IS THE VALUE PREMIUM REALLY A COMPENSATION FOR DISTRESS RISK?

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ABSTRACT

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JEL Classification: G11, G12, G14

Keywords: book-to-market effect, value anomaly, market efficiency, default risk, bankruptcy, credit spread, bond spread, distress risk, credit rating, size effect

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1. INTRODUCTION

While numerous studies document that value stocks with high book-to-price ratios earn abnormal positive returns, the interpretation why they do so is more controversial. Berk (1995) relates size-related anomalies, such as the value effect, to systematic risk that is unmeasured by conventional asset pricing models. Fama and French (1992) postulate that book-to-price ratios proxy for the relative distress factor of Chan and Chen (1991), and Fama and French (1998) find that a factor model that incorporates a risk factor for relative distress captures the value premium in international equity returns. A large number of important studies in the field of empirical finance also consider the HML (High-Minus-Low) factor of Fama and French (1993) to be a priced risk factor [see, e.g., Zhang (2005)]. And several asset management companies point out that the higher returns they expect to earn for their investors through engaging in value strategies stem from taking increased levels of risk. However, empirical evidence does not appear to unambiguously indicate that the value anomaly is related to financial distress. In fact, the literature reports inconsistent conclusions on whether distress risk is a systematic risk factor that is priced in the cross-section of stock returns.

Dichev (1998) and Griffin and Lemon (2002) employ accounting models to estimate corporate bankruptcy risk and find a *negative* relation between distress risk and equity returns. The authors show that stocks with higher levels of distress risk as measured by Altman's model (1968) and Ohlson's model (1980) earn anomalously low returns and conclude that distress risk is therefore unlikely to account for the book-to-market effect. Piotroski (2000) reports that financially healthy, high book-to-market firms generate higher returns than firms that have less healthy financial statements. And recently, Campbell, Hilscher and Szilagyi (2008) use a comprehensive set of accounting and equity market variables to measure distress risk and find that stocks with high risk of default deliver abnormal low returns and that returns of growth and value stocks are significantly negatively related to default risk.[1]

On the other hand, Vassalou and Xing (2004) employ a structural approach to measure distress risk and use Merton's (1974) option pricing model to compute individual firms' default probabilities. When the authors assess the effect of distress risk on equity returns, they conclude that default risk is positively priced in the stock market and that a large portion of the book-to-price effect can be attributed to default risk. Chava and Purnanandam (2010) also use Merton's (1974) model to measure distress risk and investigate its relation with equity returns back to the early 1950s. They find that the underperformance of distressed stocks reported by Dichev (1998), Griffin and Lemon (2002), and Campbell, Hilscher and Szilagyi (2008) is specific to the 1980s. Once they exclude this decade from their sample, the underperformance of high-risk stocks disappears. They do not investigate if the value anomaly is related to distress risk. And more recently, Avramov, Chordia, Jostova and Philipov (2011) asses distress risk through credit downgrades and argue that value strategies derive their profitability from taking long positions in high credit risk firms that are prone to distress risk.

The different conclusions that are drawn by the above mentioned studies may be attributed to the different measures that are used to proxy for distress risk. Vassalou and Xing (2004) express their concerns about the use of accounting models in estimating the default risk of equities. They argue that accounting models use backward-looking information from financial statements, while the Merton (1974) model they use in their study contains forward-looking information that is better suited for calculating the likelihood that a firm may default. More recently, Anginer and Yıldızhan (2010) also criticise the use of estimated probabilities of default to proxy for distress risk as done in Dichev (1998), Griffin and Lemon (2002), and

[1] The negative relation between stock returns and distress risk documented by Campbell, Hilscher and Szilagyi (2008) is only observed when returns are adjusted for the three Fama and French (1992, 1993, 1996) factors.

Campbell, Hilscher and Szilagyi (2008). They argue that accounting models implicitly assume that stocks with high probabilities of distress also have high exposures to systematic distress risk. The estimated probabilities of default, however, do not take into account that some portion of the distress risk may be diversified away by investors and therefore may not be priced. In addition, George and Hwang (2009) point out that a firm's estimated probability of default does not necessarily reflect the firm's exposure to the costs of financial distress, which is a better candidate for assessing the relevance of financial distress risk to security pricing. The authors argue that firms choose less leverage if their operations expose them to high financial distress costs.

Anginer and Yıldızhan (2010) not only criticize the use of accounting models to predict firm defaults, but also the use of structural models. According to the authors, structural models make simplified assumptions about the capital structure of a firm. And just like the estimated probabilities of default derived from accounting models, the probabilities resulting from structural models not necessarily capture the systematic component of distress risk; the only type of risk that should be rewarded with a premium. The authors propose corporate credit spreads to proxy for distress risk as these reflect the market consensus view of the credit worthiness of the underlying firm and contain a risk-premium for systematic risk. And although Elton, Gruber, Agrawal and Mann (2001) find that credit spreads cannot fully be explained by expected default losses, Anginer and Yıldızhan (2010) provide evidence that bond spreads contain default information above and beyond the measures commonly used in the literature. Using credit spreads, they find neither a positive, nor a negative significant relation between distress risk and equity returns. The authors, however, do not investigate the relation between the value premium and distress risk measured by credit spreads. It is currently unclear what relation will be found if credit spreads are used to proxy for financial distress.

When we consider these results all together, it seems that there is no consensus in the literature on which measure best proxies distress risk and that the findings regarding the pricing of default risk are sensitive to the used risk measure. As a consequence, the literature is also inconclusive as to whether the value premium is a compensation for financial distress. In the first part of this paper we aim to obtain better insight into the sensitivity of the results in the literature to the use of alternative risk measures to ultimately come up with a conclusion regarding the relation between the value effect and distress risk.

We start with setting up a comprehensive data set of alternative proxies for firms' distress risk for the 1,500 largest U.S. firms over the period September 1991 to December 2009. From accounting data, we measure a firm's default risk by its financial leverage. Probabilities of default are also obtained using the structural model of Merton (1974). Given the results of Anginer and Yıldızhan (2010) that credit spreads are a good proxy for financial distress, we additionally consider the difference between the bond yield and the corresponding maturity-matched treasury rate as a measure for firms' distress risk. Finally, we consider credit ratings that have been used by Avramov, Chordia, Jostova and Philipov (2007, 2009, 2011) to proxy for distress risk. We merge our distress risk data with monthly equity price data.

In our first empirical analysis we evaluate the predictive power of the variables for firms' financial distress using Moody's (2000) Accuracy Profiles. While we do find some differences between the variables, it appears that all variables have predictive power for firms' financial distress. We find that structural models and credit ratings do a better job in predicting financial distress than accounting measures, and that credit spreads have some predictive value over estimates resulting from structural models and credit ratings. Although stock rankings based on these measures are positively correlated, the correlations are not very high. This result indicates that our different risk measures capture distinct dimensions of financial distress.

Next, we construct double-sorted portfolios of stocks ranked on book-to-market ratios and distress risk to explore the relation between our measures of distress risk and the value premium. While we find above-average distress risk exposures for value stocks, none of the distress measures yields strong evidence that default risk is a priced factor in the cross-section of equity returns. We observe at most a weak positive relation between default risk and the returns of value stocks. Moreover, once we correct for the size effect, there is no evidence of a positive relation between value and distress risk. This result holds irrespective of which measure we use for distress risk.

Furthermore, we investigate if the seemingly contradictory findings in the literature can be attributed to the use of different methodologies to test for the relation between value and distress. The first alternative methodological setup we employ is in the spirit of Lakonishok, Shleifer and Vishny (1994). With this approach we investigate if value stocks are riskier than growth stocks by testing if value stocks underperform growth stocks in the bad states of the world. As a measure for good and bad states of the world we take the NBER's Business Cycle indicators for economic expansions and recessions, respectively. We find that value stocks outperform growth stocks both during expansions and recessions. At the same time, we find that high-risk stocks based on all our different distress measures exhibit large underperformance during recessions corroborating our finding that our distress proxies have predictive power for financial distress. The second alternative setup we investigate is the use of cross-sectional Fama and MacBeth (1973) regressions at the individual stock level to estimate if there is a value premium above and beyond distress risk effects. All regression results consistently indicate a significant value premium and no relation between stock returns and distress risk exposures.

