Risk-shifting, Equity Risk, and the Distress Puzzle

Keming Li

keming_li@hotmail.com

Department of Finance and Real Estate

University of Minnesota – Duluth

Jimmy Lockwood

jimmy.lockwood@colostate.edu

Department of Finance and Real Estate

Colorado State University

Hong Miao

hong.miao@colostate.edu

Department of Finance and Real Estate

Colorado State University

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Abstract

This paper examines the relationship between financial distress and equity returns. Using strategic action proxies, we find that financial distress is a robust and negative predictor of future stock returns apart from the effect of strategic shareholder actions. This shows that the distress puzzle cannot be fully explained by shareholder strategic actions or shareholder advantages. The distress effect also cannot be explained by traditional risk factors, characteristics, or mispricing. However, the results presented in this paper are consistent with the risk-shifting hypothesis. Three findings support this claim. First, distressed firms tend to overinvest, earn low profits, and exhaust their cash flows. This effect is concentrated in low growth opportunity firms and in hard-to-value firms. Second, distress effects are concentrated in firms without credit ratings or convertible debt and in which CEOs have equity holdings. Third, distressed firms tend to have high credit spreads.

JEL classification: G02; G11; G33

Keywords: Financial Distress; Bankruptcy; Insolvency; Risk-Shifting; Credit Spread; Risk Return.

Financial distress risk is commonly cited as an underlying cause of several cross-sectional return anomalies. The basic argument is that investors should demand higher premiums for holding stocks with higher levels of financial distress risk. However, empirical studies have shown that firms exhibiting higher levels of financial distress risk do not consistently earn higher returns, resulting in the creation of the so-called distress puzzle. Several empirical studies have found a negative relationship between financial distress and stock returns. [1] That is, stocks with higher measures of financial distress actually earn lower returns. One explanation of this result pertains to market mispricing — investors fail to demand a sufficient premium that is commensurate with the degree of financial distress. Proponents of this explanation argue that this is particularly true of firms exhibiting a high degree of financial distress, which investors fail to grasp.

However, beyond behavioral explanations, the distress puzzle remains anomalous. While investors are expected to require a premium to hold distressed stocks, the evidence shows that they discount these stocks. A possible explanation for the distress puzzle stems from the agency theory of debt. The risk-shifting hypothesis (Jensen and Meckling 1976) states that managers of financially distressed firms maximize shareholder benefits by accepting excessive risk whereby firms invest in risk-increasing projects that offer improbable high pay-offs at the expense of bondholders.

Intuitively speaking, firms in distress present abnormally large leverage ratios, and proportions of equity are relatively small within they capital structure. At the same time, shareholders are likely to lose value, as interest payments may dominate the total cash flow. Even trivial shocks to a firm's cash flows may result in default. Consequently, shareholders of firms in distress have different preferences for operating risks — rather, they prefer to accept risky (possibly value-reducing) projects. When these projects are successful, shareholders repay their bondholders and retain the surplus. Conversely, when these projects fail, shareholder downside risks are limited to their stake in the firm upon bankruptcy. Furthermore, a

[1] See, for example, Dichev (1998), Griffin and Lemmon (2002), and Campbell, Hilscher, and Szilagyi (2008).

firm's residual value can decrease dramatically. As a result, risky projects result in a transfer of risk from shareholders to debt holders.

Related to the risk-shifting hypothesis, recent studies by Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011) contend that strategic equity holder actions during distressed firm debt renegotiation can explain the distress puzzle. More specifically, Garlappi, Shu, and Yan (2008) argue that distressed firms with a greater "shareholder advantage" should state lower expected returns. The authors define shareholder advantage as shareholder capacities to take advantage of other claimholders. Shareholder advantage is measured by asset size, R&D intensity, and liquidation cost, and it is high for large firms with lower R&D costs and higher liquidation costs (proxied by asset specificity).[2]

In this study, we examine the shareholder advantage hypothesis in a cross-sectional setting. More specifically, using proxies for strategic actions, we find that distress risk is a robust and negative predictor of future stock returns after controlling for the effects of strategic shareholder actions. We employ proxies of shareholder advantage with firm-specific variables suggested by Davydenko and Strebulaev (2007), including asset tangibility, market-to-book ratio of total assets, and the current-to-total liability ratio. Distress risk is measured based on default probability levels following Campbell, Hilscher, and Szilagyi (2008). Primary measures of equity risk are a firm's CAPM beta and conditional beta as described in Avramov and Chordia (2006). Following McLean's (2011) methodology, we find that equity risk does not become less sensitive to firm cash flow fluctuations during the sample periods.[3] This finding raises doubts regarding whether the shareholder advantage hypothesis explains the distress puzzle.

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[2] Favara, Schroth, and Valta (2012) present empirical evidence that is consistent with the shareholder advantage hypothesis across different countries.

[3] Favara, Schroth, and Valta (2012) argue that the prospect of a favorable debt renegotiation can encourage shareholders to predict the timing of a default. This indicates that equity risk will be less sensitive to firm cash flow fluctuations over time.

Our results are robust to alternative definitions of stock returns and equity risk, as revealed through Fama and French's (1992) methodology. In addition, we show that the negative relationship between distress risk and stock returns is not concentrated in post-1980s periods. The problem is not sample-specific, nor is it due to a different proxy of distress risk. Furthermore, this relationship is less likely to be caused by mispricing issues, as event-time analyses show persistent underperformance patterns and lower equity returns in high default risk firms.

In this study, we show that default risk is related to the likelihood of risk-shifting behaviors rather than to shareholder advantage. Three major findings support this claim. First, high default firms tend to overinvest, earn low profits, and exhaust their cash flow. These effects are concentrated in low-growth-opportunity firms and in hard-to-value firms. Second, distress effects are concentrated in firms without a credit rating or convertible debt and in firms where CEOs hold equity. Third, high distress firms tend to exhibit higher credit spreads.

The remainder of the paper is organized as follows. Section I reviews the literature on distress risk. Section II describes the data and estimations of default probabilities. Section III tests the shareholder advantage hypothesis. Section IV confirms the risk-shifting hypothesis for the fundamental data. Section V tests different risk-shifting incentives across different subsamples. Section VI shows the effects of distress risk on credit spread, and Section VIII concludes the paper.

I. Related Literature

Financial distress has been hypothesized in the asset-pricing literature to explain the empirical findings of anomalies (e.g., the size and value effects) in the cross-section of stock returns.[4] Default risk is generally

[4] For example, Chan and Chen (1991) claim that size effects are caused by "marginal" firms exhibiting high leverage and cash flow problems. Fama and French (1992) suggest that the book-to-market ratio serves as a proxy

defined as the probability that levered firms cannot fulfill their financial obligations, leading to bankruptcy or restructuring debts.[5] This alludes to an empirical question: How is distress risk really priced? Several influential studies have claimed the existence of a default risk premium in the cross-section of equity returns, as financially distressed firms tend to move together as systematic risk (see, for example, Fama and French (1992, 1993, 1996), Chan and Chen (1991), and Ferguson and Shockley (2003)). To compensate investors for bearing these risks, firms that are close to defaulting must offer higher expected returns than healthy firms (Vassalou and Xing 2004).

However, the existing evidence for this argument is ambiguous. Size and value premiums have been claimed to serve as distress proxies and have been found to be positively and monotonically related to future returns.[6] Shumway (1997) documents that firms exhibiting high levels of exchange delisting risk earn abnormal positive returns. Griffin and Lemmon (2002) and Vassalou and Xing (2004) support this conclusion by showing that high default risk firms are concentrated in small portfolios and in high book-to-market portfolios. Other studies found a negative relationship between default risk and realized returns using direct estimates of default risk. Dichev (1998), Griffin and Lemmon (2002), and Campbell, Hilscher, and Szilagyi (2008) find that high default probability firms are not rewarded by higher future returns. These findings raise doubts as to whether default risk is systematic risk.

for distress risk. However, Griffin and Lemmon (2002) use an O-score as a proxy for distress risk and find that the distress risk and book-to-market ratio capture different distress effects within cross-sectional returns.

[5] As described in Morellec, Nikolov, and Schurhoff (2012), Garlappi, Shu, and Yan (2008), and Garlappi and Yan (2011).

[6] Chan and Chen (1991) and Fama and French (1996) have used distress risks to explain anomalies in cross-sectional returns. The positive relationship between realized returns and default risks serves as evidence that distress risks are compensated by markets.

The recent literature addresses this distress risk puzzle and proposes different mechanisms or models to help reconcile the relationship between distress risk and stock returns. Garlappi, Shu, and Yan (2008) show that by relaxing the absolute priority rule (APR) assumption, the anomalous relationship may be explained by shareholder advantage. George and Hwang (2010) bring financial distress and leverage costs into the picture to explain the negative relationship between default risk and realized stock returns. Chava and Purnanandam (2010) claim that realized returns can constitute a noisy proxy for expected returns, resulting in conflicting findings. These authors use the implied cost of capital (ICC) to estimate expected returns, and they find a positive relationship between default risk and expected returns. Similar to George and Hwang (2010), Chava and Purnanandam (2010) demonstrate that the anomalous relationship between default risk and realized returns becomes more evident after 1980. Garlappi and Yan (2011) incorporate financial leverage into an equity valuation model to understand the mechanisms of lower returns in high default risk firms. The model reveals a hump-shaped relationship between expected returns and default probability in the presence of shareholder recovery.

