# Default Risk in Equity Returns

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## Abstract

This is the first study that computes default measures for individual firms using Merton's (1974) option pricing model, to assess the effect that default risk has on equity returns. We find that both size and book-to-market (BM) exhibit a strong link with default risk. There is a very strong size effect (45.84% per annum), which is however present *only* within the segment (one-fifth) of the market that contains the stocks with the highest default risk. There is *no* size effect in the remaining of the market. A similar result is obtained for the BM effect (30.5% p.a.) which is however present in the two-fifths of the stocks in the market with the highest default risk. Again, no BM effect exists in the remaining stocks of the market. High default stocks earn significantly higher returns than low default stocks, but *only if* they are small in size or high BM. Default risk in systematic risk. The Fama-French (FF) factors SMB and HML contain some default-related information, but this is not the main reason why the FF model can explain the cross-section of equity returns.



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**JEL classification: G33, G12**

A firm defaults when it fails to service its debt obligations. Therefore, default risk induces lenders to require from borrowers a spread over the risk-free rate of interest. This spread is an increasing function of the probability of default of the individual firm.

Although considerable research effort has been put in modeling default risk for the purpose of valuing corporate debt and derivative products written on it, little attention has been paid on the effects of default risk on equity returns.[1] The effect that default risk may have on equity returns is not obvious, since equity holders are the residual claimants on a firm's cash flows and there is no promised nominal return in equities.

Previous studies that examine the effect of default risk on equities focus on the ability of the default spread to explain or predict returns. The default spread is usually defined as the yield or return differential between long-term BAA corporate bonds and long-term AAA or US Treasury bonds.[2] However, as Elton, Gruber, Agrawal and Mann (2001) show, much of the information in the default spread is unrelated to default risk. In fact, as much as 85% of the spread can be explained as reward for bearing systematic risk, unrelated to default. Furthermore, differential taxes seem to have a more important influence on spreads than expected loss from default has. These results lead us to conclude that, independently of whether the default spread can explain, predict, or otherwise relate to equity returns, such a relation cannot be attributed to the effects that default risk may have on equities. In other words, we still know very little about how default risk affects equity returns.

[1] For papers that model default risk see for instance, Madan and Unal (1994), Duffie and Singleton (1995, 1997), Jarrow and Turnbull (1995), Longstaff and Schwartz (1995), Zhou (1997) and Duffee (1999), among others.

[2] For instance, many studies have shown that the yield spread between BAA and AAA corporate bond spread can predict expected returns in stocks and bonds. Such studies include those of Fama and Schwert (1977), Keim and Stambaugh (1986), Campbell (1987), and Fama and French (1989) among others. In addition, Chen, Roll, and Ross (1986), Fama and French (1993), Jagannathan and Wang (1996) and Hahn and Lee (2001) consider variations of the default spread in asset pricing tests.

The purpose of this paper is exactly to address this question. Instead of relying on information about default obtained from the bonds market, we estimate default likelihood indicators for individual firms using equity data. These default likelihood indicators are nonlinear functions of the default probabilities of the individual firms. They are calculated using the contingent claims methodology of Black and Scholes (BS) (1973) and Merton (1974). Consistent with the Elton et al (2001) study, we find that our measure of default risk contains very different information from the commonly used aggregate default spreads. This is despite the fact that our default likelihood indicators can indeed predict actual defaults.

We find that default risk is intimately related to the size and book-to-market (BM) characteristics of a firm. There is a very strong size effect of the order of 45% per annum (p.a.) which is however present *only* within the segment of the market that contains the stocks with the highest default risk. There is no size effect in the remaining stocks in the market. The small stocks within the highest default risk segment of the market are typically the smallest of the small caps, have the highest BM ratios and the highest default risk, even within the highest default risk category.

A similar result is obtained for the BM effect. The BM effect is only present within the segment of the market with the highest default risk. However, this segment is now twice as large as that in the case of the size effect. Within the quintile with the highest default risk, the BM effect is of the order of 30% p.a., and within the quintile with the second highest default risk is equal to 12.7% p.a. There is no BM effect in the remaining stocks of the market. Again, within the highest default risk category, the high BM (value) stocks have the highest default risk, and the smallest market value of equity (size).

We also find the existence of a default effect, defined as a positive return difference between high default risk stocks and low default risk stocks. Nevertheless, this default effect is *only* present within the smallest size quintile, and the highest BM quintile. Medium or big firms with high default risk do not earn on average higher returns than low default risk firms. Similarly, firms that do not belong to the quintile with the highest BM ratios do not earn higher returns than low default risk stocks, even if their default risk is high.

We finally examine whether default risk is systematic. We find that it is indeed systematic and therefore priced in the cross-section of equity returns. The change in the aggregate survival indicator, which is equal to one minus the aggregate default likelihood indicator, receives a positive risk premium.

Fama and French (1996) argue that the SMB and HML factors of the Fama-French (FF) model proxy for financial distress. Our asset pricing results show that although SMB and HML contain default-related information, this is not the reason why the FF model can explain the cross-section. SMB and HML appear to contain important priced information, unrelated to default risk.

Several studies in the corporate finance literature examine whether default risk is systematic but their results are often conflicting. Denis and Denis (1995), for example, show that default risk is related to macroeconomic factors and it varies with the business cycles. This result is consistent with ours since our measure of default risk varies with the business cycle. Opler and Titman (1994), and Asquith, Gertner and Sharfstein (1994), on the other hand, find that bankruptcy is related to idiosyncratic factors and therefore does not represent systematic risk. The asset pricing results of the current study show that default risk is systematic.

Contrary to the current study, previous research has used either accounting models or bond market information to estimate a firm's default risk and produced in some cases different results than ours.

Examples of papers that use accounting models include those of Dichev (1998), and Griffin and Lemmon (2002). Dichev (1998) examines the relation between bankruptcy risk and systematic risk. Using Altman's (1968) Z-score model and Olson's (1980) conditional logit model, he computes measures of financial distress and finds that bankruptcy risk is not rewarded by higher returns. He concludes that the size and BM effects are unlikely to proxy for a distress factor related to bankruptcy. A similar conclusion is reached in the case of the BM effect by Griffin and Lemmon (2002) who use Olson's model and conclude that the BM effect must be due to mispricing.

There are several concerns about using accounting models to estimate the default risk of equities. Accounting models use information derived from financial statements. Such information is inherently backward-looking, since financial statements aim to report a firm's past performance, rather than its future prospects. In contrast, Merton's model uses the market value of a firm's equity in calculating its default risk. It also estimates its market value of debt, rather than use the book value of debt, as accounting models do. Market prices reflect investors' expectations about a firm's future performance. As a result, they contain forward-looking information, which is better suited for calculating the likelihood that a firm may default in the future.

In addition, and most importantly, accounting models do not take into account the volatility of a firm's assets in estimating its risk of default. Accounting models imply that firms with similar financial ratios will have similar likelihoods of default. This is not the case in

Merton's model, where firms may have similar levels of equity and debt, but very different likelihoods to default, if the volatilities of their assets differ. Clearly, the volatility of a firm's assets provides crucial information about a firm's probability to default. Volatility is a key input in the Black-Scholes option-pricing formula.

As mentioned, an alternative source of information for calculating default risk measures is the bonds market. One may use bond ratings or individual spreads between a firm's debt issues and an aggregate yield measure to deduce the firm's risk of default. When a study uses bond downgrades and upgrades as a measure of default risk, it implicitly relies on the following assumptions: That all assets within a rating category share the same default risk and that this default risk is equal to the historical average default risk. Furthermore, it assumes that it is impossible for a firm to experience a change in its default probability, without also experiencing a rating change.[3] Typically, however, a firm experiences a substantial change in its default risk prior to its rating change. This change in its probability of default is only observed with a lag, and measured crudely through the rating change. Bond ratings may also represent a relatively noisy estimate of a firm's likelihood to default because equity and bond markets may not be perfectly integrated, and because the corporate bond market is much less liquid than the equity market.[4] Merton's model does not require any assumptions about the integration of bond and equity markets or their efficiencies, since all information needed to calculate the default risk measures is obtained from equities.

[3] See also, Kealhofer, Kwok, and Weng (1998).

[4] For instance, Kwan (1996) shows that lagged stock returns can predict current bond yield changes. However, Hotchkiss and Ronen (2001) find that although the correlation between bond and stock returns is positive and significant, there is no causal relationship between the two markets.

Examples of studies that use bond ratings to examine the effect of upgrades and downgrades on equity returns include those of Holthausen, and Leftwich (1986), Hand, Holdhausen, and Leftwich (1992), and Dichev and Piotroski (2001) among others. The general finding is that bond downgrades are followed by negative equity returns. The effect of an increase in default risk on the subsequent equity returns is not examined in the current study.

The remainder of the paper is organized as follows. Section 1 describes the methodology used to compute default likelihood indicators for individual firms. Section 2 describes the data, and provides summary statistics. Section 3 examines the ability of the default likelihood indicators to predict actual defaults. In Section 4 we report results on the performance of portfolios constructed on the basis of default-risk information. In Section 5, we provide asset pricing tests that examine whether default risk is priced. We conclude in Section 6 with a summary of our results.

## 1. Measuring Default Risk

### 1.1 Theoretical Model

In Merton's (1974) model, the equity of a firm is viewed as a call option on the firm's assets. The reason is that equity-holders are residual claimants on the firm's assets after all other obligations have been met. The strike price of the call option is the book value of the firm's liabilities. When the value of the firm's assets is less than the strike price, the value of equity is zero.

Our approach in calculating default risk measures using Merton's model is very similar to the one used by KMV and outlined in Crosbie (1999).[5] We assume that the capital structure of the firm includes both equity and debt. The market value of a firm's underlying assets follows a Geometric Brownian Motion (GBM) of the form:

$$dV_A = \mu V_A dt + \sigma_A V_A dW , \qquad (1)$$

where $V_A$ is the firm's assets value, with an instantaneous drift $\mu$, and an instantaneous volatility $\sigma_A$. $W$ is a standard Wiener process.

We denote by $X_t$ the book value of the debt at time $t$, that has maturity equal to $T$. As noted earlier, $X_t$ plays the role of the strike price of the call, since the market value of equity can be thought of as a call option on $V_A$ with time to expiration $T$. The market value of equity, $V_E$, will then be given by the Black and Scholes (1973) formula for call options:

$$V_E = V_A N(d_1) - Xe^{-rT} N(d_2) , \qquad (2)$$

where $d_1 = \dfrac{\ln(V_A / X) + \left( r + \frac{1}{2}\sigma_A{}^2 \right) T}{\sigma_A \sqrt{T}}$, $d_2 = d_1 - \sigma_A \sqrt{T}$, $r$ is the risk free rate, and $N$ is the cumulative density function of the standard normal distribution.

To calculate $\sigma_A$ we adopt an iterative procedure. We use daily data from the past 12 months to obtain an estimate of the volatility of equity, $\sigma_E$, which is then used as an initial value for the estimation of $\sigma_A$. Using the Black-Scholes formula, and for each trading day of the past 12 months, we compute $V_A$ using as $V_E$ the market value of equity of that day. In this manner, we obtain daily values for $V_A$. Based on them, we compute a new $\sigma_A$. The new $\sigma_A$ is used as a new input in the Black-Scholes formula. The procedure is repeated until the new $\sigma_A$ computed

[5] There are two main differences between our approach and the one used by KMV. They use a more complicated method to assess the asset volatility than we do, which incorporates Bayesian adjustments for the country, industry and size of the firm. They also allow for convertibles and preferred stocks in the capital structure of the firm, whereas we only allow equity, as well as short and long-term debt.

converges to the previous one. Our tolerance level for convergence is 10E-4. For most firms, it takes only a few iterations for $\sigma_A$ to converge. Once the converged value of $\sigma_A$ is obtained, we use it to back out $V_A$ through equation (2).

The above process is repeated every end of the month, resulting in the estimation of monthly values of $\sigma_A$. The estimation window is always kept equal to 12 months. The risk-free rate used for each monthly iterative process is the one-year T-bill rate observed at the end of the month.

