1980 - 2005$ using 1198 bankruptcies.

	$hazard_{shumway}$		$hazard_{reduced}$	
	Estimate	t-val	Estimate	t-val
$nita$	-0.1217	(-1.27)	-0.6992	(-7.54)
$tlta$	3.3667	(28.26)	3.4954	(28.25)
$sigma$	3.7166	(11.75)	4.4618	(15.62)
$exret$	-0.8395	(-9.19)		
$rsize$	-0.2286	(-12.50)		
$logta$			-0.0003	(-0.02)
$intercept$	-9.9958	(-47.05)	-7.4880	(-64.18)

A.2 Distance to Default model

Distance to Default is computed based on Merton (1974). We closely follow Bharath and Shumway (2004) for the construction of the distance to default measures. In the Merton model, the firm value is assumed to follow a geometric brownian motion

$$\frac{dV}{V} = \mu dt + \sigma_V dW$$

where V is the total value of the firm, μ is the expected continuously compounded return on V , σ_V is the volatility of firm value and dW is a standard Weiner process. Under the assumptions of the Merton model, the equity of the firm is a call option on the underlying value of the firm with a strike price equal to the face value of the firms debt and a time-to-maturity of T. Based on the Black-Scholes formula, value of the equity is

$$E = V\mathcal{N}(d_1) - e^{-rT} F\mathcal{N}(d_2)$$

where where E is the market value of the firms equity, F is the face value of the firms debt, r is the instantaneous risk-free rate, $\mathcal{N}()$ is the cumulative standard normal distribution function,

$$d_1 = \frac{log(V/F) + (r + \sigma_V^2/2)T}{\sigma_V \sqrt{T}}$$

and

$$d_2 = d_1 - \sigma_V \sqrt{T}$$

In this model, the second equation, using an application of Ito's lemma and the fact that $\frac{\partial E}{\partial V} = \mathcal{N}(d_1)$, links the volatility of the firm value and the volatility of the equity.

$$\sigma_E = \frac{V}{E}\mathcal{N}(d_1)\sigma_V$$

The unknowns in these two equations are the firm value V and the asset volatility σ_V. The known quantities are equity value E, face value of debt or the default boundary F, risk-free interest rate r, time to maturity T. F is taken as short-term debt plus half of long-term debt. Since we have two equations and two unknowns, we can solve for V, σ_V directly. Alternately, as in KMV model, we can iteratively solve for V, σ_V, by starting with an initial value of σ_V, using the equity option equation to solve for asset value V for the sample period, construct the time-series of asset value and use this to compute the an estimate of σ_V. This process is repeated till the value of σ_V converges. See Bharath and Shumway (2004) for more details on the construction of this iterative process.

Once we compute V, σ_V, the probability of first passage time to the default boundary is given by $EDF = \mathcal{N}(-DD)$ where DD is the distance to default and is defined as

$$DD \equiv \frac{log(V/F) + (\mu - \sigma_V^2/2)T}{\sigma_V \sqrt{T}}$$

where V is the total value of the firm; F is a face value of firm's debt; μ is the expected rate of return on the firm's assets; σ_V is the volatility of the firm value, and T is the time horizon that is set to one year.

Following Bharath and Shumway (2004), we also construct a naive alternative to distance to default, DD_{naive} that is defined as

$$DD_{\text{naive}} \equiv \frac{log(E + F/F) + (r_{it-1} - \text{Naive}\sigma_V^2/2)T}{\text{Naive}\sigma_V \sqrt{T}}$$

where

$$\text{Naive}\sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25 * \sigma_E)$$

and r_{it-1} is the firms stock return over the previous year

The following figures plot the average expected return for each default-risk group against the default group rank where firms are divided into 20 groups based on EDF and hazard model implied default probabilities. In the first figure the r_e^{base} is the measure of expected return and in the second figure, the measure of expected return is the average across five expected return measures described in section 4: of r_e^{base}, r_e^{10year}, r_e^{loweps}, $r_e^{higheps}$ and, $r_e^{expplow}$.