II. Data and Estimation

This study uses Center for Research in Securities Prices (CRSP) daily and monthly stock files and COMPUSTAT quarterly and annual research files of NYSE-, AMEX-, and NASDAQ-listed firms. The CRSP database includes data on daily and monthly returns, prices, dividends, and outstanding shares. The COMPUSTAT database includes quarterly and annual accounting data on balance sheet, income statement, and cash flow statement items.

The sample period ranges from January of 1971 to December of 2010. These periods are selected, as bankruptcies were extremely infrequent until the late 1960s, as indicated in Campbell, Hilscher, and Szilagyi (2008). We eliminate financial and utility companies, as these firms have restricted capital structures. We also exclude firms with stock prices of less than one dollar.[7] Other studies remove stocks with prices of less than five dollars to minimize market microstructure issues. We do not exclude low-priced stocks, as Garlappi and Yan (2011) claim that sample selection problems associated with eliminating low-price firms can alter empirical test results. For obvious reasons, high default probability firms are concentrated in the low-price deciles. To be included in the analysis, firms are required to have 36 monthly observations in the dataset to circumvent well-known COMPUSTAT survival bias effects. Firms must offer sufficient data in order for us to calculate default risks and other variables. We conduct analysis with quarterly accounting data from COMPUSTAT and monthly stock market data from CRSP

In a subsequent analysis, we use corporate bond yield data for July of 2002 to December of 2010 drawn from the TRACE (Trade Reporting and Compliance Engine) database. These data include FINRA over-the-counter (OTC) corporate bond market real-time prices. Included in the data set are details on all eligible corporate bonds, including investment grade, high yield, and convertible debt. TRACE represents 100 % of OTC activity and over 99% of total U.S. corporate bond market activity. We also use ExecuComp data on executive stock and option holdings and on CEO characteristics.

A. Default Probability

An accurate measure of default risk is needed to study the relationship between default risk and returns. Default risk has traditionally been measured based on hazard rate and option-pricing models. Before the option-pricing based model started to be used, the finance literature documented that accounting variables carry predictive power in bankruptcy filings. Altman (1968) formulates the Z-score to estimate the probability that a firm will file for bankruptcy within two years. Later, the O-score proposed by Ohlson (1980) is used as a proxy for distress risk. For example, these two measures are used by Dichev (1998), Griffin and Lemmon (2002), and Ferguson and Shockley (2003). Shumway (2001) and Chava and Jarrow

[7] To minimize problems associated with the bid-ask bounce and transaction costs, see Amihud (2002).

(2004) present a hazard model that uses a logistic regression to estimate the default probability based on a bankruptcy database of US market data. Recently, Campbell, Hilscher, and Szilagyi (2008) adopted this methodology to measure default probability levels and to thereby capture actual distress risk levels for a firm. The authors use a logistic model based on various market-originated variables whereby the dependent variable is a default or failure dummy variable. Their default probability has been proven to serve as a good indicator of distress risk.

For the empirical analysis, we use the default probability (DP) measure presented in Campbell, Hilscher, and Szilagyi (2008) as a measure of default risk. This measure provides a precise proxy of the distress probability as indicated in the literature, and quarterly data are available from 1971 through 2010.[8] Consistent with Campbell, Hilscher, and Szilagyi (2008), we combine quarterly accounting data from COMPUSTAT with monthly stock market data from CRSP by lagging two months in the accounting data. We calculate the Distress Probability (DS) variable using their best model (last column in Table 3) as follows:

$$DS_{i,t} = P_{i,t}\left(Y_{i,t} = 1\right) = \frac{1}{1+\exp\left(-z_{i,t}\right)} \tag{1}$$

where

$$\begin{aligned} z_{i,t} = {} & -9.08 - 29.67NIMTAAVG_{i,t} + 3.36TLMTA_{i,t} - 7.35EXRETAVG_{i,t} \\ & +1.48SIGMA_{i,t} + 0.082RSIZE_{i,t} - 2.40CASHMTA_{i,t} \\ & + 0.054MB_{i,t} - 0.937PRICE_{i,t} \end{aligned} \tag{2}$$

$$NIMTAAVG_{i,t} = \frac{1-\Phi^3}{1-\Phi^{12}}\left(NIMTA_{i,q1} + \cdots + \Phi^9 NIMTA_{i,q4}\right) \tag{3}$$

$$EXRETAVG_{i,t} = \frac{1-\Phi}{1-\Phi^{12}}\left(EXRET_{i,m1} + \cdots + \Phi^{11} EXRET_{i,m12}\right) \tag{4}$$

[8] See, for example, Campbell, Hilscher, and Szilagyi (2008), Anginer and Yildizhan (2010), and Ozdagli (2010).

where $\Phi = 2^{-\frac{1}{3}}$. The weights are constant in each quarter for NIMTAAVG and in each month for EXRETAVG. EXRET is the natural log of monthly excessive returns over market returns. When the lagged EXRET is missing, we substitute the cross-sectional average. NIMTA is equal to the quarterly net income divided by the quarterly total market value. If the market value is missing, we use the product of prices per share and shares outstanding from the last month of CRSP data from the quarter in lieu of the total market value. TLMTA is equal to total liabilities divided by the quarterly market value. SIGMA is defined as the standard deviation of daily returns over last three months. RSIZE is the relative size measured as the log ratio of firm market capitalization to that of the market. CASHMTA is calculated as cash and short term assets divided by market value. Finally, PRICE is equal to the log price per share and is truncated at $15.

There are two advantages to using the hazard model rather than the option-pricing based model. First, the hazard model utilizes either accounting or market data in estimating default risk, which are publically available. This relatively low-cost and easily accessible information can be accurately priced for expected returns without delays or complications. Second, the hazard model does not rely on an assumption of an absence of arbitrage opportunities and market friction. Various studies have noted the limits of arbitrage either based on theoretical models or empirical evidence.[9] When basic assumptions are violated, default risk estimates, such as the market-based expected default frequency (EDF) converted from distance-to-default, are noisy.[10] In addition, default probability levels range from 0 to 100 without truncation.[11] Dichev (1998) shows that both the Altman Z-score and Ohlson O-score offer high levels of predictive

[9] See, for example, Shleifer and Vishny (1997), Gromb and Vayanos (2002), Gabaix, Krishnamurthy, and Vigneron (2007), Kondor (2009), and Xiong (2001).

[10] Distance-to-default values are computed using the option-pricing model developed by Merton (1974). See Vassalou and Xing (2004) and Bharath and Shumway (2008) for further information.

[11] The Moody's KMV (Kealhofer, McQuown and Vasicek) dataset truncates default probability (EDF) data at 20%.

power for out-of-sample bankruptcy. Incremental benefits of using the hazard model are also described in in Campbell, Hilscher, and Szilagyi (2008), who find higher pseudo-R^2 statistics for their best model both in-sample and out-of-sample in the hazard model vis-a-vis the option pricing-based model.

Table 1 presents mean values of default probability and historical events associated with abnormal upsurges in average default probability by year. For the 40-year sample period, 27 years show an average default probability over 0.1%, and the majority of these spikes are related to peak financial crises. Average default probability values are much higher during the two most recent crises. The average default probability of the dot-com bubble in 2001 is 1.80% and that of the CURRENT financial crisis is 6.63%. By contrast, the average default probability of the secondary banking crisis in 1976 is 0.03% and that of the 1981 energy crisis is 0.05%.[12]

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|Insert Table 1|

B. Summary Statistics

Table 2 provides summary statistics of firm-level characteristics, stock returns, and equity risks measured by the equity beta. The sample includes approximately 1 million firm-month observations with complete data. Panel A in Table 2 presents the distribution of firm characteristics. Panel B reports the average value of firm characteristics by default probability quintile. Panel C shows the mean value of stock returns and equity risk (equity beta) by default probability quintile.

For each month, observations are sorted by default probability levels into five quintiles. Numbers shown in Table 2 denote time-series averages of the cross-sectional mean of each variable. Size is defined as the log value of total market capitalization at the end of fiscal year t-1. BM is the book-to-market ratio, which is calculated as the book value of stockholder equity at year t-1 divided by the market value of

[12] Default probability in this paper is slightly lower than that shown in Campbell, Hilscher, and Szilagyi (2008), as we eliminate lower price stocks and financial firms.

stockholder equity at the end of fiscal year t-1. These variables are matched with monthly returns from July of year t to June of year t+1. MOM is the stock Momentum, which is defined as stock returns over the prior 12 months. All of these variables are calculated following methods proposed by Daniel, Grinblatt, Titman, and Wermers (DGTW 1997). Illiquid denotes Amihud's (2002) illiquidity measure for the past 12 months of daily trading data. Leverage denotes the total liability over total assets.

For each month from January of 1971 to December of 2010, we match monthly return data from CRSP data to the quarterly default probability of the previous section (lagged by two months). We measure future returns as t+1 month returns following portfolio formation. For delisted observations, delisting returns are replaced with the prior month's returns or with the median of delisting returns, depending on availability levels.[13] Delisting observations are critical to the analysis, as this paper analyzes default probability levels and future returns.