In addition, we investigate the relation between the size premium and financial distress. The reason we address this issue is because we found some interaction between the value premium, distress risk and the size effect and because it seems that the literature is not conclusive about the explanations for the existence of the size anomaly. We also find no evidence that the size effect can be attributed to distress risk. While small-cap stocks do have a substantially higher probability to get into financial distress, it is not the case that small-cap stocks only yield positive abnormal returns if they run higher levels of distress risk. In fact, it seems that the size premium is concentrated in low-risk small-cap stocks.

We extend our investigation on the relation between the size premium and distress risk with an analysis of the premium during different states of the business cycle. If small-cap stocks are riskier than large-cap stocks they must underperform large-cap stocks in the bad states of the world. However, it appears that for all our risk measure we find large positive size premiums during recessions. In addition, the cross-sectional Fama and MacBeth (1973) regressions at the individual stock level show a stronger size premium once corrected for distress risk. Our results on the size premium are therefore inconsistent with the notion that this premium is a compensation for distress risk.

Finally, we investigate if the large empirical explanatory power of the Fama-French (1993) SMB (Small-Minus-Big) and HML (High-Minus-Low) factors for the size and value effects can be attributed to these factors being exposed to distress risk. Because of the way the SMB and HML factors are constructed, we may expect the factors to be prone to distress risk. To investigate this issue we construct distress-risk neutral SMB and HML factors. We observe that the premiums of the factors do not decrease when distress-risk neutrality is imposed. At the same time, the distress-risk-neutral factors exhibit lower risk levels. Furthermore, we do not observe a deterioration of the explanatory power of the distress-risk-neutral factors for the variation in returns of the 25 portfolios sorted on market capitalization and book-to-price and the decile portfolios sorted on dividend yield from the webpage of Kenneth French.

Overall, based on our results we conclude that the reported weak positive relation between value and financial distress is fragile at closer inspection and sensitive to correction for size effects. Once properly corrected for the size effect we find persuasive evidence against a risk-based interpretation of the value anomaly. Our results call for further research on the development and testing of theories that potentially provide an explanation for the size and value effects.

The remainder of this paper is organized as follows. Section 2 describes the construction of our data set. Section 3 presents our main empirical results, Section 4 reports our results for tests that examine if there is a relation between the size effect and distress risk, and Section 5 presents results for analyses that investigate if the empirical explanatory power of the SMB and HML factors can be attributed to their exposures to distress risk. Finally, Section 6 summarizes our main findings and concludes.

2. DATA

Our sample covers the 1,500 largest stocks of the Citigroup US Broad Market Index (BMI) over the period September 1991 until December 2009. This universe roughly corresponds to the CRSP universe excluding the 25 percent of stocks with the smallest market capitalization over this time period and covers more than 95 percent of the total U.S. equity market capitalization. Our sample starts in 1991 because we could not obtain high-quality credit spread data before this date. We intentionally leave out micro-cap stocks from our sample to ensure that our findings are not prone to market micro-structure concerns.

The first proxy we consider for distress risk to obtain a firm's probability of default is based on accounting data and measures risk through financial leverage, i.e., the firm's debt-to-assets ratio. We use quarterly Compustat data to construct the debt-to-assets ratio, where debt is defined as total debt including both short- and long-term debt. In case Compustat data are not available, we use annual data from Worldscope.

Our second proxy for distress risk is a firm's probability to default derived from a structural model. This probability is based on the distance-to-default measure, which we compute using a similar approach as Moody's KMV [see, e.g., Crosbie and Bohn (2003)] based on Merton's (1974) option pricing model. The input data we need to compute a firm's distance-to-default are the firm's market value of equity, its equity volatility and its book value of debt. Data on equity market values and equity returns to estimate volatilities are obtained from FactSet Prices. More specific, we define a firm's distance-to-default (DD) as follows:

$$(1)\ DD = \frac{\ln(V_a / K) + (\mu - r_f - 0.5\sigma_a^2)T}{\sigma_a \sqrt{T}}$$

where V_a is the market value of a firm's assets, K its default point (or the book value of the debt for which we use total debt), σ_a the volatility of assets, μ is the excess drift in the underlying asset value which we proxy with 0.06 in line with Campbell, Hilscher and Szilagyi (2008), r_f is the risk-free rate and we assume T to be one year. The distance-to-default measures how many standard deviations the firm is away from default. The smaller the difference between the asset value V_a and the default point K, the larger the probability on default.

As the market value of assets and the volatility of assets are not directly observable, we model these using Merton's (1974) option pricing model. In this model, the equity value of a firm is viewed as a European call option on the firm's assets where the strike price of the call option is the book value of the firm's debt. As a result, we obtain:

$$(2)\ V_e = V_a N(d_1) - Ke^{-r_f T} N(d_2)$$

$$d_1 = \frac{\ln(\frac{V_a}{K}) + (r_f + 0.5\sigma_a^2)T}{\sigma_a \sqrt{T}}$$

$$d_2 = d_1 - \sigma_a \sqrt{T}.$$

where V_e is the market value of equity and N is the cumulative distribution function of the standard normal distribution. As this equation has two unknowns, we use an iterative process similar to that of KMV to obtain the market value of assets V_a and the volatility of assets σ_a. First, we set the initial value for the volatility of assets equal to the standard deviation of the past 250 daily stock returns. Next, we back out the market value of assets using Equation (2) and compute monthly asset value returns. We can then obtain a new estimate for σ_a by calculating the standard deviation of the past twelve asset value returns, which is used for the next iteration. This procedure is repeated until the difference between two subsequent estimates for σ_a is less than 10E-4. With the resulting estimated σ_a and V_a, we compute the *DD* using Equation (1).

Our third measure for distress risk are credit spread data which we obtained from Barclays Capital (formally Lehman Brothers). The data cover debt issues that are constituents in the Barclays Capital Investment Grade Corporate and High Yield bond indexes. For each firm at each point in time we take the spread of the firm's debt issue with the largest amount outstanding in the Barclays indexes. Our distress proxy based on credit spread is defined as the difference between the option-adjusted bond yield and the corresponding maturity-matched treasury rate.

For our fourth proxy of distress risk, we use credit ratings issued by S&P. We merge the data of the four proxies for distress risk with monthly stock returns and book-to-market ratios. Quarterly book values are obtained from Compustat. In case Compustat data are not available, we use annual data from Worldscope.

3. EMPIRICAL ANALYSES

3.1 Predictive power of distress risk proxies

In our first empirical analysis we test the extent to which our proxies actually predict financial distress. We consider a firm to be in financial distress if it receives a CCC credit rating or worse.[2] Under this definition, roughly 0.3 percent of the firms in our sample get into financial distress each year. This figure varies over time and peaks to 0.78 percent in 2001 and 1.36 percent in 2008 during the collapse of the IT bubble and the credit crisis, respectively. The percentage of firms that gets into financial distress in our sample seems to be somewhat lower than the failure rates reported by Campbell, Hilscher and Szilagyi (2008). This is not unexpected since our study includes fewer small-cap stocks that have been reported to run higher risks to default than large-cap stocks.

To investigate the predictive power of our measures of distress risk, we employ so-called Cumulative Accuracy Profiles [see, e.g., Moody's (2000)]. To generate the Accuracy Profiles we monthly compute what percentage of the firms that gets into financial distress in the subsequent 12 months is ranked in the top x percent of stocks on their probabilities to default estimated using our four proxies for distress risk. Here, x ranges from 1 to 100. Figure 1 shows the time-series averages of these percentages for our four proxies for distress risk. The Accuracy Profile of a measure that has no predictive power for financial distress follows a line from the origin of the graph and has a slope of one. The Accuracy Profile of a measure that does have predictive power for financial distress also departs from the origin, but shows a concave pattern indicating that firms are more likely to get into financial distress if their estimated probabilities of default are relatively high according to this measure.

