Is Default-Risk Negatively Related to Stock Returns?

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Abstract

Contrary to theoretical arguments, financially distressed stocks have earned anomalously low returns during the post-1980 period. We argue that realized returns are too noisy to detect the true relation between default risk and expected return in small samples. We use the implied cost of capital as an alternative measure of the expected return and find evidence in support of a positive relation between default risk and stock returns. Extending the sample period back to 1952, 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 risk-premium for bearing default risk, but in the the decade of 1980 they were negatively surprised by higher-than-expected bankruptcy filings and lower-than-expected earnings of high default risk stocks.

JEL Codes: G11, G12, G13, G14.

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

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1 Introduction

The relation between default risk and stock returns has important implications for risk-reward trade-off in the financial markets. If default risk is systematic, then investors should demand a positive risk-premium for bearing this risk. The standard implementation of Capital Asset Pricing Model might fail to completely capture the default 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 (2008) among others) document a negative relation between default risk and realized stock returns in the post-1980 period. This evidence suggests that the cost of equity capital decreases with default risk, a finding that has important implications for corporate financial policies also.

At first glance, the documented negative relation between default risk and stock returns can be taken as evidence in support of market inefficiency. However, it remains unclear why some rational investors are not able to arbitrage away this anomaly. We argue that it is difficult to uncover the true risk-return relation using realized return as a proxy for the expected return in small samples (Elton (1999)). This concern is especially severe for portfolios of high default risk stocks because of their high return volatility. As an alternative to realized returns, we use the implied cost of capital computed using analysts' forecasts as a measure of the market's ex-ante expectations (see Pastor, Sinha, and Swaminathan (2008)) and find a strong *positive* relation between default risk and stock returns.

While it is a natural first step to analyze the relation between default risk and realized stock returns, it is the relation between the *expected* return and default risk that matters for the asset pricing theory. Did investors discount the expected cash flows of high default risk stocks at sufficiently high rates to earn a positive premium for default risk? Or did they *expect* to earn negative risk premium for default risk as suggested by the low realized returns of high default risk stocks? Our interpretation of the post-1980 finding and its implications for the asset pricing theories crucially depend on the answers to these questions.

In tests involving realized returns, it is assumed that the ex-post return provides a good estimate of the ex-ante expected return. The realized return, however, can be a very noisy proxy of the expected return, especially in small samples. Elton (1999) provides several examples to demonstrate that even for reasonably long time periods the relation between realized return and risk can be anomalously negative.[1] He argues that significant information events such as large earnings surprises might not cancel each other out in small periods, making realized return a poor proxy of the expected return. If large information shocks affect many stocks in a portfolio in similar ways, then even a portfolio-based analysis is not able to solve this problem. Earlier contributions by Blume and Friend (1973) and Sharpe (1978) also note that realized returns can be very noisy. Merton (1980) shows that estimating the first moment of returns is a difficult empirical task. Lundblad (2007) 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 the return process, the longer it takes to detect the true relation between risk and return inherent in the underlying data-generating process.

By construction, the average stock in a high default risk portfolio is more likely to default in future and lose considerable value. The positive portfolio return must come from some stocks that perform really well. This in turn implies that the volatility of such a portfolio is likely to be very high: an assertion that is strongly supported by the data. In addition, a stock that performs reasonably well after entering the high default risk portfolio is likely to be classified out of this portfolio during the next period. Such a re-balancing strategy further adds to the volatility of high default risk portfolios. Finally, stocks in high default risk portfolios are likely to be affected by economic shocks and information surprises in similar ways. This implies that even at a portfolio level information surprises might not cancel each other in small samples of high default risk stocks. These arguments highlight the potential difficulties in using the ex-post realized return as a proxy for the expected return in estimating the risk-return trade-off for high default risk stocks.

Pastor, Sinha, and Swaminathan (2008) develop the argument on expected and realized returns further and advocate the use of implied cost of capital as a proxy for the expected return. They 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, the implied cost of capital can be a very good proxy for the expected return. 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

[1]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.

future cash-flows based on the analysts' forecasts.[2]

Using the implied cost of capital as a measure of the expected return, we find a *positive* relation between default risk and the expected return. We find that stocks in the top 1% of default risk are expected to earn 1.5-2% per annum higher risk-premium than the median stock. The relation between default risk and the expected return is positive and stable throughout the sample period. Our analysis reveals that investors discount the future earnings of high default risk firms at sufficiently higher rates to earn a positive premium for default risk. We conduct several robustness checks to ensure that our results are not driven by measurement errors in the estimation of the implied cost of capital. In particular, we establish that the relation between default risk and the implied cost of capital is not driven by biases in analysts' forecasts or stale forecasts.

Next, we use realized returns over a longer time period to assess the effect of default risk on stock returns. In the post-1980 period, we find evidence of a large under-performance of high default risk stocks consistent with Campbell, Hilscher, and Szilagyi (2008). However, we find no reliable evidence of under-performance of high default risk stocks during the earlier time period of 1952-1980. The economic magnitude of under-performance drops considerably for the entire 1952-2005 period as compared to the post-1980 period. We carefully analyze the post-1980 result and find that most of the under-performance is concentrated in the decade of 1980. The under-performance of high default risk stocks disappears if we exclude this decade from the sample.

These results show that investors expected to earn positive risk-premium for bearing default risk, but they were negatively surprised by lower-than-expected returns in the decade of 1980. In terms of *ex-ante* expectation, which is what matters for the risk-return trade-off, the relation between default risk and stock returns has been significantly positive during the post-1980 period. 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. Overall, these results show that the post-1980 under-performance of high default risk stocks does not represent an asset pricing anomaly, rather it is a result of surprisingly low realized returns during the decade of 1980.

[2]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 (2008) use dividend growth models to estimate the ex-ante expected returns at the market and portfolio levels, respectively. Brav, Lehavy, and Michaely (2005) use a measure of expected return from the Value Line database to uncover the relation between market beta and expected return.

How were investors surprised in the 1980s? We document four pieces of evidence to support the investor-surprise argument. We begin by comparing actual bankruptcy filings with the expected filings and show that there were higher-than-expected bankruptcies during this decade.[3] There was a significant upward surge in bankruptcy filings during this decade as compared to the historical frequency as well. We analyze forecast errors in earnings and long-term growth rates in our next tests. The forecast errors are computed as the difference between actual and forecasted values of earnings and growth rates. We find that high default risk stocks had significantly higher negative forecast errors than low default risk stocks in the 1980s. In other words, realized cash flows of high default risk stocks were considerably lower than their expectations during this decade. The evidence is equally strong for forecast errors in earnings and long-term growth rates. In the subsequent period, we do not find statistically or economically meaningful relation between forecast errors and default risk.

In our final test, we analyze the accounting performance of high and low default risk stocks in a difference-in-difference framework. We compare the difference in one-year ahead accounting performance of high and low default risk stocks during the 1980s with the corresponding difference in other decades. This estimation approach is designed to detect abnormal under-performance of high default risk stocks during the 1980s as compared to the long-run averages. We find that high default risk stocks had considerably lower accounting profitability and growth rate in this decade as compared to the long-run averages. Our estimation results show that during this decade, high default risk stocks delivered cash flows and growth rates that were 10-20% lower than the long-run averages.

These results provide direct evidence that investors were negatively surprised by higher-than-expected bankruptcy filings and lower-than-expected cash flow realizations of high default risk stocks in this decade. The simultaneous occurrence of low returns and lower-than-expected cash flow news of high default risk stocks support our claim that investors were negatively surprised in the 1980s.

Our study is related to a growing literature in this area. Griffin and Lemmon (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 (2008) argue that potential violation of Absolute Priority Rule (APR) can help explain the negative relation between default risk and stock returns. George and Hwang (2007) argue that the negative relation between returns and leverage can explain the anomaly. Avramov et al. (2007) show that most of the negative return for high default risk stocks

[3] We use the hazard rate model (Shumway, 2001) to compute the expected bankruptcy filings.

is concentrated around rating downgrades. Vassalou and Xing (2004) find some evidence that distressed stocks, mainly in the small value group, earn higher returns.

We contribute to the wider asset pricing literature by showing that the measurement of expected return plays a crucial role in the tests of asset pricing models. We show that conclusions regarding risk-return trade-off can change significantly depending on the way the expected return is measured. It can be a fruitful task in future empirical exercise to construct better measures of the expected return to uncover the true risk-return trade-off in the financial markets.

The rest of the paper is organized as follows. Section 2 describes the construction of default risk measures. We investigate the link between default risk 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 documents evidence of investor-surprise in the 1980s. Section 6 concludes the paper.

2 Default risk measures

There is a large literature on the measurement of default risk dating back to Altman (1968). We use two measures of default risk that have become popular in the literature in recent years. Our first measure is based on the hazard rate estimation methodology of Shumway (2001), Chava and Jarrow (2004), and Campbell, Hilscher, and Szilagyi (2008). The second measure, called the expected default frequency (EDF), is based on the valuation concept of option-pricing models (Merton (1974)).

2.1 Hazard rate model

We closely follow the methodology of Shumway (2001) to estimate the hazard rate model. A brief description of this estimation methodology is provided in Appendix A.1. This method uses historical bankruptcy data to obtain the maximum likelihood estimator of default probability. We use a comprehensive database of bankruptcies that includes the majority of bankruptcies filed by publicly traded firms on AMEX, NYSE, or NASDAQ during 1963-2005. As in Campbell, Hilscher, and Szilagyi (2008), our bankruptcy data comes from Chava and Jarrow (2004). Following Shumway (2001), we model default risk as a function of profitability, leverage, size, return volatility, and the past returns. The model is estimated on June 30 of every year to obtain the default probability of each surviving firm for the following year.

We estimate the model on a rolling basis, making use of all the historical information available as of the estimation date. Consistent with earlier studies, in unreported results we find that default probability increases with the firm's leverage and stock return volatility and decreases with its size and the past year's stock returns. A limitation of this methodology is that it requires historical bankruptcy data to estimate the probability of bankruptcy. Due to this constraint, earlier studies have concentrated on the post-1980 period for estimating this model. We follow these conventions and estimate the hazard rate model from 1980 onwards, taking the 1963-1980 bankruptcy data as the starting point.

2.2 Option-pricing based model

Our second measure is based on structural models of default that consider equity as a call option on firm value (Merton (1974)). Applying this concept, we compute the firm's distance-to-default, which measures the distance between the firm's current value and its bankruptcy threshold. We convert distance-to-default to expected default frequency (EDF), which measures the default likelihood of the firm (see Duffie, Saita, and Wang (2007)). We provide further estimation details in Appendix A.2.

We need information on the market value and volatility of assets of a firm to compute its EDF. We follow the methodology of Bharath and Shumway (2008) to construct the EDF of all sample firms as of June 30 of each year. There are alternative measures of EDF that use different methodologies for estimating the volatility and market value of assets. Some of these measures are based on proprietary information that are not available to us. Bharath and Shumway (2008) demonstrate that their measure performs reasonably well as compared to these alternatives.

Because of the data requirement, hazard rate-based studies are typically limited to the post-1980 period. The distance-to-default model, on the other hand, can be estimated without the historical bankruptcy data. To estimate this model, we need information of a firm's equity value, its debt obligations, and the volatility of its stock returns. These inputs are readily available from CRSP and COMPUSTAT databases dating back to 1952. Thus, we are able to conduct out-of-sample tests for the relation between default risk and realized stock returns based on this measure.[4]

[4]Option pricing models came into existence almost two decades after the beginning of our sample period. 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)). Since we use the EDF measure only to rank stocks into different default risk groups, our empirical exercise is unlikely to suffer from any significant bias due to this concern.

Table 1 presents the summary statistics of both measures of default risk. 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.[5] The correlation is high, but they do have some independent information in them. As we show later, we find negative relation between default risk and realized stock returns in the post-1980 period using either measure of default risk. This gives us confidence that our out-of-sample test using the EDF measure is not an artifact of different model of default risk. We defer the discussion on default risk and realized returns to Section 4 of the paper.