Based on the literature on time-varying and conditional betas, we employ two approaches to estimate annual time-varying beta levels, which are updated monthly. First, we use the time-vary beta methodology presented in Lewellen and Nagel (2006), Ang and Kristensen (2010) and Boguth et al. (2010). We use rolling regressions of daily returns from the CRSP daily stock file using a standard market model ($r^i_t = \alpha^i + \beta^i r^m_t + \varepsilon^i_t$), but a rolling window of 12 months rather than one month is used. The use of a 12-month window is advantageous in that sufficient observations are available for each regression.[14] This increases the precision of coefficient estimations without compromising the benefits of using a time-varying beta, allowing us to generate an equity risk estimate based on pre-formation data. The results based on Fama and French's (1992) beta estimation are robust.

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Second, we use a version of Avramov and Chordia's (2006) conditional model to estimate time-varying and conditional beta. Theoretical justifications for this approach are presented in Ferguson and Shockley

[13] Following Shumway (1997) and Shumway and Warther (1999).

[14] Observations with less than 50 daily data pieces over the 12-month estimation period are eliminated.

(2003). The authors show that empirical estimations of CAPM beta using an equity-only proxy for the market portfolio can lead to a downward bias. To correct these errors, equity beta estimations should incorporate firm-specific variables that correlate with relative distress or relative leverage patterns. As a result, several recent papers relate equity beta to firm characteristics (e.g., the book-to-market ratio).[15] Furthermore, Avramov and Chordia (2006) show that the conditional beta, wherein the beta varies according to firm characteristics, outperforms the traditional beta in capturing variations in cross-sectional returns. The importance of financial leverage is also illustrated by Garlappi and Yan (2011), who theoretically derive levered equity beta, which consist of book-to-market ratio and distress variables. Motivated by these findings, we employ a time-varying rolling regression of daily returns in the following model:

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$$r_t^i - r_t^f = \alpha^i + beta^{mktrf,i} * \left(r_t^{mkt} - r_t^f\right) + beta^{BM,i} * BM_t * \left(r_t^{mkt} - r_t^f\right) + \varepsilon_t^i \qquad (5)$$

where r^i_t is the daily stock return, r^f_t is the risk-free rate, α^i is the intercept, $beta^{mktrf,\,i}$ is the unconditional beta of market excess returns, and $beta^{BM,i}$ is the additional beta conditional on BM (the book-to-market ratio). A rolling window of 12 months is used to reflect that of the time-varying beta. The conditional beta is calculated as follows:

$$beta^{conditional,i} = beta^{mktrf,i} + beta^{BM,i} * BM_t \qquad (6)$$

where $beta^{conditional,i}$ is the conditional beta and includes both the unconditional and conditional beta on BM.

|Insert Table 2|

[15] See, for example, Brennan, Chordia, and Subrahmanyam (1998), Berk, Green, and Naik (1999), Gomes, Kogan, and Zang (2003), Carlson, Fisher, and Giammarino (2004), Sagi and Seasholes (2007), and Zhang (2005).

According to Panel A of Table 2, the average default probability is 1.312%, and the median is 0.002%. Thus, the default probability distribution is significantly and positively skewed.[16] This is confirmed in Panel B of Table 2. Only the highest default quintiles show an average default probability of over one percent. It is important to note that the distributions are likely to be dominated by small companies, as we weigh all observations equally for each year. The size and BM distributions are symmetric and normal. BM shows a positive and monotonic relationship with default probability. This fact is important to consider in empirical analyses, as BM has been proposed as a default risk measured in the finance literature.[17] Recently, this has motivated several researchers to relate firm characteristics (e.g., BM) to equity beta.[18] We follow their example and present a version of conditional beta that relates to BM.

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Surprisingly, MOM is negatively related to default probability. This raises doubts surrounding empirical evidence presented by Avramov. Chordia, Jostova, and Philipov (2007). However, the results presented here do not contradict Avramov. Chordia, Jostova, and Philipov's (2007) findings, as they focus on Momentum strategies that demonstrate a long position for winners and a short position for losers in each credit rating quintile. Their profits, which are concentrated within the low-credit-rating quintile, are derived primarily from the short position of losers. Winning firms present low positive Momentum and losing firms present high negative Momentum in the high default quintile. Both winning and losing firms exhibit high positive Momentum in the low default quintile. This also complements results presented in Table 2, Panel B. Momentum in the low default quintile is significantly positive (0.306), while Momentum in the high default quintile is significantly negative (-0.211).

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[16] This coincides with evidence presented by Campbell, Hilscher, and Szilagyi (2008), who show a relatively small number of bankruptcies and failures per year for sample of active firms.

[17] See, for example, Fama and French (1992, 1993, 1996), Griffin and Lemmon (2002), and Vassalou (2004).

[18] See, for example, Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Avramov and Chordia (2006), Sagi and Seasholes (2007), Novy-Marx (2008), and Garlappi and Yan (2011), and Zhang (2005).

Table 2 also presents the Amihud (2002) illiquidity measure and leverage ratio results. The illiquidity measure is estimated from prior 12-month daily data. Echoing the findings of Garlappi and Yan (2011), high default risk is found to coincide with high illiquidity. The high default quintile has an average illiquidity level of 0.752 compared to the low default quintile average illiquidity level of 0.235. This raises substantial concerns that the results may have been driven by mispricing effects. Shleifer (2000) argues that high trading costs may prevent informed investors from acting on available information if potential profits cannot compensate for transaction costs. Sadka and Scherbina (2007) document price-correction behaviors in illiquid and high-analyst dispersion firms. Default risk may serve as a proxy of illiquidity, and lower returns of high default risk stocks may result price-correction patterns.[19] This issue will be addressed in a subsequent event-time analysis. Leverage is positively related to default probability, complementing the results of George and Hwang (2010).

Panel C of Table 2 presents results based on value-weighted returns with similar findings. Value-weighted and adjusted returns strongly and monotonically decline in default quintiles.[20] The average return for the lowest default quintile is 0.805% per month and is 0.073% for the highest default quintile. The difference between these returns is significantly negative. A long–short portfolio involving selling the highest default quintile and buying the lowest default quintile earns monthly returns of 0.732%.

We employ the characteristic adjustment methodology proposed by Daniel, Grinblatt, Titman, and Wermers (DGTW 1997).[21] The sample period for DGTW-adjusted returns covers the period running from

[19] Avramov. Chordia, Jostova, and Philipov (2009) show that the dispersion effect on stock returns is especially prominent among high distress stocks.

[20] Excess returns are defined as the difference between raw returns and the risk-free rate.

[21] The matching procedure is based on cutoffs of size, the book-to-market ratio, and Momentum characteristics drawn from Professor Russ Wermer's web page:

http://www.rhsmith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

June of 1975 to December of 2010 due to data availability levels. The average characteristic-adjusted return on the lowest default quintile is 0.053% per month and is -0.651% for the highest default quintile. A portfolio selling the highest and buying the lowest default quintile earns monthly returns of 0.704%.

We employ the methodology proposed by Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003) in adjusting for risk. All alphas negatively and monotonically decline as the default probability increases. For example, the three-factor alpha for the lowest default quintile is 0.507% and is 0.981% for the highest default quintile. A portfolio selling the highest default quintile and buying the lowest default quintile earns risk-adjusted monthly returns of 1.488%. We cannot rule out the possibility that model misspecification may have affected these results, though these models have been used extensively in previous studies to capture equity risk levels. A negative and monotonic relationship is found between distress risk and equity risk when time-varying and conditional beta are used as proxies of equity risk, which is consistent with the literature. The difference in time-varying betas (conditional betas) between the lowest and highest default quintiles is a statically significant at 0.094 (0.104).

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III. Strategic Actions, Distress Risk, and Equity Beta

This section documents tests of the shareholder advantage effect on distressed stock returns based on Fama-MacBeth regressions and a time-trend analysis.

A. Fama-MacBeth Regression — Equity Returns and Equity Risk

To test whether strategic actions can explain the distress puzzle, we employ the Fama-MacBeth regression with strategy proxies including TANGIBILITY, MBTA, and CURRENT, as recommended by Davydenko and Strebulaev (2007). TANGIBILITY is defined as one minus the ratio of net property, plant and equipment over book total assets. MBTA is the market-to-book ratio of total assets. CURRENT is the ratio of CURRENT to total liabilities.[22] To alleviate skewness problems in default probability levels, we use a distress portfolio dummy (DSD) as a proxy for distress risk — which takes a value ranging from one (when a firm occupies the lowest default quintile) through five (when a firm occupies the highest default quintile). To control for other peripheral effects, we consider the following firm characteristics: Firm Size, BM, MOM for Equity Returns and CashFlow, Cash, Sales Growth, R&D, and DY for Equity Risk. Size constitutes the log value of market capitalization. BM is the ratio of equity book-to-market. MOM denotes prior year returns ranging from -12 months to -2 months. CashFlow denotes the operating cash flow over total assets. Cash denotes cash and short-term investments over total assets. Sales growth is the average sales percentage change over the last three years. R&D denotes research and development expenditures over total assets. DY denotes dividends per share divided by the end-of-month share price.

Rows one through six of Table 3 use one-month holding period returns divided by the risk-free rate, and Columns seven through 12 present the time-varying beta as the dependent variable, with Newey-West adjusted standard errors. For each dependent variable, we report the results of five specifications: (1) DSD; (2) DSD and controls; (3) DSD, TANGIBILITY, and controls; (4) DSD, MBTA, and controls; and (5) DSD, CURRENT, and controls. These specifications are designed to determine whether distress effects have incremental explanatory power after controlling for strategic action effects. Consistent with the prior literature, Table 3, Panel A shows a coefficient of DSD in specification (1) of -0.303 (t=-4.99). This suggests that distress risk is a significant and negative predictor of returns, indicating that stock

[22] Other strategic action proxies are excluded for data availability reasons or because they are likely to have similar indications as those presented in the risk-shifting hypothesis. For example, the shareholder advantage hypothesis argues that the friction of equity owned by a firm's CEO represents the equity bargain power, while the risk-shifting hypothesis interprets friction as the degree of alliance between managers and shareholders.

returns decline by 0.30% when a firm moves up one level from a default portfolio.[23] Specification (2) confirms this result after controlling for firm characteristics.