[INSERT FIGURE 1 ABOUT HERE]

[2] We also investigate the predictive power of our distress risk proxies where we consider a firm to be in financial distress if it receives a D rating. The results of these tests are virtually identical to those resulting from tests where we consider a firm to be in financial distress if it receives a CCC rating or worse. For the sake of brevity, we do not report these results in tabular form.

When we consider the Accuracy Profiles of the four measures we use in this study, it appears that all of them have significant predictive power for financial distress. Roughly 35 percent of the firms that get into financial distress are ranked in the top quintile of firms based on financial leverage. The other measures even do a somewhat better job in predicting financial distress than accounting measures, since 70 to 75 percent of the firms that get into financial distress are ranked in the top quintile based on their estimated probabilities of default derived from credit ratings and the structural model, respectively. This figure is 85 percent when firms are ranked on their credit spread, indicating that spreads appear to have the highest predictive value.

We also investigate the extent to which a firm’s book-to-market value proxies for distress risk. To this end, we additionally compute the Accuracy Profile for this measure. The results of this analysis are also presented in Figure 1. It appears that a firm’s book-to-market value has predictive power for financial distress. About 45 percent of the firms that get into financial distress are ranked in the top quintile of firms based on book-to-market. However, at the same time, the convex shape of the Accuracy Profile at the bottom end of the book-to-market spectrum (top right in Figure 1) indicates that growth stocks with a low book-to-market ratio also have a higher probability to get into financial distress. Approximately 30 percent of the firms that get into financial distress are ranked in the bottom quintile based on book-to-market. So even though high book-to-market ratios seem to pick up some form of distress risk, it seems unlikely that value stocks earn higher returns than growth stocks because value stocks are exposed to higher levels of distress risk.

Finally, we consider the average rank correlations for stock rankings on the different distress risk measures. While all measures are positively correlated, the correlations are not very high ranging between 0.31 and 0.77. Financial leverage yields the lowest correlations with the other risk measures (i.e., 0.31 to 0.45). Distance-to-default, credit spread and credit rating show correlations ranging between 0.57 and 0.77. All in all, our results indicate that our risk measures capture distinct dimensions of financial distress.

3.2 Distress risk characteristics of value stocks

We continue our empirical analysis by investigating the distress risk characteristics of value versus growth stocks. To this end, we monthly sort stocks into quintile portfolios based on their book-to-market ratio and evaluate the portfolios' equally-weighted returns over the subsequent month, as well as their median market capitalizations, debt-to-assets ratios, distances-to-default, credit spreads and credit ratings. The results of this analysis are presented in Table 1. We first consider the return differential between value and growth stocks that are ranked in the first and fifth quintile portfolio, respectively. Consistent with most studies we observe a monotonically decreasing return pattern from the top to the bottom quintile portfolio and document a large value premium of 7.0 percent per annum.

[INSERT TABLE 1 ABOUT HERE]

We next consider the quintile portfolios' distress risk characteristics. Irrespective of the risk measure, it appears that value stocks are more exposed to distress risk than the average stock. The median debt-to-assets ratio of a value stock is 0.31 compared to 0.26 for the average stock in our sample. Value stocks are 1.9 (= 7.3 minus 5.4) standard deviations closer to their estimated point of default than the average stocks. Also, the credit spreads of firms with high book-to-market ratios are 51 (= 202 minus 151) basis points higher than those of the average stock. And firms with high book-to-market ratios generally have less favourably credit ratings, with a median rating corresponding to BBB versus an average rating of BBB+ in our sample. Additionally we observe that value stocks with a high book-to-market ratio are smaller than the average stock. We again conclude that high book-to-market ratios are related to distress risk.

However, the observation that value stocks have relatively higher probabilities to default is not a sufficient condition to attribute the value premium to distress disk. If the value premium indeed is a compensation for distress risk, growth stocks should have lower probabilities to default to justify their below-average returns. But when we consider the results in Table 1, we find that growth stocks are not substantially less exposed to distress risk compared to the average stock. In fact, growth stocks appear to be more risky than stocks ranked in the fourth quintile portfolio, as they have higher debt-to-assets ratios (0.23 versus 0.22); higher credit spreads (149 versus 132 basis points); and less favourable credit ratings (BBB versus BBB+). These results corroborate our previous finding that both stocks with high and low book-to-market ratios have higher probabilities to get into financial distress and are inconsistent with the notion that the value effect is a compensation for distress risk.

3.3 The value premium and distress risk

To investigate the relation between distress risk and equity returns in more detail we construct double-sorted portfolios of stocks ranked on their book-to-market ratios and our four measures of distress risk. This rank portfolios approach is the most common methodology in the stream of literature on empirical asset pricing to investigate the interaction between stock characteristics and returns. More specifically, every month we sort stocks into terciles based on their debt-to-assets ratio, distance-to-default, credit spread or credit rating. Next, for each tercile portfolio we sort stocks further into quintiles based on their book-to-market ratio. For the 15 resulting stock portfolios we compute their median values of the distress risk measures used to construct the portfolios and their equally-weighted return over the subsequent month. In addition, we compute their median market capitalization. The results are presented in Table 2.

[INSERT TABLE 2 ABOUT HERE]

We start by considering the portfolios' distress risk characteristics in Panel 1 of Table 2. Subpanel 1A of Table 2 shows the risk characteristics for double sorts on book-to-price and debt-to-assets; Subpanel 1B for book-to-price and distance-to-default; Subpanel 1C for book-to-price and credit spread; and Subpanel 1D for book-to-price and credit rating. Two observations are apparent. First, there is a large dispersion in distress risk characteristics among the stocks in our sample for all four measures we use in our study: we observe debt-to-assets ratios of 0.08 and 0.44 for low- and high-risk stocks, respectively (see the "low risk" and "high risk" portfolios in the third column with median book-to-price ratios of Subpanel 1A); distance-to-default estimates of 12.8 and 3.6, respectively; credit spreads of 95 and 294 basis points, respectively; and credit ratings of A and BB, respectively. Second, it appears that value stocks are only marginally more risky than growth stocks in terms of default risk: mid-risk value stocks have a debt-to-assets ratio of 0.28; a distance-to-default of 7.0; a credit spread of 164 basis points; and a credit rating of BBB. These figures are 0.26, 7.3, 157 basis points; and BBB+ for mid-risk growth stocks, respectively.

Continuing our analysis further, we consider the portfolios' returns in Panel 2 of Table 2. If the value premium is a compensation for distress risk we should observe the following two return patterns: (i) high-default-risk stocks should earn higher returns than low-risk stocks and (ii) the high (low) returns of value (growth) stocks should be concentrated in the high-default-risk (low-default-risk) segment, i.e., the "high-risk/high book-to-price" ("low-risk/low book-to-price") portfolio. However, for none of our four distress risk measures we find strong evidence that default risk is a priced factor in the cross-section of equity returns. In fact, the annualized return of stocks with high debt-to-assets ratios (i.e., stocks in the "high risk/median book-to-price" portfolio) is only 0.4 percent higher than stocks with low debt-to-assets ratios. For the three other measures, the returns even appear to be negatively related to distress risk. When distress risk is measured using our distance-to-default measure we observe a negative relation between distress risk and equity returns, as the difference between the returns of high- and low-risk stocks is negative at 2.2 percent per annum. Stocks with the highest credit spreads earn a 3.4 percent lower return per annum than stocks with the lowest credit spreads. And also when we use credit rating as a proxy for distress risk we find that high-risk stocks earn a 4.2 percent lower return than low-risk stocks. In addition, we do not observe a consistent pattern that the high returns of value stocks are concentrated in the high-default-risk segment. In fact, when debt-to-assets is used as measure for distress risk, it appears that high-risk value stocks earn lower returns than low-risk value stocks. And while we observe that high-risk value stocks earn a higher return than low-risk value stocks when distance-to-default, credit spread or rating are used as measures for distress risk, the return differentials of 0.9, 0.3 and 2.1 percent, respectively, are only small and statistically insignificant. Furthermore, low-risk growth stocks do not earn the lowest return. In fact, for three out of our four risk measures we find up to -3.2 percent lower returns for the high-risk growth stocks compared to low-risk growth stocks. These results are difficult to reconcile with the risk-based explanation that has been put forward in the literature to explain the value anomaly.