Once daily values of $V_A$ are estimated, we can compute the drift, $\mu$, by calculating the mean of the change in $lnV_A$.

The default probability is the probability that the firm's assets will be less than the book value of the firm's liabilities. In other words,

$$P_{def,t} = \Pr ob\left(V_{A,t+T} \leq X_t \mid V_{A,t}\right) = \Pr ob\left(\ln\left(V_{A,t+T}\right) \leq \ln\left(X_t\right) \mid V_{A,t}\right)$$

Since the value of the assets follow the GBM of equation (1), the value of the assets at any time t is given by:

$$\ln\left(V_{A,t+T}\right) = \ln\left(V_{A,t}\right) + \left(\mu - \frac{\sigma_A{}^2}{2}\right)T + \sigma_A \sqrt{T}\varepsilon_{t+T}\,. \qquad (3)$$

$$\varepsilon_{t+T} = \frac{W(t+T) - W(t)}{\sqrt{T}},$$
$$\varepsilon_{t+T} \sim N(0,1)$$

Therefore, we can rewrite the default probability as follows:

$$P_{def,t} = \Pr ob\left( \ln\left(V_{A,t}\right) - \ln\left(X_t\right) + \left( \mu - \frac{\sigma_A{}^2}{2} \right) T + \sigma_A \sqrt{T} \varepsilon_{t+T} \leq 0 \right)$$

$$P_{def,t} = \Pr ob\left( -\frac{\ln\left(\frac{V_{A,t}}{X_t}\right) + \left( \mu - \frac{\sigma_A{}^2}{2} \right) T}{\sigma_A \sqrt{T}} \geq \varepsilon_{t+T} \right) \quad (4)$$

We can then define the distance to default (DD) as follows:

$$DD_t = \frac{\ln(V_{A,t} / X_t) + (\mu - \frac{1}{2}\sigma_A{}^2)T}{\sigma_A \sqrt{T}} \quad (5)$$

Default occurs when the ratio of the value of assets to debt is less than one, or its log is negative. The DD tells us by how many standard deviations the log of this ratio needs to deviate from its mean in order for default to occur. Notice that although the value of the call option in (2) does not depend on μ, DD does. This is because DD depends on the future value of assets which is given in equation (3).

We use the theoretical distribution implied by Merton's model, which is the normal distribution. In that case, the theoretical probability of default will be given by:

$$P_{def} = N(-DD) = N\left( -\frac{\ln(V_{A,t} / X_t) + (\mu - \frac{1}{2}\sigma_A{}^2)T}{\sigma_A \sqrt{T}} \right) \quad (6)$$

Strictly speaking, $P_{def}$ is not a default probability, because it does not correspond to the true probability of default in large samples. In contrast, the default probabilities calculated by KMV are indeed default probabilities because they are calculated using the empirical distribution of defaults. For instance, in the KMV database, the number of companies times the years of data is over 100,000, and includes more than 2,000 incidents of default. We have a much more limited database. For that reason, we do not call our measure default probability, but rather default likelihood indicator (DLI). [6]

It is important to note that the difference between our measure of default risk and that produced by KMV is not material for the purpose of our study. The default likelihood indicator of a firm is a nonlinear function of its default probability. Since we use our measure of default risk to examine the relation between default risk and equity returns rather than price debt or credit risk derivatives, this nonlinear transformation cannot affect the substance of our results.

## 2. Data and Summary Statistics

We use the COMPUSTAT annual files to get the firm's "Debt in One Year" and "Long-Term Debt" series for all companies. COMPUSTAT starts reporting annual financial data in 1963. However, prior to 1971, only a few hundred firms have debt data available. Therefore, we start our analysis in 1971.

As book value of debt we use the "debt due in one year" plus half the "long-term debt". It is important to include long-term debt in our calculations for two reasons. First, firms need to service their long-term debt, and these interest payments are part of their short-term liabilities. Second, the size of the long-term debt affects the ability of a firm to roll-over its short-term debt, and therefore reduce its risk of default. How much of the long-term debt should enter our calculations is arbitrary, since we do not observe the coupon payments of the individual firms. In our opinion, 50% is a plausible percentage, although admittedly arbitrary.

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[6] Our procedure also differs from the one used in KMV with respect to the way we calculate the distance to default. Whereas we use the formula that follows from the Black-Scholes model, KMV uses the one below:
DD = (Market value of Assets – Default Point)/(Market value of Assets * Asset Volatility).

We use annual data for the book value of debt. To avoid problems related to reporting delays, we do not use the book value of debt of the new fiscal year, until four months have elapsed from the end of the previous fiscal year.[7] This is done in order to ensure that all information used to calculate our default measures was available to the investors at the time of the calculation.

We get the daily market values for firms from the CRISP daily files. The book value of equity information is extracted from COMPUSTAT. Each month, the book-to-market (BM) ratio of a firm is the six-month prior book value of equity divided by the current month's market value of equity. Firms with negative BM ratios are excluded from our sample.

As risk-free rate we use monthly observations of the one-year Treasury Bill rate obtained from the Federal Reserve Board Statistics. Table 1 reports the number of firms per year for which DLI could be calculated, as well as the number of firms that filed for bankruptcy (Chapter 11) or were liquidated.

The aggregate default likelihood measure P(D) is defined as a simple average of the default likelihood indicators of all firms. A graph of the P(D) is provided in Figure 1 for the whole sample period (1971:1-1999:12). The shaded areas represent recession periods as defined by the NBER. The graph shows that default probabilities vary greatly with the business cycle and increase substantially during recessions.

We define the aggregate survival rate, SV as one minus P(D). The change in aggregate survival rate Δ(SV) at time t is given by $SV_t - SV_{t-1}$. Summary statistics for SV and Δ(SV) are presented in Panel A of Table 2.

[7] SEC requires firms to report 10K within 3 months after the end of the fiscal year, but a small percentage of firms report it with a longer delay.

The default return spread is from Ibbotson Associates and it is defined as the return difference between BAA Moody's-rated bonds and AAA Moody's –rated bonds. Similarly, the default yield spread is defined as the yield difference between Moody's BAA bonds and Moody's AAA bonds. The series is obtained from the Federal Reserve Bank of St. Louis. The change in spread $\Delta(spread)$ is obtained from Hahn and Lee (2001). The spread in Hahn and Lee is defined as the difference in the yields between Moody's BAA bonds and 10-year government bonds. $\Delta(spread)$ is the change in that spread.

Panel B of Table 2 provides the correlation coefficients between the above-defined default spreads and $\Delta(SV)$. The correlations are very low and reveal that the information captured by our measure is markedly different from that captured by the commonly used default spreads. This is consistent with the findings of Elton et al. (2001).

The Fama-French factors HML and SMB, and the market factor EMKT are obtained from Kenneth French's webpage.[8] Panel C of Table 2 reports the correlation coefficients between $\Delta(SV)$ and the Fama-French factors. The correlations of $\Delta(SV)$ with EMKT and SMB are positive and of the order of 0.5 whereas that with HML is negative and equal to –0.18. This suggests that EMKT and SMB contain potentially significant default-related information. The regressions of Panel D in Table 2 show that $\Delta(SV)$ can explain a substantial portion of the time-variation in EMKT and SMB. This does not mean, however, that the priced information in EMKT and SMB is related to default risk. The default-related content in SMB and HML will be examined in Section 5.

[8] We thank Ken French for making the data available. Details about the data, as well as the actual data series can be obtained from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

Finally, given that the need to compute default likelihood indicators for each stock constrain us to use only a subset of the US equity market as presented in Table 1, it is important to verify that our results are representative of the US market as a whole. To this end, we construct the Fama-French factors HML and SMB within our sample, and compare them with those constructed by Fama and French using a much larger cross-section of US equities. The results are reported in Panel E of Table 2. The distributional characteristics of the HML and SMB factors constructed within our sample are similar to those of the HML and SMB factors provided by Fama and French. Furthermore, their correlations are quite large and of the order of 0.95 for SMB and 0.86 for HML. The above comparisons reveal that the subsample we use in our study is largely representative of the US equity samples used in other studies of equity returns.

## 3. Measuring Model Accuracy

In this section, we evaluate the ability of our default measure to capture default risk. To do that, we employ Moody's Accuracy Ratio. In addition, we compare the default likelihood indicators of actually defaulted firms with those of a control group that did not default.

### *3.1 Accuracy Ratio*

The accuracy ratio (AR) proposed by Moody's reveals the ability of a model to predict actual defaults over a five-year horizon.[9]

[9] See, "Rating Methodology: Moody's Public Firm Risk Model: A Hybrid Approach to Modeling Short Term Default Risk", Moody's Investors Service, March 2000. The AC ratio is somewhat related to the Kolmogorov-Smirnov test.

Let us suppose a model ranks the firms according to some measure of default risk. Suppose there are $N$ firms in total in our sample and $M$ of those actually default in the next five years. Let $\theta = \frac{M}{N}$ be the percentage of firms that default. For every integer $\lambda$ between 0 and 100, we look at how many firms actually defaulted within the $\lambda\%$ of firms with the lowest default risk. Of course, this number of defaults cannot be more than $M$. We divide the number of firms that actually defaulted within the first $\lambda\%$ of firms by $M$ and denote the result by $f(\lambda)$. Then $f(\lambda)$ takes values between 0 and 1, and is an increasing function of $\lambda$. Moreover, $f(0) = 0$ and $f(100) = 1$.

Suppose we had the "perfect measure" of future default likelihood and we were ranking stocks according to that. We would then have been able to capture all defaults for each integer $\lambda$, and $f(\lambda)$ would be given by

$$f(\lambda) = \frac{\lambda}{\theta} \text{ for } \lambda < \theta \text{ and } f(\lambda) = 1 \text{ for } \lambda \geq \theta. \qquad (6)$$

Suppose we also calculate the average $f(\lambda)$ for all months covered by the sample. The graph of this function of average $f(\lambda)$ is shown as the kinked line in Figure 2, graph B.

At the other extreme, suppose we had zero information about future default likelihoods, and we were ranking the stocks randomly. In that case, $f(\lambda)$ would be just equal to $\lambda$. Graphically, the average $f(\lambda)$ would correspond to the 45 degree line in the graphs of Figure 2.

We measure the amount of information in a model by how far the graph of the average $f(\lambda)$ function lies above the 45 degree line. Specifically, we measure it by the area between the 45 degree line and the graph of average $f(\lambda)$. The accuracy ratio of a model is then defined as the ratio between the area associated with that model's average $f(\lambda)$ function and the one associated with the "perfect" model's average $f(\lambda)$ function. Under this definition, the "perfect" model has accuracy ratio of one, and the zero-information model has an accuracy ratio of zero.

The measure implied by Merton's model is the distance-to-default (DD). Therefore, if we rank stocks according to DD, the accuracy ratio we obtain is equal to 0.592. Note that the accuracy ratio obtained by ranking stocks simply on the basis of their market value of equity is equal to 0.089. In other words, DD contains important information beyond that conveyed by the size of the firms. It can be considered rather informative, given the simplicity of Merton's model.

### *3.2. Comparison Between Defaulted Firms and Non-Defaulted Firms*

As a further test of the ability of our measure to capture default risk, we compare the default likelihood indicators of firms that actually defaulted with those of a control group of firms that did not default. Similar comparisons have been performed in the past in Altman (1968) and Aharony, Jones, and Swary (1980). To make the comparison meaningful, we choose firms in the control group that have similar size and industry characteristics as those in the experimental group. In particular, for every firm that defaults, we select a firm with a market capitalization similar to that of the firm in the experimental group before it defaulted. In addition, the firm in the control group shares the same 2-digit industry code as the one in the experimental group.