3 Expected Returns

We analyze the relation between default risk and the implied cost of capital in this section. Our study differs from the prior literature in the way we measure the expected return. While the prior literature uses noisy ex-post realized return as an estimate of the expected return, we use ex-ante estimates based on the implied cost of capital.

3.1 Estimation of the implied cost of capital

We compute the implied cost of capital using the 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 free cash flows to the current price. The stock price $P_{i,t}$ of firm i at time t is represented by the following equation:

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

$FCFE_{i,t+k}$ is the free cash flow to equity 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 implied cost of capital (ICC). We take this rate as our measure of the ex-ante expected return at time t.

To implement this model, we need reasonable forecasts of future earnings of the firm. We use the analysts' consensus forecasts, available from the I/B/E/S database, for this purpose. This methodology relies on the assumption that the consensus forecast is a

[5] 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%).

good estimator of investors' expectation. We explicitly forecast future earnings for the next 15 years and capture the effect of subsequent cash flows using a terminal value computation. We obtain earnings forecasts for year $t + 1$ and $t + 2$ using one-year and two-year ahead consensus forecasts. For the subsequent years, we project earnings based on the long-term growth rate, which is also obtained from I/B/E/S. Since we closely follow Pastor, Sinha, and Swaminathan (2008) for the implementation of this model, we defer the estimation details to the Appendix.

The implied cost of capital has two noticeable advantages over the realized return as a proxy of the expected return. First, by construction it is a forward looking measure. This is the rate at which investors discount a firm's future earnings. The implied cost of capital, therefore, provides us with a reasonable proxy of the *expected return*. Second, this measure does not rely on any specific asset pricing model. After an anomaly is discovered, there is often a spirited debate in the literature on whether the anomaly represents a failure of market efficiency or a failure of the underlying asset pricing model (see Campbell, Lo, and MacKinlay, 1997). Our use of ICC as a measure of the expected return is free from this critique. On the flip side, we need to rely on the analysts' forecasts to estimate the ICC model. Therefore, it is important to establish that our results are not driven by measurement errors due to biases in analysts' forecasts or staleness of forecasts. After presenting our main results, we carry out a series of robustness checks to alleviate this concern.

3.2 Default risk and the implied cost of capital

We estimate the implied cost of capital for every firm covered in the intersection of CRSP, COMPUSTAT, and I/B/E/S databases as of June 30 of each year from 1980 to 2005. We remove financials and utilities from this analysis. We subtract the prevailing one-year risk-free rate from the ICC to obtain the expected risk-premium.

3.2.1 Descriptive Statistics

Panel B of Table 1 provides descriptive statistics of the consensus forecasts of earnings and long-term growth rate. The median firm's earnings per share forecast is \$1.04 for the next fiscal year ($EPS1$) and \$1.31 two years ($EPS2$) hence. The long-term growth (LTG) forecast for the median firm is 16% in our sample.

Panel C of Table 1 provides the distribution of the implied risk-premium, i.e., the implied cost of capital in excess of the risk-free rate. To ensure that our results are not driven by outliers, we winsorize the implied cost of capital at 1% from both tails. The expected risk-premium for the base model (r_e^{base}) is 4.31% (5.09%) per annum for the median (mean) stock. As expected, we find a wide distribution of the expected risk-premium across stocks. The difference between the 75^{th} and the 25^{th} percentiles of the expected risk-premium is about 4.70% per annum. These estimates are broadly in line with the earlier papers in the literature.

We also provide the distribution of excess expected return for six alternative models that are used for robustness tests. Broadly speaking, in these models we change the assumptions made for the estimation of future cash flows as compared to the base case. We discuss these models in detail in the robustness sections.

3.2.2 Univariate Tests

We start our analysis by computing the expected risk-premium across various deciles of default risk. We assign stocks into decile portfolios based on the yearly distribution of default risk. We compute the average expected risk-premium for every portfolio and then average them across years on a decile-by-decile basis. Table 2 reports the results. We find a positive relation between default risk and the expected risk-premium. This result holds for both the EDF and the hazard rate-based models of default. Based on the hazard rate model, we find that investors expect to earn a positive risk-premium of 8.15% per annum for stocks in the top decile of default risk. In contrast, the expected risk-premium for the bottom-most decile is only 3.24% per annum. We find a similar pattern for portfolios sorted on the basis of the EDF measure. We also provide the expected risk-premium for the top 5% portfolio since the effect of default risk may be more pronounced at very high levels of default probability. We find that stocks in this portfolio command even higher risk-premium than the top decile portfolio.

These results establish a positive relation between default risk and the expected risk-premium at the univariate level. Some of the differences across high and low default risk portfolios can be explained by differences in their characteristics that may not be related to distress risk. We conduct formal statistical tests in the remainder of this section to control for these effects. We also provide a series of robustness tests to rule out the possibility that our results are driven by stale forecasts or biases in the analysts' forecasts.

3.2.3 Cross-sectional Regression

As compared to low default risk firms, high default risk firms are smaller in size and have higher book-to-market ratio, leverage, and stock return volatility. In cross-sectional studies, Gebhardt, Lee, and Swaminathan (2001) find robust relation between the implied cost of capital and some of these firm attributes. Pastor, Sinha, and Swaminathan (2008) find a positive relation between expected market return and volatility.

In our multivariate tests, we regress the implied risk-premium on the firm's default risk along with several well known cross-sectional determinants of the implied cost of capital. Instead of directly using the probability of default in these regressions, we use the firm's percentile rankings based on the yearly distribution of default risk. The percentile ranking is called the Default Risk Percentile (DRP) in the rest of the paper. This transformation removes the outlier problem and makes the interpretation of DRP regression coefficient easier. This coefficient measures the difference in the expected risk-premium between the highest (DRP=1) and the lowest (DRP=0) default risk stocks.

We include firm size and market-to-book ratio as control variables in all regression models. We estimate the implied cost of capital as of June 30 of each year based on the most recent forecasts available as of that day. If some value relevant negative information arrives in the market between the release of the most recent forecasts and the estimation date (i.e., June 30), then our estimate of the ICC is likely to be upward biased. We include the past one month's stock return to control for staleness in the forecasts. In addition, we control for the firm's leverage and stock return volatility in a stepwise manner. All covariates are winsorized at 1% and 99% to minimize the effect of outliers. Since DRP itself is a non-linear function of some of these variables, we expect to find some decrease in its significance as we include these variables in the regression model.

We use the Fama-MacBeth estimation approach to analyze the relation between default risk and expected return. In the first step, we estimate cross-sectional regressions at yearly frequency. We report time-series averages of the cross-sectional estimates in Table 3. In the computation of earnings forecast, we make explicit use of the analysts' earnings forecasts for the first two years and the long-term growth rate forecasts for the subsequent years. This introduces autocorrelation in the expected risk-premium. We find that the autocorrelation coefficients are not significant beyond the first three lags. Thus, we correct for autocorrelations up to three lags in computing the standard errors.

Panel A of Table 3 presents the estimation results based on the hazard rate model. Controlling for size, market-to-book ratio, and the past month's stock return, we find a statistically significant coefficient of 3.64% on DRP_{hazard}. Thus, investors expected to earn a positive risk-premium of 3.64% per annum from their investment in stocks that fall in the top 1% of default risk distribution as compared to stocks that fall in the bottom 1%. The expected risk-premium is higher for smaller stocks and stocks with lower return in the past one month. These results remain robust to the inclusion of leverage and stock return volatility. In Model 3, we find that the expected risk-premium increases with the past return volatility. Our key results remain similar for the EDF measure (reported in Panel B). Depending on the model specification, we find that the expected risk-premium increases by 3.14-3.89% per annum between the two extreme percentiles of default risk. These estimates suggest that investors expect a positive risk-premium of 1.6-1.9% per annum for investing in the highest default risk stock as compared to the median stock. These results are consistent with the theoretical prediction that investors demand positive risk-premium for bearing default risk. In the remainder of this section, we conduct a series of robustness tests. We address two important concerns with our study: (a) biases in analysts forecasts and (b) staleness of these forecasts.

3.3 Robustness: Biases in Analyst Forecasts

Our analysis assumes that the analysts' consensus forecast provides an unbiased estimate of the investors' expectations. There is ample evidence in the literature showing that investors react in the same direction as the analysts' forecast error. This provides support for our use of consensus forecast as a measure of investors' expectations on average. If analysts are systematically biased in favor of higher default risk stocks, then our estimates of the ICC will be biased upward for these stocks. This measurement error will help us in finding a positive cross-sectional relation between default risk and the expected return. If analysts are biased in general for all stocks, then we do not suffer from any bias. Therefore, our main concern is with the possibility of a positive correlation between default risk and analyst bias.

We consider two empirical approaches to deal with the issue of measurement error in the implied cost of capital. In the first approach, we focus directly on firms and analysts that are likely to suffer from these biases. In the second approach, we analyze the extent of forecast errors across different default risk portfolios. For expositional clarity, we discuss the first approach in this section, leaving the discussion of the second approach to Section 5 of the paper.

3.3.1 External financing by firms

There is a large literature relating analyst optimism to investment banking conflicts. Rajan and Servaes (1997) find that analysts issue overly optimistic forecasts for firms with recent IPOs. Bradshaw, Richardson, and Sloan (2006) extend their analysis to a broader measure of external financing and show that analysts are biased in favor of firms with large investment banking business. They measure investment banking business by the amount of cash raised by a firm through its corporate financing activities such as equity and debt issues. Based on these findings, we argue that the forecasts are likely to be more optimistic for firms with large investment banking business. In our first robustness test, rather than using the consensus forecast we compute a modified measure of earnings forecast that accounts for this bias.

We first construct the net external financing as in Bradshaw, Richardson, and Sloan (2006). Every year we compute the percentile rankings of all sample firms based on the amount of net external financing (debt and equity issues) raised by them during the year. For a firm with the percentile ranking nef_i, we take the earnings forecast as $EPS_i = nef_i * LOWEPS_i + (1 - nef_i) * HIGHEPS_i$. $LOWEPS$ and $HIGHEPS$ are the lowest and the highest earnings per share estimates available from I/B/E/S. In this method, we assign the most pessimistic forecasts to the firm with the highest nef ranking and the most optimistic forecast to the firm with the lowest nef ranking. The weighting scheme assigns linearly declining weight to the most optimistic forecasts as the firm's net external financing activities increase. This weighting scheme assumes that the pessimistic forecast is a more reliable measure of investors' expectations for firms with large investment banking business. Of course, if all analysts are biased in favor of firms with high nef ranking, then this technique will not be able to eliminate the bias. However, even in that extreme case, this method alleviates the effect of the bias.

Using the modified EPS measure, we re-estimate the implied cost of capital ($r_e^{netextfin}$) and provide the regression results in Table 4. The point estimate on the DRP variable is 2.99% for the hazard rate model and 3.35% for the EDF model. These estimates are 15-25 basis points lower than the corresponding estimates based on the consensus forecasts. They remain statistically significant at 1% level. In unreported results, we re-estimate this model with only equity or debt issuance as the proxy for net external financing. Our results remain similar.

3.3.2 Affiliated analysts

Several studies find that the analysts issue biased recommendations when they are affiliated with investment banks that have business ties with the covered firm (see Michaley and Womack (1999), Dechow, Hutton, and Sloan (2000), and Ljungqvist et al. (2007)). In our second test, we re-estimate the implied cost of capital after removing the affiliated analysts' forecasts from the consensus estimates. We follow Ljungqvist et al. (2007) and Kumar (2008) to identify the affiliated analysts. We consider an analyst as affiliated if she works for a brokerage house that has underwritten the covered firm's IPO in the past five year, any SEO in the past two years or any bond issue in the past one year. Data on IPOs, SEOs, and bond issues are obtained from the SDC database.