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|Insert Table 3|

Table 3, Panel A specifications three through six show that none of the strategy proxies can fully subsume the effects of distress risk. The coefficient for the distress portfolio (DSD) remains negative and statistically significant. The specifications also confirm the existence of several well-known asset-pricing anomalies in the sample. For example, small size and value and high momentum firms tend to earn higher returns (see Fama and French 1992 and Jegadeesh and Titman 1993). The goodness of fit value for all of these specifications is moderate. This finding is consistent with prior findings on cross-sectional regressions of equity returns on firm characteristics.

In the equity risk regressions, the coefficient on DSD remains significant and negative, indicating that high distress risk is associated with low equity risk. Specification (1) of Panel B in Table 3 reveals a DSD coefficient of -0.049 (t=-9.54). That is, the equity risk declines by 0.049 when a firm advances by one level from a default portfolio.

B. Time Trends in Equity Beta

If a strategic default can explain distress effects, the prospect of a favorable recovery in debt renegotiations causes shareholders to attempt to predict the timing of a default. Consequently, equity risk levels should be less sensitive to a firm's degree of cash flow risk (Favara, Schroth, and Valta (2012)). To test this hypothesis, following a procedure documented in McLean (2011), we estimate cross-sectional

[23] The coefficient for DSD is modest in terms of economic magnitude; however, it is comparable to other firm characteristics.

regressions similar to those presented in the above subsection for the highest distress portfolio. The model specification is as follows:

$$Beta_i = \alpha + \beta_1 * CashFlow_i + \beta_2 * Controls_i + \varepsilon_i \quad (7)$$

where Beta is a time-varying or conditional beta. Controls include Cash, Sales Growth, R&D, and Dividend Yields.

The estimated coefficients for all months produce a time series of equity risk sensitivities to cash flow in the highest distress portfolio. Time trends are estimated by regressing each estimated coefficient in equation (7) on a time trend variable and four lags. These lags control for autocorrelation in each coefficient. The time variable ranges from one in January of 1971 through 480 in December of 2010. The trend coefficient represents the average increase (decrease) in the dependent variable. The strategic action hypothesis implies that there is a negative and significant time trend in the cash flow coefficient. Table 4 uses a time-varying or conditional beta as a measure of equity risk.

|Insert Table 4|

Table 4 shows that the CashFlow coefficient trend is positive and statistically significant. This indicates that the average sensitivity of equity risk to CashFlow increases during the sample period. The time parameter is equal to 0.02 basis points with a t-statistic of 3.75. The Durbin-Watson statistic cannot detect any serial correlation after four lags.

Overall, these findings fail to support the hypothesis of strategic shareholder action on an equity return or for equity risk. This raises significant doubts concerning the shareholder advantage hypothesis. The results are robust with respect to alternative equity risk measures, such as CAPM betas or Fama and French three-factor betas estimated using a rolling window from months t-60 through t-1. In the following section, we perform robustness tests on various subsamples based on different explanations of the distress puzzle.

IV. Alternative Explanations

The previous section revealed a negative relationship between distress risk and future returns and a negative relationship between distress risk and equity risk. In this section, we replicate results reported in Table 3 in different subsamples to address concerns regarding the negative relationship between returns and default risk shown in the literature. Finally, we present an event-time analysis.

George and Hwang (2008) and Chava and Purnanandam (2010) show that the negative relationship between default risk and future returns is concentrated in periods following 1980. We divide the entire sample into two subsamples: January of 1971 to December of 1980 and January of 1981 to December of 2010. The first sample period covers 10 years of monthly data, and the second sample period covers 30 years of monthly data. For the sake of brevity, we only present DSD (distress portfolio dummy) coefficients that are similar to specification (6) in Table 3 for equity returns and equity risk. Panel A of Table 5 presents the results for both periods. Consistent with Campbell, Hilscher, and Szilagyi (2008), George and Hwang (2008) and Chava and Purnanandam (2010), the distress effect is more pronounced during the post-1980 period. The economic magnitude of underperformance in the high distress portfolio is large. The coefficient of -0.37 (t=-5.99) on the DSD shows that firms earn, on average, 0.37% per month more than firms in the next highest default portfolio. We also find smaller equity betas in the high default risk portfolios. For the pre-1980 period, the return data confirm a negative relationship between distress risk and equity returns after controlling for confounding effects. However, the equity risk data show no relationship (consistent with George and Hwang 2008 and Chava and Purnanandam 2010). This puzzling result may be driven by problems associated with short time series data, as historical stock returns are nonexperimental in nature. Noise in the equity risk measures may also be a cause.

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The results presented in previous sections constitute a product the specific default risk measure used. To further validate the results of Tables 3 and 4, we repeat the tests using Ohlson's (2001) O-score as a measure of default risk. A detailed calculation of the O-score can be found in the Appendix. Table 5,

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Panel C presents similar patterns with weaker results in terms of excess return, time-varying beta, and conditional beta values.

|Insert Table 5|

Da, Guo, and Jagannathan (2012) argue that poor empirical evidence for the capital asset pricing model (CAPM) is attributable to the real option component in stock returns. In their study, firms can accept, reject, or postpone new projects and can change or end CURRENT projects. These options allow managers to maximize the firm value levels, and risk factors can change in nonlinear settings when real options are accounted for. Concerns regarding prior estimations of stock returns and equity beta may arise from Da, Guo, and Jagannathan's (2012) arguments. The risk-shifting hypothesis suggests that the real option component can serve as a significant element in the negative relationship. Managers may take advantage of difficulties of determining real option values and may shift equity risks to bondholders. To alleviate this concern, we adapt their means of adjusting stock returns and equity beta (time-varying beta). For each month, we regress stock returns (time-varying beta) on the real option proxies as follows:

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$$Ret_i = \alpha' OP_i^{dm} + Ret_i^{OA} \tag{8}$$

$$beta_i = \alpha' OP_i^{dm} + beta_i^{OA} \tag{9}$$

where Ret denotes excess future t+1 month returns over the risk-free rate; OP^{dm} are the (cross-sectionally demeaned) real option proxies including BM, IR, asset growth, and ROA; Ret^{OA} is the residual of return model 8 (option-adjusted returns); beta is the equity beta (either time-varying or conditional beta); and $beta^{OA}$ is the residual of the beta of equation (9) (the option-adjusted beta).

Table 5, Panel C presents the results of option-adjusted excess returns and equity betas for different distress portfolios. Based on this measure of equity return and risk, a negative relationship between stock returns/equity betas is maintained after considering the real option effect. Consistent with earlier findings of lower magnitude, we find that the coefficient of -0.11 (t=-3.65) shows that firms earn 0.11% fewer filtered returns than firms in the next highest default portfolio. We also find a negative and significant coefficient on equity risk. These results confirm that the earlier findings are not driven by the real option component of equity returns and equity risk.

|Insert Table 5|

The high correlation between default risk and illiquidity presented in Table 2 raises concerns regarding the fact that the earlier results may have been driven by mispricing effects. Default risk may serve as a proxy of illiquidity, and lower returns in high default risk stocks may be caused by price corrections. We address this concern through an event-time analysis shown in Figure I. For each month, we form five portfolios based on default probability levels, and we track individual stock performance levels over a 12-month period via portfolio formation. All factor loadings are estimated by regressing monthly excess returns over a risk-free rate on Fama and French and momentum factors using the prior five-years of monthly returns with a minimum of 36 months. Abnormal returns are calculated as the return net of post-formation predicted returns using updated factors for each month, which are accumulated over the 12-month post-formation period. The numbers shown in Figure I first represent value-weighted values for each portfolio and then average values over the sample period.

If the previous results were caused by a price convergence of high default risk firms to fundamental value, long-term default portfolio performance should converge. However, this is not the case. Figure I show that low default risk firms consistently perform better than high default risk firms over 12 months after portfolio formation. Interesting patterns in the highest default portfolio can be found. Cumulative abnormal returns decrease for two months and then revert back to upward trends. This shows that high default risk stocks are initially overpriced but eventually correct back to the fundamental value. However, price corrections cannot fully explain the negative relationship between default risk and returns.

V. Risk-shifting and Distress Puzzle

We provide evidence that the negative relationship between equity return/risk and distress risk is robust with respect to shareholder advantage effects. This finding rejects the notion that the shareholder advantage hypothesis explains the distress puzzle. These results provide support for the risk-shifting hypothesis. In this section, we explore this hypothesis in depth.

Some of the results presented in Sections II through IV are consistent with the risk-shifting hypothesis. Distress risk may be interpreted as a proxy of the probability that shareholders take advantage of debt contracts by accepting excessive risk projects. This can lead to low equity risk levels among high distress firms. Consistent with Campbell, Hilscher, and Szilagyi (2008), Table 2 shows that equity risk (measured by both time-varying and conditional betas) is negatively related to distress risk. Indeed, this evidence is confirmed in Table 4 through various robustness checks.