Figure 1: **Expected Return (r_e^{base}) and default-risk Groups**

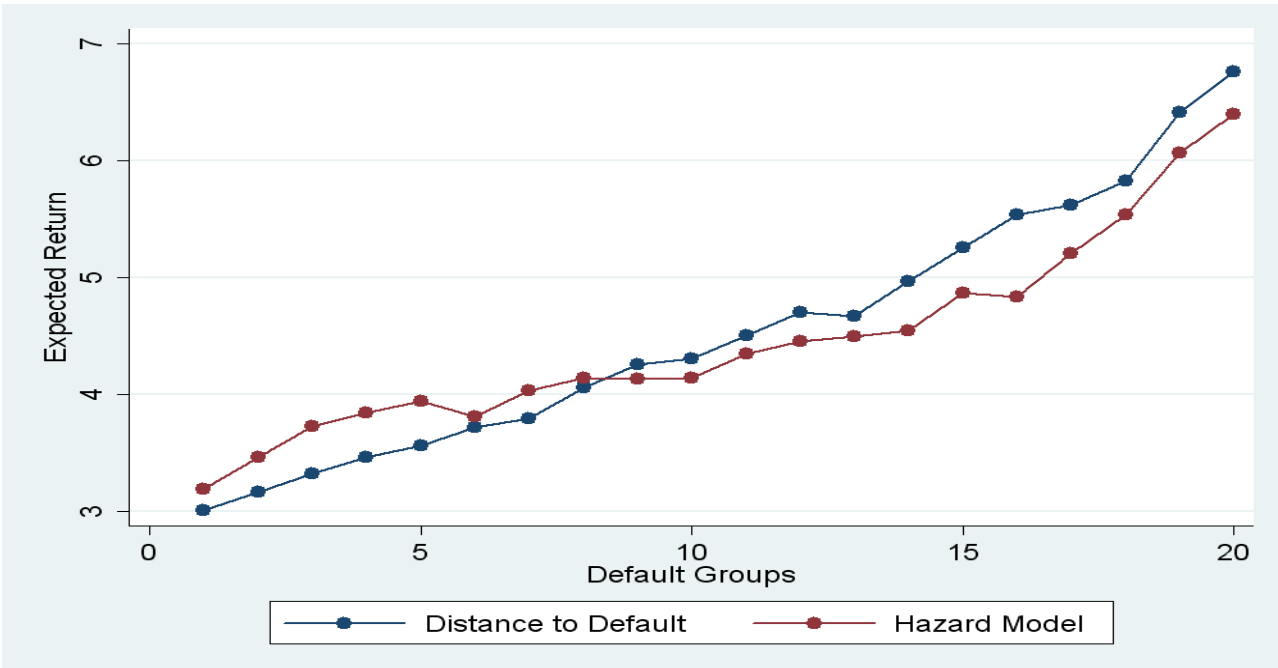

Figure 2: **Expected Return ($r_e^{composite}$) and default-risk Groups**

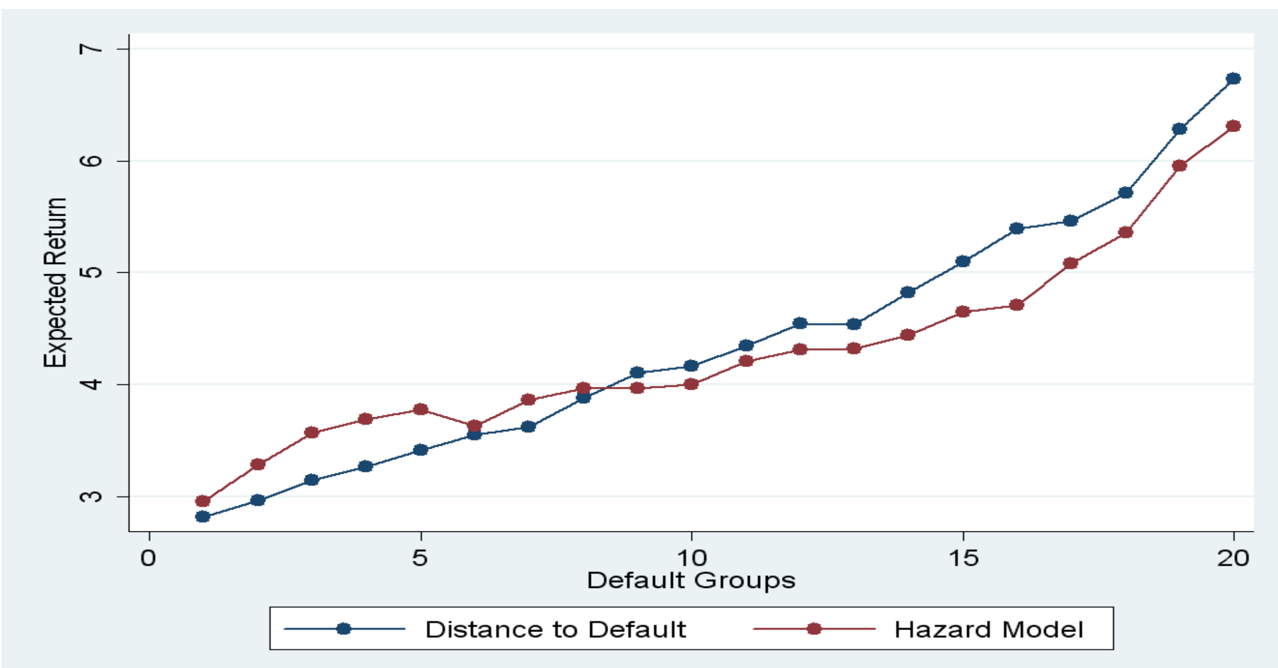

Table 1: **Descriptive statistics of Default Likelihood Indicators**

The following table presents the summary statistics for various default models. Data is restricted to firms in the intersection of CRSP, COMPUSTAT and, I/B/E/S. Sample period is from $1980 - 2005$. COMPUSTAT data are lagged by at least six months after the fiscal year end to make sure the information is available to the market. Distance to Default (DD) is constructed similar to Bharath and Shumway (2006). DD_{naive} is defined as $DD_{\text{naive}} \equiv \frac{log(E+F/F) + (r_{it-1} - \text{Naive}\sigma_V^2/2)T}{\text{Naive}\sigma_V \sqrt{T}}$ where E is the market value of equity, F is the face value of debt, $\text{Naive}\sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25 * \sigma_E)$ and r_{it-1} is the firms stock return over the previous year, σ_E is the equity return volatility and T is the time horizon that is set to one year. $Hazard_{shumway}$ denotes out-of-sample default probabilities constructed from Shumway (2001) model with the following covariates: $\frac{\text{net income}}{\text{total assets}}, \frac{\text{total liabilities}}{\text{total assets}}, log(\frac{\text{market capitalization}}{\text{market capitalization of all NYSE, AMEX, NASDAQ}})$, idiosyncratic volatility of firm's stock returns over the past 12 months, excess return of the stock over the market. Appendix A.1 gives more details on the construction of out-of-sample default probabilities based on the hazard models. $Hazard_{reduced}$ denotes out-of-sample default probabilities constructed based on a hazard model that includes the following covariates:$log(\text{total assets}), \frac{\text{net income}}{\text{total assets}}, \frac{\text{total liabilities}}{\text{total assets}}$ and, idiosyncratic volatility of firm's stock returns over the past 12 months.