We finally consider the portfolios' market capitalizations in Panel 3 of Table 2. It appears that there are large differences in market capitalizations when distress risk is measured through distance-to-default, credit spreads and credit ratings. More specifically, high-distress-risk portfolios contain more small-cap stocks. For example, the market capitalizations of portfolios of stocks with high credit spreads or ratings are more than seven times smaller than those with low credit spreads or ratings. Moreover, consistent with our findings in Table 1, we find that value stocks generally have a smaller market capitalization than growth stocks. All together, we observe that small-cap (large-cap) stocks have a substantially higher probability to end up in the high-risk value (low-risk growth) portfolios.

As small-cap stocks on average earn higher returns than large-cap stocks [see, e.g., Fama and French (1992)], this effect could potentially impact our conclusions on the relation between the value anomaly and distress risk. In the following subsection we investigate this issue in detail.

3.4 The value premium and distress risk corrected for the size effect

To investigate the impact of the size effect in our previous analysis, we conduct a second analysis where we evaluate the relation between distress risk and equity returns for size-neutral risk portfolios. To this end, we construct triple-sorted portfolios of stocks ranked on their market capitalization, book-to-market ratios and each of our four measures of distress risk. More specifically, every month we sort stocks into terciles based on their market capitalization. Then, for each size portfolio we sort stocks into terciles based on their debt-to-assets ratio, distance-to-default, credit spread or rating. Next, we merge the small-, mid- and large-cap portfolios of high-risk stocks. We also merge the three market cap portfolios of low- and mid-risk stocks. Finally, for each aggregated tercile portfolio we sort stocks further into quintiles based on their book-to-market ratios. This triple sort ensures that the three resulting risk portfolios exhibit only minor differences in their market capitalizations and is in spirit similar to the approach used by Fama and French (1993) to construct the HML (High-Minus-Low) factor orthogonal to the size factor. Like in our previous analysis, we compute the equally-weighted returns over the subsequent month of the 15 portfolios, as well as the portfolios' median distress risk characteristics. The results are listed in Table 3.

[INSERT TABLE 3 ABOUT HERE]

We first consider the portfolios' distress risk characteristics in Panel 1 of Table 3 to investigate if the portfolios still exhibit a large dispersion in their distress risk characteristics after correcting for the size effect. We observe that the dispersion in distress risk characteristics for the size-corrected portfolios is roughly as large as for the portfolios in the previous analysis where the size effect was not taken into account: the debt-to-assets ratios and the distance-to-default estimates for the high- and low-risk stock portfolios are nearly identical for the double- and triple sorted stocks portfolios in Table 2 and 3, respectively. The differences in credit spreads and ratings between the high- and low-risk portfolios are slightly smaller for the size-neutral stock portfolios. Nonetheless, the dispersion in distress risk exposures remains large: the difference in credit spread between the high- and low-risk median book-to-price portfolios is 162 basis points for the size-neutral portfolios and 198 basis points for the portfolios without size correction. While the median credit rating for the low-risk book-to-price portfolio is A for both the portfolios with and without size correction, for the high-risk median book-to-price portfolios these ratings are BB+ and BB for respectively the size-corrected portfolio versus the portfolio without size correction. Because the stock portfolios still exhibit a large dispersion in their distress risk characteristics after correcting for the size effect, we ensure that return differences between the double- and triple-sorted portfolios cannot be attributed to the triple-sorted portfolios reflecting less variation in exposures to distress risk.

Next, we consider the portfolios' returns in Panel 2 of Table 3. If the value premium is a compensation for distress risk we should observe a positive relation between default risk and returns; in particular for value and growth stocks. However, once corrected for the size effect, stock returns appear to be negatively related to distress risk as we observe negative returns for most of the high-minus-low portfolios. In particular, this result holds for the average book-to-market portfolio irrespective of which measure we use for distress risk. The differences between the returns of the high- and low-risk stock portfolios range from -0.2 percent per annum when distressed risk is measured using our debt-to-assets measure to -4.8 percent using credit spreads as a measure for distress risk. Moreover, we observe that once corrected for the size effect, the relation between distress risk and returns for value stocks has become weaker. When we measure distress risk using distance-to-default, the high-minus-low-risk value return spread turns negative from 0.9 percent to -0.9 percent. For credit spread this difference also turns negative from 0.3 percent to -3.2 percent. And when credit ratings are used as a measure for distress risk, the high-minus low-risk value return spread decreases from 2.1 percent to 0.4 percent. The previously found negative relation between high- and low-risk value stocks based on the debt-to-assets ratio remains negative once corrected for size effects. Furthermore, returns of growth stocks remain negatively related to distress risk for three out of four distress risk measures with the size correction. We conclude that once size effects are taken into account, absolutely no evidence is found that the value premium can be attributed to distress risk related to default. In fact, once corrected for the size effect, the return of value stocks seems to be negatively related to distress risk in most of the cases.

3.5 The value premium and distress risk during bad states of the world

So far, we constructed double- and triple-sorted portfolios to investigate the interaction of book-to-price ratios and distress risk characteristics with stock returns. When we consider the literature on the economic origin of the value anomaly we see that several other frameworks have been employed. In the following sections we investigate if the different conclusions drawn regarding the relation between the value premium and distress risk can be attributed to the use of different methodologies.

We start our analyses with a methodological setup in the spirit of Lakonishok, Shleifer and Vishny (1994). This setup relies on the premise that value stocks must underperform growth stocks in the bad states of the world when the marginal utility of wealth is high if value stocks are indeed fundamentally riskier than growth stocks. As a measure for good and bad states of the world we take the NBER's Business Cycle indicators for economic expansions and recessions, respectively. This measure indicates two recessions during our sample period: the first one from March to November 2001 and the second one from December 2007 to June 2009. We evaluate the relation between distress risk and equity returns for size-neutral risk portfolios that are constructed using the procedure outlined in the previous section. For all portfolios we compute their returns during expansions and recessions. The results are listed in Table 4.

[INSERT TABLE 4 ABOUT HERE]

When we consider the portfolio returns during expansions and recessions in Panels 1 and 2 of Table 4, respectively, it appears that stock returns are highly positive on average during expansions and negative during contractions. This result clearly indicates that the NBER's Business Cycle indicators differentiate between good and bad states of the economy. Next, we consider the return differential between value and growth stocks during expansions and recessions. It appears that value stocks outperform growth stocks during expansions, irrespective of which distress risk measure is used to construct the portfolios. The average return in expansions of value stocks with median distress risk compared to growth stocks with median distress risk ranges from 3.5 (= 19.5 – 16.0) percent per annum in case distance-to-default is used to construct the portfolios to 7.4 (20.9 – 13.5) percent in case debt-to-assets is used. Value stocks, however, also show a better performance than growth stocks during recessions. In fact, in three out of four cases (for sorts using debt-to assets, distance-to-default and credits ratings in Panels 2A, 2B and 2D, respectively) there is a large positive value premium during recessions. These results are very difficult to reconcile with the risk-based explanation for the value premium that predicts the opposite.

At the same time, we do not observe a particular return pattern for stocks with different distress risk characteristics during expansions. High-risk stocks with a relatively high debt-to-assets ratio earn somewhat higher returns than stocks with a low debt-to-assets ratio, but for our other risk measures we do not observe such a pattern. Interestingly, we observe a clear return pattern for stocks with different levels of distress risk during economic recessions in Panel 2 of Table 4. For all risk measures, we see that high-risk stocks earn lower returns than low-risk stocks during recessions. When distance-to-default, credit spreads and ratings are used as risk measures, the return differentials between high- and low-risk stocks are over 10 percent per annum. These results indicate that all our risk measures capture some form of distress risk.