We take the median forecasts issued by only the *unaffiliated analysts* and compute the implied cost of capital ($r_e^{unaffiliated}$) using the modified forecasts. We re-estimate the Fama-Macbeth regression models and provide the estimation results in Table 4. We find that both DRP_{hazard} and DRP_{EDF} have positive and statistically significant coefficients in this specification as well. Though the point estimates are lower than the base case, they remain large in economic terms. If the key source of analyst optimism is the investment banking pressure, then these results alleviate concerns regarding analysts biases to a large extent.

3.3.3 Optimistic versus pessimistic forecasts

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 starts with the assumption that there is a positive bias in favor of high default risk stocks. However, it is less likely that the most pessimistic forecast for the high default risk stocks is still upward biased as compared to the most optimistic forecasts for the low default risk stocks. Every year we compute the percentile ranking of all sample firms based on their default likelihood. For a firm with percentile ranking d_i, we take the earnings forecast as $EPS_i = d_i * LOWEPS_i + (1 - d_i) * HIGHEPS_i$. This method assigns the most optimistic forecast to the lowest default risk firm ($d_i = 0$) and the most pessimistic forecast to the highest default risk firm ($d_i = 1$). For the intermediate firms, it assigns linearly increasing weight to the lowest forecast as the firm's default risk increases. We construct a similar measure where we bias the long run growth forecasts against finding our result.

In these tests, we introduce a bias in the computation of earnings or growth forecasts in a manner that makes it harder for us to find a positive relation between default risk and the implied cost of capital. Results are provided in Table 4. As expected, the coefficients on DRP_{hazard} and DRP_{EDF} come down considerably for these specifications as compared to the base case analysis. However, they still remain positive and significant, both in statistical and economic terms.

These tests alleviate concerns regarding bias at the level of individual analysts. If all analysts are positively biased in favor of high default risk stocks, then these tests may not be able to completely remove the effect of analyst bias from our analysis. We address this issue more directly by analyzing the forecast errors of analysts' estimates across high and low default risk stocks. Since we make use of forecast errors to partly address the issue of investors' surprise in the post-1980 period, we discuss these results in Section 5 of the paper after analyzing the relation between default risk and realized stock returns. In that section, we show that high default risk stocks had large negative forecast errors in the 1980s, which disappeared in the later periods.

3.4 Robustness: Impact of Stock Price

Firms with high default risk have lower stock price on average. To separate the mechanical effect of low stock price on the implied cost of capital, we re-estimate the Fama-MacBeth regression model after including the inverse of the stock price, *invprice*, as an additional regressor in the model. Results are provided in Table 5 (Model 1 of Panels A and B). The coefficient on DRP remains positive and significant. As compared to the corresponding base model, the point estimate on DRP decreases by about 50-80 basis points in this model. However, the effect is still large in economic terms.

3.5 Robustness: Stale Forecasts

We estimate the implied cost of capital based on the firm's stock price and its most recent analyst forecast available as of June 30 of every year. If some adverse information arrives in the market between the release of the most recent analyst forecast and the estimation date (i.e., June 30), then our estimate of the ICC is likely to be upward biased. In these cases, while the stock price already incorporates the effect of new information, earnings forecast is still based on the old information. We include the past one month's stock return in all regression models to control for this effect. However, if analysts are slow in updating their forecasts, then the past one month's return may not be sufficient to remove the stale forecast bias.

We re-estimate the regression model with the past three-, six- and twelve-month returns to ensure that the relation between the ICC and the DRP remains robust to the inclusion of past returns at various lags. Results are reported in Models 2, 3 and 4 of Table 5. The slope coefficient on DRP remains positive and statistically significant in all the models. As the lag increases, the effect of past return on the ICC decreases both in statistical and economic terms. In unreported results, we also include past two- and three-year returns in the model and obtain similar results. Our results are unlikely to be an artifact of sluggishness in the analysts' forecast revisions.

3.6 Robustness: Simulated Bankruptcy Time

We consider firms as going concerns for the estimation of the implied cost of capital. If analysts incorporate the bankruptcy probability by sufficiently lowering the mean forecasts of higher default risk firms, then our estimation exercise does not suffer from any bias. As a robustness exercise, in this section we explicitly incorporate the possibility of bankruptcy in the forecasts of future cash-flows (see Damodaran (2006)).

We start with the estimation of future cash flows for every firm-year observation as in the base case. In addition, for every firm we estimate a time-to-bankruptcy based on a simulation exercise. The simulation is conducted as follows. We first obtain the annual default probability (p_t) of every sample firm based on the hazard rate estimation of year t. We obtain a draw from the Bernoulli distribution with success probability p_t for every subsequent year. If the outcome of this draw is one, then we assume that the firm goes bankrupt in that year. All future cash-flows are then identically set to zero after the bankruptcy date. We re-estimate the implied cost of capital ($r_e^{poisson}$) based on these truncated cash-flows. By construction, this model ensures that firms with high default risk experience higher bankruptcy rates in future.

In Table 6, we reproduce the result of Fama-McBeth regression using this new measure of the ICC. Our results remain robust. Compared to the base case regression, the coefficient on the DRP variable is lower, but it remains positive and significant both in statistical and economic terms.

3.7 Robustness: Different Forecasting Horizon

In the implied cost of capital model, we forecast cash flows for the first 15 years and capture the effect of subsequent cash flows using a terminal value calculation. As a robustness check, we re-estimate the implied cost of capital (called $r_e^{10years}$) using a forecasting horizon of 10 years. In unreported Fama-MacBeth regressions, we confirm the robustness of our results to the re-estimated implied cost of capital. We find a significant coefficient of 3.72% (3.40%) per annum on the DRP variable based on the hazard rate (EDF) model.

3.8 Robustness: Other Measures of Bankruptcy

We use two alternative ways to form portfolios based on default risk. In the first measure, we use a simplified version of hazard rate model by dropping the firm's market capitalization and past stock return as covariates (see Appendix A.1 for details). This model predicts a firm's default likelihood based on its total assets, accounting profitability, book leverage, and the idiosyncratic volatility of stock returns. Thus, this model excludes the firm's market price and market capitalization from the estimation of its default likelihood. We undertake this robustness exercise to ensure that our results are not mechanically driven by lower market price or market capitalization of high default risk stocks.

In the second measure, we use a simple sorting strategy that does not rely upon either the hazard rate estimation or the option-pricing model. In this method, we sort stocks based on their *leverage* and *stock return volatility*. We define *leverage* as the ratio of total debt (sum of long-term debt and short-term debt) to the market value of assets (sum of long-term debt, short-term debt, and market value of equity) and *volatility* as the standard deviation of the stock returns computed using daily returns over the past one year. Our exercise is based on the assumption that a firm's bankruptcy risk can be captured reasonably well by its leverage and volatility in operating income. We sort stocks into ten groups along these two dimensions and classify a stock as a high default risk stock if it falls in the top deciles of both measures.[6] Though coarse, the advantage of this model is that it doesn't require any assumptions on the bankruptcy likelihood function or the model of default. All our results are robust to these simple measures of default. In the interest of space and clarity, we do not report results based on these models.

Overall, we provide evidence in support of a positive relation between default risk and the expected stock return. We show that our key result is unlikely to be explained away by analyst biases or stale forecasts. The result is robust to alternative measures of

[6]Our simple sorting technique based on the market leverage and return volatility provides a reasonable measure of bankruptcy risk. For example, more than 85% of stocks sorted into the top decile of both leverage and volatility are classified into the top 10% of distress likelihood using the EDF measure.

default risk and several alternative ways of computing the implied cost of capital.

4 Realized Returns

We now analyze the relation between default risk and stock returns using realized returns over a long period of time. We consider all NYSE, AMEX, and NASDAQ domestic common stocks covered by CRSP and COMPUSTAT databases from 1952 to 2006. Following Campbell, Hilscher, and Szilagyi (2008), we remove firms with stock price of less than one dollar as of the portfolio formation date. We sort all available stocks into default risk portfolios as of July 1 of each year. We hold a stock in the assigned portfolio till the next re-balancing period or de-listing date, whichever is earlier. We obtain monthly returns from CRSP tapes. In the month of de-listing, we take the de-listing return whenever available from CRSP (Shumway, 1997).

4.1 Evidence from the post-1980 period

We start our analysis by replicating the key results of Campbell, Hilscher, and Szilagyi (2008) for the 1981-2006 period. We form portfolios of stocks in the top 5% and 10% of default risk based on the hazard rate model estimates. We compute the value-weighted return of these portfolios on a monthly basis and regress the portfolio return in excess of risk-free rate on the Fama-French three factors and the momentum factor. Results are provided in Panel A of Table 7. Consistent with the findings of Campbell, Hilscher, and Szilagyi (2008), we find significant negative intercepts for both portfolios. The economic magnitude of under-performance is large as well: -1.22% per month for the top 5% and -0.69% per month for the top 10% portfolio. In unreported results, we find that the under-performance is even larger (-1.41% per month) for the top 1% portfolio.

We find significant positive loadings on market, SMB, and HML factors in these regressions. These factor loadings are consistent with the intuition that distressed stocks are predominantly small and value stocks. We find significant negative coefficients on the momentum factor, confirming that distressed stocks behave like recent losers. We also compute annual standard deviation of the excess portfolio return (unreported). These numbers are in the range of 27%-41% depending on the portfolio. As expected, these numbers are remarkably higher than the market volatility. The top 1% default risk portfolio has the highest return volatility of 41.85%. The return volatility decreases monotonically to 27.23% for the top 10% portfolio.

We extend the Campbell, Hilscher, and Szilagyi (2008) study by using other measures of default risk. We estimate four-factor regression model for portfolios sorted on the basis of the EDF measure. The estimation results are provided in Panel A of Table 7. Consistent with the hazard rate-based portfolio regressions, we find evidence of significant under-performance for high default risk portfolios based on the EDF measure as well: -0.98% per month for the top 5% and -0.72% per month for the top 10% portfolio. In unreported results, we find that the under-performance is even larger (-1.50% per month) for the top 1% portfolio. Both the hazard rate model and the EDF model provide similar results in the post-1980 period, which gives us confidence in using the EDF measure for the pre-1980 period.

In unreported results, we use yet another measure of default risk based on a two-way sorting technique. We sort stocks into ten groups based on their market leverage and the past year's stock return volatility. A stock is assigned to the top 1% portfolio if it falls into the top most decile of both dimensions. It is assigned to the top 5% (10%) portfolio if it falls into the top two (three) deciles of both dimensions.[7] The portfolios of stocks in the top 1%, 5%, and 10% of default risk under-perform the four factor benchmark by 1.48%, 0.73%, and 0.59% per month, respectively. The under-performance of high default risk stocks reported by Campbell, Hilscher, and Szilagyi (2008) and Dichev (1998) is robust to alternative measures of default risk.

4.2 Evidence from the pre-1980 period

In this section, we conduct an out-of-sample test of the default risk anomaly. We sort stocks into high default risk portfolios based on the EDF measure and investigate the portfolios' value weighted returns during the pre-1980 period.[8] Since economic data are often non-experimental in nature, it is advisable to conduct out-of-sample tests in these settings (see Campbell, Lo, and MacKinlay, 1997 and Lo and MacKinlay, 1990). A longer time-series also allows us to minimize problems associated with the use of noisy realized returns data. Conrad, Cooper, and Kaul (2003) discuss the usefulness of out-of-sample tests especially for portfolios sorted on firm characteristics.

We extend the sample back to 1952 based on the availability of COMPUSTAT and CRSP data. Results are provided in Panel B of Table 7. We provide regression results

[7]Though there are fewer than 5 or 10% stocks in these portfolios, we prefer this nomenclature to be consistent with the rest of the presentation.