We compute the average default likelihood indicator for each group. Figure 3 presents the results. We find that the average default likelihood indicator of the experimental group goes up sharply in the 5 years prior to default. In contrast, the average default likelihood indicator of the control group stays at the same level throughout the 5-year period. Note that in the graph, $t=0$ corresponds to about two to three years prior to default, since the database does not provide data up to the date of default. Therefore, an average default likelihood indicator of 0.57 for the experimental group can be considered high. The results of this test provide further assurance that our default likelihood indicators do indeed capture default risk.

## 4. Default Risk and Variation in Equity Returns

We start our analysis of the relation between default risk and equity returns by examining whether portfolios with different default risk characteristics provide significantly different returns. A significant difference in the returns would indicate that default risk may be important for the pricing of equities.

Table 3 reports simple sorts of stocks based on their default likelihood indicators. At the end of each month from 1970:12 to 1999:11, we use the most recent monthly default probability for each firm to sort all stocks into portfolios. We first sort stocks into 5 portfolios. We examine their returns when the portfolios are equally-weighted or value-weighted and report the average default likelihood indicator for each one of them. Evidently, the lower the average default likelihood indicator, the lower the risk of default.

The t-values of all tests in Section 4 are computed from Newey-West (1987) standard errors. The truncation parameter $q$ was selected in each case to be equal to the number of autocorrelations in returns that are statistically significant at the 5% level.

The return difference between the equally-weighted high-default-risk portfolio and low-default-risk portfolio is 53 basis points (bps) per month or 6.36% per annum (p.a.). The difference is statistically significant at the 5% level. This is not the case for the value-weighted portfolios whose difference in returns is only 14bps per month.

When we sort stocks into ten portfolios, the results we obtain are similar. The difference in returns between the high-default risk portfolio and the low-default risk portfolio is statistically significant for the equally-weighted portfolios but not for the value-weighted portfolios. The return differential for the equally-weighted portfolios is 98bps per month or 11.76% p.a.

Notice though that the aggregate default measure for the equally-weighted portfolios assumes bigger values than it does for the value-weighted portfolios. It appears that small-capitalization stocks have on average higher default risk, and they earn as a result higher returns than big-capitalization stocks do. In addition, it is the case both for the five and ten default-sorted portfolios that the average market capitalization of the portfolio (size) and its book-to-market (BM) ratio vary monotonically with the average default risk of the portfolio. In particular, the average size increases as the default risk of the portfolio decreases, whereas the opposite is true for BM. These results suggest that the size and BM effects may be linked to the default risk of stocks. Recall that both effects are considered stock market anomalies according to the literature of the Capital Asset Pricing Model (CAPM). The reason for their existence remains unknown. The remainder of the paper investigates further the possible link between default risk and those effects. Our analysis will focus on equally-weighted portfolios, since this is the weighting scheme typically employed in studies that consider the size and BM effects.[10]

### *4.1. Size, B/M and default risk*

To examine the extent to which the size and BM effects can be interpreted as default effects, we perform two-way sorts and examine each of the two effects within different default risk portfolios.

#### *4.1.1. The Size Effect*

[10] For recent references, see for instance Chan, Hamao, and Lakonishok (1991), and Fama and French (1992).

Table 4A presents results from sequential sorts where stocks are first sorted into five quintiles according to their default risk and then within each of the five quintiles, firms are sorted into five size portfolios. We examine whether the size effect exists in all of the default sorted quintiles and in the whole sample.

The results of Panel A show that the size effect is present only within the quintile that contains the stocks with the highest default risk (DLI 1). The effect is very strong with an average return difference between small and big caps of 3.82% per month or a staggering 45.84% p.a. Notice that the difference in returns drops to close to zero for the remaining default-sorted portfolios. There is a statistically significant size effect in the whole sample but the return difference between small and big caps is more than 4 times smaller than in DLI 1.

The results of Panel A suggest that the size effect exists only within the segment of the market that contains the stocks with the highest default risk. But to what extent are we truly capturing the size effect? Is there really substantial variation in the market capitalizations of stocks within the DLI 1 portfolio? Panel B addresses this question. We see that there is indeed large variation in the market caps of stocks within the highest default risk portfolio. But in terms of the average market caps for the size quintiles formed using the whole sample, the biggest firms in DLI 1 are rather medium to large caps. On the other hand, the DLI 1–Small portfolio contains the smallest of the small firms compared to the small size quintile formed on the basis of the whole sample. In other words, the size effect is concentrated in the smallest of firms and the highest default risk segment of the market does not typically include the biggest firms.

How much riskier are the stocks in DLI 1 compared to the other default risk quintiles? Panel C of Table 4A says that they are a lot riskier. The small firms in DLI 1 are almost 14 times riskier in terms of likelihood of default than the small firms in DLI 2. They are also on average more than twice as risky in terms of default than the stocks in the small size quintile constructed using the whole sample. Therefore, the large average returns that small high default stocks earn compared to the rest of the market can be considered as compensation for the large default risk they have.

We also examine the average BM of the default- and size-sorted portfolios, in order to see the extent to which size, default risk, and BM are related. We find in Panel D that the average BMs in the size-sorted portfolios of DLI 1 are the highest in the sample. The BM decreases monotonically with DLI, which suggests that the BM effect may also be related to default risk.

The conclusion that emerges from Table 4A is that there is a very strong size effect, which is however concentrated in the segment of the market that contains the stocks with the highest default risk. There is no size effect in the remaining stocks of the market. The small stocks that enter the highest default risk quintile have on average less than half the size of the typical small firm in the market, twice as high likelihood of default, and almost twice as high BM ratio.  This profile suggests that the size effect may simply be a compensation for default risk.

*4.1.2. The BM Effect*

Table 4B presents results from similar sortings to those of Table 4A, which are now targeted, however, to examine the link between BM and default risk. In particular, stocks are first sorted into 5 default risk quintiles, as in Table 4A, and then within each of the five default quintiles, firms are sorted into five BM portfolios. We examine whether there is a BM effect within each of the five default-sorted quintiles, as well as for the market as a whole.

Panel A shows that the BM effect is prominent only in the two highest default risk portfolios, and the return differential between high and low BM stocks is almost two and a half times bigger in DLI 1 than in DLI 2. This suggests that the BM effect is strongest among the highest default risk stocks. There is also a BM effect in the whole sample, but the return differential between high and low BM stocks is about half as big as that found in DLI 1.

There is a lot of dispersion in the average BM ratios within the DLI portfolios. This is particularly true for DLI 1 and 2, which means that indeed the return differential we examine captures a BM effect. In fact, the average BM ratio varies more across portfolios in DLI 1 than it does across BM portfolios formed using the whole sample. Both in the case of DLI 1 and 2, the average BM ratios of the BM –sorted portfolios are higher than for the BM-sorted portfolios that use the whole sample, suggesting again a relation between default risk and BM ratios. Notice, however, that the average default risk in Panel C exhibits a monotonic relation with BM only in DLI 1 and 2, that is, the two default portfolios within which the BM effect is significant. For the rest of the sample, the relation between default risk and BM ratios does not appear to be linear. The same result emerges from Table 4A, Panel C. Default risk varies monotonically with size only within the two highest default risk quintiles. It seems that there are linear relations between default risk and size, and default risk and BM, only to the extent that that default risk is sizeable. When the risk of default of a company is very small, the linearity in the relationships between default and size and default and BM disappears, probably because defaults are very unlikely to occur in those cases.

Panel D shows again that DLI 1 contains mainly small caps. However, size does not vary monotonically with BM, except within the two highest default risk quintiles. The same conclusion can be reached from Panel D of Table 4A. The average BM ratios vary monotonically with size only within the two highest default risk quintiles. In both cases the variation is small.

It seems that size and BM proxy to some extent for each other only within the segment of the market with the highest default risk. This implies that they are not identical phenomena. Furthermore, the return premium of small caps over big caps is more than 1% larger than that of high BM stocks over low BM stocks. In addition, the size effect is present in a subset of the segment of the market in which the BM effect exists. Both are linked, however, to a common risk measure, that is, default risk.

### *4.2. The Default Effect*

If size and BM effects are intimately linked to default risk, as Tables 4A and 4B show, there must also be a significant default effect in the data. We define default effect as a positive average return differential between high and low default risk firms.

#### *4.2.1. The Default Effect in Size-Sorted Portfolios*

In Table 5A we examine whether there is a default effect in size-sorted portfolios by reversing the sorting procedure of Table 4A. In particular, we first sort stocks into five size quintiles, and then sort each size quintile into five default portfolios. As we will see below, this exercise allows us also to obtain a better understanding of the small caps as an asset class.

Panel A shows that there is a statistically significant default effect only within the small size quintile. The average monthly return is 2.2% or 26.4% p.a. In most of the remaining size quintiles, the difference in returns between high and low default risk portfolios is negative. It seems that high default risk firms earn a higher return than low default risk firms, only if they are very small.

Indeed, Panel B shows that all five high default risk portfolios contain stocks with substantial default risk, independently of whether they are small or big. This is particularly true for the three smallest size quintiles. Nevertheless, only in the smallest size quintile there is a positive difference in average returns between high and low default risk portfolios. This result may indicate that firms differ in their ability to successfully emerge out of Chapter 11. If small firms are less likely to emerge as public firms from the restructuring process, investors may require a bigger risk premium to hold them, compared to what they require for bigger size-high default risk firms. This will induce the average returns of small high DLI firms to be higher than those of bigger high DLI firms.[11] Empirical evidence from the corporate bankruptcy literature shows that that large firms are more likely to survive Chapter 11 than small firms.[12]

Panel B of Table 5A provides also insights into the profile of small caps as an asset class. Notice that the default likelihood within the small size quintile varies from 41. 53% to 0.09%. This implies that the small caps do not constitute a homogenous asset class, as stocks in this category can vary substantially in terms of their default risk characteristics. They can also vary significantly in terms of their returns characteristics, as Panel A shows. In that sense, small caps do not constitute a homogeneous asset class.

Finally, Panel B shows that default risk decreases monotonically as size increases, confirming the close relation between size and default risk observed in Table 4A. Panels C and D

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[11] This interpretation assumes that default risk is systematic, and therefore, not diversifiable. In Section 5 we test whether default risk is priced in the cross-section of equity returns. Our results show that default risk is indeed priced, and therefore, it constitutes a systematic source of risk.

[12] See for instance, Moulton and Thomas (1993) and Hotchkiss (1995).

show that the small - high DLI portfolio contains the smallest of the small stocks and those with the highest BM ratio. The average BM ratio of the portfolios decreases monotonically with DLI, and increases monotonically as size decreases. Finally, size increases monotonically as DLI decreases.

Two important conclusions emerge from this table. First, only the small size - high DLI portfolio earns a significantly higher average return than low DLI portfolios. Second, small firms vary substantially in terms of both their return and (default) risk characteristics, which makes small caps a non homogeneous asset class.

### *4.2.2. The Default Effect in BM-Sorted Portfolios*

Table 5B examines the presence of a default effect in BM-sorted portfolios. Assets are first sorted in five BM quintiles, and subsequently, each BM-sorted quintile is subdivided into five default-sorted portfolios.

Panel A reveals that the default effect is again present only within the high BM quintile. This result is consistent with that of Table 5A. Since the smallest high DLI firms are also typically the highest BM firms, the same interpretation applies here.

Once again, Panel B shows that stocks in the BM-sorted portfolios may vary substantially in terms of their default risk. This is particularly the case for the high BM (value) portfolio. In other words, and similarly to the case of small caps, value stocks differ significantly in terms of their return and default risk characteristics. As a result, they do not form a homogeneous asset class.

The findings of Panels C and D also confirm the previously-made observation that the high BM – high DLI portfolio includes the stocks with the highest average BM ratio, and the smallest average size.

The results of Table 5B are consistent and analogous to those of Table 5A. The messages that emerge are the following. First, only the high BM – high DLI portfolio earns a significantly higher return than the low DLI portfolios. Second, value stocks can differ dramatically in terms of their risk and return characteristics.