3.6 Cross-sectional Fama-MacBeth regressions

Proceeding further, we perform cross-sectional Fama-MacBeth regressions [see Fama and MacBeth (1973)] using individual stock returns to investigate if the magnitude of the estimated value premium is affected by including stock exposures to distress risk in the regressions. The primary attractive feature of Fama-MacBeth regressions compared to the rank portfolio approaches we employed in our previous analyses is that Fama-MacBeth regressions enable us to control for multiple other effects that might affect the relation between stock returns, valuation and distress risk. For example, in our earlier analyses we only control for size when investigating the relation between value and distress risk. This requires us to construct triple-sorted portfolios. It would not be feasible to correct for an additional factor and construct quadruple-sorted portfolios because the number of stocks ending up in the resulting portfolios would become too small. With the Fama-MacBeth regressions on the other hand, we can easily include multiple factors when estimating the value premium.

In our first analysis we monthly regress stock returns on book-to-price ratios while controlling for market beta, intermediate-term return momentum, short-term return reversal and industries:

(3) $r_{i,t} = a_t + b1_t BM_{i,t} + b2_t BETA_{i,t} + b3_t MOM_{i,t} + b4_t REV_{i,t} + \delta_t Z_i + \varepsilon_{i,t}$

where $r_{i,t}$ is the return of stock i in month t, $BM_{i,t}$ is the normalized book-to-market ratio of stock i in month t, $BETA_{i,t}$ is the normalized market beta of stock i in month t estimated using a thee-year rolling window using weekly returns and the BMI index as proxy for the market return, $MOM_{i,t}$ is the normalized 11-month one-month lagged past return of stock i in month t, $REV_{i,t}$ is the normalized return of stock i over the past month in month t, and Z_i is a vector containing industry dummies for stock i based on the MSCI/S&P GICS level 1 classification of ten industries.[3] Next, we augment our base case regression in Equation (3) with the normalized probabilities of our four alternative proxies for distress risk and rerun the regressions. Panel 1 of Table 5 presents the average coefficient estimates of the different regression models together with their *t*-values computed using Fama-MacBeth standard errors. In addition, the table shows the average adjusted R-squared values of the regressions.

[INSERT TABLE 5 ABOUT HERE]

When we consider the resulting coefficient estimates of our base case regression in column (1), we observe a large and significant value premium: the coefficient estimate of 0.13 percent for *BM* indicates that stocks earn an additional return of 0.13 percent per month for a one-standard deviation increase in their book-to-price ratio. The large negative coefficient estimate for *REV* indicates a negative autocorrelation in stock returns. We find only weak evidence supporting an intermediate-term momentum effect in stock returns using the Fama-MacBeth regressions. Columns (2) to (5) in Panel 1 of Table 5 show the coefficient estimates when we augment our base case regression model with our normalized measures of distress risk. If the value premium can be attributed to distress risk, we should observe that augmenting the cross-sectional regressions of stock returns on book-to-price ratios with our

[3] We normalize the explanatory variables in the Fama-MacBeth regressions by substracting the cross-sectional median from each observation and by dividing this difference by the cross-sectional standard deviation of the observations in each month. In addition, we winsorize the resulting normalized variables by imposing a maximum of 3 and a minimum of -3.

measures of distress risk should lead to a significant decrease of the estimated value premium. At the same time the measures for distress risk should encompass the explanatory power of stocks' book-to-price ratios and their coefficient estimates should become positive and significant. However, in all cases we observe that the coefficient estimate for *BM* remains nearly unchanged. Moreover, none of the coefficient estimates for our distress risk measures turns out significantly positive. In fact, in three out of four cases we observe a negative coefficient estimate for distress risk. These results are consistent with our earlier findings that there is no distress risk premium and that the value anomaly cannot be attributed to distress risk.

Given our earlier results that firm size has an important impact on the relation between stock returns, valuation and distress risk, we run additional regressions where we augment the five regression models we estimated in the previous analysis with normalized market capitalizations. The results of these regressions are presented in Panel 2 of Table 5. Two observations are apparent: first, the value premium seems to become somewhat smaller, although still statistically significant, once firm size in taken into account. Second, the relation between stock returns and distress risk becomes more negative once the regressions are augmented with the logarithm of market capitalizations (normalized). This finding is consistent with our earlier finding that some high-distress-risk stocks earn higher returns because they are small cap stocks.

Overall, the results of our Fama-MacBeth regression analysis are consistent with our results based on rank portfolios and conditional time series analyses. It appears that the results we documented in the previous sections are not affected by market beta, momentum, reversal and industry effects and that our finding that the value premium is unrelated to distress risk is robust to the method that is used to investigate the relation between the two variables.

4. THE SIZE PREMIUM AND DISTRESS RISK

We now turn to addressing the question if the size premium is related to financial distress. We believe that there are at least two good reasons to investigate this issue. First, we found that there is some interaction between the value premium, distress risk and the size effect. In particular, we found that there is a weak positive relation between value and distress risk if we do not control for size effects. If our aim is to better understand the interaction between value and distress risk, it is therefore of importance to understand how the size effect and distress risk relate as well. Second, it seems that the literature is not conclusive about the explanations for the existence of the size anomaly. On the one hand side, a strand of literature attributes the size effect to a common risk factor. Chan, Chen and Hsieh (1985), Chan and Chen (1991), Petkova (2006), and Hwang, Min, McDonald, Kim, and Kim (2010) examine the correlation between the return differential between small- and large-cap stocks and several risk factors over time. Chan, Chen and Hsieh (1985) find evidence that the default spread and other factors that are related to changes in the economic environment are positively related to the small-cap premium. Chan and Chen (1991) find that small-cap portfolios contain a disproportional large amount of marginal firms with low production efficiency and high financial leverage. Petkova (2006), and Hwang, Min, McDonald, Kim, and Kim (2010) find that the SMB (Small-Minus-Big) factor of Fama and French (1993) is positively correlated with innovations in variables that describe investment opportunities, such as the default spread. And Vassalou and Xing (2004) employ a cross-sectional approach to investigate the relation between size and distress risk and show that the small-cap premium is fully concentrated in high-risk stocks. On the other hand, there are also several papers that argue that the size effect is unrelated to risk [see, e.g., Daniel and Titman (1997), Knez and Ready (1997), Ferson, Sarkissian and Simin (1999), Berk (2000)]. The comprehensive framework we use in this study can shed new light on the interaction between size and distress risk.

We start our analysis by investigating the size effect in our sample of the largest 1,500 U.S. stocks by monthly ranking the stocks on their market capitalization, sorting them into quintile portfolios and computing the equally-weighted returns over the subsequent month. Our results show that the 20 percent smallest stocks outperform the 20 percent largest stocks with 2.0 percent per annum over the period September 1991 to December 2009. Consistent with evidence in the academic literature, the size premium is of significant smaller magnitude than the value premium we found in our sample of 7.0 percent per annum. In fact, several studies even suggest that the size effect disappeared after 1980 [e.g. Horowitz, Loughran and Savin (2000) and Hirshleifer (2001)].

To investigate if the higher returns of small cap stocks are indeed concentrated in stocks with high distress risk, we construct portfolios of stocks ranked on their market capitalization and each of our four measures of distress risk. Since we noted earlier that high-risk stocks typically have a smaller market capitalization than low-risk stocks, we form triple-sorted portfolios of stocks to ensure that the market capitalizations of the high- and low-risk portfolios are in the same order of magnitude and that any return differences between portfolios in the same size segment cannot be attributed to differences in market capitalization. More specifically, every month we sort stocks into quintile portfolios based on their market capitalization. Then, within each size portfolio we further sort stocks into terciles based on their market capitalization. Then, for each size sub-portfolio we sort stocks into terciles based on their debt-to-assets ratio, distance-to-default, credit spread and credit rating. Finally, we merge the small-, mid- and large-cap sub-portfolios of high-risk stocks within each size quintile portfolio. We also merge the three market cap sub-portfolios of mid- and low-risk stocks within each size sub-portfolio. We compute the equally-weighted returns over the subsequent month for the resulting 15 portfolios, as well as the portfolios' median distress risk characteristics. The results are listed in Table 6.