[8]In unreported tests, we also use the two-way sort based on leverage and equity return volatility to conduct the out-of sample validity of distress risk anomaly. Our results remain similar to the results based on the EDF measure.

for the market-model and the four-factor model. We do not find any evidence of under-performance in the market-model regressions with insignificant intercepts of -0.12% and -0.07% per month for the top 5% and the top 10% portfolios, respectively. In the four-factor model, the negative intercepts become a little more pronounced; however, they remain statistically insignificant. The addition of SMB, HML, and the momentum factors weakens the model's power to explain portfolio returns as compared to the one-factor market model. We conduct several tests (unreported) to ensure the robustness of the results in the pre-1980 time period. Results are similar if we consider the top 20% default risk portfolio or use a measure of default risk based on the fitted values of hazard rate model estimated using the 1980-2005 data. In a nutshell, there is no reliable evidence of under-performance of high default risk stocks in the pre-1980 period. These results are consistent with Dichev (1998) who notes that the anomaly is weaker in 1965-1980 period.

4.3 Evidence from the entire period

We present market-model and four-factor model estimation results for the entire sample period in Panel C of Table 7. The market model intercepts are negative but insignificant at the conventional levels for both portfolios. In the four-factor regression model, we find negative and significant intercepts. However, the economic magnitude of the under-performance is considerably lower as compared with the the under-performance in the post-1980 period. Based on the EDF measure, the top 5% portfolio earned negative abnormal return of 11.76% per annum in the post-1980 period. In contrast, the under-performance of this portfolio drops to 6.48% per annum for the entire 1952-2006 period. We find a similar pattern for the top 10% portfolio. In unreported tests, we also find similar results for portfolios formed on the basis of two-way sorting on leverage and stock return volatility. Overall, we find a significant decline in the under-performance of high default risk stocks for the longer sample period as compared to the post-1980 period. We also find that the market-model does a better job in explaining the returns of high default risk portfolios as compared to the four-factor model.

4.4 Evidence without the decade of 1980s

In this section we analyze the post-1980 under-performance of high default risk stocks in further detail. We show that a significant part of the under-performance is concentrated in the decade of 1980. We estimate the four-factor regression model separately for the decade of 1980 and the remaining period. Results are provided in Table 8. Panel A provides estimation results for the decade of 1980, Panel B for the remaining period. During the 1980s, we find an intercept of -2.36% per month (-28.32% per year) for the top 5% portfolio sorted on the basis of the hazard rate default probability. The intercept is -1.40% per month (-16.80% per year) for the top 10% portfolio. These estimates show that the magnitude of under-performance is large in the decade of 1980. Similar results hold for portfolios sorted on the basis of the EDF measure.

In Panel B, we provide regression estimates after excluding the decade of 1980 from the sample. In the hazard rate model, which now includes only the post-1990 period, there is no evidence of under-performance. The same result holds for the EDF model estimated with the pre-1980 and post-1990 data. The factor loadings remain stable across these two sub-samples.

We conclude that the post-1980 under-performance of high default risk stocks can be attributed to the poor performance of one decade. On the other hand, the relation between default risk and the implied cost of capital remains stable throughout the sample period. These results suggest that investors expected to earn a positive risk-premium for bearing default risk throughout the sample period, but they were negatively surprised in the 1980s. We revisit this issue with more direct evidence in support of the negative surprise argument later in the paper.

4.5 Robustness: Fama MacBeth regressions

As a robustness check, we estimate annual cross-sectional regressions of excess stock returns on the default risk percentile. The dependent variable is the cumulative monthly excess return (over risk-free rate) of a stock from July of year t to June of year $t+1$.[9] We regress it on the default risk percentile (DRP), market capitalization, and market-to-book ratio of the firm measured as of June 30 of year t. We rank all covariates from zero to one based on their yearly distribution. The regression coefficients measure the difference between the realized returns of extreme portfolios.

After estimating the cross-sectional regressions, we compute the time-series mean and t-statistics of the coefficient on DRP. In un-tabulated results, we find that the time-series average of the coefficient on DRP_{EDF} is -11.17% per annum (t-statistics of 3.24) in the post-1980 period. Similar result holds for the hazard rate model. Using the EDF measure, we estimate this model for the pre-1980 period and find an insignificant coefficient of -1.71% per annum (t-statistics of 0.53) on DRP_{EDF}. For the entire sample

[9] Similar results are obtained if we use buy-and-hold returns over the next one year.

period, the coefficient on DRP_{EDF} is -6.18% per annum (t-statistics of 2.56). These results are consistent with the calender time regression results presented earlier.

4.6 Robustness: CRSP-only model

A potential concern with the pre-1980 analysis is the effect of COMPUSTAT survivorship bias on our results (see Davis (1994)). Chan, Jegadeesh, and Lakonishok (1995) argue that the survivorship bias in COMPUSTAT data is small. We carry additional tests to alleviate this concern. We estimate a naive model of default risk that does not require any data from the COMPUSTAT. Shumway (2001) and Chava and Jarrow (2004) show that the market-based variables, namely the past stock return, volatility, and market capitalization, are the most important predictors of future default. Since these variables are available from the CRSP tapes, we are able to estimate a naive model of default based on these market-based measures without the requirement of COMPUSTAT coverage. An obvious limitation of this approach is that the default risk estimates of this model are likely to be less accurate than the other measures of default used in the paper.

We consider all bankruptcies from 1963 onwards as in our base case analysis. We augment this set with liquidations or performance-related de-listings obtained from the CRSP tapes for the earlier period going back to 1926. We estimate a naive hazard rate model with the past year's stock return, return volatility, and market capitalization. The model is estimated on a rolling basis as of July 1 of every year starting from 1952.

In un-tabulated results, we find that the top 5% portfolio has a significant market model intercept of -1.11% per month in the post-1980 period. The four-factor model intercept is -0.80% for the top 5% portfolio, which is significant at the 1% level as well. The under-performance disappears in the 1952-1980 period. We find an insignificant market-model intercept of 0.30% per month for the top 5% portfolio during this period. The four-factor model intercept is insignificant as well. These results alleviate concerns about COMPUSTAT survivorship bias in our analysis.

4.7 Robustness: IBES sub-sample

Our expected return tests are limited to the sub-sample of I/B/E/S-covered firms. We do not impose this data requirement for the realized returns tests. To address the issue of sample selectivity in the expected return analysis, we re-estimate the Fama-French and Fama-MacBeth models for the sub-sample of I/B/E/S-covered firms in the post-1980 period. In unreported tests, we confirm the negative relation between default risk and stock returns for this sub-sample as well.

5 How Were Investors Surprised?

We show that investors expected to earn positive risk-premium for bearing default risk, but they were negatively surprised in the decade of 1980. How exactly were investors negatively surprised? We analyze the extent of bankruptcy filings, forecast errors in growth rates, forecast errors in earnings, and operating performance of high default risk stocks to provide more direct evidence in support of the negative-investor-surprise argument.

5.1 Bankruptcy filings

We first analyze the relation between actual and expected bankruptcy filings during the 1980s and other periods. Based on the hazard rate model estimates, we compute the expected number of bankruptcies as of the beginning of each year. We subtract it from the actual number of bankruptcies during the year and scale the difference by the number of firms in our sample as of the beginning of the year. We take the scaled measure as a proxy of the surprise in bankruptcy filings during the year. We start this estimation exercise in 1970. We consider all filings during 1963-1969 as the starting estimation period and update the bankruptcy prediction model on a rolling basis for the subsequent years. This exercise produces a time-series of bankruptcy-surprises from 1970 to 2005. We regress it on an indicator variable *dec80* that equals one if the estimation year falls in the 1980s, and zero otherwise.

Results are provided in Model 1 of Panel A in Table 9. We find a positive and significant coefficient on *dec80*, indicating that investors were surprised by higher-than-expected frequency of bankruptcy filings during the 1980s as compared to the remaining period. The slope coefficient of 0.0022 implies that the bankruptcy filing rate was 0.22% higher than the expectation during this decade. The unconditional mean of default probability is 0.50% in our sample (see Table 1). These estimates suggest that the economic magnitude of bankruptcy-surprise in the 1980s was high as well. These results are consistent with Campbell, Hilscher, and Szilagyi (2008), who report that the bankruptcy prediction model under-predicted the actual bankruptcy during much of the 1980s (see their Figure 1).

As a robustness check, we create an additional measure of bankruptcy-surprise. There is a monotonic increase in the number of sample firms over time. To make sure that our results are not driven by any relaxation in the listing standards over time, the second measure is defined as the difference between the actual and expected defaults scaled by the actual number of defaults during the year.[10] Results are provided in Model 2 of Panel A. Consistent with the earlier model, we find a significant and positive coefficient on *dec80*. The slope coefficient shows that the actual bankruptcy filings in the 1980s were approximately 48% higher than the expected filings.

There has been a remarkable jump in the frequency of bankruptcies during the 1980s even on an unconditional basis (see Chava and Jarrow (2004) and Campbell, Hilscher, and Szilagyi (2008)). While the bankruptcy filing was in the range of 0.10-0.20% of active firms during much of the 1960s and 1970s, it increased considerably to 1.30-1.80% in the 1980s.

These findings suggest that based on both the historical frequency as well as the predicted frequency, the decade of 1980 had much higher incidence of bankruptcy as compared to the other periods. It is plausible that changes in regulatory environment such as the implementation of the Bankruptcy Reform Act of 1978 or changes in financial markets such as the rise and collapse of the junk-bond market contributed to the higher-than-expected bankruptcies during this decade. We leave the exercise of exploring precise linkages between these institutional changes and bankruptcy surprises for future work.

5.2 Forecast errors

In our second test, we investigate whether investors were negatively surprised by lower-than-expected cash flow realizations of high default risk stocks during the 1980s. We analyze surprises in earnings per share and long-term growth rate by computing the forecast errors of these variables. The forecast errors are computed by subtracting the analysts' consensus forecasts from the realized earnings and growth rates for the corresponding period. We closely follow the prior literature to compute these measures.

5.2.1 Forecast errors in growth rate

We follow Dechow, Hutton and Sloan (2000) and Core, Guay, and Rusticus (2006) to compute forecast errors in long-term growth rate. We obtain data on both realized and expected growth rates from I/B/E/S. The expected growth rate is same as the consensus forecast of the analysts. In addition to forecasts, I/B/E/S also provides a measure of

[10] We obtain similar results if we scale the difference by expected bankruptcy filings.

the realized growth rate. This measure is estimated by fitting a least squares growth line to the logarithms of past six annual earnings observations. Dechow and Sloan (1997) describe this procedure in detail and highlight the benefits of this estimation method over other alternatives.

We obtain the consensus analysts' forecast for each sample firm as of June 30 of every calendar year t. This forecast is typically available after the end of fiscal year $t-1$, but before the end of fiscal year t. We use the I/B/E/S-reported realized growth rate for fiscal year $t+3$ as the corresponding realization for this forecast.[11] The forecast error is defined as the difference between the realized and the expected growth rates. If a firm is not present in the I/B/E/S database in year $t+3$ (e.g., due to reasons such as bankruptcy), then we are unable to compute its forecast error. We know from our earlier analysis that the realized bankruptcy was significantly higher than the expected bankruptcy during the 1980s. In this decade, therefore, there is a higher likelihood that the missing observations are due to the bankruptcies of high default risk stocks. This introduces a bias against finding our results.

We estimate the following regression model with the pooled data:

$$fe_{it} = \alpha + \beta dec80_{it} + \gamma DRP_{it} * (1 - dec80_{it}) + \eta DRP_{it} * dec80_{it} + \epsilon_{it} \qquad (2)$$

fe_{it} measures the forecast error of the firm i in year t, DRP_{it} is the default risk percentile, $dec80_{it}$ is an indicator variable that equals one for observations in the 1980s, and zero otherwise. We interact DRP with $dec80$ and its complement to separately assess the impact of DRP during the decade of 1980 and the remaining period. The coefficient on $dec80$ captures the average effect of this decade on the forecast error. η measures the difference in forecast errors for high default risk stocks as compared to low default risk stocks in the 1980s. We estimate this model using median regression to minimize the effect of outliers. All standard errors are bootstrapped with firm-level clustering to account for the correlation in error terms of multiple observations of a firm.[12]

Results are provided in Panel B of Table 9. To save space, we report estimation results for the EDF model only. In unreported results, we find equally strong results for

[11] Our results remain equally strong if we take year $t+4$ or $t+5$ numbers for the realized growth rate. As we move from year $t+3$ to $t+5$, sample size decreases due to bankruptcies and mergers. We report results based on year $t+3$ since it provides us with a good balance between the sample size and a meaningful measure of realized growth rate.