variable	mean	10^{th} percentile	50^{th} percentile	90^{th} percentile	std.dev.
DD_{naive}	6.7756	1.5198	5.9650	12.9377	4.9675
$Hazard_{shumway}$	0.0044	0.0005	0.0022	0.0090	0.0092
$Hazard_{reduced}$	0.0055	0.0009	0.0030	0.0103	0.0114

Table 2: **Descriptive Statistics of Expected Returns**

Descriptive statistics of inputs to the expected return computation are given in Panel A. EPS1 and EPS2 denotes the consensus EPS estimate of the firm for fiscal years $t+1$ and $t+2$ respectively. *LTG* denotes the consensus long term growth forecast for the firm. I/B/E/S is the source for all the analyst forecast data. Panel B gives the descriptive statistics for various alternate measures of expected return computed using equation 8. r_e^{base} denotes the implied cost of capital estimated with the consensus mean earnings and long-term growth forecast with the terminal date set to 15 years. r_e^{10year} is constructed similar to r_e^{base} except the terminal date is set to 10 years. For r_e^{loweps} and $r_e^{higheps}$, instead of using the consensus mean earnings forecast for the firm, we use the lowest eps and highest eps forecast respectively. $r_e^{expplow}$ is constructed by assuming an exponential decline in the plowback rate against the linear decline assumed in the other measures.

Panel A: Inputs for Expected Return Computation

variable	mean	25^{th} percentile	50^{th} percentile	75^{th} percentile	std.dev.
EPS1	1.41	0.50	1.11	2.00	1.76
EPS2	1.79	0.76	1.42	2.40	1.86
LTG	0.21	0.12	0.16	0.25	0.17

Panel B: Measures of Expected Return

variable	mean	25^{th} percentile	50^{th} percentile	75^{th} percentile	std.dev.
r_e^{base}	4.66	1.91	4.11	6.56	5.22
r_e^{10year}	3.61	1.13	3.23	5.55	4.52
r_e^{loweps}	4.03	1.18	3.52	6.02	5.39
$r_e^{higheps}$	5.32	2.53	4.73	7.24	5.21
$r_e^{expplow}$	4.87	1.98	4.21	6.72	5.55

Table 3: **Expected Returns by Default Likelihood Groups**

In the following table average values of expected returns are summarized for various default likelihood groups. *rebase* is the implied cost of capital computed using equation 8. Firms are ranked on default likelihood indicators into three groups: 0-20th percentile, 21-80th percentile and 81-100th percentile. The mean value of expected return for each group is presented. Data is restricted to firms in the intersection of CRSP, COMPUSTAT and, I/B/E/S. Sample period is from $1980-2005$. Firms whose stock price is less than a dollar as of their fiscal year end are deleted. COMPUSTAT data are lagged by at least six months after the fiscal year end to make sure the information is available to the market. Distance to Default (DD) is constructed similar to Bharath and Shumway (2006). DD_{naive} is defined as $DD_{\text{naive}} \equiv \frac{log(E+F/F)+(r_{it-1}-\text{Naive}\sigma_V^2/2)T}{\text{Naive}\sigma_V\sqrt{T}}$ where E is the market value of equity, F is the face value of debt, $\text{Naive}\sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05+0.25*\sigma_E)$ and r_{it-1} is the firms stock return over the previous year, σ_E is the equity return volatility and T is the time horizon that is set to one year. $Hazard_{shumway}$ denotes out-of-sample default probabilities constructed from Shumway (2001) model with the following covariates: $\frac{\text{net income}}{\text{total assets}}, \frac{\text{total liabilities}}{\text{total assets}}, log(\frac{\text{market capitalization}}{\text{market capitalization of all NYSE, AMEX, NASDAQ}})$, idiosyncratic volatility of firm's stock returns over the past 12 months, excess return of the stock over the market. Appendix A.1 gives more details on the construction of out-of-sample default probabilities based on the hazard models. $Hazard_{reduced}$ denotes out-of-sample default probabilities constructed based on a hazard model that includes the following covariates:$log(\text{total assets}), \frac{\text{net income}}{\text{total assets}}, \frac{\text{total liabilities}}{\text{total assets}}$ and, idiosyncratic volatility of firm's stock returns over the past 12 months.