A. Risk-shifting in Fundamentals

An implication of the risk-shifting hypothesis pertains to the fact that distressed firms tend to accept excessive risk projects at the cost of bondholders. We examine this implication in the fundamental data. If risk shifting can explain the distress puzzle, there should be evidence of risk-shifting behaviors in fundamental data that can be traced. Eisdorfer (2008) provides empirical evidence for risk-shifting behaviors in distressed firms. His findings are in line with the theoretical papers of Galai and Masulis (1976) and Jensen and Meckling (1976).

In this section, we present empirical evidence of risk-shifting behaviors in accounting data that is motivated by Eisdorfer (2008). In particular, we use annual accounting data drawn from COMPUSTAT combined with the default probability value shown in Section II. Following Eisdorfer (2008), investment intensity is defined as capital expenditure relative to total assets. Firm profitability is measured via ROE. Cash flow is operational cash flow relative to total assets. For each year, observations are sorted into quintiles based on the default probability level of the previous year. Table 6 reports the time-series average of investment intensity, profitability, and cash flow intensity levels for each default quintile and the difference of high minus low.

Table 6 shows that the default probability is positively associated with investment intensity and is negatively associated with profitability and cash flow. Table 8, Panel A reveals an average investment intensity in the low default quintile of 0.077 and a high default quintile of 0.082. The difference is 0.005, significant at the 10% level. The average ROE of the low default quintile is positive at 0.011 and that of the high default quintile is negative at -0.081.The difference is -0.092, significant at 1%. This supports the risk-shifting hypothesis principle that managers of high default risk firms engage in value-destroying or negative NPV investment decisions.[24] The difference in cash flow fails to show any evidence of risk-shifting behavior, but the coefficient sign is as expected.

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Eisdorfer (2008) proposed that empirical evidence of risk-shifting can be examined under real option or conditional settings. In the first conditional setting, firms with different growth perspectives should exhibit different investment behaviors. To explore empirical evidence on risk-shifting behaviors, we use Tobin's Q, or MB, as a proxy of firm growth opportunities. More specifically, we first sort firms into five quintiles by a firm's MB. For each MB quintile, we then further divide our observations into five default quintiles.

Table 6, Panel B presents the results of risk-shifting behaviors controlling for MB. For the high MB quintile, the average investment intensity of low default probability firms is 0.095 and that of high default probability firms is 0.097. The difference between high and low levels is negligible. These results are consistent with the real options hypothesis. A firm's investment decisions depend on its growth opportunities. For high-growth opportunity firms, investment is a natural consequence of maintaining firm growth. This is supported in Panel B of Table 6, where differences in investment intensity levels

[24] See Esty (1996) and Gan (2004) for empirical evidence found in the banking industry and Huang, Sialm, and Zhang (2011) for empirical evidence related to mutual funds.

between high MB and low MB firms are statistically and economically significant. The magnitudes are similar for both low and high default quintiles. For high-growth opportunity firms, the distinction between high and low default risk firms should be based on the quality of investments and on marginal resources used for investing. High default risk companies invest in all projects, including negative NPV projects, and they earn low average returns from their investments. Table 6, Panel B shows that for the high MB quintile, high default risk firms exhibit an average ROE value of -0.288, and low default risk firms show an average ROE value of -0.120. The difference is a statistically significant at -0.168. Similarly, for the high MB quintile, high default risk firms show an average cash flow level of 0.230, and low default risk firms have an average cash flow level of 0.257. The difference is a statistically significant at -0.027.

By contrast, investment opportunities available to low-growth opportunity firms are scarce. High default risk and low growth opportunity firms tend to overinvest. Table 6, Panel B shows that, for the low MB quintile, the average investment intensity level for low default probability firms is 0.057 and that of high default probability firms is 0.063. The difference is 0.006, significant at 5%. Under the low MB quintile, high default risk firms have an average ROE value of -0.041, and low default risk firms have an average ROE value of 0.017. The difference is -0.058 and is statistically significant. Similarly, for the low MB quintile, high default risk firms have an average cash flow of 0.091, and low default risk firms have an average cash flow of 0.109. The difference is -0.027 and is statistically significant.

Table 6, Panel C presents the results of another conditional setting. We use idiosyncratic risk (IR) proposed by Ang et al. (2006) as a proxy for the valuation uncertainty of individual firms. The intuition is that hard-to-value firms can hide their risk-shifting behaviors so as to not suffer from high issuing debt costs. However, transparent firms with low IR levels are likely to be constrained by debt covenants or regulations to mitigate debt agency problems. Table 6, Panel C shows that the difference in investment intensity levels between high and low default risk firms is significant only within the high IR quintile. At the same time, the difference in investment intensity levels between high and low IR firms is significant only in the high default quintile. For profitability and cash flow measures, both high IR and low IR quintiles show default effects, but such effects are stronger for the high IR quintile.

|Insert Table 6|

To explore the possibility that industry effects on bankruptcy and default risk may have generated the previous results, we present industry-adjusted results in Table 7. For each year, we subtract each observation by the Standard Industrial Classification (SIC) two-digit industry average of investment, profitability, and cash flow. We replicate the results of Table 6 using these industry-adjusted variables.

The results shown in Table 7 are quite similar to those shown in Table 8, but are of greater significance. Table 7, Panel A shows that, on average, high default firms overinvest, earn low profits, and exhaust their cash flows relative to their industry mean. An obvious difference of Panel A of Table 7 is that cash flows of the high default quintile are significantly lower than those of the low default quintile. Panels B and C of Table 7 confirm the conditional results of Panels B and C in Table 6.

|Insert Table 7|

B. Risk-shifting Behaviors in Different Subsamples

To further analyze whether the distress puzzle is attributed to risk-shifting behaviors, we test distress effects in different subsamples based on different risk-shifting incentives or constraints. We establish the conditions under which effects of distress risk on equity returns (or equity risk) are likely to be more pronounced. Generally speaking, there is information asymmetry between managers/shareholders and debt holders. Shareholders (through managers) may take action to maximize stock prices that are harmful to creditors, especially when firms are in distress. With different incentives or constraints, the magnitude of agency costs of debt may vary.

Credit Rating

If low equity returns in high distress firms are caused by risk-shifting behaviors, distress effects should be significantly weaker in firms (followed by credit agencies) than in firms without credit ratings. Healy and Palepu (2001) argue that information intermediaries such as rating agencies can serve as outside monitors and can restrict managerial misconduct. More public attention to corporate bonds can reduce agency costs of debt in these firms. Credit ratings are viewed by investors as important information sources on the credit-worthiness and resultant value of a corporate bond. To obtain a credit rating, a firm must go through the scrutiny of the rating agency, which verifies the firm's ability to meet its financial obligations.

Convertible Debt

As convertible bonds are exchangeable into equity, an implication of the risk-shifting hypothesis is that these behaviors should be seen less in firms with convertible debt. For firms with convertible bonds, shareholder incentives to accept risk are largely reduced (see Barnea, Haugen, and Senbet (1980), Frierman and Viswanath (1993), Chesney and Gibson-Asner (2001), Ozerturk (2002), Hennessy and Tserlukevich (2004), and Green (1984)). Data on convertible debt are available through the COMPUSTAT annual file.

CEO Equity Holdings

According to Jensen and Meckling (1976), there is a trade-off relationship between the agency cost of debt and the agency cost of equity. When the agency cost of equity increases, the agency cost of debt decreases. Brander and Poitevin (1992), John and John (1993), and Subramanian (2003) find that managerial compensation structures can affect risk-shifting behaviors. CEO equity holding acts as a compensation structure that aligns manager interests with shareholders' interest. It also can be interpreted as an alternative form of corporate governance. CEO equity holding data were obtained from Execucomp

Annual Compensation for the period running from 1992 to 2010.[25] Execucomp contains data on companies from the S&P 1500 Plus. Risk-shifting behaviors should be more pronounced when shareholders' and managers' interests are more closely aligned.

We determine the effects of these factors by incorporating the interaction variables. More specifically, we first divide the full sample into two subsamples based on specific criteria. These criteria include whether a firm is followed by a credit agency (RD), whether a firm has convertible bonds (CD), and whether a firm's CEO has an equity holding above the sample median (PD). These variables are equal to one if a firm belongs to certain subsamples and is zero otherwise. We then regress either the equity return or equity risk on an interaction variable between financial distress (DSD) and the dummy variable (similar to specifications six and 12 in Table 3).

|Insert Table 8|

The results shown in Table 8 indicate that rating agencies and convertible debt can mitigate risk-shifting behaviors, but CEO equity holding can enhance these behaviors. In particular, coefficients of financial distress are significantly lower in firms with credit ratings or convertible debt and in which CEOs have smaller equity holdings. All effects of financial distress (DSD) are in the predicted direction, but are insignificant for CEO equity holding. By contrast, all interaction effects are significant. For example, in Panel A of Table 8, the coefficient of DSD_RD is 0.111 (t-statistic 2.44), suggesting that the presence of a credit rating reduces the effect of financial distress on equity returns by 31%. The interaction effect reverses the distress effect on equity risk.

C. Credit Spread and Distress Risk

[25] In 2006, the FAS123R changed reporting requirements. This change did not alter my results, as after eliminating the sample for 2006 to 2010, we found qualitatively similar results.