[12] Core, Guay, and Rusticus (2006) also use median regression to analyze the relation between forecast errors and corporate governance variables. Our results are similar for OLS specification after we winsorize the forecast error variable from both tails of its distribution.

the hazard-rate model. We find negative and significant coefficient on the interaction of DRP and $dec80$. In the decade of 1980, realized growth rates were significantly lower than the expected growth rates for high default risk stocks. The economic magnitude of the surprise is large as well. As compared to the lowest default risk firm, the highest default risk firm's realized growth rate was 5.34% lower than the expectation during the 1980s. For the subsequent period, we do not find any evidence of negative surprise for high default risk firms.

In unreported results, we estimate the model after controlling for firm characteristics such as size and market-to-book ratio and obtain similar results. In another unreported test, we separately estimate the regression of forecast error on DRP for the decade of 1980 and the other periods. Results are similar.

5.2.2 Forecast errors in earnings per share

We follow Livnat and Mendenhall (2006) to compute forecast error in earnings per share. They compute forecast error as the difference between actual and expected quarterly earnings scaled by the firm's stock price. This measure has been widely used in the accounting literature to study the relation between earnings surprises and earnings announcement day return. Since our methodology is same as Livant and Mendenhall (2006), we do not reproduce the estimation details in this paper (see pages 184-186 of their paper for details).

We compare forecast errors in earnings per share across high and low default risk stocks by estimating a pooled median regression model as described in the previous section. Results are provided in Panel B of Table 9. We find economically large and statistically significant coefficient on the interaction of DRP and $dec80$ indicator variable. The coefficient on this interaction term is -0.0031, which is about three times larger than the sample mean of forecast errors. The coefficient on the interaction of DRP and $(1 - dec80)$ is insignificant, both in statistical and economic terms. In fact, the coefficient on $DRP\text{x}(1 - dec80)$ is close to zero in economic terms. The difference in the coefficients on the two interaction terms is statistically significant at the 1% significance level. Consistent with the negative surprise argument, these results show that the realized earnings of high default risk stocks were considerably lower than the expectations during the decade of 1980.

As an alternative specification, we estimate Fama-Macbeth regression model with quarterly cross-sectional data. In the first step, every quarter we estimate a cross-sectional median regression with forecast error as the dependent variable and default risk percentile as the explanatory variable. We average the estimated coefficient on DRP separately for the decade of 1980 and the later period. The time-series mean (t-statistics) of this coefficient is -0.0037 (-8.29) for the 1980s and -0.0001 (-1.39) for the later periods. These results are consistent with the pooled estimation model.

We perform several unreported robustness tests. Results are similar if we estimate the model with the OLS method instead of the median regression. We also experiment with different scaling variables in the computation of forecast errors. Instead of using the firm's stock price, we use total assets per share and the expected earnings as alternate scaling variables. Finally, we use annual earnings forecast error in place of quarterly forecast errors. Our main results remain similar. A consistent pattern emerges from all these analyses. We find economically large and statistically significant negative forecast error for high default risk stocks during the 1980s in all model specifications. In the later periods this relation either disappears or weakens considerably. In some model specifications, we find negative coefficient on DRP during the later periods as well. However, even in these specifications, the economic magnitude of the coefficient on $DRP\text{x}(1 - dec80)$ is much lower - about 80-90% lower - than the coefficient on the $DRP\text{x}dec80$ interaction term. Together with the earlier result on surprises in the growth rates, these results suggest that investors were negatively surprised by lower-than-expected earnings news of high default risk stocks during the 1980s.

5.3 Operating performance of high default risk stocks

In our final test, we focus on the relation between default risk and operating performance. Our goal is to analyze whether higher default risk stocks performed relatively worse than their low default risk counterparts during the 1980s as compared to other decades. An advantage of this exercise is that it can be estimated for the entire sample period (1952-2005) since it does not require data from I/B/E/S. On the flip side, an obvious limitation of this approach is that we do not have any explicit expectation model to compute surprises.

We estimate the following firm fixed effect regression model with pooled data covering the entire sample:

$$y_{i,t+1} = \mu_i + \beta DRP_{it} + \gamma dec80_{it} + \eta DRP_{it} * dec80_{it} + \epsilon_{it} \tag{3}$$

$y_{i,t+1}$ measures the operating performance of firm i during fiscal year $t + 1$; DRP_{it} measures the default risk percentile of firm i as of June 30 of year t; $dec80_{it}$ is an indicator variable that takes a value of one for observations in 1980s and zero otherwise. μ_i stands for firm fixed effect. Since we do not have an explicit expectation model for this test, we include firm fixed effects to separate the effect of unobserved firm heterogeneity from the effect of default risk. This specification allows us to estimate the differential effect of DRP on the next year's operating performance in a difference-in-difference setting.[13]

Instead of forecast errors, in this model we compare the difference in operating performance of high and low default risk stocks during the 1980s with the difference in other periods. Under the assumption that the long run average relation between default risk and operating performance provides a good measure of investors' expectations, β measures the expected relation between default risk and operating performance. η, therefore, measures the surprise in the decade of 1980s as compared to the long run expectation.

Our choice of operating performance measures is motivated by the discounted cash flow valuation model. We use measures that capture the firm's growth rate, operating profitability, net cash flows, and operating efficiency. We use year-over-year change in the logarithm of the firm's sales as a proxy for the growth rate. We use growth rate in sales since growth rates based on yearly earnings can be notoriously noisy. We use three measures of realized cash flows: net profits, cash flows, and earnings before interest, taxes, and depreciation, all scaled by total assets. Finally, we use asset turnover rate defined as sales-to-asset ratio to measure the operating efficiency of firms. We obtain these data from the COMPUSTAT annual tapes (see Appendix for the details). We winsorize all accounting data at 2.5% from both tails since accounting ratios have large outliers.[14] For profitability measures, we also include the lagged value of the firm's log (assets) to control for variations in profitability and growth rates across firm size. All our results are robust to the exclusion of this control variable.

Results are provided in Table 10. We only report results based on the EDF model since results based on the hazard rate model are similar. As expected we find statistically significant negative coefficient on the DRP variable for all five performance measures. Firms with higher default risk have lower growth rate, return on assets, cash flows/assets, EBITDA/assets, and asset turnover in the next year. This is expected since the DRP measure is constructed to detect the under-performing firms in the next year.

The slope coefficient on the interaction term $DRP\text{x}dec80$ is negative and significant for all five measures. During the decade of 1980, high default risk stocks per-

[13]Results are similar for pooled regression without firm fixed effects (i.e., for a specification that is similar to the forecast error regression model). Since we want to focus on difference-in-difference estimator, we present results for the fixed effect specification only.

[14]Our results remain similar if we winsorize the data at 1% or 5% from both tails.

formed much worse than their low default risk counterparts as compared to their relative under-performance during the other decades. The economic magnitude of the under-performance is large as well. For example, in Model 1 we find a difference of 11.47% in the growth rates of the highest and the lowest default risk stocks during normal periods. The coefficient on the interaction term is -2.60%, indicating that the growth rate difference between the extreme portfolios of default risk was about 23% lower during the 1980s as compared to the unconditional long-run average. Similarly, we find a slope coefficient of -12.08% on DRP in the ROA regression model. As compared to this long run average, there was an additional difference of -1.23% during the 1980s. Overall, these estimates suggest that during this decade high default risk stocks delivered cash flows and growth rates that were 10-20% lower than the long run averages. We perform several robustness checks by changing the econometric specifications and by including additional control variables in the model. Results are robust (unreported).

These results show that the decade of 1980 was especially disappointing for high default risk stocks. Both as compared to the explicit expectation models and the unconditional long-run averages, high default risk stocks performed much worse during this period. These findings lend support to our basic argument that investors were negatively surprised by lower-than-expected cash flow news of high default risk stocks in the decade of 1980. This is also the decade when we find significant negative relation between default risk and realized returns. During the remaining time period, when we do not find strong evidence of under-performance in terms of realized returns, we do not find reliable evidence of negative forecast errors either. The relation between the ICC and DRP, on the other hand, remains positive and significant throughout the entire sample period. These findings also show that our main result relating DRP to the ICC is unlikely to be driven by systematic biases in the consensus forecasts.

Overall, our findings are consistent with the view that investors and analysts have similar expectations. Investors expected to earn positive risk-premium for bearing default risk throughout the sample period. In the 1980s, their expectations were not met. This in turn resulted in large negative forecast errors and large negative realized returns.

6 Conclusion

We study the relation between default risk and stock returns in this paper. Unlike prior studies that use ex-post estimates of the expected return, our study uses an ex-ante proxy based on the implied cost of capital. While the prior literature finds a *negative* relation between default risk and realized stock return in the post-1980 period, we find a strong *positive* relation between default risk and the expected stock return. We extend the realized returns sample back to 1952 and show that the anomalous negative relation between default risk and realized stock returns is absent during the earlier period. A closer investigation of the post-1980 analysis shows that the anomaly is predominantly driven by large under-performance of high default risk stocks during the decade of 1980. We argue that investors expected to earn positive risk-premium for bearing default risk throughout the sample period, but they were negatively surprised in the decade of 1980. We show that investors were negatively surprised by higher-than-expected bankruptcy filings and lower-than-expected cash flow realizations of high default risk stocks in the 1980s.

Our results show that the post-1980 under-performance of high default risk stocks does not represent an asset pricing anomaly, rather it is an outcome of surprisingly low realized returns of high default risk stocks during this decade. In terms of *ex-ante* expectation, which is what matters for the risk-return trade-off, the relation between default risk and stock returns is positive. 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 weakens considerably.

We contribute to the broader financial economics literature by showing that the measurement of expected return plays a crucial role in the tests of asset pricing models. We show that conclusions regarding risk-return trade-off can change significantly depending on the way the expected return is measured. It can be a fruitful task for future empirical work to construct better measures of the expected return to uncover the true risk-return trade-off in the financial markets.

Appendix

A.1 Hazard Models

We follow Shumway (2001) and Chava and Jarrow (2004) for the construction of hazard models. We estimate the discrete time hazard model using the logistic model. Our data contains one record for each year 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 *defexit* takes a value of one in the year of default, and zero otherwise. Our definition of default is either a Chapter 7 or a Chapter 11 bankruptcy filing. Our bankruptcy database is comprehensive and includes the majority of defaults of publicly listed firms during 1963-2005. Chava and Jarrow (2004), Chava, Stefanescu, and Turnbull (2008) provide more information on this bankruptcy database. This is the same database that is used in Campbell, Hilscher, and Szilagyi (2008).

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 the latest available accounting data from the annual COMPUSTAT files. We lag the data by six months to ensure that it is available as of the model estimation date. For example, if a firm's fiscal year ends in Dec 2002, we consider this information available as of July 1, 2003. We follow Shumway (2001) to estimate the hazard model with the following covariates: $\frac{\text{net income}}{\text{total assets}}$, $\frac{\text{total liabilities}}{\text{total assets}}$, log of market capitalization of the firm to the toal market capitalization of all NYSE, AMEX, NASDAQ stocks, 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. We exclude any firm-year observations with less than 10 monthly returns from the volatility estimation. We also consider an alternative 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.

The default probabilities are constructed as out-of-sample default probabilities from these hazard models using rolling regressions. For example, for year 1980 we estimate the hazard model using default data from 1963-1979 and obtain the next year's default probability based on the 1980 covariates. For each subsequent year, the model is updated and out-of-sample default probabilities are constructed for the next year.