[INSERT TABLE 6 ABOUT HERE]

We first consider the portfolio's distress risk characteristics in Panel 1 of Table 6. We observe a strong relation between the market capitalization of stocks and their distress risk characteristics: small-cap stocks exhibit higher distress risk than large-cap stocks. The median distance-to-default is 5.3 for mid-risk small-cap stocks, while 10.1 for mid-risk large-cap stocks. Also for credit spread and credit rating we observe large differences between small- and large cap stocks. The median credit spread and credit rating for mid-risk small-cap stocks are 281 basis points and BB+, respectively, and 96 basis points and A for mid-risk large-cap stocks, respectively. Only when we consider debt-to-assets as distress risk measure it appears that small-cap stocks are only marginally more risky with a debt-to-assets ratio of 0.26 for small-cap stocks and 0.25 for large-cap stocks. At the same time we observe that there are also large differences in distress risk characteristics between the high- and low-risk portfolios within each size quintile. For example, the difference between high- and low-risk debt-to-assets portfolios is 0.43 within the small cap portfolio. These findings indicate that not all small cap stocks exhibit equally high exposures to distress risk.

We continue our analysis by investigating the portfolio's returns in Panel 2 of Table 6. Indeed we observe a size effect in the sense that the small-cap portfolios earn higher returns than the large-cap portfolios. If small-cap stocks earn higher returns because they have more distress risk, we should observe a positive relation between default risk and returns of small-cap stocks. However, for three out of our four distress risk measures, we do not observe that the high returns of small-cap stocks are concentrated in the high-default-risk segment. In fact, when distance-to-default, credit spread and credit rating are used as measures for distress risk, it appears that high-risk small-cap stocks earn up to 5.5 percent lower returns than low-risk small-cap stocks. Additionally, if the small-cap premium is a compensation for distress risk, large-cap stocks earn lower returns because they have less distress risk and we should also observe a positive relation between default risk and returns of large-cap stocks. Conversely, we find that for all four distress risk measures the low returns of large-cap stocks are concentrated in the high-default-risk segment. Therefore, it seems unlikely that distress-risk drives the small-cap premium.

We also evaluate the performance differential between small- and large-cap stocks over different states of the business cycle. If small-cap stocks run more distress risk than large-cap stocks, they must underperform large-cap stocks in the bad states of the world. As with our business cycle analysis in the previous section, we take the NBER's Business Cycle indicators for economic expansions and recessions and evaluate the relation between distress risk and equity returns for our triple-sorted portfolios on market capitalization and distress risk. For all portfolios we compute their returns during expansions and recessions. The results are listed in Table 7.

[INSERT TABLE 7 ABOUT HERE]

When we consider the portfolio returns during expansions and recessions in Panels 1 and 2 of Table 7, respectively, it appears that stock returns are highly positive on average during expansions and negative during recessions. Using distance-to-default, credit spread and credit ratings as measures for distress risk, we observe that high-risk stocks earn lower returns than low-risk stocks during recessions. When credit spreads are used to measure distress risk, the return differential between high- and low-risk stocks is more than 25 percent per annum. At the same time, however, it appears that small-cap stocks do not only outperform large cap stocks during expansions, but also during recessions. In fact, for all four different risk measures we find a large positive size effect during recessions. These results corroborate our earlier result that it seems unlikely that the size effect can be attributed to distress risk.

Finally, we turn back to our regression results in the previous section to analyze the relation between the size effect and distress risk using cross-sectional Fama-MacBeth regressions. If a portion of the size effect is related to distress risk, we should observe that the coefficient estimate for *Market cap* in Panel 2 of Table 5 should become less significant once the regression model is augmented with our distress risk variables. However, in all four cases it appears that the coefficient estimate for *Market cap* becomes more negative once our distress risk variables are added to the model. In fact, we find an insignificant size premium which becomes significant once distress risk is included in the regression. These results indicate that small-cap stocks with high distress risk earn lower returns than small-cap stocks with a more healthy financial status and are again inconsistent with the notion that small-cap stocks earns higher returns because of increased distress risk.

5. THE FAMA-FRENCH (1993) SMB AND HML FACTORS AND DISTRESS RISK

The typical approach in the stream of literature on empirical asset pricing to correct for the size and value effects is using the Fama-French (1993) three factor model that augments the one-factor market model with the SMB (Small-Minus-Big) and HML (High-Minus-Low) factors. Perhaps the most important reason why many researchers adopted the use of the SMB and HML factors is because of the factors' large empirical explanatory power for differences in the cross-section of stock returns. Because of the way the SMB and HML factors are constructed, we may expect the factors to be prone to distress risk (we refer to the webpage of Kenneth French for a detailed documentation on the construction of the SMB and HML factors and to the recent work of Cremers, Petajisto, and Zitzewitz (2011) for an in-depth analysis of the impact of small cap stocks on the returns of the SMB and HML factors).

In this section we investigate if the large empirical explanatory power of the Fama-French (1993) factors can be attributed to these factors being exposed to distress risk. More specifically, we investigate if the empirical explanatory power of the SMB and HML factors is negatively affected when distress-risk neutrality is imposed when the factors are constructed. To conduct our analysis we use the 5x5 double-sorted portfolios on market capitalization and book-to-price and the decile portfolios sorted on dividend yield from the webpage of Kenneth French as test assets. Pricing errors are estimated using the one-factor CAPM model

(4) $r_{i,t} = a + bRMRF_t + \varepsilon_{i,t}$

and the three-factor Fama-French model

(5) $r_{i,t} = a + bRMRF_t + sSMB_t + hHML_t + \varepsilon_{i,t}$.

In these equations, $r_{i,t}$ is the return of portfolio *i* at time *t* in excess of the risk-free rate. $RMRF_t$, SMB_t, and HML_t are the returns on Fama and French (1993) factors for respectively market, size, and value at time *t*. Return data for the risk-free rate and the market factor are from the webpage of Kenneth French. We construct the SMB and HML factors using our sample covering the 1,500 largest stocks of the Citigroup US Broad Market Index (BMI) over the period September 1991 until December 2009 and the methodology as outlined on the webpage of Kenneth French. More specifically, following Fama and French (1993) we first construct six value-weighted portfolios on market capitalization and book-to-price. These portfolios, which are constructed at the end of each month, are the intersections of two portfolios formed on market capitalization, and three portfolios formed on book-to-price. The size breakpoint for month *t* is the median market capitalization at the end of month *t*. The book-to-price for month *t* is the book equity for the most recent fiscal quarter divided by market capitalization at the end of month *t*. The book-to-price breakpoints are the 33th and 66th percentiles for month *t*. SMB is the average value-weighted return on the three small portfolios minus the average value-weighted return on the three big portfolios,

$$
(5)\quad \begin{aligned} \text{SMB} &= 1/3\,(\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) \\ &- 1/3\,(\text{Big Value} + \text{Big Neutral} + \text{Big Growth}) \end{aligned}
$$

and HML is the average value-weighted return on the two value portfolios minus the average value-weighted return on the two growth portfolios,

$$
(6)\quad \text{HML} = 1/2\,(\text{Small Value} + \text{Big Value}) - 1/2\,(\text{Small Growth} + \text{Big Growth}).
$$

Additionally, we construct return series for SMB and HML imposing distress-risk neutrality. To impose distress-risk neutrality we perform a triple sort where we first sort stocks into distress risk terciles and next perform the double sort on market capitalization and book-to-price as outlined above. The six base portfolios that are used to construct the SMB and HML factors are now the average value-weighted return series for the distress risk terciles. For example, Small Value is now the average of the return series for the Low Risk/Small Value, Mid Risk/Small Value, and High Risk/Small Value portfolios. And Big Growth, for example, is the average of the return series for the Low Risk/Big Growth, Mid Risk/Big Growth, and High Risk/Big Growth portfolios. The distress risk breakpoints are the 33th and 66th percentiles for month *t*. We construct distress-risk neutral SMB and HML factors using our four measures for distress risk.