	EDF	$Hazard_{shumway}$	$Hazard_{reduced}$
0-20 percentile	3.24	3.55	3.89
21-80 percentile	4.44	4.31	4.36
81-100 percentile	6.15	5.80	5.32
top 10 percentile	6.59	6.23	5.56

Table 4: **Default-risk and Expected Returns**

The following table presents the estimates from a Fama-Macbeth regression of various default likelihood indicators on expected return. Sample is restricted to firms in the intersection of CRSP, COMPUSTAT and I/B/E/S. Sample period is from 1980-2005. Firms whose stock price is less than a dollar as of their fiscal year end are deleted. All the accounting data is lagged by at least 6 months after the fiscal year end and taken as of July 1. *logta* denotes log(total assets) of the firm, *mtb* is the market-to-book ratio of the firm, *booklev* is the book leverage of the firm computed as the ratio of total debt (sum of long-term and short-term debt) of the firm to total assets of the firm. *retstd* is the standard deviation of the firm's stock returns over the past 12 months. $Hazard_{reduced}$ denotes out-of-sample default probabilities constructed based on a hazard model that includes the following covariates:$log(\text{total assets})$, $\frac{\text{net income}}{\text{total assets}}, \frac{\text{total liabilities}}{\text{total assets}}$ and, idiosyncratic volatility of firm's stock returns over the past 12 months. $Hazard_{shumway}$ denotes out-of-sample default probabilities constructed from Shumway (2001) model with the following covariates: $\frac{\text{net income}}{\text{total assets}}, \frac{\text{total liabilities}}{\text{total assets}}, log(\frac{\text{market capitalization}}{\text{market capitalization of all NYSE, AMEX, NASDAQ}})$, idiosyncratic volatility of firm's stock returns over the past 12 months, excess return of the stock over the market. Appendix A gives more details on the construction of out-of-sample default probabilities based on the hazard models. Distance to Default (DD) is constructed similar to Bharath and Shumway (2006). DD_{naive} is defined as $DD_{\text{naive}} \equiv \frac{log(E + F/F) + (r_{it-1} - \text{Naive}\sigma_V^2/2)T}{\text{Naive}\sigma_V \sqrt{T}}$ where E is the market value of equity, F is the face value of debt, $\text{Naive}\sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25 * \sigma_E)$ and r_{it-1} is the firms stock return over the previous year, σ_E is the equity return volatility and T is the time horizon that is set to one year. EDF is computed as $\mathcal{N}(-DD)$ where $\mathcal{N}(.)$ is the cumulative standard normal distribution function. t-statistics are based on standard errors adjusted for Newey-West correction for up to 2 lags.

Panel A: Hazard Model

	Model 1		Model 2		Model 3	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
DLP	0.0157	(7.12)	0.0162	(4.11)	0.0131	(4.74)
logta	-0.6121	(-8.03)	-0.6091	(-7.96)	-0.4804	(-5.04)
mtb	-0.3941	(-3.14)	-0.3852	(-3.26)	-0.4852	(-3.29)
booklev			-0.1080	(-0.18)	-0.2919	(-0.59)
retstd					0.1126	(2.34)
intercept	7.9057	(11.96)	7.9131	(10.99)	6.4110	(4.89)

Panel B: Distance to Default

	Model 1		Model 2		Model 3	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
DLP	0.0265	(6.46)	0.0325	(5.01)	0.0315	(6.22)
logta	-0.6289	(-11.77)	-0.5876	(-12.43)	-0.5478	(-7.29)
mtb	-0.3095	(-2.99)	-0.3018	(-3.11)	-0.3518	(-3.11)
booklev			-1.7490	(-2.12)	-1.9271	(-3.00)
retstd					0.0497	(1.07)
intercept	7.4587	(11.36)	7.3605	(11.14)	6.9684	(5.59)

Panel C: Reduced Hazard Model

	Model 1		Model 2		Model 3	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
DLP	0.0169	(11.26)	0.0200	(8.41)	0.0171	(6.87)
logta	-0.6953	(-8.93)	-0.6772	(-8.99)	-0.5568	(-5.87)
mtb	-0.4780	(-3.28)	-0.4869	(-3.26)	-0.5613	(-3.21)
booklev			-0.7598	(-1.72)	-0.8801	(-3.94)
retstd					0.1062	(2.09)
intercept	8.4789	(12.84)	8.4220	(12.71)	7.0206	(5.32)

Table 5: **Composite Default-Risk Percentile and Different Measures of Expected Returns**

The following table presents the estimates from a Fama-Macbeth regression of a composite default likelihood percentiles on various measures of expected returns. Sample is restricted to firms in the intersection of CRSP, COMPUSTAT and I/B/E/S. Sample period is from 1980-2005. Firms whose stock price is less than a dollar as of their fiscal year end are deleted. All the accounting data is lagged by at least 6 months after the fiscal year end and taken as of July 1. Composite DLP is constructed as the average rank based on $Hazard_{reduced}$, $Hazard_{shumway}$ and EDF default likelihood measures. Appendix A gives more details of the various default likelihood computations. Alternate measures of expected return computed using equation 8 are used as the dependent variables in Models 1-5. For example, in model 1, r_e^{base} is the dependent variable and so on. r_e^{base} denotes the implied cost of capital estimated with the consensus mean earnings and long-term growth forecast with the terminal date set to 15 years. r_e^{10year} is constructed similar to r_e^{base} except the terminal date is set to 10 years. For r_e^{loweps}, instead of using the consensus mean earnings forecast for the firm, we use the lowest eps forecast. $r_e^{mixture}$ is constructed by taking the pessimistic forecasts for high default-risk stocks and optimistic forecasts for low default-risk ones. $r_e^{expplow}$ is constructed by assuming an exponential decline in the plowback rate against the linear decline assumed in the other measures. *logta* denotes log(total assets) of the firm, *mtb* is the market-to-book ratio of the firm, *booklev* is the book leverage of the firm computed as the ratio of total debt (sum of long-term and short-term debt) of the firm to total assets of the firm. *retstd* is the standard deviation of the firm's stock returns over the past 12 months. Panel A presents the results without controlling for the inverse of price where as Panel B and C include the inverse of price as of the previous fiscal year-end (*invprice*) and past month's return (*pastret*), respectively as additional covariates. t-statistics are based on standard errors adjusted for Newey-West correction for up to 2 lags.