### *4.3. Independent Sorts*

Independent sorts have the disadvantage that they do not guarantee equal number of stocks in all portfolios. They may assign hundreds of stocks in some portfolios, and a handful or even none in others. However, it is still interesting to perform these tests and see how independent sorts will assign the stocks into portfolios and whether our results will continue to hold.

#### *4.3.1. Independent Sorts on Size and Default Risk*

Table 6A reports the results of independent sorts of stocks into size and default portfolios. The procedure used in the following. All assets are sorted into five size portfolios. All assets are also sorted into five default risk portfolios. The 25 portfolios are now created from the intersection of those two sets of five portfolios.

Panel A shows again that the default premium exists only within the small size quintile. It also shows that the size effect exists only within DLI 1. Both results are consistent with those from the sequential sorts. The magnitudes of the returns differentials are lower, however. The reason for this can be found in Panel E. As mentioned earlier, the independent sorting procedure does not guarantee an equal number of stocks in each portfolio. We can see from Panel E that most stocks are concentrated in the two extreme portfolios: small–DLI 1 (242 stocks), and big–DLI 5 (217 stocks). In the sequential sorts, the average number of stocks in each portfolio is 100. Therefore, the large number of stocks in the small–DLI 1 portfolio dilutes both the default and size effect, since both effects are strongest for the smallest of small stocks. The remaining panels in the table confirm the findings discussed in Sections 4.1 and 4.2.

#### *4.3.2. Independent Sorts on BM and Default Risk*

Table 6B provides the results from independent sorts on BM and default risk. The 25 portfolios are now constructed from the intersection of five BM portfolios and five default risk-sorted portfolios.

Panel A confirms that the default effect exists only within the highest BM portfolio. It also confirms that the BM effect is present only within the DLI 1 and 2 quintiles. The difference in the profitability of the two trading strategies is only slightly lower than that reported in Tables 4B and 5B. Panel E shows that most of the stocks are concentrated again in the two corner portfolios. But since the BM effect is present in a larger segment of the market, that is the DLI 1 and 2 quintiles, the effect of having many more than 100 stocks in the high BM – DLI 1 portfolio is small. The remaining results of Table 6B confirm those discussed in the context of Tables 4B and 5B.

## 5. The Pricing of Default Risk

The results of the previous section imply that the size and BM effects are compensations for the high default risk that very small stocks and high BM stocks exhibit. But does this mean that default risk is systematic? The answer to this question is not obvious, since defaults are rare events and affect only a small number of firms. However, when a default occurs, equity-holders typically lose everything because they are the residual claimants on the firm's cash flows.

The purpose of this section is to investigate through asset pricing tests, whether default risk is systematic and therefore priced in the cross-section of equity returns.

### *5.1. The Tested Hypotheses*

Two hypotheses are examined as part of our asset pricing tests. First, we test whether default risk is priced. To test this hypothesis, we need to consider a plausible empirical asset pricing specification in which default risk appears as a factor.

It is clear that an asset pricing model that includes only default as a risk factor would be most certainly misspecified, since even if default risk is priced, it is unlikely to be the only risk factor that affects equity returns. For that reason, we consider an asset pricing model that includes as factors the excess return on the market portfolio (EMKT), and the aggregate survival measure $\Delta(SV)$. The empirical asset pricing specification is given below.

$$R_t = a + bEMKT_t + d\Delta(SV)_t + \varepsilon_t \qquad (7)$$

where $R_t$ represents the return at time t of a stock in excess of the risk-free rate.

Such a model can be understood in the context of an Intertemporal Capital Asset Pricing Model (ICAPM) as in Merton (1973). One can postulate a version of ICAPM where default risk affects the investment opportunity set, and therefore, investors want to hedge against this source of risk.

The second hypothesis examined is whether the Fama-French (1993) (FF) factors SMB and HML proxy for default risk. Recall that the FF model is empirical in nature, and includes apart from the market factor, a factor related to size (SMB) and a factor related to BM (HML). Fama and French (1996) argue that SMB and HML proxy for financial distress. . We test this hypothesis here, by including $\Delta(SV)$ in the FF model. In other words, we test the following empirical specification:

$$R_t = a + bEMKT_t + sSMB_t + hHML_t + d\Delta(SV)_t + \varepsilon_t \qquad (8)$$

If indeed all the priced information in SMB and HML is related to financial distress, we would expect to find that in the presence of $\Delta(SV)$, SMB and HML lose all their ability to explain equity returns.

To get a sense of the performance of the two empirical specifications examined, we also present results from tests of the CAPM and FF model. These two models act as benchmarks for comparison purposes.

*5.2. The Test Assets*

As previously mentioned, two hypotheses are examined in our asset pricing tests. First, whether default risk is priced, and second, whether SMB and HML proxy for default risk. This implies that there are three variables against which the test assets have to exhibit maximum dispersion: $\Delta(SV)$, size, and BM. By test assets we mean the portfolios whose returns the asset pricing models will be called upon to explain.

To obtain maximum dispersion against all three variables, we perform a three-way independent sort. All equities in our sample are sorted in three portfolios according to $\Delta(SV)$. They are also sorted in three portfolios according to size. Finally, they are sorted in three portfolios according to BM. Twenty-seven equally-weighted portfolios are formed from the intersection of the three independent sorts. Summary statistics of the 27 portfolios are provided in Table 7.

### *5.3. Empirical Methodology of the Asset Pricing Tests*

To test the asset pricing models of Section 5.1, we use the Generalized Methods of Moments (GMM) methodology of Hansen (1982), and employ the asymptotically optimal weighting matrix. For each model considered, we also compute Hansen's (1982) J-statistic on its overidentifying restrictions. In addition, we report a Wald test (Wald(b)) on the joint significance of the coefficients of the pricing kernel implied by each model.

To compare the alternative models, we use the Hansen and Jagannathan (1997) (HJ) distance measure. To calculate the p-value of the HJ-distance we simulate the weighted sum of *n*-*k* $\chi^2(1)$ random variables 100,000 times, where *n* is the number of test assets, and *k* is the number of factors in the model examined.[13]

### *5.4. Asset Pricing Results*

The results from the asset pricing tests are reported in Table 8. The rows labeled "coefficient" refer to the coefficient(s) of the factor(s) in the pricing kernel, whereas the rows labeled "premium" refer to the risk premium(s) implied for the factor(s).

The first panel shows the results of the model that includes the market and $\Delta(SV)$ as factors. We see that $\Delta(SV)$ commands a positive and statistically significant risk premium. This implies that default risk is systematic and it is priced in the cross-section of equity returns. As expected, the J-test, and the HJ-distance measure have both very small p-values, which means

[13] See Jagannathan and Wang (1996).

that the model cannot price assets correctly. Even though both the EMKT and $\Delta(SV)$ are priced, it appears that there are other factors that may be important for explaining the cross-sectional variation in equity returns, and which are not considered here. Despite this implication, the model considered has a smaller HJ distance than both the CAPM (Panel B) and the FF model (Panel C). This means that, any misspecification present in this model translates into at least as small an annualized pricing error as those resulting from the two standard asset pricing models in the literature, the CAPM and FF model.[14]

Panel D reports the results from testing the hypothesis that SMB and HML proxy for default risk. In particular, we test the model of equation (8). The results show that $\Delta(SV)$ continues to receive a positive and statistically significant risk premium, even when it is considered as part of the augmented model. HML is also priced again, as in Panel C, and SMB is not priced either in Panel C or Panel D.

Notice, however, that the coefficients of SMB and HML are very different in Panel D than they are in Panel C, and this is particularly the case for SMB. The fact that the coefficients of SMB and HML change in the presence of $\Delta(SV)$ suggests that SMB and HML share some common information with $\Delta(SV)$. The dramatic change in the coefficient of SMB between Panels C and D is an indication that SMB shares more common information with $\Delta(SV)$ than HML does. In general, we expect the coefficients to change when the factors in the pricing kernel are not orthogonal. Table 2 shows that $\Delta(SV)$ is positively and highly correlated with EMKT and SMB, but has a small and negative correlation with HML.

[14] For an interpretation of the HJ-distance as the maximum annualized pricing error, see Campbell and Cochrane (2000).

Recall that statistically significant coefficients in the pricing kernel imply that the corresponding factors help price the test assets, whereas a statistically significant premium means that the corresponding factor is priced.[15] The results in Panel D show that although all factors help price the test assets, SMB is not a priced factor.

Notice also that the coefficient on SMB is not statistically significant in Panel C whereas it is in Panel D. This may be the case if the FF model is more mispecified than the model in Panel D. It seems that SMB needs the presence of $\Delta(SV)$ in the pricing kernel in order for its coefficient to become significant. The fact that the coefficient of SMB becomes significant in this case, further shows that although there is some common information between SMB and $\Delta(SV)$, there is also residual information in both factors which is important for pricing the test assets.

This interpretation is also supported by the values of the HJ-distance measures for the models of Panels C and D. The HJ distance for the FF model is larger in value than that of the model in Panel D. This suggests that the FF model maybe more mispecified than the model in Panel D. An implication of this result is that although there is some common information between $\Delta(SV)$ and the FF factors, there is also a lot of additional important information in SMB and HML which helps explain the test assets, but which is unrelated to default risk.[16]

Figure 4 plots the loadings of the 27 portfolios on $\Delta(SV)$ from the models of Panels A and D. The portfolios are ordered in the same way as in Table 7. It is interesting to note that the loadings on $\Delta(SV)$ for the model of Panel A are equal or larger than one, for 20 of the 27

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[15] See Cochrane (2001), Section 13.5.

[16] Vassalou (2002) shows, for instance, that a model which includes the market factor along with news about future GDP growth absorbs most of the priced information in SMB and HML. In the presence of news about future GDP growth in the pricing kernel, SMB and HML lose virtually all their ability to explain the cross-section.

portfolios. This means that default risk is important for a large segment of the cross-section that includes apart from small firms, also medium-size and big firms. In other words, the pricing of default risk is not driven by only a handful of portfolios.

Once SMB and HML are included in the pricing kernel, the loadings of $\Delta(SV)$ are reduced to close to zero for all portfolios except for those two portfolios that include small, high BM stocks with high or medium level of default risk. For those two portfolios, the loadings are also significantly reduced, but they remain around one. The fact that the loadings of $\Delta(SV)$ are so drastically reduced for most of the 27 portfolios, suggests again that SMB and HML include important default-related information.

The conclusion that emerges from the asset pricing tests is that default risk is priced, and it is priced even when $\Delta(SV)$ is included in the FF model. SMB and HML contain some default-related information. However, this information does not appear to be the reason why the FF model is able to explain the cross section of equity returns.

## 6. Conclusions

This paper uses for the first time the Merton (1974) model to compute monthly default likelihood indicators for individual firms, and examine the effect that default risk may have on equity returns.

We find that there is a very strong size effect which is present, however, *only* in the segment of the market that contains the stocks with the highest default risk. The stocks that enter the small size-high default risk portfolio are typically the smallest of small caps with the highest default risk and the highest BM ratios. There is no size effect in the remaining stocks of the market.

A similar result is obtained for the book-to-market effect. It exists *only* in the segment of the market with the highest default risk, although this segment is now twice as large as that in the case of the size effect, and covers about two fifths of the equities in the market. Once again, the stocks in the high BM-high default risk portfolio are typically small and have particularly high default risk and BM ratios.

There is also a strong default effect in equity returns, in the sense that high default risk stocks earn higher average returns than low default risk stocks. However, this return difference exists *only* within the small cap category which covers approximately one fifth of the stocks in the market. High default risk stocks with larger market capitalization do not earn higher returns than low default risk stocks.

We finally examine through asset pricing tests whether default risk is systematic. We find that it is indeed systematic. We also test whether the Fama-French factors SMB and HML proxy for default risk, as follows from the Fama and French (1996) analysis. Our results show that, although SMB and HML contain some default-related information, this is not the reason why the Fama-French model is able to explain the cross-section of equity returns. SMB and HML appear to contain other priced information, unrelated to default risk.