A.2 Distance to Default Model

Distance to Default is computed based on Merton (1974). We follow Bharath and Shumway (2008) to construct this measure as given below:

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

where $\sigma_V = \frac{E}{E+F}\sigma_E + \frac{F}{E+F}(0.05 + 0.25 * \sigma_E)$ and, r_{it-1} is the firms' stock return over the previous year. E is the market value of equity, F is the face value of debt, σ_E is the stock return volatility estimated over the past one year. T is set to one year. EDF (expected default frequency) is computed as $\mathcal{N}(-DD)$ where $\mathcal{N}(.)$ is the cumulative standard normal distribution function. See Bharath and Shumway (2008) for further details.

A.3 Computation of the Expected Return

We follow Pastor, Sinha, and Swaminathan (2008) and Lee, Ng, and Swaminathan (2007) to compute the implied cost of capital. Equation 1 in the paper models current stock price as the discounted sum of all future cash-flows. We explicitly forecast cash flows for the next $T = 15$ years and capture the effect of subsequent cash flows using a terminal value calculation. We estimate the free cash-flow to equity of firm i in year $t+k$ by using the following formula:

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

$FE_{i,t+k}$ 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. We use one-year and two-year ahead consensus (median) forecasts as proxies for $FE_{i,t+1}$ and $FE_{i,t+2}$, respectively. We compute the earnings estimate for year $t+3$ by multiplying the year $t+2$ estimate with the consensus long-term growth forecast. I/B/E/S provides the long-term consensus growth forecast for most firms. In case of missing data, we compute the growth rate using earnings forecasts for 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 the outlier problems. We forecast earnings from year $t+4$ to $t+T+1$ 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:

$$g_{i,t+k} = g_{i,t+k-1} * exp^{\frac{ln(g/g_{i,t+3})}{T-1}} \tag{5}$$

Using these growth rates, we compute earnings as follows:

$$FE_{i,t+k} = FE_{i,t+k-1} * (1 + g_{i,t+k}) \tag{6}$$

Next we compute the plowback rate (i.e., one minus the payout ratio) from the most recent fiscal year data. The payout is defined as the sum of dividends (Compustat item 21) and share repurchases (item 115) minus any issuance of new equity (item 108). We get the payout ratio by dividing this number by net income (item 18) if it is positive. If we are unable to compute the plowback ratio based on this method, then we set it to the industry (two-digit SIC code) median payout ratio. 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. We use the plowback ratio computed using the above procedure for the first year of estimation and mean-revert it to a steady state value by year $t+T+1$. The steady state formula assumes that the product of return on new investments ROI and plowback rate is equal to the growth rate in earnings in steady state (i.e., $g = ROI * b$ in steady-state). 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:

$$b_{i,t+k} = b_{i,t+k-1} - \frac{b_{i,t+1} - b_i}{T} \tag{7}$$

$$b_i = \frac{g}{r_{i,e}} \tag{8}$$

We compute terminal value as the following perpetuity:

$$TV_{i,t+T} = \frac{FE_{i,t+T+1}}{r_{i,e}} \tag{9}$$

Collecting all the terms, we get the following:

$$P_{i,t} = \sum_{k=1}^{k=T} \frac{FE_{i,t+k} * (1 - b_{i,t+k})}{(1 + r_{i,e})^k} + \frac{FE_{i,t+T+1}}{r_{i,e}(1 + r_{i,e}^T)} \tag{10}$$

We solve this equation for $r_{i,e}$ to get the implied cost of capital.

A.4 Variable Definitions

EPS1, EPS2 are the consensus EPS estimates (from I/B/E/S) for fiscal years $t+1$ and $t+2$, respectively.

LTG denotes the consensus long-term growth forecast, also obtained from I/B/E/S.

$\mathbf{r_e^{base}}$ denotes the implied cost of capital estimated using equation 10 with the consensus earnings and long-term growth forecast with the terminal date set to 15 years.

$\mathbf{r_e^{10year}}$ is constructed similar to r_e^{base} except the terminal date is set to 10 years.

$\mathbf{r_e^{extfin}}$ denotes the implied cost of capital for a model that assigns the highest earnings forecast to the firm with the lowest net external financing (NEF) and the lowest earnings forecast for the firm with the highest net external financing. For the remaining firms it linearly weights highest and lowest forecasts based on net external financing.

$\mathbf{r_e^{unaffiliated}}$ denotes the implied cost of capital estimated using the consensus forecast only for the *unaffiliated analysts*.

$\mathbf{r_e^{pessimistic\_eps}}$ ($\mathbf{r_e^{pessimistic\_growth}}$) assigns the highest earnings forecast (highest long-term growth estimate) to the safest firm and the lowest earnings forecast (lowest long-term growth estimate) for the riskiest firm. For the remaining firms it linearly weights highest and lowest forecasts based on net external financing.

$\mathbf{r_e^{poisson}}$ is the implied cost of capital computed after directly incorporating bankruptcy probabilities into the cash flow forecasts.

$\mathbf{DRP_{EDF}}$ and $\mathbf{DRP_{hazard}}$ are the default percentile rankings based on EDF and hazard rate model-based default probabilities, respectively.

logta, **mtb** and **booklev** denote the log of total assets (COMPUSTAT item 6), market-to-book ratio (sum of book value debt and market value of equity scaled by book value of assets) and book leverage (COMPUSTAT items 9 plus 34 scaled by 6), respectively. **ROA** is computed as the ratio of net income to total assets (COMPUSTAT item 18 scaled by 6); **CF/TA** is computed as the ratio of net cash flows to total assets (COMPUSTAT item 18 plus 14 scaled by item 6); **EBITDA/TA** is computed as the ratio of COMPUSTAT item 13 scaled by item 6; **Sales/TA** is computed as the ratio of item 12 to item 6.

$\mathbf{ret_{t-1,t}}$, $\mathbf{ret_{t-3,t}}$, $\mathbf{ret_{t-6,t}}$, $\mathbf{ret_{t-12,t}}$ denote the cumulative stock return over the past one, three, six, and twelve months respectively. **retstd** is the standard deviation of the firm's stock returns measured over the past 12 months.

invprice is one divided by the stock price as of the estimation date of the expected return.

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

This table presents the descriptive statistics of key variables. Panel A provides the statistics for default risk measures. Panel B provides the distribution of consensus analysts' forecasts. $EPS1$ and $EPS2$ measure the one- and two-year ahead earnings per share forecasts. LTG measures the long-term growth rate forecast. Panel C provides the distribution of the implied cost of capital measure. r_e^{base} denotes the implied cost of capital for the base case estimation. Other measures of r_e denote the implied cost of capital for several alternative model specifications that are described in full detail in the Appendix.

variable	mean	10^{th} percentile	25^{th} percentile	50^{th} percentile	75^{th} percentile	90^{th} percentile	standard deviation
Panel A: Default Models							
Distance to Default (DD)	6.73	1.40	3.27	5.81	9.13	13.10	5.11
Hazard Model Default Probability(x100)	0.50	0.03	0.08	0.19	0.47	1.10	1.19
Panel B: Inputs for Expected Return Computation							
EPS1	1.40	0.13	0.48	1.04	1.87	3.09	1.70
EPS2	1.76	0.35	0.73	1.31	2.25	3.60	1.79
LTG	0.21	0.09	0.12	0.16	0.25	0.35	0.17
Panel C: Measures of Expected Return							
r_e^{base}	5.09	-0.02	2.13	4.31	6.83	10.42	5.39
r_e^{extfin}	5.01	-0.26	2.06	4.32	6.89	10.52	5.38
$r_e^{unaffiliated}$	4.66	0.11	2.09	4.10	6.39	9.37	4.62
$r_e^{pessimistic\_eps}$	5.01	-0.14	2.16	4.32	6.77	10.23	5.37
$r_e^{pessimstic\_growth}$	5.26	0.18	2.38	4.52	6.98	10.52	5.32
$r_e^{poisson}$	4.02	-0.55	1.91	4.11	6.55	9.85	8.44
r_e^{10year}	3.98	-0.78	1.28	3.39	5.80	9.01	4.69

Table 2: **Expected Returns by Default Likelihood Groups**

This table presents the distribution of the implied cost of capital across portfolios of stocks formed on the basis of default risk. We assign stocks into decile portfolios based on the yearly distribution of default risk. We first compute the average expected risk-premium for each decile-portfolio every year. We report time-series mean of these yearly averages in the table. We also report the average risk-premium for the top 5% portfolio. Decile 1 corresponds to the lowest default risk portfolio, decile 10 the highest. Default risk is estimated by either Merton-model based expected default frequency (EDF) or the hazard-rate model-based probability of default. Sample period is from 1980 − 2005.

Decile	EDF	$HazardModel$
1 (bottom 10 percentile)	3.16	3.24
2	3.59	3.41
3	3.84	3.77
4	4.25	3.99
5	4.53	4.47
6	4.89	4.69
7	5.27	5.24
8	5.74	5.77
9	6.46	6.26
10 (top 10 percentile)	8.06	8.15
top 5 percentile	8.65	8.81

Table 3: **Default-risk and Expected Returns**

This table presents the Fama-Macbeth regression results. The dependent variable is the expected risk-premium calculated as the difference between the implied cost of capital and one-year risk-free rate. We estimate annual cross-sectional regressions and report the time-series mean of the estimated coefficients in the table. Panel A is based on the hazard-rate model of default, Panel B on the expected default frequency. DRP_{hazard} and DRP_{EDF} are the annual percentile rankings based on hazard-rate and the EDF model, respectively. *logta* is the natural logarithm of total assets, *mtb* is the market-to-book ratio of the firm, $ret_{t-1,t}$ is the past month's stock return, *booklev* is the book leverage, and *retstd* is the standard deviation of the past one year's stock return. All t-statistics are based on Newey-West autocorrelation correction with three lags.

Panel A: Hazard Model

	Model 1		Model 2		Model 3	
	Estimate	*t*-val	Estimate	*t*-val	Estimate	*t*-val
DRP_{hazard}	0.0364	(8.98)	0.0348	(7.60)	0.0314	(6.98)
logta	-0.4748	(-3.87)	-0.4990	(-3.74)	-0.3625	(-2.84)
mtb	-0.1873	(-1.43)	-0.1725	(-1.34)	-0.1807	(-1.38)
$ret_{t-1,t}$	-4.2579	(-8.96)	-4.3717	(-10.46)	-4.4297	(-10.65)
booklev			0.7061	(1.60)	0.6154	(1.30)
retstd					0.0239	(4.60)
intercept	6.0368	(5.49)	6.1002	(5.25)	4.4763	(3.78)

Panel B: EDF Model

	Model 1		Model 2		Model 3	
	Estimate	*t*-val	Estimate	*t*-val	Estimate	*t*-val
DRP_{EDF}	0.0360	(11.11)	0.0389	(10.06)	0.0359	(5.60)
logta	-0.5468	(-5.66)	-0.5328	(-5.37)	-0.5037	(-5.45)
mtb	-0.1566	(-1.04)	-0.1406	(-1.00)	-0.1196	(-1.32)
$ret_{t-1,t}$	-4.9148	(-10.90)	-4.8058	(-11.61)	-4.8521	(-11.97)
booklev			-0.7441	(-1.59)	-0.4732	(-0.83)
retstd					0.0041	(0.38)
intercept	6.5243	(6.98)	6.4567	(6.81)	6.1636	(6.31)

Table 4: **Robustness: Biases in Analysts' Forecasts**

This table presents the Fama-Macbeth regression results for alternate measures of the implied cost of capital. The dependent variable is the expected risk-premium calculated as the difference between the implied cost of capital and one-year risk-free rate. r_e^{extfin} measures the implied risk-premium after accounting for biases in analysts' forecasts for firms with higher intensity of corporate financing activities; $r_e^{unaffiliated}$ is based on earnings estimate of unaffiliated analysts only; $r_e^{pessimistic\_eps}(r_e^{pessimistic\_growth})$ is based on earnings estimate that assigns more weight to pessimistic earnings (growth) forecast for high default risk stocks. We estimate annual cross-sectional regressions and report the time-series mean of the estimated coefficients in the table. Panel A is based on the hazard-rate model of default, Panel B on the expected default frequency. DRP_{hazard} and DRP_{EDF} are the annual percentile rankings based on hazard-rate and the EDF model, respectively. *logta* is the natural logarithm of total assets, *mtb* is the market-to-book ratio of the firm, $ret_{t-1,t}$ is the past month's stock return, *booklev* is the book leverage, and *retstd* is the standard deviation of the past one year's stock return. All t-statistics are based on Newey-West autocorrelation correction with three lags.