The risk-shifting hypothesis suggests that distress risk reduces equity risk and increases debt risk. The above sections confirm a negative relationship between equity return (risk) and distress risk. In this section, we further test the risk-shifting hypothesis for bond data. The bond data used, supplied by the Trade Reporting and Compliance Engine (TRACE), include FINRA over-the-counter corporate bond market real-time price information, including bond prices, yields to maturity, maturity dates, and volumes. TRACE consolidates bond prices daily data for July 1, 2002 through December 31, 2010, representing 100% of OTC activity and over 99% of total U.S. corporate bond market activity in over 30,000 securities.

We construct monthly credit spreads in two steps. First, we obtain monthly yield data from the last trading observation of each month. We then use monthly treasury security data from FRED published by the Federal Reserve Bank of St. Louis as a risk free rate[26]. Second, we take the difference between the yield to maturity on the corporate bond and the treasury rate as the corporate credit spread. Following Davydenko and Strebulaev (2007), we only examine bonds with more than one year of remaining time to maturity. To maintain comparability levels, we exclude bonds issued by financial and utility firms and bonds with missing data on corporate credit spreads and default probability. The final sample includes 509,385 monthly observations for 21,118, and unique bonds for 1,695 unique firms.

|Insert Table 9|

Table 9 presents the results of the Fama and MacBeth regressions of corporate credit spreads on the quintile of the default probability (DSD). The independent variables are DSD, Ln_amt, Year, Rating, Std,

[26] FRED includes monthly data on treasury bonds and notes for one-, two-, three-, five-, seven-, 10-, 20- and 30-year constant maturity rates. We match the corporate bond data to the corresponding treasury rate. For example, if a corporate bond's remaining time to maturity is more than five years and less than seven years, we match it to a seven-year constant maturity rate. For corporate bonds with a period to maturity of more than 30 years, we use the 30-year constant maturity rate.

ROA, and Runup. DSD is the quintile of the default probability. Ln_amt is the log value of the bond face value. Year denotes the number of years to maturity. Rating denotes the credit rating of the corporate bond. Std denotes the prior 12-month historic equity price volatility level. ROA denotes net income relative to the firm's total assets. Runup is the percentage change in equity prices over the past year.

Without controlling for any bond or firm characteristics, the credit spread increases by 0.37% in row (1) when a stock moves into a higher distress portfolio. The second specification controls bond characteristics including bond sizes, time to maturity, and credit ratings. Consistent with Cremers, Nair, and Wei (2007) and Davydenko and Strebulaev (2007), bondholders require higher yields for smaller sizes, longer periods to maturity, and inferior credit ratings. The third specification controls firm characteristics, including those of stock volatility, ROA, and price run-up. As expected, stock volatility increases bond yields with a coefficient of 70.689 and a t-statistic of 16.31. However, firm profitability has no effect on credit spreads. The coefficient of the price run-up represents the effect of demand in equity on demand in debt. Not surprisingly, the price run-up reduces credit spreads. More importantly, the effect of distress risk does not change after controlling for different bond and firm characteristics. The average R^2 ranges from 4.27% to 37.91%.

Rows (4) through (7) of Table 9 show that none of the strategy proxies can fully subsume the effects of distress risk, as the coefficient of a distress portfolio (DSD) remains positive and statistically significant. MBTA has a strongly negative and significant coefficient that is equal to -0.073 with a t-statistic of -2.26. However, the coefficient for TANGIBILITY is insignificant with the predicted sign. CURRENT has a negative and significant coefficient that is equal to -0.517% with a t-statistic of -3.57. This result is consistent with the risk-shifting hypothesis and refutes the strategic action hypothesis.

VI. Conclusions

This paper examines causes of the distress puzzle. We test the shareholder advantage hypothesis (as proposed by Garlappi, Shu, and Yan 2008 and Garlappi and Yan 2011) in reconciling the negative relationship between financial distress and equity returns. In our cross-sectional regressions, we show that financial distress serves as a negative and significant predictor of future stock returns and equity risk over strategic action proxies proposed by Davydenko and Strebulaev (2007). Furthermore, using McLean's (2011) methodology, we find that equity risk does not become less sensitive to firm cash flow fluctuations during sample periods. This evidence is inconsistent with the shareholder advantage hypothesis.

This paper supports risk-shifting explanations for the default risk puzzle. We find that high default risk firms tend to overinvest, earn lower profits, and exhaust their cash flows relative to low default risk firms. These effects are concentrated in low growth opportunity firms and in hard-to-value firms.

The distress effect on equity return (risk) varies significantly in the presence of different incentives or supervision mechanics. In particular, we examine distress effects for different subsamples. We find that the effect of distress risk concentrates in firms without credit ratings or convertible debt and in firms where CEOs have equity holdings.

Finally, we find that financial distress increases credit risks of debt. Distress risk, on average, has a significantly positive effect on credit spread. The effects of distress risk on credit spread cannot be explained by strategy proxies presented by Davydenko and Strebulaev (2007).

Appendix: O-score Definition

Following Ohlson (1980), the O-score is calculated using the best model presented in their paper (Model 1 in Table 4) as follows:

$$O_{i,t} = -1.32 - 0.407\text{SIZECPI} + 6.03TLTA - 1.43WCTA + 0.757CLCA - 2.37NITA - 1.83FUTL + 0.285INTWO - 1.72OENEG - 0.521CHIN \qquad \text{(A5)}$$

where SIZECPI is equal to the log of total assets over CPI; TLTA is the total liability divided by total assets; WCTA is total working capital over total assets; CLCA is the CURRENT liability divided by total assets; OENEG is a dummy variable that is equal to one if the total asset is less than total liability and that is equal to zero otherwise; NITA is the net income over total assets; FUTL denotes cash flows in operation divided by total liability; INTWO is a dummy variable that is equal to one if the net income is negative for last two years and that is zero otherwise; and CHIN is equal to the change in net income divided by the sum of absolute and lagged net income values.

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Table 1: Summary Statistics of Default Probability

This table reports summary statistics of default probability (in percentages) presented by Campbell, Hilscher, and Szilagyi (2008). The sample period runs from January of 1971 to December of 2010. The table reports the annual average of default probability and corresponding historical events. N denotes the number of firms per year.

Year	N	Default Probability	Historical Event (Peak)
1971	761	0.014	
1972	1,348	0.010	
1973	1,483	0.013	Oil Crisis and Stock Market Crash
1974	1,488	0.009	
1975	1,486	0.019	
1976	1,414	0.029	United Kingdom Secondary Banking Crisis
1977	1,532	0.021	
1978	1,491	0.035	
1979	1,456	0.058	The 1979 Energy Crisis and the U.S. Recession
1980	1,407	0.027	
1981	1,388	0.049	Latin American Debt Crisis and the U.S. Double
1982	2,090	0.043	
1983	2,535	0.055	
1984	2,708	0.119	
1985	2,648	0.166	
1986	2,666	0.222	
1987	2,830	0.247	
1988	2,752	0.435	Black Monday 1987
1989	2,653	0.558	United States Savings & Loan Crisis
1990	2,524	0.574	Japanese Asset Pricing Bubble Collapse
1991	2,557	0.529	Black Wednesday

1992	2,845	0.530	
1993	3,168	0.531	
1994	3,516	0.616	Economic Crisis in Mexico
1995	3,682	0.618	
1996	3,968	0.627	
1997	4,241	0.680	Asian Financial Crisis
1998	4,172	0.829	Russian Financial Crisis
1999	3,952	0.914	
2000	3,931	1.005	The Early 2000s Recession
2001	3,554	1.801	The U.S. dot-com Bubble Crisis
2002	3,250	1.311	
2003	3,183	0.993	
2004	3,184	0.769	
2005	3,139	0.812	
2006	3,161	2.608	
2007	3,110	3.421	
2008	2,972	6.634	The U.S. Financial Crisis
2009	2,784	11.894	
2010	2,857	5.678	The European Sovereign Debt Crisis

Table 2: Summary Statistics of Firm Characteristics and Default Probability

This table reports summary statistics of firm characteristics and default probability. The sample period runs from January of 1971 to December of 2010. For each month, observations are sorted by default probability into five quintiles. The table reports the time-series average of default probability, the corresponding number for each quintile, and the difference of the high minus the low. Panel A reports summary statistics of firm characteristics for the entire sample. Panel B reports summary statistics of firm characteristics based on the quintiles. Panel C reports excess returns over the risk-free rate, risk-adjusted returns, DGTW (1997) characteristic-adjusted returns, time varying beta, and conditional beta. Risk-adjusted returns and characteristic-adjusted returns are based on t+1 month returns. * denotes a 10% significance level, ** denotes a 5% significance level, and *** denotes a 1% significance level.