Panel A

	r_e^{base}		r_e^{10year}		r_e^{loweps}		$r_e^{mixture}$		$r_e^{expplow}$	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
compositeDLP	0.0364	(6.64)	0.0381	(6.88)	0.0308	(5.51)	0.0182	(3.05)	0.0394	(6.71)
logta	-0.4817	(-4.43)	-0.3388	(-3.14)	-0.7581	(-9.75)	-0.5041	(-4.57)	-0.5102	(-4.46)
mtb	-0.4125	(-2.84)	-0.5629	(-3.58)	-0.4249	(-2.59)	-0.5057	(-2.98)	-0.4283	(-2.79)
booklev	-2.9735	(-4.86)	-3.0522	(-5.05)	-2.0515	(-3.64)	-2.4350	(-3.27)	-3.0473	(-4.86)
retstd	0.0738	(1.38)	0.0318	(0.68)	0.0135	(0.30)	0.0775	(1.37)	0.0904	(1.56)
intercept	6.3273	(4.27)	5.1465	(3.76)	8.1225	(6.31)	7.2325	(5.10)	6.4233	(4.14)

Panel B

	r_e^{base}		r_e^{10year}		r_e^{loweps}		$r_e^{mixture}$		$r_e^{expplow}$	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$compositeDLP$	0.0321	(6.63)	0.0351	(7.02)	0.0261	(5.30)	0.0144	(2.65)	0.0342	(6.63)
$logta$	-0.4043	(-3.61)	-0.2829	(-2.57)	-0.6759	(-8.44)	-0.4423	(-4.12)	-0.4172	(-3.53)
mtb	-0.3291	(-2.50)	-0.5026	(-3.44)	-0.3406	(-2.21)	-0.4364	(-2.62)	-0.3276	(-2.39)
$booklev$	-2.9505	(-4.68)	-3.0438	(-4.98)	-1.9977	(-3.47)	-2.3758	(-3.11)	-3.0148	(-4.66)
$retstd$	0.0525	(1.07)	0.0169	(0.40)	-0.0089	(-0.21)	0.0591	(1.09)	0.0640	(1.20)
$invprice$	5.7339	(4.10)	4.1068	(3.62)	5.9125	(4.75)	4.5886	(4.22)	6.9218	(4.47)
$intercept$	5.7735	(3.79)	4.7414	(3.41)	7.5464	(5.73)	6.7941	(4.77)	5.7651	(3.61)

Panel C

	r_e^{base}		r_e^{10year}		r_e^{loweps}		$r_e^{mixture}$		$r_e^{expplow}$	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
$compositeDLP$	0.0327	(7.19)	0.0344	(7.53)	0.0281	(5.49)	0.0155	(2.93)	0.0355	(7.24)
$logta$	-0.4765	(-4.01)	-0.3399	(-2.93)	-0.7499	(-8.61)	-0.5205	(-4.62)	-0.5049	(-4.05)
mtb	-0.4746	(-2.81)	-0.6305	(-3.39)	-0.4892	(-2.54)	-0.5154	(-3.05)	-0.4950	(-2.79)
$booklev$	-2.9102	(-3.85)	-2.9219	(-4.12)	-2.0150	(-2.79)	-2.1778	(-2.85)	-2.9890	(-3.87)
$retstd$	0.0810	(1.50)	0.0377	(0.83)	0.0177	(0.40)	0.0782	(1.44)	0.0965	(1.65)
$pastret$	-4.5583	(-7.99)	-4.8225	(-8.72)	-3.8331	(-6.19)	-3.4621	(-5.87)	-4.9171	(-8.14)
$intercept$	6.4969	(4.28)	5.3675	(3.87)	8.2703	(6.29)	7.4256	(5.22)	6.6265	(4.18)