[INSERT TABLE 8 ABOUT HERE]

Before testing the empirical explanatory power of the SMB and HML factors with and without distress-risk neutrality imposed, we first consider the summary statistics and investigate the distress risk exposures of the SMB and HML factors, the differential premiums after neutralization, the factors' risks, and their correlations. Panel 1 of Table 8 shows the summary risk and return statistics of the market factor and the SMB and HML factors with and without distress-risk neutrality imposed. When we consider the last four rows in Panel 1, we observe that the SMB factor is exposed to distress risk as the negative distance-to-default and the credit spread of 145 basis points indicate that small caps are more exposed to distress risk than large caps. Also the BB+ rating for small caps is worse than the A- rating for large caps. Only based on debt-to-assets small caps do not seem to be more risky than large caps. These findings are consistent with our earlier results. When we consider the exposures of the HML factor, we observe that the factor is only marginally exposed to distress risk as the debt-to-assets ratios, credit spreads and credit ratings are almost equal for stocks with a high and low book-to-market ratio. Only based on the distance-to-default measure we observe that value stocks are more risky than growth stocks. These results already indicate that it is unlikely that the HML factor picks up distress risk and the factor's explanatory power is driven by distress risk exposure. Furthermore, we observe that the distress-risk neutral SMB and HML factors are, by construction, generally less exposed to distress risk than the standard SMB and HML factors. The distress-risk neutral SMB factors have distances-to-default and credit spreads closer to zero and a smaller difference in credit rating between small and large caps. And also the distress-risk neutral HML factor has distances-to-default closer to zero.

Interestingly, we observe that the premiums of the SMB and HML factor are still present when distress-risk neutrality is imposed. The risk premiums of the SMB and HML distress-risk neutral factors range from 2.16 to 3.70 percent and from 3.16 to 3.67 percent per annum, respectively, compared to a 2.00 percent SMB premium and a 3.40 percent HML premium without neutrality being imposed. When we consider the risks of the factors, we find in almost all cases that the distress-risk neutral factors exhibit substantially lower levels of risk as measured by lower return standard deviations and lower extreme negative returns (i.e., 5th and 25th percentile returns). The same return levels together with the lower risk levels result in higher Sharpe ratios for our distress-risk neutral factors. These results indicate that distress risk is not driving the premiums of the SMB and HML factors. We additionally estimate correlations between the return series which are presented in Panel 2 of Table 8.

Correlations between the Fama and French SMB factor and the distress-risk neutral SMB factors range between 0.43 and 0.96. For the Fama and French HML factor the correlations range between 0.86 and 0.94. Although the correlations are high as expected, the results indicate that the regressions in Equation 4 and 5 might result in different outcomes. This raises the question which factors are better able to explain the variability in returns of our test assets.

We continue our empirical analysis by estimating pricing errors for the CAPM and the Fama-French (1993) three-factor model using the SMB and HML factors with and without distress-risk neutrality. We consider average and median pricing errors and adjusted R-squared values of the regressions to measure the descriptive power of the factors. The results of our analysis using the 5x5 double-sorted portfolios on market capitalization and book-to-price as test assets are presented in Table 9. For each of the 25 portfolios, the table presents annualized returns, annualized constants (*a*) and associated *t*-values, and the adjusted R-squared values of the different regression models. In addition, the table shows the average and median pricing errors of the models for the 25 portfolios based on the absolute values of the constants and *t*-values.

[INSERT TABLE 9 ABOUT HERE]

We first consider the results of the CAPM. Consistent with a size and value anomaly, we find that the market factor does not suffice to describe the cross-section of stock returns of portfolios sorted on market capitalization and book-to-price. The average adjusted R-squared value of the CAPM model is only 66 percent. Also, we observe large average and median absolute pricing errors of, respectively, 3.97 and 3.44 percent. When we consider the empirical explanatory power of the three-factor Fama-French model, we observe a significantly better performance. The average adjusted R-squared value is 85 percent and both the average and median pricing errors of, respectively, 2.39 and 1.71 percent are substantially lower than those of the CAPM.

We continue by investigating the explanatory power of the distress-risk neutral SMB and HML factors. If the large empirical explanatory power of the Fama-French (1993) factors can be attributed to the factors being exposed to distress risk we should observe an increase in pricing error when the returns of the test assets are evaluated using the SMB and HML factors that are constructed imposing distress-risk neutrality. However, we do not observe deterioration in explaining the variation in returns of the 25 portfolios. In fact, in three out of four cases the average and median pricing errors decrease when imposing distress risk neutrality. More specifically, the average (median) pricing error of the Fama-French model is 2.39 (1.71) percent and ranges between 2.00 (1.42) percent and 2.57 (2.13) percent for the risk-neutral models. In addition, we still observe substantial higher adjusted R-squared values compared to the CAPM. We can therefore conclude that it is not necessary to be exposed to distress-risk to be able to explain the differences in returns of the 25 Fama-French portfolios.

[INSERT TABLE 10 ABOUT HERE]

Next, we perform a similar test where we use the decile portfolios sorted on dividend yield from the webpage of Kenneth French as test assets. The results are presented in Table 10. When we compare the results of the CAPM for the ten dividend yield portfolios with the results for the 25 portfolios sorted on value and size as in Table 9, we observe that the pricing errors are smaller, although the average and median errors are still substantial with 2.15 and 2.06 percent, respectively. We find that the Fama-French (1993) model is again better capable in describing the cross-section of dividend yield portfolio returns, as the median and average pricing errors are smaller and the adjusted R-squared values are larger than those resulting from the CAPM. Again, if distress risk is effective in explaining cross-sectional return differences, then neutralizing this risk in the SMB and HML factors should lead to an increase in pricing errors. However, we observe that in almost all cases the average and median pricing errors become smaller when distress risk neutrality is imposed, corroborating our previous finding that distress risk-exposure is not the driving force behind the large empirical explanatory power of the SMB and HML factors.

6. CONCLUDING COMMENTS

Following the work of Fama and French (1992, 1993), a large stream of literature has been developed on the value anomaly and numerous attempts have been made to better understand the economic origin of this anomaly. In particular, several papers attribute the value anomaly to a common risk factor and contend that the value premium is a compensation for investors bearing distress risk. Notably, there are also a number of papers that dispute this assertion and document that it is unlikely that the value premium can be attributed to distress risk. At first sight, it seems that these contradictory findings in the literature may be attributed to the use of different measures and methodologies. In this article, we contribute to the extant literature by shedding new light on the sensitivity of the reported results to the use of alternative risk measures and methodologies and try to come up with a unified conclusion regarding the relation between the value effect and distress risk.

Consistent with most studies we find that value stocks are prone to somewhat higher levels of distress risk than the average stock. However, at the same time we find that the value premium cannot be attributed to distress risk. Irrespective of whether we measure stocks' probabilities on financial distress using accounting models, structural models, credit spreads or credit ratings, we find that the value premium cannot be absorbed by distress risk. In fact, we find no evidence whatsoever that default risk is a priced factor in the cross-section of equity returns. The results are also robust to the method that is used to investigate the relation between the two variables. Irrespective of whether we use rank portfolios, business cycle analyses a la Lakonishok, Shleifer and Vishny (1994), or cross-sectional Fama-MacBeth (1973) regressions, we find no positive relation between value and distress. Only if we do not properly control for the size effect we find a weak positive relation between the two variables for some of our risk measures. Interestingly, we also find no evidence that the size effect can be attributed to distress risk. While small cap stocks do have a higher probability to get into financial distress, it is not the case that small cap stocks only yield positive abnormal returns if they run higher levels of distress risk. In fact, it seems that the size premium is concentrated in low-risk small cap stocks. Finally, our results indicate that the empirical explanatory power of the Fama-French (1993) SMB and HML factors cannot be attributed to these factors being exposed to distress risk. Overall, our results are difficult to reconcile with a risk-based interpretation of the value anomaly and call for further research on the development and testing of theories that potentially provide an explanation for the size and value effects.