Panel A: Summary Statistics of Firm Characteristics

	Mean	**Median**	**Std**	**Min**	**Max**
Default Probability	1.312	0.002	10.672	0	100
Size	4.821	4.704	1.927	1.477	8.498
BM	0.782	0.605	0.583	0.155	2.419
MOM	0.069	-0.002	0.464	-0.648	1.107
Illiquidity	0.200	0.003	0.441	0	1.750
Leverage	0.474	0.476	0.218	0.115	0.938

Panel B: Firm Characteristics by Default Probability Quintile

	Low Quintile				**High Quintile**
	1	**2**	**3**	**4**	**5**
Default Probability	0.000	0.001	0.003	0.789	11.041
Size	5.191	5.305	4.785	4.030	3.268
BM	0.620	0.699	0.882	1.040	1.170
MOM	0.306	0.133	0.036	-0.066	-0.211
Illiquidity	0.235	0.323	0.449	0.610	0.752
Leverage	0.341	0.450	0.510	0.554	0.622

Panel C: Returns and Equity Risk by Default Probability Quintile

	Low Quintile				High Quintile
	1	**2**	**3**	**4**	**5**
Returns	0.805	0.456	0.586	0.250	0.073
Char-adjusted Returns	0.053	-0.345	-0.241	-0.582	-0.651
CAPM Alpha	0.303	-0.017	0.086	-0.349	-0.623
3-factor Alpha	0.507	0.054	0.049	-0.530	-0.918
4-factor Alpha	0.279	0.094	0.248	-0.100	-0.341
5-factor Alpha	0.268	0.081	0.202	-0.081	-0.352
Time-varying Beta	1.099	1.026	1.003	1.002	1.005
Conditional Beta	1.109	1.047	1.024	1.005	1.005

Table 3: Fama-MacBeth Regression-Equity Return and Risk

This table represents the Fama-MacBeth regression of equity risk on distress risk. The dependent variable is either equity returns or equity risk. Equity returns are one-month holding period returns over the risk-free rate, and equity risk is a time-varying beta as defined in Table 4. The independent variables are DSD, CashFlow, Cash, Sales Growth, R&D, DY, TANGIBILITY, MBTA, and CURRENT. DSD is the quintile of default probability. Size is the log value of market capitalization. BM denotes book-to-market ratios. MOM denotes prior year returns ranging from -12 months to -2 months. CashFlow is the operating cash flow over total assets. Cash is the cash and short-term investment over total assets. Sales growth is the average sales percentage change over the last three years. R&D denotes research and development costs over total assets. DY is the dividend per share over the price per share at the end of the month. MBTA is the market-to-book ratio of the asset. TANGIBILITY is defined as one minus property, plant and equipment over total assets. CURRENT is the ratio of current liability over total liability. The t-stat scores are shown in parentheses. * denotes a 10% significance level, ** denotes a 5% significance level, and *** denotes a 1% significance level.

Panel A Equity Returns

Constant	DSD	Size	BM	MOM	TANGIBILITY	MBTA	CURRENT	Average R^2
1.525***	-0.303***							1.23%
(5.72)	(-4.99)							
1.740***	-0.318***	-0.109***	0.273**	0.612***				3.07%
(4.94)	(-7.45)	(-2.67)	(4.55)	(3.46)				
2.054***	-0.318***	-0.118***	0.253***	0.577***	-0.328			3.54%
(6.71)	(-7.29)	(-2.99)	(4.45)	(3.40)	(-1.38)			
1.841***	-0.319***	-0.107***	0.236***	0.602***		-0.046***		3.21%
(5.31)	(-7.38)	(-2.65)	(4.06)	(3.40)		(-2.18)		
2.214***	-0.339***	-0.128***	0.251***	0.054***			-0.460***	3.46%

(7.08)	(7.19)	(-3.28)	(4.50)	(3.19)					(-2.48)	
2.383***	-0.339***	-0.126***	0.204***	0.524***			-0.109	-0.057**	-0.410***	3.89%
(7.56)	(-7.13)	(-3.27)	(3.81)	(3.14)			(-0.55)	(-2.42)	(-267)	
Panel B Equity Risk										
Constant	**DSD**	**CashFlow**	**Cash**	**Sales Growth**	**R&D**	**DY**	**TANGIBILITY**	**MBTA**	**CURRENT**	**Average R^2**
0.944***	-0.049***									2.53%
(39.28)	(-9.40)									
0.903***	-0.036***	-0.144***	0.189***	0.135***	1.387***	-0.009*				7.92%
(27.26)	(-6.32)	(-4.53)	(4.24)	(3.14)	(5.88)	(-1.78)				
0.779***	-0.031***	-0.084***	0.091**	0.125***	1.319***	-0.003	0.162***			9.45%
(16.94)	(-4.98)	(-3.02)	(2.16)	(3.24)	(5.92)	(-0.56)	(3.70)			
0.762***	-0.026***	-0.139***	0.057	0.126***	1.074***	-0.008		0.098***		10.43%
(18.80)	(-3.98)	(-4.51)	(1.36)	(2.90)	(4.98)	(-1.62)		(7.17)		
0.928***	-0.037***	-0.143***	0.222***	0.134***	1.421***	-0.009*			-0.055**	8.53%
(23.12)	(-6.04)	(-4.49)	(5.70)	(3.13)	(5.88)	(-1.73)			(-2.45)	
0.651***	-0.024***	-0.046*	-0.005	0.100***	1.028***	-0.002	0.275***	0.112***	-0.202***	12.93%
(12.29)	(-3.70)	(-1.70)	(-0.15)	(3.17)	(5.12)	(-0.31)	(4.96)	(9.12)	(-8.30)	

Table 4: Equity Risk Sensitivity Trends

This table presents trends in the equity risk sensitivities of the highest distress risk portfolio (DSD=5). Equity risk sensitivities are coefficients of monthly cross-sectional regressions of equity risk on cash flow variables, as shown in the following model:

$$Beta_{i,t} = \alpha + \beta_1 * CashFlow_{i,t} + \beta_2 * Controls_{i,t} + \varepsilon_{i,t}$$

This beta is either a time-varying or conditional beta. CashFlow is defined in Table 3. The controls used are variables including Cash, Sales Growth, R&D, and Dividend Yields, which are defined in Table 3. The t-stat scores are shown in parentheses. * denotes a 10% significance level, ** denotes a 5% significance level, and *** denotes a 1% significance level. Durbin-Watson statistics are reported at the bottom of each panel.

	Time-Varying Beta	**Conditional Beta**
Constant	-0.072***	-0.108***
	(-4.12)	(-4.99)
Trend	2.05e-04***	3.18e-04**
	(3.75)	(4.46)
Lag 1	0.549***	0.628***
	(11.94)	(13.66)
Lag 2	0.105**	0.017
	(2.01)	(0.31)
Lag 3	0.091*	0.037
	(1.74)	(0.68)
Lag 4	0.048	-0.003
	(1.04)	(-0.06)
Months	476	476
Durbin-Watson	2.009	2.006

Table 5: Robustness Tests

This table replicates previous tests (specification six in Table 3) in different subsamples to check the robustness of relationships between portfolio returns and default probability and between portfolio risk and default probability. For each month, observations are sorted based on distress risk levels (default probability) into five quintiles. Panel A presents results for the sample period running from January of 1971 to December of 1980 and the sample period of January of 1981 to December of 2010. Panel B presents results on which the distress portfolios are constructed based on Ohlson's (1980) O-score. Panel C reports the results based on the option-adjusted returns and beta. The option-adjusted variables are constructed as residuals by regressing raw variables (cross-sectionally demeaned) for BM, IR, Asset Growth, and ROA. The table reports coefficients of DSD that are similar to specification six shown in Table 3, and t-stat scores are shown in parentheses. * denotes a 10% significance level, ** denotes a 5% significance level, and *** denotes a 1% significance level.

Panel A: Subsample Periods

	Sample Period (1971-1980)	**Sample Period (1981-2010)**
Equity Returns	-0.263***	-0.369***
	(-4.25)	(-5.99)
Equity Risk	0.037	-0.041***
	(0.31)	(-7.09)

Panel B: Alternative Distress Measure

	O-score
Equity Returns	-0.234***
	(-8.16)
Equity Risk	-0.029***
	(-3.34)

Panel C: Real Option-Adjusted	
Equity Returns	-0.107***
	(-3.65)
Equity Risk	-0.013***
	(-11.85)

Table 6: Investment, Profitability, Cash Flow, and Default Probability

This table presents the relationships between firm fundamentals and default probability. The sample period runs from 1971 to 2010. Panel A shows the results based on quintiles sorted by default probability levels. Panel B shows the results based on quintiles that are first sorted by the market-to-book ratio (MB) and then by default probability. Panel C presents the results based on quintiles that are first sorted by idiosyncratic risk (IR) and then by default probability. The investment intensity level is denoted by capital expenses over total assets as proposed by Eisdorfer (2008). Firm profitability levels are determined by returns on equity (ROE). The cash flow intensity is the operational cash flow over total assets. For each year, observations are sorted based on default probability levels into five quintiles. The table reports the time-series average of investment intensity, profitability, and cash flow intensity for each default quintile and the difference of high minus low. * denotes a 10% significance level, ** denotes a 5% significance level, and *** denotes a 1% significance level.