Table 6: **Default-risk and Expected Returns with Simulated Bankruptcy Time**

The following table presents the estimates from a Fama-Macbeth regression of default likelihood indicators on expected return. In this model, we explicitly incorporate the possibility of default in the estimation of future cash-flows of the firm, required for the estimation of ICC. Sample is restricted to firms in the intersection of CRSP, COMPUSTAT and I/B/E/S. Sample period is from 1980-2005. We use the percentile default probability rankings (DLP) based on the full hazard model ($Hazard_{Shumway}$), the distance-to-default (EDF) based measure and the hazard rate model without price level variables ($Hazard_{reduced}$). *logta* denotes log(total assets) of the firm, *mtb* is the market-to-book ratio of the firm, *booklev* is the book leverage of the firm computed as the ratio of total debt (sum of long-term and short-term debt) of the firm to total assets of the firm. *retstd* is the standard deviation of the firm's stock returns over the past 12 months. *invprice* is the inverse of stock price as of the prior fiscal year. *pastret* is past month's stock return. $Hazard_{reduced}$ denotes out-of-sample default probabilities constructed based on a hazard model that includes the following covariates:log(total assets)$\frac{\text{net income}}{\text{total assets}}$, $\frac{\text{total liabilities}}{\text{total assets}}$ and, idiosyncratic volatility of firm's stock returns over the past 12 months. $Hazard_{shumway}$ denotes out-of-sample default probabilities constructed from Shumway (2001) model with the following covariates: $\frac{\text{net income}}{\text{total assets}}$, $\frac{\text{total liabilities}}{\text{total assets}}$, $log(\frac{\text{market capitalization}}{\text{market capitalization of all NYSE, AMEX, NASDAQ}})$, idiosyncratic volatility of firm's stock returns over the past 12 months, excess return of the stock over the market. Distance to Default (DD) is constructed similar to Bharath and Shumway (2006). DD_{naive} is defined as $DD_{\text{naive}} \equiv \frac{log(E+F/F)+(r_{it-1}-\text{Naive}\sigma_V^2/2)T}{\text{Naive}\sigma_V\sqrt{T}}$

where E is the market value of equity, F is the face value of debt, $\text{Naive}\sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05+0.25*\sigma_E)$ and r_{it-1} is the firms stock return over the previous year, σ_E is the equity return volatility and T is the time horizon that is set to one year. EDF is computed as $\mathcal{N}(-DD)$ where $\mathcal{N}(.)$ is the cumulative standard normal distribution function. t-statistics are based on standard errors adjusted for Newey-West correction for up to 2 lags.

	Model 1		Model 2		Model 3	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
compositeDLP	0.0240	(4.67)	0.0235	(4.90)	0.0213	(4.31)
logta	-0.4882	(-4.15)	-0.4610	(-3.69)	-0.5069	(-4.25)
mtb	-0.5035	(-3.41)	-0.4664	(-3.38)	-0.5148	(-3.48)
booklev	-4.3582	(-6.81)	-4.4666	(-6.96)	-4.0709	(-6.22)
retstd	0.0312	(0.54)	0.0255	(0.46)	0.0309	(0.55)
invprice			2.1510	(1.50)		
pastret					-4.1786	(-7.22)
intercept	7.5633	(4.58)	7.3148	(4.24)	7.7938	(4.71)

Table 7: **Default-risk and Realized Returns: 1981-2006**

This table provides results from Fama-French calendar time portfolio return regressions for trading strategies based on default-risk. As of June 30 of every sample year from 1981 to 2005, we sort all sample firms into different percentiles of distress-risks based on the default likelihood. In Panel A, we use the Hazard Rate Implied default probability as the default-risk measure. Panel B uses expected default frequency measure (EDF) based on option-pricing models. Panel C, uses a two-way sorting technique based on firm's market leverage and return volatility. For Panel A and B, we include firms that fall in Top 1%, 5% or 10% of the default likelihood based on the respective measures into these three high default-risk portfolio. In Panel C, we perform a two-way sort based on market leverage and return volatility. If a stock falls in the top (tenth) decile on both dimensions, we classify it into the top 1% distress group. If it falls in top two (three) deciles on both dimension, it is included in top 5%(10%) of distress-risk portfolio. Portfolios are re-balanced every year. We compute the value-weighted return of the portfolio every month from the July of year t till June of year t+1 and regress it on four factors. For each portfolio, we regress the mean portfolio return in excess of risk-free rate on excess return on market along with SMB, HML and UMD factors. SMB is the monthly return on a portfolio of small stocks minus large stocks; HML is the monthly return on high Book-to-Market stocks minus low Book-to-Market stocks; UMD is the return on a portfolio of prior winners minus prior losers. All factor returns are provided by Prof. Ken French. We estimate the regression models with 306 monthly observations from July, 1981 till June, 2006. Robust t-statistics are provided in the brackets. The annual volatility of the monthly returns of each portfolio is provided in the last row.

Panel A: Hazard Rate Model

	Top 1%		Top 5%		Top 10%	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
$mktrf$	1.2851	(11.17)	1.2883	(17.18)	1.2691	(23.76)
smb	1.7828	(10.04)	1.4458	(13.56)	1.2261	(14.38)
hml	0.1459	(0.75)	0.3738	(2.78)	0.4476	(3.92)
umd	-0.3473	(-2.25)	-0.5040	(-3.52)	-0.4123	(-5.26)
$intercept$	-1.2333	(-2.45)	-0.7949	(-2.12)	-0.6682	(-2.84)
R^2	0.520		0.663		0.778	
N	306		306		306	
σ	41.45%		32.63%		27.25%	

Panel B: Distance to Default Model

	Top 1%		Top 5%		Top 10%	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
$mktrf$	1.5950	(13.84)	1.4534	(19.95)	1.3805	(22.44)
smb	1.3609	(6.52)	0.7905	(6.91)	0.6801	(7.56)
hml	1.0789	(4.56)	0.7686	(5.97)	0.6855	(6.20)
umd	-0.6853	(-3.92)	-0.3275	(-3.80)	-0.2799	(-3.87)
$intercept$	-1.4952	(-2.82)	-0.9776	(-3.44)	-0.7170	(-2.98)
R^2	0.460		0.659		0.715	
N	306		306		306	
σ	41.10%		27.41%		24.63%	