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**Table 1: Firm data**

| Year | # of stocks in sample | # of bankruptcy | # of liquidations |
|---|---|---|---|
| 1971 | 1355 | 13 | 1 |
| 1972 | 1532 | 8 | 4 |
| 1973 | 2347 | 15 | 4 |
| 1974 | 2490 | 13 | 4 |
| 1975 | 2612 | 13 | 6 |
| 1976 | 2885 | 18 | 8 |
| 1977 | 2952 | 12 | 9 |
| 1978 | 2957 | 17 | 10 |
| 1979 | 2956 | 14 | 26 |
| 1980 | 2928 | 18 | 23 |
| 1981 | 2958 | 8 | 22 |
| 1982 | 3054 | 13 | 23 |
| 1983 | 3083 | 24 | 13 |
| 1984 | 3311 | 12 | 17 |
| 1985 | 3386 | 19 | 16 |
| 1986 | 3343 | 60 | 29 |
| 1987 | 3425 | 24 | 16 |
| 1988 | 3577 | 45 | 16 |
| 1989 | 3515 | 42 | 8 |
| 1990 | 3408 | 11 | 6 |
| 1991 | 3379 | 52 | 20 |
| 1992 | 3461 | 42 | 31 |
| 1993 | 3570 | 70 | 37 |
| 1994 | 3830 | 48 | 24 |
| 1995 | 4004 | 48 | 14 |
| 1996 | 4177 | 41 | 11 |
| 1997 | 4462 | 33 | 17 |
| 1998 | 4495 | 54 | 11 |
| 1999 | 4250 | 67 | 13 |

Note: The second column of the table reports the number of firms each year for which default likelihood indicators could be calculated. The third column reports the number of firms that filed for bankruptcy (Chapter 11), whereas the fourth one reports the number of liquidations.

**Table 2: Summary Statistics**

Panel A: Summary statistics on on Aggregate Survival Indicator (SV)

| | Mean | Std | Skew | Kurt | Auto |
|---|---|---|---|---|---|
| SV | 0.9579 | 0.0292 | -1.8956 | 7.9054 | 0.9384 |
| Δ(SV) | -0.0004 | 1.0472 | -0.1785 | 13.2094 | 0.1657 |

Panel B: Correlation between Δ(SV) and other default measures

| | Δ(SV) | RDEF | YDEF | Δ(Spread) |
|---|---|---|---|---|
| Δ(SV) | 1 | | | |
| RDEF | 0.0758 | 1 | | |
| YDEF | 0.1424 | 0.0702 | 1 | |
| Δ(Spread) | 0.0998 | 0.1416 | -0.1130 | 1 |

Panel C: Correlation between Δ(SV) and other factors

| | Δ(SV) | MKT | SMB | HML |
|---|---|---|---|---|
| Δ(SV) | 1 | | | |
| MKT | 0.5375 | 1 | | |
| SMB | 0.5214 | 0.2839 | 1 | |
| HML | -0.1709 | -0.4382 | -0.1422 | 1 |

Panel D: Time-series Regression of Fama French factors on Δ(SV)

| factor | | constant | Δ(SV) | |
|---|---|---|---|---|
| MKT | coef | 0.0064 | 2.321 | 0.2869 |
| | t-value | (3.4197) | (6.0689) | |
| SMB | coef | 0.0009 | 1.4331 | 0.2697 |
| | t-value | (0.6299) | (5.0854) | |
| HML | coef | 0.0031 | -0.4509 | 0.0264 |
| | t-value | (1.8150) | (-2.0671) | |

Panel E: Firm Characteristic and Default Risk

Average Cross-sectional Correlation between firm characteristics

| | SIZE | BM | DLI |
|---|---|---|---|
| Size | 1 | | |
| BM | -0.3165 | 1 | |
| DLI | -0.3084 | 0.4332 | 1 |

Average time-series Correlation between firm characteristics

| | SIZE | BM | DLI |
|---|---|---|---|
| SIZE | 1 | | |
| BM | -0.7155 | 1 | |
| DLI | -0.4119 | 0.4320 | 1 |

Panel F: SMB and HML within Sample

| | Mean | t-value | Std | Auto |
|---|---|---|---|---|
| SMB | 0.0864 | (0.5600) | 2.8783 | 0.1374 |
| SMB within Sample | 0.0730 | (0.4763) | 2.8634 | 0.1451 |
| HML | 0.3076 | (2.0770) | 2.7627 | 0.1850 |
| HML within Sample | 0.3345 | (2.4816) | 2.5181 | 0.2000 |

Note: SV denotes the survival rate and it is equal to one minus the aggregate default likelihood indicator. Δ(SV) is the change in the survival rate. Mean, Std, Skew, Kurt and Auto refer to the mean, standard deviation, skewness, kurtosis and autocorrelation at lag 1 respectively.
RDEF is the return difference between Moody's BAA corporate bonds and AAA corporate bonds YDEF is the yield difference between Moody's BAA bonds and Moody AAA corporate bonds. Δ(spread) is the default measure used in Hahn and Lee (2001) which is defined as: $\Delta(spread) = \left(y_t^{BAA} - y_t^{TB}\right) - \left(y_{t+1}^{BAA} - y_{t+1}^{TB}\right)$, where $y_t^{BAA}$ is the yield of the Moody's BAA corporate bonds and $y_t^{TB}$ is yield on 10 year government bonds. EMKT denotes the value-weighted excess return on the stock market portfolio over the risk-free rate; SMB and HML are the Fama French (1993) factors. Size denotes the firm's market capitalization and B/M its book-to-market ratio. DLI is the firm's default likelihood indicator. T-values are calculated from Newey-West (1987) standard errors, which are corrected for heteroskedasticity and serial correlation up to 3 lags. The $R^2$'s are adjusted for degrees of freedom. In Panel F, SMB and HML are the Fama-French (1993) factors. When the expression (within Sample) appears next to SMB and HML, it means that these factors are calculated using the data in the current study and following exactly the same methodology as in Fama and French (1993). "Auto" refers to the first-order autocorrelation.

**Table 3: Portfolios Sorted on the Basis of Default Likelihood Indicators (DLI)**

| | High 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | Low 10 | High-Low | t-value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Equally-Weighted | | | | | | | | | | | | |
| Return | 1.72 | 1.29 | 1.41 | 1.38 | 1.19 | | | | | | 0.53 | (1.96) |
| ADLI | 19.38 | 1.61 | 0.24 | 0.04 | 0.01 | | | | | | 19.37 | |
| Value-weighted | | | | | | | | | | | | |
| Return | 1.26 | 1.27 | 1.28 | 1.36 | 1.12 | | | | | | 0.14 | (0.46) |
| ADLI | 14.92 | 1.38 | 0.21 | 0.03 | 0.03 | | | | | | 14.89 | |
| Average size | 2.56 | 3.52 | 4.24 | 4.89 | 5.59 | | | | | | | |
| Average BM | 1.64 | 0.99 | 0.82 | 0.74 | 0.64 | | | | | | | |
| Equally-Weighted | | | | | | | | | | | | |
| Return | 2.12 | 1.32 | 1.25 | 1.32 | 1.44 | 1.39 | 1.37 | 1.39 | 1.24 | 1.14 | 0.98 | (2.71) |
| ADLI | 31.74 | 7.25 | 2.35 | 0.86 | 0.34 | 0.14 | 0.06 | 0.03 | 0.01 | 0.01 | 31.73 | |
| Value-weighted | | | | | | | | | | | | |
| Return | 1.20 | 1.21 | 1.19 | 1.30 | 1.19 | 1.37 | 1.29 | 1.41 | 1.31 | 1.04 | 0.16 | (0.44) |
| ADLI | 29.18 | 6.44 | 2.12 | 0.86 | 0.33 | 0.11 | 0.06 | 0.02 | 0.01 | 0.04 | 29.15 | |
| Average size | 2.24 | 2.87 | 3.32 | 3.71 | 4.08 | 4.40 | 4.73 | 5.06 | 5.40 | 5.78 | | |
| Average BM | 2.01 | 1.27 | 1.05 | 0.92 | 0.84 | 0.79 | 0.75 | 0.72 | 0.68 | 0.61 | | |

Note: From 1970.12 to 1999.11, at each month end, we use the most recent monthly default likelihood indicator of each firm to sort all portfolios into quintiles and deciles. We then compute the equally- and value-weighted returns over the next month. "Return" denotes the average portfolio return and "ADLI" the average portfolio default likelihood indicator. Portfolio 1 is the portfolio with the highest default risk and portfolio 10 is the portfolio with the lowest default risk. When stocks are sorted in quintiles, Portfolio 5 contains the stocks with the lowest default risk. "High-Low" is the difference in the returns between the high and low default risk portfolios. T-values are calculated from Newey-West standard errors. The value of the truncation parameter q was selected in each case to be equal to the number of autocorrelations in returns that are significant at the 5% level.

**TABLE 4A: Size Effect controlled by Default Risk**

Panel A: Average Return

| | Small 1 | 2 | 3 | 4 | Big 5 | Small-Big | t-stat |
|---|---|---|---|---|---|---|---|
| High DLI 1 | 4.6256 | 1.7233 | 1.1105 | 0.7801 | 0.8048 | 3.8208 | (9.5953) |
| 2 | 1.5333 | 1.2293 | 1.0915 | 1.2269 | 1.2865 | 0.2468 | (1.0464) |
| 3 | 1.4725 | 1.4583 | 1.2988 | 1.3268 | 1.3978 | 0.0747 | (0.3481) |
| 4 | 1.2973 | 1.3970 | 1.4683 | 1.3446 | 1.2946 | 0.0027 | (0.0129) |
| Low DLI 5 | 1.2755 | 1.2216 | 1.1997 | 1.0520 | 1.1286 | 0.1469 | (0.5730) |
| Whole Sample | 2.1207 | 1.1591 | 1.2032 | 1.2837 | 1.2238 | 0.8969 | (3.2146) |

Panel B: Average Size

| | Small 1 | 2 | 3 | 4 | Big 5 |
|---|---|---|---|---|---|
| High DLI 1 | 0.6883 | 1.6858 | 2.3936 | 3.1619 | 4.7013 |
| 2 | 1.4885 | 2.5637 | 3.3076 | 4.1511 | 5.7973 |
| 3 | 2.0103 | 3.2055 | 4.0250 | 4.9553 | 6.6873 |
| 4 | 2.4612 | 3.7715 | 4.6935 | 5.7503 | 7.4202 |
| Low DLI 5 | 2.9161 | 4.4122 | 5.4394 | 6.5299 | 8.2456 |
| Whole Sample | 1.5312 | 2.9019 | 3.9120 | 5.0684 | 7.0886 |

Panel C: Average DLI

| | Small 1 | 2 | 3 | 4 | Big 5 |
|---|---|---|---|---|---|
| High DLI 1 | 27.4500 | 20.6530 | 17.8550 | 16.0280 | 14.2960 |
| 2 | 2.0050 | 1.7930 | 1.6770 | 1.5870 | 1.4260 |
| 3 | 0.3170 | 0.2670 | 0.2510 | 0.2600 | 0.2200 |
| 4 | 0.0590 | 0.0510 | 0.0420 | 0.0380 | 0.0380 |
| Low DLI 5 | 0.0140 | 0.0110 | 0.0090 | 0.0060 | 0.0070 |
| Whole Sample | 11.6100 | 4.9351 | 2.5953 | 1.3932 | 0.6141 |

Panel D: Average BM

| | Small 1 | 2 | 3 | 4 | Big 5 |
|---|---|---|---|---|---|
| High DLI 1 | 2.2378 | 1.6810 | 1.5307 | 1.5022 | 1.3275 |
| 2 | 1.2604 | 1.0476 | 0.9803 | 0.9191 | 0.8581 |
| 3 | 1.0365 | 0.8571 | 0.7971 | 0.7426 | 0.7462 |
| 4 | 0.9507 | 0.7476 | 0.6963 | 0.6698 | 0.6952 |
| Low DLI 5 | 0.9150 | 0.6977 | 0.5991 | 0.5498 | 0.5059 |
| Whole Sample | 1.5111 | 1.0802 | 0.8994 | 0.7490 | 0.6646 |

Note: From 1971.1-1999.12, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their default likelihood indicators (DLI) in the previous month. Within each portfolio, stocks are then sorted into 5 size portfolios, based on their past month's market capitalization. The equally weighted average returns of the portfolios are reported in percentage terms. "Small-Big" is the return difference between the smallest and biggest size portfolios within each default quintile. "BM" stands for book-to-market ratio. The rows labeled "Whole Sample" report results using all stocks in our sample. T-values are calculated from Newey-West standard errors. The value of the truncation parameter q was selected in each case to be equal to the number of autocorrelations in returns that are significant at the 5% level.