Panel A: Hazard Model

	r_e^{extfin}		$r_e^{unaffiliated}$		$r_e^{pessimstic\_eps}$		$r_e^{pessimistic\_growth}$	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
DRP_{hazard}	0.0299	(7.08)	0.0224	(5.53)	0.0174	(3.63)	0.0179	(3.40)
logta	-0.1638	(-1.35)	-0.4236	(-5.90)	-0.3866	(-2.95)	-0.2412	(-1.73)
mtb	-0.3195	(-2.06)	-0.1318	(-3.24)	-0.2090	(-1.53)	-0.1663	(-1.19)
booklev	-0.3861	(-0.66)	0.7056	(1.57)	0.6317	(1.26)	0.5602	(1.20)
$ret_{t-1,t}$	-4.2839	(-9.21)	-3.4243	(-8.83)	-4.3299	(-9.71)	-4.4761	(-10.09)
retstd	0.0172	(3.37)	0.0122	(1.81)	0.0209	(3.77)	0.0278	(5.16)
intercept	4.1996	(3.94)	5.4879	(5.98)	5.4690	(4.60)	4.5123	(3.56)

Panel B: EDF Model

	r_e^{extfin}		$r_e^{unaffiliated}$		$r_e^{pessimstic\_eps}$		$r_e^{pessimistic\_growth}$	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
DRP_{EDF}	0.0335	(4.96)	0.0240	(5.59)	0.0235	(3.51)	0.0250	(3.16)
logta	-0.3021	(-3.53)	-0.5039	(-7.62)	-0.4664	(-4.25)	-0.3332	(-2.97)
mtb	-0.2650	(-2.60)	-0.1279	(-4.73)	-0.1501	(-1.68)	-0.0984	(-1.16)
booklev	-1.3633	(-1.73)	-0.0544	(-0.14)	-0.4040	(-0.62)	-0.5824	(-0.82)
$ret_{t-1,t}$	-4.6481	(-10.82)	-3.8231	(-7.77)	-4.2903	(-9.76)	-4.4111	(-9.76)
retstd	-0.0009	(-0.08)	0.0029	(0.33)	0.0063	(0.57)	0.0111	(0.88)
intercept	5.7963	(6.63)	6.5701	(7.39)	6.4631	(6.01)	5.6019	(5.05)

Table 5: **Robustness: Staleness in Analysts' Forecasts**

This table presents the Fama-Macbeth regression results after controlling for the effect of past stock returns at various lags. The dependent variable is the expected risk-premium calculated as the difference between the implied cost of capital and one-year risk-free rate. We estimate annual cross-sectional regressions and report the time-series mean of the estimated coefficients in the table. Panel A is based on the hazard-rate model of default, Panel B on the expected default frequency. DRP_{hazard} and DRP_{EDF} are the annual percentile rankings based on hazard-rate and the EDF model, respectively. *logta* is the natural logarithm of total assets, *mtb* is the market-to-book ratio of the firm, *booklev* is the book leverage, and *retstd* is the standard deviation of the past one year's stock return. $ret_{t-1,t}$, $ret_{t-3,t}$, $ret_{t-6,t}$ and $ret_{t-12,t}$ are the past one, three, six, and twelve months' cumulative stock returns. *invprice* is computed as one divided by the firm's stock price as of the estimation date. All t-statistics are based on Newey-West autocorrelation correction with three lags.

Panel A: Hazard Model

	Model 1		Model 2		Model 3		Model 4	
	Estimate	*t*-val	Estimate	*t*-val	Estimate	*t*-val	Estimate	*t*-val
DRP_{hazard}	0.0234	(6.40)	0.0235	(5.16)	0.0227	(5.36)	0.0317	(7.68)
logta	-0.2908	(-2.39)	-0.4013	(-3.49)	-0.4190	(-3.78)	-0.3709	(-3.25)
mtb	-0.0904	(-0.76)	-0.2301	(-1.69)	-0.2578	(-1.76)	-0.1660	(-1.23)
booklev	0.6405	(1.37)	1.1755	(2.65)	1.2412	(3.35)	0.6005	(1.78)
retstd	0.0037	(0.64)	0.0269	(4.98)	0.0268	(4.81)	0.0232	(4.06)
$ret_{t-1,t}$	-3.8684	(-8.71)						
invprice	8.7289	(8.17)						
$ret_{t-3,t}$			-3.5152	(-11.09)				
$ret_{t-6,t}$					-1.7717	(-5.45)		
$ret_{t-12,t}$							-0.4822	(-2.11)
intercept	4.4725	(3.95)	5.0562	(4.64)	5.1969	(5.10)	4.5023	(4.26)

Panel B: EDF Model

	Model 1		Model 2		Model 3		Model 4	
	Estimate	*t*-val	Estimate	*t*-val	Estimate	*t*-val	Estimate	*t*-val
DRP_{EDF}	0.0305	(5.39)	0.0267	(4.05)	0.0252	(4.05)	0.0297	(5.01)
logta	-0.3890	(-4.41)	-0.5058	(-5.70)	-0.5151	(-5.80)	-0.5082	(-5.46)
mtb	0.0010	(0.01)	-0.1934	(-2.02)	-0.2281	(-2.14)	-0.1091	(-1.15)
booklev	-0.5961	(-1.03)	0.2938	(0.56)	0.4201	(0.88)	0.0270	(0.06)
retstd	-0.0180	(-1.64)	0.0127	(1.23)	0.0140	(1.33)	0.0078	(0.78)
$ret_{t-1,t}$	-3.9160	(-8.85)						
invprice	9.9036	(8.53)						
$ret_{t-3,t}$			-3.8936	(-12.51)				
$ret_{t-6,t}$					-2.1301	(-6.89)		
$ret_{t-12,t}$							-0.9606	(-5.09)
intercept	5.7486	(6.22)	6.3636	(6.61)	6.4711	(7.04)	6.2942	(6.51)

Table 6: **Robustness: Simulated Bankruptcy Time**

This table reports the Fama-MacBeth regression results based on an estimate of the implied cost of capital that directly incorporates the effect of bankruptcy probability in the estimation of future cash flows. The dependent variable ($r_e^{poisson}$) is the expected risk-premium calculated as the difference between the implied cost of capital and one-year risk-free rate. We estimate annual cross-sectional regressions and report the time-series mean of the estimated coefficients in the table. Model 1 is based on the hazard-rate model of default, Model 2 on the expected default frequency. DRP_{hazard} and DRP_{EDF} are the annual percentile rankings based on hazard-rate and the EDF model, respectively. *logta* is the natural logarithm of total assets, *mtb* is the market-to-book ratio of the firm, $ret_{t-1,t}$ is the past month's stock return, *booklev* is the book leverage, and *retstd* is the standard deviation of the past one year's stock return. All t-statistics are based on Newey-West autocorrelation correction with three lags.

	Model 1: Hazard Model		Model 2:EDF Model	
	Estimate	t-val	Estimate	t-val
DRP_{hazard}	0.0207	(5.28)		
DRP_{EDF}			0.0323	(5.39)
logta	-0.3356	(-2.78)	-0.4459	(-5.08)
mtb	-0.2121	(-1.82)	-0.1058	(-1.33)
booklev	-0.4269	(-1.17)	-1.9704	(-4.26)
$ret_{t-1,t}$	-3.8409	(-8.02)	-3.6468	(-7.34)
retstd	0.0077	(1.48)	-0.0158	(-1.64)
intercept	5.5041	(4.37)	6.8412	(6.60)

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

This table reports the calendar time portfolio regression results for high default risk stocks. We sort stocks into top 5% and top 10% portfolios based on their default probabilities estimated as of June 30 of every year. We compute the value-weighted return of each portfolio every month from July of year t till June of year $t+1$. We regress the excess portfolio returns on market, SMB, HML and UMD factors. Panel A reports regression results based on 306 monthly observations from January 1981 till June 2006. The model is estimated for both hazard rate and the EDF-based estimates of default probability. Panel B and C report one-factor and four-factor regression results based on the EDF measure. Panel B uses 342 monthly observations from 1952 to 1980. Panel C uses the entire 648 monthly observations from 1952 to 2006. Robust t-statistics are provided in the brackets.

Panel A: Post-1980 Period

	Hazard Rate Model						**EDF Model**					
	α	Market	SMB	HML	UMD	R^2	α	Market	SMB	HML	UMD	R^2
Top 5%	-1.22	1.25	1.44	0.37	-0.49	68.40%	-0.98	1.45	0.79	0.77	-0.33	65.80%
	(-3.58)	(17.01)	(13.34)	(2.53)	(-4.33)		(-3.43)	(19.92)	(6.90)	(5.96)	(-3.79)	
Top 10%	-0.69	1.27	1.28	0.52	-0.44	79.20%	-0.72	1.38	0.68	0.68	-0.28	71.60%
	(-3.06)	(24.66)	(15.77)	(4.96)	(-6.37)		(-3.00)	(22.44)	(7.56)	(6.17)	(-3.87)	

Panel B: 1952-1980 Period: EDF Model

	α	Market	SMB	HML	UMD	R^2	α	Market	SMB	HML	UMD	R^2
Top 5%	-0.12	1.36				59.90%	-0.28	1.16	1.12	0.63	-0.24	83.10%
	(-0.51)	(16.91)					(-1.59)	(28.26)	(16.27)	(7.94)	(-4.32)	
Top 10%	-0.07	1.36				67.00%	-0.20	1.17	1.02	0.57	-0.23	88.90%
	(-0.34)	(18.74)					(-1.50)	(37.30)	(18.62)	(10.11)	(-5.57)	

Panel C: 1952-2005 Period: EDF Model

	α	Market	SMB	HML	UMD	R^2	α	Market	SMB	HML	UMD	R^2
Top 5%	-0.38	1.33				56.00%	-0.54	1.31	0.89	0.68	-0.31	73.40%
	(-1.90)	(22.49)					(-3.25)	(30.04)	(11.87)	(8.79)	(-5.40)	
Top 10%	-0.24	1.30				62.90%	-0.40	1.28	0.80	0.63	-0.28	79.70%
	(-1.40)	(25.04)					(-2.98)	(36.54)	(14.78)	(9.91)	(-5.76)	

Table 8: **Default-risk and Realized Return: Only 1980s and without 1980s**

This table reports the calendar time portfolio regression results separately for the decade of 1980 and the remaining period. We sort stocks into the top 5% and top 10% portfolios based on their default probabilities estimated as of June 30 of every year. We compute the value-weighted return of each portfolio every month from July of year t till June of year $t+1$. We regress the excess portfolio returns on market, SMB, HML and UMD factors. Panel A provides regression results based on portfolio returns during the decade of 1980. Panel B uses data from the remaining period. For the hazard rate model, it includes 198 monthly observations from January 1990 to June 2006. For the EDF model, it includes 528 monthly observations spanning 1952-1980 and 1990-2006 sub-periods. Robust t-statistics are provided in the brackets.