Panel C: Leverage-Sigma Model

	Top 1%		Top 5%		Top 10%	
	Estimate	t-val	Estimate	t-val	Estimate	t-val
$mktrf$	1.2988	(12.08)	1.3132	(18.80)	1.3742	(20.45)
smb	1.4142	(7.49)	1.4038	(10.32)	1.2362	(11.09)
hml	0.6953	(3.12)	0.4453	(2.81)	0.2727	(1.79)
umd	-0.3576	(-2.51)	-0.2860	(-2.91)	-0.4154	(-3.24)
$intercept$	-1.4811	(-3.04)	-0.7276	(-2.33)	-0.5911	(-1.87)
R^2	0.436		0.670		0.754	
N	306		306		306	
σ	36.87%		31.09%		30.31%	

Table 8: **Default-risk and Realized Return: 1953-1980**

This table provides results from Fama-French calendar time portfolio return regressions for trading strategies based on default-risk. As of June 30 of every sample year from 1953 to 1980, we sort all sample firms into different percentiles of distress-risks based on the default likelihood. We use two methods of classifying stocks into high distress group. The first method uses expected default frequency measure (EDF) based on option-pricing models. The second method uses a two-way sorting technique based on firm's market leverage and return volatility. For the EDF method, we include firms that fall in Top 1%, 5% or 10% of the default likelihood into these three high default-risk portfolio. For the leverage-sigma model, we perform a two-way sort based on market leverage and return volatility. If a stock falls in the top (tenth) decile on both dimensions, we classify it into the top 1% distress group. If it falls in top two (three) deciles on both dimension, it is included in top 5%(10%) of distress-risk portfolio. Portfolios are re-balanced every year. We compute the value-weighted return of the portfolio every month from the July of year t till June of year t+1 and regress it on four factors. For each portfolio, we regress the mean portfolio return in excess of risk-free rate on excess return on market along with SMB, HML and UMD factors. Panel A provides estimation for market model; whereas Panel B is based on all four-factors. SMB is the monthly return on a portfolio of small stocks minus large stocks; HML is the monthly return on high Book-to-Market stocks minus low Book-to-Market stocks; UMD is the return on a portfolio of prior winners minus prior losers. All factor returns are provided by Prof. Ken French. We require at least five stocks to be present in the given portfolio to allow that month to enter our estimation exercise. Robust t-statistics are provided in the brackets. The annual volatility of the monthly returns of each portfolio is provided in the last row.

	Distance to Default Model						Leverage-Sigma Model					
	Top 1%		Top 5%		Top 10%		Top 1%		Top 5%		Top 10%	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
Panel A: Market Model												
$mktrf$	1.5265	(14.06)	1.3617	(16.91)	1.3475	(18.86)	1.6360	(13.50)	1.5516	(16.37)	1.5274	(18.39)
$intercept$	-0.4919	(-1.43)	-0.1231	(-0.51)	-0.0372	(-0.18)	0.4044	(1.01)	0.2372	(0.85)	0.0925	(0.42)
R^2	0.498		0.599		0.667		0.447		0.583		0.676	
N	330		342		353		342		353		353	
Panel B: Four-Factor Model												
$mktrf$	1.2959	(18.85)	1.1569	(28.26)	1.1699	(37.84)	1.3133	(17.44)	1.2745	(28.60)	1.2809	(35.92)
smb	1.2198	(10.68)	1.1196	(16.27)	1.0129	(18.85)	1.8169	(14.24)	1.5796	(19.07)	1.3607	(22.24)
hml	0.6679	(5.69)	0.6263	(7.95)	0.5652	(10.07)	0.9021	(6.75)	0.7422	(8.23)	0.5496	(8.13)
umd	-0.3337	(-4.12)	-0.2353	(-4.33)	-0.2328	(-5.75)	0.1809	(1.71)	0.0542	(0.78)	0.0547	(1.00)
$intercept$	-0.5821	(-2.02)	-0.2785	(-1.59)	-0.1421	(-1.08)	-0.3473	(-1.09)	-0.2698	(-1.46)	-0.3186	(-2.12)
R^2	0.689		0.831		0.886		0.692		0.853		0.907	
N	330		342		353		342		353		353	
σ	31.29%		25.16%		23.44%		34.95%		28.87%		26.39%	

Table 9: **Default-risk and Realized Return: 1953-2006**

This table provides results from Fama-French calendar time portfolio return regressions for trading strategies based on default-risk. As of June 30 of every sample year from 1953 to 1980, we sort all sample firms into different percentiles of distress-risks based on the default likelihood. We use two methods of classifying stocks into high distress group. The first method uses expected default frequency measure (EDF) based on option-pricing models. The second method uses a two-way sorting technique based on firm's market leverage and return volatility. For the EDF method, we include firms that fall in Top 1%, 5% or 10% of the default likelihood into these three high default-risk portfolio. For the leverage-sigma model, we perform a two-way sort based on market leverage and return volatility. If a stock falls in the top (tenth) decile on both dimensions, we classify it into the top 1% distress group. If it falls in top two (three) deciles on both dimension, it is included in top 5%(10%) of distress-risk portfolio. Portfolios are re-balanced every year. We compute the value-weighted return of the portfolio every month from the July of year t till June of year t+1 and regress it on four factors. For each portfolio, we regress the mean portfolio return in excess of risk-free rate on excess return on market along with SMB, HML and UMD factors. Panel A provides estimation for market model; whereas Panel B is based on all four-factors. SMB is the monthly return on a portfolio of small stocks minus large stocks; HML is the monthly return on high Book-to-Market stocks minus low Book-to-Market stocks; UMD is the return on a portfolio of prior winners minus prior losers. All factor returns are provided by Prof. Ken French. We require at least five stocks to be present in the given portfolio to allow that month to enter our estimation exercise. Robust t-statistics are provided in the brackets. The annual volatility of the monthly returns of each portfolio is provided in the last row.