**Table 4B: BM Effect controlled by Default Risk**

Panel A: Average Returns

| | High BM | 2 | 3 | 4 | Low BM | High-Low | t-stat |
|---|---|---|---|---|---|---|---|
| High DLI 1 | 3.3636 | 2.0412 | 1.5164 | 1.2047 | 0.8170 | 2.5466 | (9.8984) |
| 2 | 1.7981 | 1.5438 | 1.2955 | 0.9946 | 0.7282 | 1.0699 | (3.4716) |
| 3 | 1.7420 | 1.4287 | 1.3053 | 1.2381 | 1.2338 | 0.5083 | (1.5026) |
| 4 | 1.6284 | 1.4604 | 1.1840 | 1.1864 | 1.3414 | 0.2870 | (0.9575) |
| Low DLI 5 | 1.4415 | 1.2669 | 1.0932 | 1.0688 | 1.0074 | 0.4341 | (1.5134) |
| Whole Sample | 2.1572 | 1.4893 | 1.2267 | 1.0963 | 1.0128 | 1.1445 | (4.5879) |

Panel B: Average BM

| | High BM | 2 | 3 | 4 | Low BM |
|---|---|---|---|---|---|
| High DLI 1 | 3.7233 | 1.8967 | 1.3310 | 0.9007 | 0.4191 |
| | 2.0395 | 1.2307 | 0.8848 | 0.6070 | 0.2949 |
| 3 | 1.6616 | 1.0184 | 0.7399 | 0.5065 | 0.2462 |
| 4 | 1.4547 | 0.9154 | 0.6782 | 0.4705 | 0.2339 |
| Low DLI 5 | 1.2970 | 0.8052 | 0.5733 | 0.3858 | 0.2009 |
| Whole Sample | 2.2137 | 1.1258 | 0.7861 | 0.5243 | 0.2472 |

Panel C: Average DLI

| | High BM | 2 | 3 | 4 | Low BM |
|---|---|---|---|---|---|
| High DLI 1 | 30.9210 | 19.4650 | 16.2910 | 14.7660 | 14.6620 |
| 2 | 2.0460 | 1.7450 | 1.6340 | 1.5400 | 1.5180 |
| 3 | 0.3150 | 0.2580 | 0.2500 | 0.2590 | 0.2320 |
| 4 | 0.0510 | 0.0470 | 0.0420 | 0.0460 | 0.0410 |
| Low DLI 5 | 0.0130 | 0.0070 | 0.0110 | 0.0080 | 0.0080 |
| Whole Sample | 12.0360 | 3.6598 | 2.2206 | 1.6334 | 1.5062 |

Panel D: Average Size

| | High BM | 2 | 3 | 4 | Low BM |
|---|---|---|---|---|---|
| High DLI 1 | 2.0112 | 2.4445 | 2.6701 | 2.7970 | 2.7742 |
| 2 | 2.9754 | 3.4027 | 3.5753 | 3.6821 | 3.6893 |
| 3 | 3.6649 | 4.1947 | 4.3284 | 4.4044 | 4.3099 |
| 4 | 4.2412 | 4.8918 | 5.0060 | 5.0645 | 4.9220 |
| Low DLI 5 | 4.4908 | 5.3668 | 5.6338 | 6.0028 | 6.0942 |
| Whole Sample | 2.8680 | 3.9437 | 4.3643 | 4.6518 | 4.7197 |

Note: From 1971.1-1999.12, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their default likelihood indicators (DLI) in the previous month. Within each portfolio, stocks are then sorted into 5 book-to-market (BM) portfolios, based on their past month's BM ratio. The equally weighted average returns of the portfolios are reported in percentage terms. "High-Low" is the return difference between the highest BM and lowest BM portfolios within each default quintile. The rows labeled "Whole Sample" report results using all stocks in our sample. T-values are calculated from Newey-West standard errors. The value of the truncation parameter q was selected in each case to be equal to the number of autocorrelations in returns that are significant at the 5% level.

**TABLE 5A: Default Effect controlled by Size**

Panel A: Average Returns

| | High DLI | 2 | 3 | 4 | Low DLI | High -Low | t-stat |
|---|---|---|---|---|---|---|---|
| Small | 3.7315 | 2.1580 | 1.8666 | 1.4127 | 1.5020 | 2.2295 | (5.9430) |
| 2 | 0.7852 | 1.0599 | 1.3095 | 1.3212 | 1.3200 | -0.5348 | (-1.8543) |
| 3 | 0.8748 | 1.2387 | 1.3406 | 1.3623 | 1.1947 | -0.3198 | (-1.7375) |
| 4 | 1.1115 | 1.2662 | 1.4690 | 1.3171 | 1.2542 | -0.1427 | (-0.8505) |
| Big | 1.3714 | 1.2954 | 1.2391 | 1.1717 | 1.0428 | 0.3286 | (1.7074) |

Panel B: Average DLI

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| Small | 41.5360 | 12.7980 | 3.8906 | 0.8832 | 0.0955 |
| 2 | 20.4190 | 3.4020 | 0.7731 | 0.1516 | 0.0239 |
| 3 | 11.6090 | 1.1100 | 0.2276 | 0.0528 | 0.0091 |
| 4 | 6.3550 | 0.4880 | 0.1014 | 0.0284 | 0.0096 |
| Big | 2.9220 | 0.1200 | 0.0315 | 0.0075 | 0.0063 |

Panel C: Average Size

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| Small | 1.2008 | 1.4570 | 1.5742 | 1.6668 | 1.7450 |
| 2 | 2.8306 | 2.8830 | 2.9113 | 2.9332 | 2.9510 |
| 3 | 3.8612 | 3.8901 | 3.9172 | 3.9374 | 3.9537 |
| 4 | 4.9955 | 5.0381 | 5.0718 | 5.1008 | 5.1357 |
| Big | 6.7779 | 6.9570 | 7.0820 | 7.2114 | 7.4129 |

Panel D: Average BM

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| Small | 2.4472 | 1.5668 | 1.3194 | 1.1538 | 1.1031 |
| 2 | 1.6172 | 1.1213 | 0.9548 | 0.8645 | 0.8460 |
| 3 | 1.3290 | 0.9027 | 0.8036 | 0.7345 | 0.7286 |
| 4 | 1.0048 | 0.7531 | 0.7028 | 0.6765 | 0.6087 |
| Big | 0.8774 | 0.7187 | 0.6731 | 0.6013 | 0.4538 |

Note: From 1971.1-1999.12, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their market capitalization (size) in the previous month. Within each portfolio, stocks are then sorted into 5 portfolios, based on past month's default likelihood indicator (DLI). Equally weighted average portfolio returns are reported in percentage terms. "HDLI-LDLI" is the return difference between the highest and lowest default risk portfolios within each size quintile. T-values are calculated from Newey-West standard errors. The value of the truncation parameter q was selected in each case to be equal to the number of autocorrelations in returns that are significant at the 5% level.

**TABLE 5B: Default Effect controlled by Book-to-Market (BM)**

Panel A: Averge Returns

| | High DLI | 2 | 3 | 4 | Low DLI | High -Low | t-stat |
|---|---|---|---|---|---|---|---|
| High BM | 3.2285 | 2.1825 | 1.9488 | 1.8361 | 1.6243 | 1.6042 | (3.9785) |
| 2 | 1.3880 | 1.4370 | 1.5597 | 1.5544 | 1.5098 | -0.1218 | (-0.4580) |
| 3 | 1.1506 | 1.2602 | 1.3190 | 1.1712 | 1.2307 | -0.0802 | (-0.3317) |
| 4 | 0.9077 | 1.1734 | 1.1679 | 1.1064 | 1.1246 | -0.2169 | (-0.8294) |
| Low BM | 0.7044 | 0.9765 | 1.2983 | 1.1074 | 0.9711 | -0.2667 | (-0.8369) |

Panel B: Average DLI

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| High BM | 42.0930 | 13.1080 | 4.4229 | 1.3284 | 0.2008 |
| 2 | 15.6030 | 2.1510 | 0.5362 | 0.1186 | 0.0149 |
| 3 | 10.1880 | 0.7840 | 0.1623 | 0.0389 | 0.0104 |
| 4 | 7.7070 | 0.4180 | 0.0895 | 0.0244 | 0.0066 |
| Low BM | 7.3560 | 0.2140 | 0.0534 | 0.0152 | 0.0063 |

Panel C: Average BM

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| High BM | 3.1427 | 2.2544 | 2.0319 | 1.8890 | 1.7795 |
| 2 | 1.1569 | 1.1390 | 1.1245 | 1.1105 | 1.0985 |
| 3 | 0.8018 | 0.7886 | 0.7854 | 0.7798 | 0.7748 |
| 4 | 0.5375 | 0.5280 | 0.5237 | 0.5219 | 0.5107 |
| Low BM | 0.2464 | 0.2473 | 0.2477 | 0.2493 | 0.2453 |

Panel D: Average Size

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| High BM | 1.9664 | 2.4581 | 2.8438 | 3.3376 | 3.7075 |
| 2 | 2.7494 | 3.4317 | 4.0187 | 4.5993 | 4.9060 |
| 3 | 3.0165 | 3.8540 | 4.5044 | 5.0304 | 5.4005 |
| 4 | 3.2014 | 4.1530 | 4.7369 | 5.3104 | 5.8360 |
| Low BM | 3.1744 | 4.1586 | 4.6966 | 5.2828 | 6.2550 |

Note: From 1971.1-1999.12, at the beginning of each month, stocks are sorted into 5 portfolios on the basis of their book-to-market ratio in the previous month. Within each portfolio, stocks are then sorted into 5 portfolios, based on past month's default likelihood indicator (DLI). Equally weighted average portfolio returns are reported in percentage terms. "HDLI-LDLI" is the return difference between the highest and lowest default risk portfolios within each size quintile. T-values are calculated from Newey-West standard errors. The value of the truncation parameter q was selected in each case to be equal to the number of autocorrelations in returns that are significant at the 5% level.