	Hazard Rate Model						**EDF Model**					
Panel A: Decade of 1980												
	α	Market	SMB	HML	UMD	R^2	α	Market	SMB	HML	UMD	R^2
Top 5%	-2.36	1.30	1.29	0.44	-0.28	69.90%	-1.71	1.49	0.92	0.73	-0.32	77.60%
	(-5.89)	(11.23)	(8.23)	(2.19)	(-2.25)		(-4.65)	(18.90)	(6.76)	(5.76)	(-3.54)	
Top 10%	-1.40	1.24	1.28	0.40	-0.25	79.90%	-1.33	1.41	0.69	0.69	-0.30	84.40%
	(-4.36)	(14.55)	(10.56)	(2.51)	(-2.42)		(-5.06)	(23.82)	(6.92)	(7.48)	(-4.22)	
Panel B: Excluding the decade of 1980												
	α	Market	SMB	HML	UMD	R^2	α	Market	SMB	HML	UMD	R^2
Top 5%	-0.63	1.22	1.46	0.36	-0.53	68.30%	-0.27	1.25	0.90	0.69	-0.33	73.00%
	(-1.41)	(11.85)	(11.46)	(2.02)	(-4.22)		(-1.44)	(24.72)	(10.78)	(7.97)	(-4.97)	
Top 10%	-0.28	1.28	1.28	0.57	-0.48	79.40%	-0.19	1.25	0.82	0.63	-0.28	79.10%
	(-0.96)	(18.38)	(13.60)	(4.51)	(-6.17)		(-1.27)	(29.29)	(13.55)	(8.72)	(-5.07)	

Table 9: **Surprise in Bankruptcy Filings and Realized Earnings**

This table provides estimation results for surprises in bankruptcy filings and realized earnings during the decade of 1980. Panel A provides regression results for the bankruptcy filings. In Model 1, the dependent variable is the difference between the actual and the expected defaults scaled by the total number of firms. In Model 2, we use the actual number of defaults during the year as the scaling variable. We regress the annual bankruptcy surprise measures on an indicator variable $dec80$ that equals one for years in 1980-1989, and zero otherwise. We estimate these models with the OLS method using 36 annual observations from 1970 to 2005. All t-statistics are based on robust standard errors. Panel B provides estimation results for the forecast errors in long-term growth rates (Model 1) and quarterly earnings (Model 2). Model 1 is estimated with yearly data, Model 2 with quarterly. DRP_{EDF} is the default percentile ranking based on the EDF model. Both models in Panel B are estimated with median regressions and the t-statistics are based on bootstrapped standard errors with firm-level clustering.

Panel A: Actual minus expected defaults

	Model 1		Model 2	
	Estimate	t-val	Estimate	t-val
$dec80$	0.0022	(1.90)	0.4847	(2.54)
intercept	0.0002	(0.26)	-0.2427	(-1.38)
N	36		36	

Panel B: Actual minus forecasted earnings

	Model 1 Surprise in Growth		Model 2 Surprise in Earnings	
	Estimate	t-val	Estimate	t-val
$DRP_{EDF} * dec80$	-5.3406	(-3.67)	-0.0031	(-12.65)
$DRP_{EDF} * (1 - dec80)$	1.6600	(1.76)	-0.0000	(-0.38)
$dec80$	-2.1520	(-3.67)	0.0039	(0.51)
intercept	-5.5004	(-15.00)	0.0362	(18.44)
N	29269		108110	

Table 10: **Operating Performance During 1980s**

This table presents the firm fixed effect regression results relating default risk to one-year ahead operating performance. The dependent variables are: (i) $SalesGrowth$ measured as the log change in annual sales; (ii) ROA measured as the ratio of net income to total assets; (iii) $\frac{CF}{TA}$ measured as the ratio of net cash flow to total assets; (iv) $\frac{EBITDA}{TA}$ measured as the ratio of earnings before interest, taxes, and depreciation to total assets; and (v) $\frac{Sales}{TA}$ measured as the ratio of sales to total assets. Each of these performance measures is regressed on the firm's default risk, an indicator variable for the decade of 1980 and their interaction term. $dec80$ is an indicator variable that equals one for years in 1980-1989, and zero otherwise. DRP_{EDF} is the default risk percentile ranking based on the EDF model. $logta$ is the natural logarithm of total assets measured with one year lag. All models include firm fixed effects.

Dependent Variable	Sales Growth		ROA		$\frac{CF}{TA}$		$\frac{EBITDA}{TA}$		$\frac{Sales}{TA}$	
	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val	Estimate	t-val
DRP_{EDF}	-0.1147	(-30.83)	-0.1208	(-90.69)	-0.1147	(-88.90)	-0.1144	(-89.07)	-0.1209	(-22.18)
$dec80$	0.0201	(5.95)	0.0047	(3.86)	0.0047	(4.06)	0.0015	(1.32)	0.0410	(8.28)
DRP_{EDF}x$dec80$	-0.0260	(-4.28)	-0.0123	(-5.64)	-0.0130	(-6.15)	-0.0125	(-5.98)	-0.0464	(-5.21)
$logta$			-0.0104	(-35.93)	-0.0083	(-29.49)	-0.0104	(-37.38)	-0.0747	(-62.96)
R^2	15.99%		59.24%		60.44%		65.01%		82.31%	
N	115845		115832		115253		115625		115845	

References

Altman, E., 1968, Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy, Journal of Finance 23, 589-609.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2007, Credit Ratings and the Cross-Section of Stock Returns, Working Paper, University of Maryland.

Bharath, S. and T. Shumway, 2008, Forecasting Default with the Merton Distance to Default Model, Review of Financial Studies 21, 1339-1369.

Blume, M.E., and I. Friend, 1973, A New Look at the Capital Asset Pricing Model, Journal of Finance 28, 19-33.

Bradshaw, M. T., S. A. Richardson, and R. G. Sloan, 2006, The Relation between Corporate Financing Activities, Analysts Forecasts and Stock Returns, Journal of Accounting and Economics 42, 53-85.

Brav, A., R. Lehavy, and R. Michaely, 2005, Using expectations to test asset pricing models, Financial Management 34, 5-37.

Campbell, J. Y., J. Hilscher and J. Szilagyi, 2008, In Search of distress-risk, Journal of Finance, 63, 2899-2939.

Campbell, J. Y., A. W. Lo, and A. C. MacKinlay, 1997, The Econometrics of Financial Markets, Princeton University Press.

Chan, L. K. C., N. Jegadeesh, and J. Lakonishok, 1995, Evaluating the Performance of Value versus Glamor Stocks: The Impact of Selection Bias, Journal of Financial Economics 38, 269-296.

Chava, S., and R. A. Jarrow, 2004, Bankruptcy Prediction with Industry Effects, Review of Finance 8, 537-569.

Chava, S., C. Stefanescu, and S. Turnbull, 2008, Modeling Expected Loss with Unobservable Heterogeneity, Working Paper, Texas A&M University.

Chen, L., R. Petkova and L. Zhang, 2008, The expected value premium, Journal of Financial Economics, 87, 269-280.

Claus, J., and J. Thomas, 2001, Equity Premia as Low as Three Percent? Evidence from Analysts Earnings Forecasts for Domestic and International Stock Markets, Journal of Finance 56, 1629-1666.

Conrad, J., M. Cooper, and G. Kaul, 2003, Value versus Glamour, Journal of Finance 58, 1969-1995.

Core, J. E., W. R. Guay, and T. O. Rusticus, 2006, Does Weak Governance Cause Weak Stock Returns? An Examination of Firm Operating Performance and Investors' Expectations, Journal of Finance 61, 655-687.

Damodaran, A., 2006, The Cost of Distress: Survival, Truncation Risk, and Valuation, Working Paper, New York University.

Davis, J. L., 1994, The Cross-section of Realized Stock Returns: The Pre-COMPUSTAT Evidence, Journal of Finance 49, 1579-1593.

Dechow, P., A. Hutton, and R. Sloan, 2000, The Relation between Analysts' Forecasts of Long-Term Earnings Growth and Stock Price Performance Following Equity Offerings, Contemporary Accounting Research 17, 1-32.

Dechow, P., and R. Sloan, 1997, Returns to contrarian investment strategies: Tests of naive expectations hypotheses, Journal of Financial Economics 43, 3-27.

Dichev, I., 1998, Is the Risk of Bankruptcy a Systematic Risk? Journal of Finance, 53, 1131-1148.

Duffie, D., L. Saita, and K. Wang, 2007, Multi-period Corporate Default Prediction with Stochastic Covariates, Journal of Financial Economics 83, 635-665.

Elton, E.,J., 1999, Expected Return, Realized Return, and Asset Pricing Tests, Journal of Finance 54, 1199-1220.

Fama, E. F., and K. R. French, 1996, Multifactor Explanation of Asset Pricing Anomalies, Journal of Finance 51, 55-84.

Fama, E. F., and K. R. French, 2002, The Equity Premium, Journal of Finance 57, 637-659.

Fan, H., and S. Sundaresan, 2000, Debt Valuation, Renegotiation, and Optimal Dividend Policy, Review of Financial Studies, 13, 1057-1099.

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

Friend, I., R. Westerfield, and M. Granito, 1978, New Evidence on the Capital Asset Pricing Model, Journal of Finance 33, 903917.

Garlappi, L., T. Shu, and H. Yan, 2008, Default-risk, Shareholder Advantage, and Stock Returns, Review of Financial Studies 21, 2743-2778.

Gebhardt, W. R., C. M. C. Lee, and B. Swaminathan, 2001, Toward an Implied Cost of Capital, Journal of Accounting Research 39, 135-176.

George, T., and C. Y. Hwang, 2007, Leverage, Financial Distress and the Cross Section of Stock Returns, Working Paper, University of Houston.

Griffin, J. M. and M. L. Lemmon, 2002, Book-to-Market Equity, Distress-risk, and Stock Returns, Journal of Finance 57, 2317-2336.

Kaplan, S. N., and R. S. Ruback, 1995, The Valuation of Cash Flow Forecasts: An Empirical Analysis, Journal of Finance 50, 10591093.

Kumar, A., 2008, Do Markets Under-Estimate the Forecasting Abilities of Female and Minority Equity Analysts?, Working Paper, University of Texas at Austin.

Lee, C. M. C., D. Ng, and B. Swaminathan, 2007, The Cross-section of International Cost of Capital, forthcoming, Journal of Financial & Quantitative Analysis.

Livnat, J., and R. R. Mendenhall, 2006, Comparing the PostEarnings Announcement Drift for Surprises Calculated from Analyst and Time Series Forecasts, Journal of Accounting Research 44, 177-205.

Ljungqvist, A., F. Marston, L. Starks, K. Wei, and H. Yan, 2007, Conflicts of interest in sell-side research and the moderating role of institutional investors, Journal of Financial Economics 85, 420-456.

Lo, A., and A. C. MacKinlay, 1990, Data-snooping Biases in Tests of Financial Asset Pricing Models, Review of Financial Studies 3, 431-468.

Lundblad, C. , 2007, The Risk Return Tradeoff in the Long-run: 1836-2003, Journal of Financial Economics 85, 123-150.

Merton, R. C., 1973, An Intertemporal Capital Asset Pricing Model, Econometrica 41, 867-887.

Merton, R. C., 1974, On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, Journal of Finance 29, 449-470.

Merton, R. C., 1980, On Estimating the Expected Return on the Market: An Exploratory Investigation, Journal of Financial Economics 8, 323-361.

Michaley, R., and K. Womack, 1999, Conflict of Interest and the Credibility of Underwriter Analyst Recommendations, Review of Financial Studies 12, 653-686.

Moore, L., and S. Juh, 2006, Derivative Pricing 60 Years Before Black-Scholes: Evidence from the Johannesburg Stock Exchange, Journal of Finance, 61, 3069-3098.

Pastor, L., M. Sinha and B. Swaminathan, 2008, Estimating the Intertemporal Risk-Return Tradeoff Using the Implied Cost of Capital, Journal of Finance 63, 28592897.

Rajan R., and H. Servaes, 1997, Analyst Following of Initial Public Offering, Journal of Finance 52, 507-529.

Sharpe, W.F., 1978, New Evidence on the Capital Asset Pricing Model: Discussion, Journal of Finance 33, 917-920.

Shumway, Tyler, 1997, The delisting bias in CRSP data, Journal of Finance 52, 327–340.

Shumway, Tyler, 2001, Forecasting Bankruptcy More Accurately: A Simple Hazard Model, Journal of Business 74, 101-124.

Vassalou, Maria and Yuhang Xing, 2004, Default-risk in Equity Returns, Journal of Finance 59, 831-868.