	Distance to Default Model						Leverage-Sigma Model					
	Top 1%		Top 5%		Top 10%		Top 1%		Top 5%		Top 10%	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
Panel A: Market Model												
$mktrf$	1.4860	(17.24)	1.3348	(22.50)	1.2974	(25.09)	1.4535	(16.32)	1.4628	(21.76)	1.5061	(25.40)
$intercept$	-0.8420	(-2.56)	-0.3751	(-1.90)	-0.2146	(-1.28)	-0.3577	(-1.09)	-0.1432	(-0.62)	-0.2694	(-1.40)
R^2	0.366		0.560		0.628		0.352		0.512		0.608	
N	636		648		659		648		659		659	
Panel B: Four-Factor Model												
$mktrf$	1.4144	(20.62)	1.3089	(30.06)	1.2811	(36.77)	1.3396	(20.85)	1.3151	(31.43)	1.3445	(33.82)
smb	1.2075	(9.51)	0.8946	(11.87)	0.8004	(14.85)	1.5575	(14.24)	1.4671	(18.39)	1.2564	(18.31)
hml	0.7967	(5.72)	0.6818	(8.80)	0.6296	(9.88)	0.7948	(6.09)	0.5569	(6.28)	0.3491	(3.74)
umd	-0.5487	(-4.58)	-0.3130	(-5.41)	-0.2807	(-5.80)	-0.1643	(-1.59)	-0.1658	(-2.36)	-0.2455	(-2.66)
$intercept$	-0.8933	(-2.83)	-0.5429	(-3.25)	-0.3691	(-2.75)	-0.7782	(-2.62)	-0.4126	(-2.22)	-0.3395	(-1.76)
R^2	0.541		0.734		0.796		0.552		0.755		0.812	
N	636		648		659		648		659		659	
σ	36.34%		26.24%		23.99%		35.98%		29.94%		28.29%	

Table 10: **Default-risk and Realized Return: Only 1980s and Without 1980s**

This table provides results from Fama-French calendar time portfolio return regressions for trading strategies based on two sub-periods: (a) decade of 1980s and (b) period after 1980s. As of June 30 of every sample year, we sort all sample firms into different percentiles of distress-risks based on the default likelihood measured by expected default frequency measure (EDF). Portfolios are re-balanced every year. We compute the value-weighted return of the portfolio every month from the July of year t till June of year t+1 and regress it on four factors. For each portfolio, we regress the mean portfolio return in excess of risk-free rate on excess return on market along with SMB, HML and UMD factors. Panel A provides estimation for market model; whereas Panel B is based on all four-factors. SMB is the monthly return on a portfolio of small stocks minus large stocks; HML is the monthly return on high Book-to-Market stocks minus low Book-to-Market stocks; UMD is the return on a portfolio of prior winners minus prior losers. Robust t-statistics are provided in the brackets.

	1980s Decade						After 1980s					
	Top 1%		Top 5%		Top 10%		Top 1%		Top 5%		Top 10%	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
Panel A: Market Model												
$mktrf$	1.3960	(9.24)	1.3197	(12.22)	1.2282	(14.59)	1.4812	(7.36)	1.3003	(10.24)	1.2594	(11.06)
$intercept$	-1.3759	(-1.63)	-1.2759	(-2.98)	-0.9230	(-2.69)	-1.1426	(-1.50)	-0.3196	(-0.74)	-0.1518	(-0.40)
R^2	0.354		0.652		0.722		0.249		0.459		0.525	
N	108		108		108		198		198		198	
Panel B: Four-Factor Model												
$mktrf$	1.6451	(10.18)	1.5059	(15.90)	1.4405	(20.59)	1.4953	(9.17)	1.4016	(13.00)	1.3452	(13.99)
smb	1.1150	(3.31)	0.9204	(5.76)	0.7256	(6.14)	1.4593	(5.92)	0.7725	(5.67)	0.6685	(6.13)
hml	1.0099	(2.96)	0.7243	(4.33)	0.7631	(6.41)	1.1257	(3.88)	0.7838	(5.04)	0.6668	(4.88)
umd	-0.1287	(-0.55)	-0.2891	(-2.26)	-0.2748	(-2.64)	-0.8334	(-4.42)	-0.3524	(-3.44)	-0.2907	(-3.36)
$intercept$	-2.1403	(-2.69)	-1.7155	(-3.87)	-1.4225	(-4.63)	-1.1516	(-1.73)	-0.5315	(-1.41)	-0.3423	(-1.03)
R^2	0.409		0.749		0.826		0.490		0.616		0.663	
N	108		108		108		198		198		198	

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