**TABLE 6A: Independent Sorts into Size and Default Quintiles**

Panel A: Average Returns

| | High DLI | 2 | 3 | 4 | Low DLI | High -Low | t-stat |
|---|---|---|---|---|---|---|---|
| Small | 2.7387 | 1.4586 | 1.5999 | 1.5000 | 1.1862 | 1.5525 | (3.5197) |
| 2 | 0.8112 | 1.1510 | 1.4047 | 1.2308 | 1.3852 | -0.5740 | (-2.2741) |
| 3 | 0.7105 | 1.2010 | 1.3340 | 1.3976 | 1.1300 | -0.4195 | (-1.9107) |
| 4 | 0.7392 | 1.2867 | 1.3325 | 1.4439 | 1.2313 | -0.4921 | (-2.4935) |
| Big | 1.5335 | 1.3305 | 1.4232 | 1.2997 | 1.1028 | 0.4307 | (1.4318) |
| Small-Big | 1.2052 | 0.1281 | 0.1766 | 0.2003 | 0.0835 | | |
| t-stat | (3.6800) | (0.5230) | (0.7841) | (0.8388) | (0.2599) | | |

Panel B: Average DLI

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| Small | 22.8490 | 1.9756 | 0.3262 | 0.0681 | 0.0232 |
| 2 | 16.7590 | 1.7526 | 0.2777 | 0.0558 | 0.0124 |
| 3 | 15.0920 | 1.5968 | 0.2495 | 0.0437 | 0.0086 |
| 4 | 13.3460 | 1.5238 | 0.2589 | 0.0416 | 0.0094 |
| Big | 13.8780 | 1.3650 | 0.2133 | 0.0371 | 0.0070 |

Panel C: Average Size

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| Small | 1.3763 | 1.6371 | 1.7137 | 1.7666 | 1.7824 |
| 2 | 2.8402 | 2.8990 | 2.9295 | 2.9483 | 2.9573 |
| 3 | 3.8534 | 3.8848 | 3.9166 | 3.9411 | 3.9561 |
| 4 | 4.9663 | 5.0138 | 5.0454 | 5.0868 | 5.1299 |
| Big | 6.6747 | 6.7650 | 6.8759 | 7.0244 | 7.2907 |

Panel D: Average BM

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| Small | 1.8798 | 1.2226 | 1.0952 | 1.0914 | 1.2129 |
| 2 | 1.5193 | 1.0262 | 0.8847 | 0.8388 | 0.8682 |
| 3 | 1.4481 | 0.9387 | 0.8029 | 0.7288 | 0.7297 |
| 4 | 1.2238 | 0.8521 | 0.7354 | 0.6848 | 0.6180 |
| Big | 1.2186 | 0.8721 | 0.7521 | 0.6855 | 0.5312 |

Panel E: Average Number of Firm in Each Portfolio

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| Small | 242 | 123 | 64 | 38 | 25 |
| 2 | 129 | 140 | 108 | 73 | 46 |
| 3 | 70 | 113 | 125 | 110 | 79 |
| 4 | 37 | 80 | 115 | 134 | 132 |
| Big | 14 | 41 | 85 | 143 | 217 |

Note: At the beginning of each month from 1971.1 to1999.12, stocks are sorted into 5 portfolios on the basis of their market value of equity (size) in the previous month. They are also sorted into five portfolios on the basis of their DLI in the previous month. The 25 portfolios are then constructed from the intersection of the two independent sorts. All other comments in Tables 4A and 5A apply here as well.

**TABLE 6B: Independent Sorts into BM and Default Quintiles**

Panel A: Average Returns

| | High DLI | 2 | 3 | 4 | Low DLI | High -Low | t-stat |
|---|---|---|---|---|---|---|---|
| High BM | 2.4923 | 1.8109 | 1.7485 | 1.6492 | 1.2644 | 1.2279 | (3.6403) |
| 2 | 1.4104 | 1.4670 | 1.4953 | 1.5391 | 1.4951 | -0.0846 | (-0.3227) |
| 3 | 1.2998 | 1.1456 | 1.3065 | 1.2427 | 1.1984 | 0.1014 | (0.3553) |
| 4 | 1.0644 | 0.9250 | 1.2215 | 1.1712 | 1.1184 | -0.0541 | (-0.1616) |
| Low BM | 0.5543 | 0.8077 | 1.2202 | 1.2864 | 1.0006 | -0.4463 | (-1.1981) |
| High-Low | 1.9380 | 1.0032 | 0.5284 | 0.3627 | 0.2638 | | |
| t-stat | (6.9529) | (3.1338) | (1.5460) | (1.1675) | (0.9669) | | |

Panel B: Average DLI

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| High BM | 23.8220 | 2.0009 | 0.3356 | 0.0617 | 0.0175 |
| 2 | 15.4600 | 1.7205 | 0.2667 | 0.0473 | 0.0072 |
| 3 | 14.5910 | 1.5720 | 0.2495 | 0.0439 | 0.0101 |
| 4 | 14.2650 | 1.5472 | 0.2542 | 0.0444 | 0.0103 |
| Low BM | 15.3910 | 1.4705 | 0.2324 | 0.0437 | 0.0087 |

Panel C: Average BM

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| High BM | 2.5855 | 1.9535 | 1.8440 | 1.7751 | 1.7464 |
| 2 | 1.1564 | 1.1377 | 1.1204 | 1.1075 | 1.0964 |
| 3 | 0.8041 | 0.7924 | 0.7865 | 0.7798 | 0.7756 |
| 4 | 0.5407 | 0.5332 | 0.5254 | 0.5228 | 0.5130 |
| Low BM | 0.2414 | 0.2507 | 0.2492 | 0.2513 | 0.2499 |

Panel D: Average Size

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| High BM | 2.2828 | 3.0116 | 3.5016 | 3.8073 | 3.6118 |
| 2 | 2.7448 | 3.4539 | 4.1157 | 4.7029 | 4.8919 |
| 3 | 2.8179 | 3.6145 | 4.3086 | 4.9411 | 5.3856 |
| 4 | 2.7935 | 3.7366 | 4.4013 | 5.0560 | 5.7579 |
| Low BM | 2.7517 | 3.6597 | 4.3235 | 4.9242 | 6.0212 |

Panel E: Average Number of Firm in Each Portfolio

| | High DLI | 2 | 3 | 4 | Low DLI |
|---|---|---|---|---|---|
| High BM | 232 | 114 | 69 | 47 | 34 |
| 2 | 99 | 115 | 107 | 99 | 80 |
| 3 | 64 | 99 | 109 | 117 | 109 |
| 4 | 49 | 86 | 108 | 121 | 133 |
| Low BM | 48 | 84 | 105 | 114 | 144 |

Note: At the beginning of each month from 1971.1 to1999.12, stocks are sorted into 5 portfolios on the basis of their book-to-market (BM) ratio in the previous month. They are also sorted into five portfolios on the basis of their DLI in the previous month. The 25 portfolios are then constructed from the intersection of the two independent sorts. All other comments in Tables 4B and 5B apply here as well.

**Table 7: Summary Statistics on the 27 Size, BM, and DLI Sorted Portfolios**

| | SIZE | BM | DLI | Average Return | size | BM | DLI |
|---|---|---|---|---|---|---|---|
| 1 | small | High | High | 2.4229 | 1.8015 | 2.2192 | 18.9380 |
| 2 | small | High | Medium | 1.6977 | 2.1021 | 1.6630 | 0.4960 |
| 3 | small | High | Low | 1.6124 | 2.0410 | 1.6420 | 0.0240 |
| 4 | small | Medium | High | 1.3834 | 2.0606 | 0.7734 | 10.2640 |
| 5 | small | Medium | Medium | 1.4333 | 2.3183 | 0.8019 | 0.4410 |
| 6 | small | Medium | Low | 0.9525 | 2.2164 | 0.8777 | 0.0290 |
| 7 | small | Low | High | 0.8020 | 2.0956 | 0.3068 | 9.4810 |
| 8 | small | Low | Medium | 1.1139 | 2.4143 | 0.3099 | 0.2850 |
| 9 | small | Low | Low | 1.0843 | 2.3665 | 0.3453 | 0.0430 |
| 10 | Medium | High | High | 1.1913 | 3.7834 | 1.8675 | 12.0920 |
| 11 | Medium | High | Medium | 1.6750 | 3.9597 | 1.4046 | 0.3380 |
| 12 | Medium | High | Low | 1.5653 | 4.0343 | 1.3088 | 0.0170 |
| 13 | Medium | Medium | High | 0.7646 | 3.8382 | 0.8152 | 5.9680 |
| 14 | Medium | Medium | Medium | 1.3332 | 4.0316 | 0.7673 | 0.2930 |
| 15 | Medium | Medium | Low | 1.3354 | 4.1092 | 0.7711 | 0.0200 |
| 16 | Medium | Low | High | 0.6980 | 3.8611 | 0.3363 | 4.8230 |
| 17 | Medium | Low | Medium | 1.0774 | 4.0249 | 0.3248 | 0.2180 |
| 18 | Medium | Low | Low | 1.1680 | 4.1068 | 0.3315 | 0.0220 |
| 19 | Big | High | High | 1.6955 | 5.8582 | 1.7436 | 10.0360 |
| 20 | Big | High | Medium | 1.6261 | 6.3154 | 1.3537 | 0.2530 |
| 21 | Big | High | Low | 1.5171 | 6.7343 | 1.1435 | 0.0180 |
| 22 | Big | Medium | High | 0.9546 | 5.8168 | 0.8355 | 5.9050 |
| 23 | Big | Medium | Medium | 1.3203 | 6.1914 | 0.7767 | 0.2560 |
| 24 | Big | Medium | Low | 1.2019 | 6.5926 | 0.7227 | 0.0140 |
| 25 | Big | Low | High | 0.8634 | 5.8207 | 0.3560 | 3.5250 |
| 26 | Big | Low | Medium | 1.3465 | 6.1598 | 0.3510 | 0.2250 |
| 27 | Big | Low | Low | 1.1793 | 6.7712 | 0.3373 | 0.0150 |

Note: The 27 portfolios are constructed from the intersection of three independent sorts of all stocks into three size, three book-to-market (BM) and three default risk portfolios. Default risk is measured by the default likelihood indicator (DLI). The second, third, and fourth columns describe the characteristics of each portfolio in terms of its size, BM, and DLI. Size refers to the market value of equity. Equally-weighted average returns are reported in percentage terms.

**TABLE 8: Optimal GMM Estimation of Competing Asset Pricing Models**

Panel A: The EMKT+$\Delta$(SV) model

| | Constant | EMKT | $\Delta$(SV) | Test: | J-test | Wald(b) | HJ |
|---|---|---|---|---|---|---|---|
| Coefficient | 1.0200 | 1.5398 | -44.3823 | Statistic | 63.6054 | | 0.8678 |
| t-value | (39.2795) | (0.8804) | (-3.8607) | p-value | (0.0000) | (0.0001) | (0.0000) |
| Premium | | 0.0079 | 0.0043 | | | | |
| t-value | | (2.8024) | (4.2752) | | | | |

Panel B: The CAPM

| | Constant | EMKT | Test: | J-test | Wald(b) | HJ |
|---|---|---|---|---|---|---|
| Coefficient | 1.0030 | -2.2689 | Statistic | 69.4761 | | 0.8991 |
| t-value | (85.2437) | (-2.0283) | p-value | (0.0000) | (0.0425) | (0.0000) |
| Premium | | 0.0047 | | | | |
| t-value | | (2.0283) | | | | |

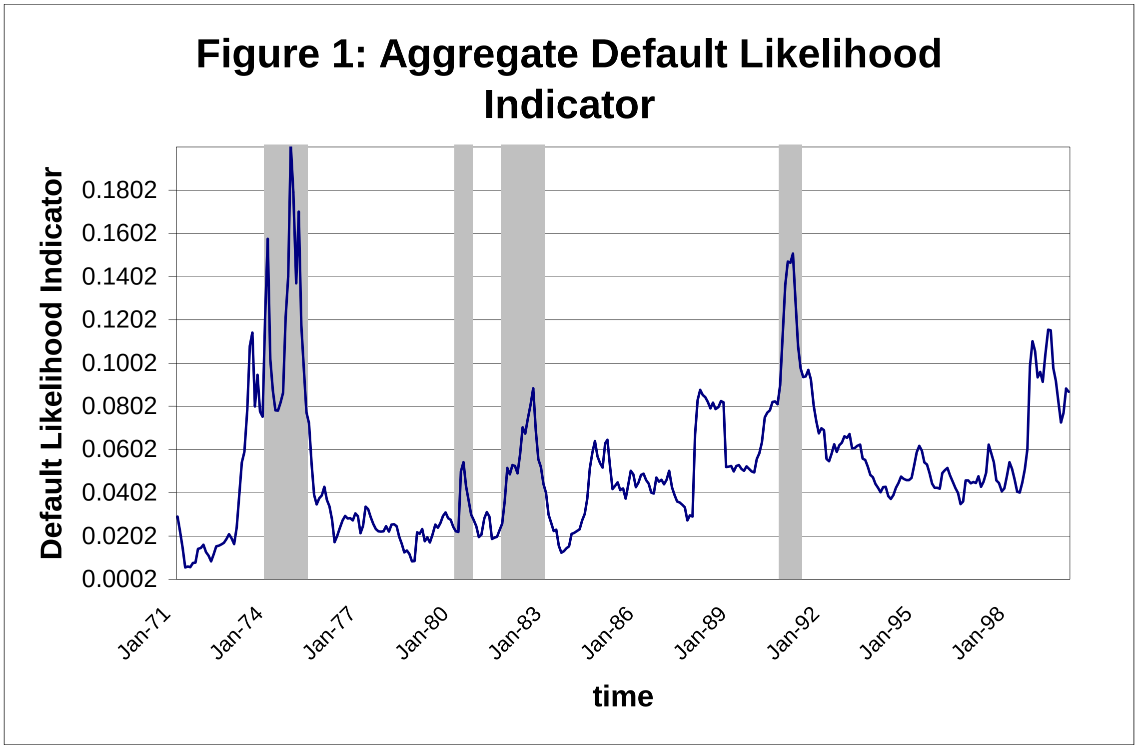
Panel C: The Fama-French model

| | Constant | EMKT | SMB | HML | Test: | J-test | Wald(b) | HJ |
|---|---|---|---|---|---|---|---|---|
| Coefficient | 1.0325 | -5.1332 | 0.0561 | -8.2368 | Statistic | 67.3000 | | 0.8766 |
| t-value | (44.4182) | (-4.0217) | (0.0270) | (-3.4076) | p-value | (0.0000) | (0.0001) | (0.0000) |
| Premium | | 0.0061 | 0.0009 | 0.0036 | | | | |
| t-value | | (2.5597) | (0.5317) | (2.0602) | | | | |