Panel A: Fundamentals by Default Probability Quintiles

	Low DP Quintile	**High DP Quintile**	**Diff.**
Investment (Capital Expense/Asset)	0.067	0.082	0.005*
Profitability (ROE)	0.155	-0.116	-0.271***
Cash Flow (Operational Cash Flow/Asset)	0.271	0.074	-0.196***

Panel B: Fundamentals Double Sorted by Default Probability and MB Quintiles

	Low Default	**High Default**	**Diff.**
Investment (Capital Expense/Asset)			
Low MB	0.057	0.063	0.006**
High MB	0.077	0.082	0.005*
Diff.	-0.030***	-0.039***	
Profitability (ROE)			
Low MB	0.077	-0.097	-0.174 ***
High MB	0.196	-0.395	-0.591***

Diff.	0.119***	-0.298***	
Cash Flow (Operational Cash Flow/Asset)			
Low MB	0.210	0.057	-0.153***
High MB	0.322	0.140	-0.182***
Diff.	0.111***	0.083***	

Panel B: Fundamentals Double Sorted by Default Probability and IR Quintiles

	Low Default	**High Default**	**Diff.**
Investment (Capital Expense/Asset)			
Low IR	0.075	0.074	-0.001***
High IR	0.073	0.087	0.014***
Diff.	0.002	0.013***	
Profitability (ROE)			
Low IR	0.168	0.072	-0.096***
High IR	0.025	-0.400	-0.425***
Diff.	-0.143***	-0.472***	
Cash Flow (Operational Cash Flow/Asset)			
Low IR	0.196	0.043	-0.153***
High IR	0.331	0.082	-0.249***
Diff.	0.135***	0.038***	

Table 7: Investment, Profitability, Cash Flow, and Default Probability (Industry-Adjusted)

This table presents relationships between firm fundamentals and default probability adjusted by the two-digit SIC industry codes. The sample period runs from 1971 to 2010. Panel A presents the results based on quintiles sorted by default probability levels. Panel B presents the results based on quintiles that are first sorted by the market-to-book ratio (MB) and then by default probability. Panel C presents the results based on quintiles that are first sorted by idiosyncratic risk (IR) and then by default probability. Investment intensity levels are capital expenses over total assets, as proposed by Eisdorfer (2008). The firm profitability is returns on equity (ROE). The cash flow intensity is the operational cash flow over total assets. For each year, observations are sorted into five quintiles based on the default probability level. The table reports the time-series average of investment intensity, profitability, and cash flow intensity of each default quintile and the difference of high minus low. * denotes a 10% significance level, ** denotes a 5% significance level, and *** denotes a 1% significance level.

Panel A: Fundamentals by Default Probability Quintiles

	Low DP Quintile	High DP Quintile	Diff.
Investment (Capital Expense/Asset)	-0.003	0.005	0.008***
Profitability (ROE)	-0.019	-0.116	-0.097***
Cash Flow (Operational Cash Flow/Asset)	0.017	0.001	-0.016***

Panel B: Fundamentals Double Sorted by Default Probability and MB Quintiles

	Low Default	High Default	Diff.
Investment (Capital Expense/Asset)			
Low MB	-0.022	-0.015	0.008***
High MB	0.015	0.025	0.010**
Diff.	0.037***	0.040***	
Profitability (ROE)			
Low MB	0.016	-0.045	-0.061***
High MB	-0.245	-0.375	-0.130***

Diff.	-0.262***	-0.330***	
Cash Flow (Operational Cash Flow/Asset)			
Low MB	-0.015	-0.038	-0.023***
High MB	0.049	0.021	-0.028***
Diff.	0.064***	0.059***	

Panel B: Fundamentals Double Sorted by Default Probability and IR Quintiles

	Low Default	**High Default**	**Diff.**
Investment (Capital Expense/Asset)			
Low IR	-0.005	-0.003	-0.002
High IR	-0.009	0.003	0.011***
Diff.	0.004*	0.006*	
Profitability (ROE)			
Low IR	0.147	0.110	-0.037***
High IR	-0.234	-0.345	-0.111***
Diff.	-0.381***	-0.454***	
Cash Flow (Operational Cash Flow/Asset)			
Low IR	-0.028	-0.037	-0.009***
High IR	0.013	-0.015	-0.027***
Diff.	0.040***	0.022***	

Table 8: Distress Effects in Different Risk-Shifting Subsamples

This table presents coefficients of specifications (6) and (12) of Table 3 with an additional interaction variable. For each month, the entire sample is first divided into two subsamples based on specific criteria. These criteria include whether a firm is followed by a credit agency (Panel A, CD), whether a firm has convertible bonds (Panel B, CD), and whether a firm's CEO has equity holdings above the sample median (Panel C, PD). Then, we construct dummy variables, which are equal to one if a firm is covered in the subsample and which are zero otherwise. The t-stat scores are shown in parentheses. * denotes a 10% significance level, ** denotes a 5% significance level, and *** denotes a 1% significance level.

	Panel A Credit Rating	
	Equity Return	**Equity Risk**
DSD	0.353***	-0.043***
	(-7.84)	(-7.24)
DSD_RD	0.111**	0.061***
	(2.44)	(6.51)
	Panel B Convertible Debt	
	Equity Return	**Equity Risk**
DSD	-0.318***	-0.061***
	(-7.51)	(-8.95)
DSD_CD	0.117*	0.061***
	(1.77)	(11.31)
	Panel C CEO Equity Holdings	
	Equity Return	**Equity Risk**
DSD	-0.066	-0.010
	(-0.62)	(-1.48)

DSD_PD	-0.112***	-0.026***
	(-2.66)	(-5.03)

Table 9: Fama-MacBeth Regression-Bond Risk and Distress Risk

This table presents the Fama-MacBeth regression of bond risk on distress risk. The dependent variable is the yield spread between the bond yield and corresponding treasury yield. The independent variables are DSD, Ln_amt, Year, Rating, Std, ROA, Runup, MBTA, Number, TANGIBILITY, and CURRENT. DSD is the quintile of the default probability. Ln_amt is the log value of the bond face value. Year is the number of years until maturity. Rating denotes the credit rating of the corporate bond. Std is the prior 12-month historic equity price volatility level. ROA is the net income over total assets for the firm. Runup is the percentage change in equity prices over the past year. MBTA is the market-to-book ratio for the assets. Number denotes the log value of the number of bond issues outstanding in a firm divided by the log value of total debt. TANGIBILITY is defined as 1-Property, Plant and Equipment/Total Asset. CURRENT is the ratio of current liability over total liability. The t-stat scores are shown in the parentheses. * denotes a 10% significance level, ** denotes a 5% significance level, and *** denotes a 1% significance level.

Constant	DSD	Ln_amt	Year	Rating	Std	ROA	Runup	MBTA	TANGIBILITY	CURRENT	Average R^2
1.022***	0.370***										4.27%
(11.91)	(13.30)										
1.236***	0.323***	-0.125***	0.017***	0.234***							29.59%
(8.01)	(10.01)	(-18.46)	(3.23)	(23.24)							
0.191	0.196***	-0.102***	0.032***	0.170***	70.689***	0.007	-0.668***				37.91%
(1.13)	(9.45)	(17.04)	(4.75)	(17.44)	(16.31)	(0.03)	(-8.47)				
0.305*	0.187***	-0.102***	0.033***	0.170***	71.70***	-0.016	-0.713***	-0.073**			38.32%
(1.84)	(9.10)	(-17.04)	(4.77)	(17.40)	(16.06)	(-0.07)	(-8.54)	(-2.26)			

0.160	0.208***	-0.099***	0.033***	0.171***	68.397***	-0.063	-0.665***		-0.024		38.63%
(0.91)	(11.10)	(-16.68)	(4.86)	(14.50)	(16.30)	(-0.33)	(-8.84)		(-0.25)		
0.426*	0.149***	-0.101***	0.033***	0.180***	68.414***	0.163	-0.685***			-0.517***	38.81%
(1.91)	(4.75)	(-17.63)	(4.80)	(17.60)	(14.43)	(0.70)	(-7.46)			(-3.57)	
0.470*	0.157***	-0.098***	0.033***	0.181***	67.391***	0.197	-0.730***	-0.059*	-0.023	-0.486***	39.83%
(2.23)	(4.87)	(-17.07)	(4.90)	(14.41)	(14.21)	(0.79)	(-8.12)	(-1.70)	(-0.25)	(-3.19)	

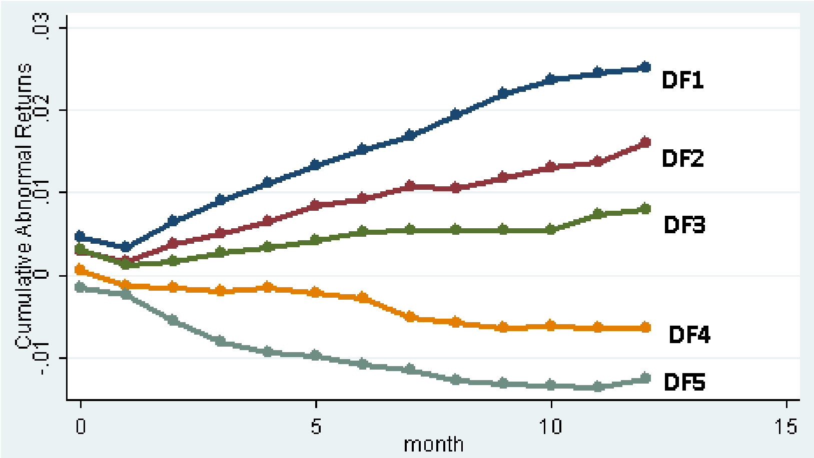

Figure I. Cumulative Abnormal Returns by Default Portfolios. This figure plots the average cumulative abnormal returns of each default portfolio (DF). For every month, firms are sorted into five groups based on default probability levels. Cumulative abnormal returns are tracked over 12 months. Numbers in the figure denote values that are first value-weighted within each portfolio and that are then averaged over the sample period. The time period ranges from January of 1971 through December of 2010. Abnormal returns are calculated return net values of the predicted returns from the Fama-French plus Momentum factor model. Loadings are estimated from the prior five-year's monthly returns with a minimum of 36 months. Abnormal returns are then accumulated over the 12-month post-formation period.