Panel D: The Fama-French model augmented by $\Delta$(SV)

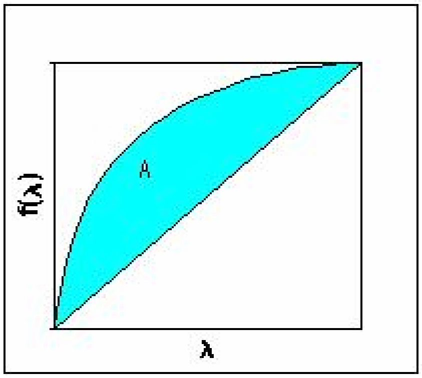
| | Constant | EMKT | SMB | HML | $\Delta$(SV) | Test: | J-test | Wald(b) | HJ |
|---|---|---|---|---|---|---|---|---|---|
| Coefficient | 0.9322 | 4.6068 | 24.7941 | -12.0076 | -135.2905 | Statistic | 46.8368 | | 0.8032 |
| t-value | (15.7444) | (1.6395) | (4.0315) | (-2.8654) | (-4.7691) | p-value | (0.0024) | (0.0000) | (0.0000) |
| Premium | | 0.0098 | -0.0025 | 0.0082 | 0.0097 | | | | |
| t-value | | (2.1551) | (-0.6916) | (2.6620) | (4.4788) | | | | |

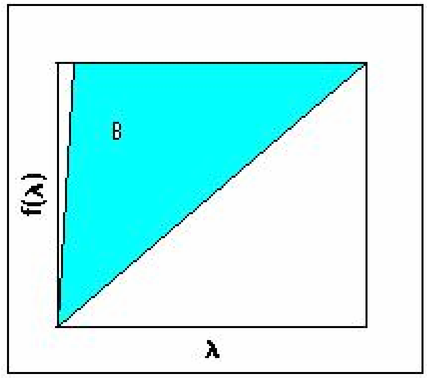
Note: The GMM estimations use Hansen's (1982) optimal weighting matrix. The tests are performed on the excess returns of the 27 equally-weighted portfolios of Table 7. EMKT refers to the excess return on the stock market portfolio over the risk-free rate. $\Delta(SV)$ is the change in the survival rate, which is defined as one minus the aggregate default likelihood indicator. HML is a zero-investment portfolio which is long on high book-to-market (BM) stocks and short on low BM stocks. Similarly, SMB is a zero-investment portfolio which is long on small market capitalization (size) stocks and short on big size stocks. The J-test is Hansen's (1982) test on the overidentifying restrictions of the model. The Wald(b) test is a joint significance test of the *b* coefficients in the pricing kernel. The J-test and Wald(b) tests are computed in GMM estimations that use the optimal weighting matrix. We denote by "HJ" the Hansen-Jagannathan (1997) distance measure. It refers to the least-square distance between the given pricing kernel and the closest point in the set of pricing kernels that price the assets correctly. The p-value of the measure is obtained from 100,000 simulations. The estimation period is from 1971.1 to 1999.12. In Panel A we test the hypothesis that default risk is priced in the context of a model that includes the excess return on the market portfolio along with a measure of default risk ($\Delta$(SV)). Panels B and C present results from tests of the CAPM and Fama-French models, which are used as benchmarks for comparison purposes. Finally, in Panel D we test the hypothesis that the Fama-French factors SMB and HML include default related information, by including in the Fama-French model our aggregate measure of default risk.

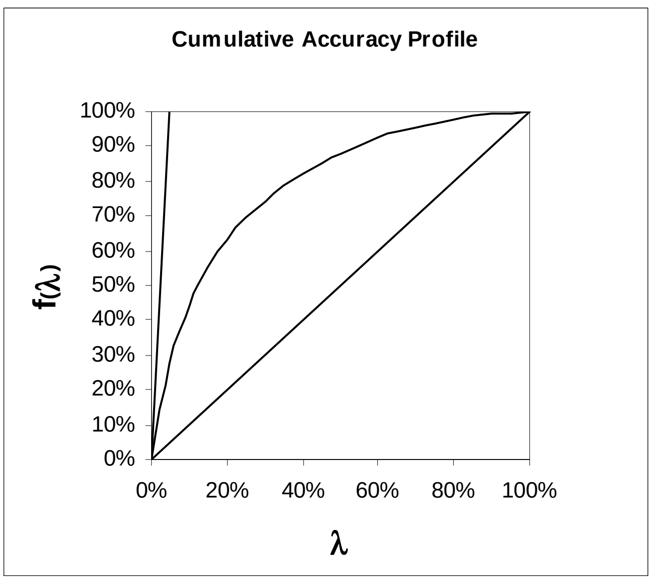



Note: The aggregate default likelihood indicator is defined as the simple average of the default likelihood indicators of all firms. The shaded areas denote recession periods, as defined by NBER.

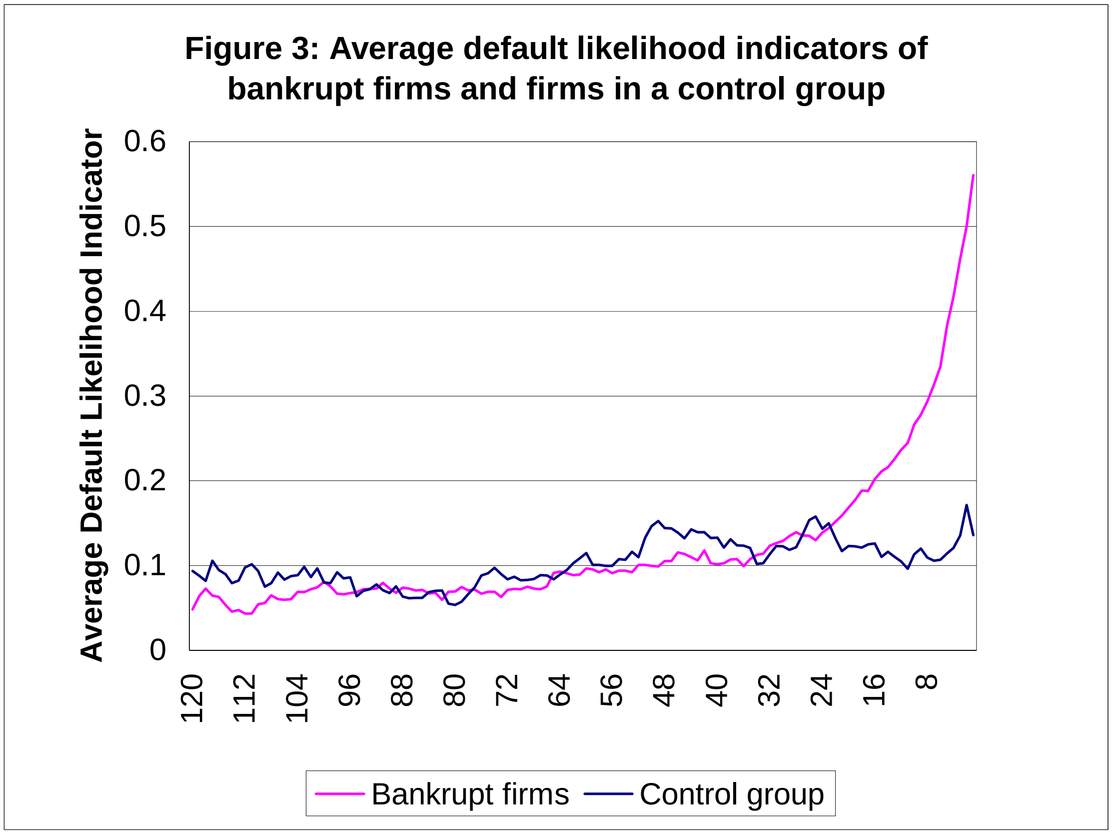
**Figure 2: Accuracy Ratio.**



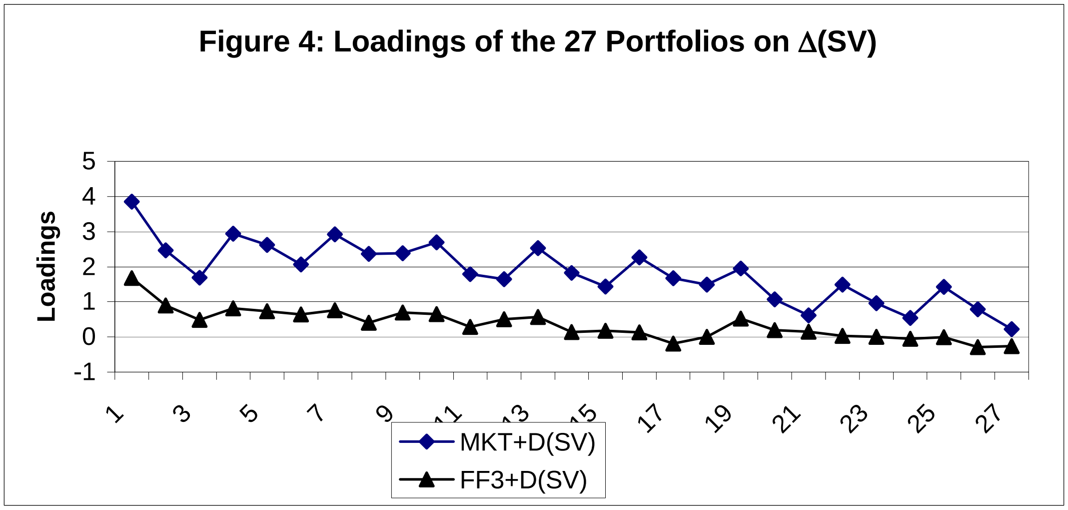




Accuracy Ratio=0.59231 (defined as the ratio of Area A over Area B)




Note: The control group contains firms with the same size and industry characteristics as those in the experimental group, that did not default. Firms are delisted two to three years prior to bankruptcy. Numbers in x-axis denote months prior to delisting, and not prior to the actual default.




<u>Note:</u> This graph shows the loadings of the 27 portfolios of Table 7 on the survival indicator Δ(SV). The portfolios are ordered in the same way as in Table 7. EMKT+Δ(SV) labels the loadings on Δ(SV) from the model that includes the market factor and Δ(SV) in the pricing kernel. Similarly, FF3+Δ(SV) labels the loadings on Δ(SV) from the augmented Fama-French (1993) model by the Δ(SV) factor. The sample period is from 1971.1-1999.12.