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FIGURE 1. Cumulative Accuracy Profiles.
This figure presents the Cumulative Accuracy Profiles of the book-to-market ratio (B/M), debt-to-assets ratio, distance-to-default, credit spread and credit rating. We monthly compute what percentage of the firms that gets into financial distress in the subsequent 12 month is ranked in the top x percent of stocks on their probabilities to default estimated using our four proxies for distress risk, with x ranging from 1 to 100. The curves show the time-series averages.

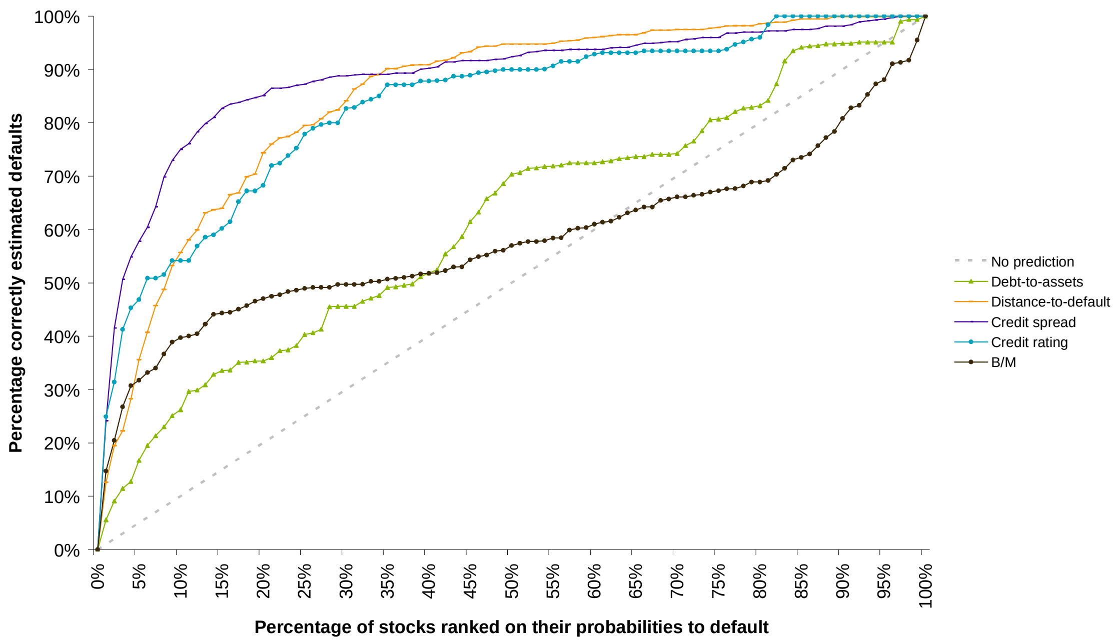

TABLE 1. Risk characteristics of portfolios sorted on the book-to-market ratio.
This table presents the annualized returns of quintile portfolios based on the book-to-market ratio (B/M) for the 1,500 largest U.S. stocks from September 1991 until December 2009. Portfolios are formed monthly and their returns are computed by equally weighting the firms. In addition, the table presents the following median firm characteristics of these portfolios: book-to-market ratio (B/M), debt-to-assets ratio, distance-to-default, credit spread, credit rating, and market capitalization (in billion U.S dollars).

	High B/M	2	3	4	Low B/M	High-Low
Return (annualized)	14.9%	11.8%	9.0%	7.8%	7.4%	7.0%
B/M	0.85	0.56	0.41	0.28	0.14	0.72
Debt-to-assets	0.31	0.30	0.26	0.22	0.23	0.08
Distance-to-default	5.4	6.7	7.3	8.5	8.5	-3.1
Credit spread	202	152	151	132	149	53
Credit rating	BBB	BBB+	BBB+	BBB+	BBB	-
Market capitalization	1265	1399	1577	1886	1940	-675

TABLE 2. Value effect controlled by distress risk

This table reports statistics of double-sorted portfolios of stocks ranked on their book-to-market ratios and distress risk for the 1,500 largest U.S. stocks from September 1991 until December 2009. Stocks are sorted monthly into terciles based on their distress risk as measured by debt-to-assets ratio, distance-to-default, credit spread and credit rating . Next, for each tercile portfolio, stocks are further sorted into quintiles based on their book-to-market ratio (B/M). Portfolio returns are computed by weighting equally the firms. Panels 1-3 report respectively median risk characteristics, annualized returns and median market capitalizations (in billion U.S. dollars).

	High B/M	2	3	4	Low B/M
Panel 1. Risk					
Panel 1A. Debt-to-assets					
Low risk	0.10	0.10	0.08	0.07	0.04
Mid	0.28	0.27	0.26	0.26	0.26
High risk	0.42	0.42	0.44	0.44	0.55
High-Low	0.33	0.33	0.36	0.38	0.51
Panel 1B. Distance-to-default					
Low risk	11.8	12.2	12.8	13.2	14.1
Mid	7.0	7.1	7.2	7.4	7.3
High risk	3.1	3.5	3.6	3.7	3.4
High-Low	-8.7	-8.7	-9.2	-9.5	-10.8
Panel 1C. Credit spread					
Low risk	103	99	95	89	79
Mid	164	158	157	157	157
High risk	328	287	294	284	320
High-Low	226	188	198	195	241
Panel 1D. Credit rating					
Low risk	A	A	A	A	A+
Mid	BBB	BBB	BBB+	BBB+	BBB+
High risk	BB+	BB	BB	BB	BB-
High-Low	-	-	-	-	-

TABLE 2 (Continued). Value effect controlled by distress risk

	High B/M	2	3	4	Low B/M
Panel 2. Annualized returns					
Panel 2A. Debt-to-assets					
Low risk	13.4%	10.0%	9.9%	3.7%	5.3%
Mid	15.8%	10.6%	9.8%	7.8%	9.4%
High risk	12.5%	10.8%	10.4%	7.2%	9.9%
High-Low	-1.0%	0.7%	0.4%	3.5%	4.6%
Panel 2B. Distance-to-default					
Low risk	12.7%	11.4%	11.6%	8.1%	8.0%
Mid	15.6%	10.6%	10.8%	8.5%	11.2%
High risk	13.6%	13.1%	9.5%	6.1%	6.3%
High-Low	0.9%	1.7%	-2.2%	-2.0%	-1.6%
Panel 2B. Credit spread					
Low risk	13.7%	9.0%	10.8%	9.5%	8.8%
Mid	13.5%	13.0%	12.9%	10.0%	10.6%
High risk	14.0%	11.7%	7.4%	8.1%	5.6%
High-Low	0.3%	2.7%	-3.4%	-1.4%	-3.2%
Panel 2D. Credit rating					
Low risk	14.7%	11.9%	11.4%	10.8%	8.7%
Mid	16.2%	15.6%	10.5%	9.9%	9.5%
High risk	16.8%	11.4%	7.1%	7.6%	8.3%
High-Low	2.1%	-0.4%	-4.2%	-3.2%	-0.3%
Panel 3. Market capitalization					
Panel 3A. Debt-to-assets					
Low risk	1173	1305	1639	2023	2188
Mid	1262	1512	1714	2315	3329
High risk	1269	1492	1620	1729	1606
High-Low	97	187	-19	-294	-582
Panel 3B. Distance-to-default					
Low risk	2033	2241	2758	3857	6358
Mid	1450	1508	1788	2064	2085
High risk	1037	1092	1187	1218	1260
High-Low	-996	-1149	-1571	-2639	-5098
Panel 3C. Credit spread					
Low risk	6493	8072	10381	13354	19592
Mid	2791	2689	3373	3849	4966
High risk	1142	1343	1401	1493	1482
High-Low	-5351	-6728	-8980	-11861	-18110
Panel 3D. Credit rating					
Low risk	3799	4232	6549	9857	16290
Mid	1564	1759	2162	2705	3691
High risk	1000	1092	1176	1452	1532
High-Low	-2799	-3140	-5373	-8405	-14758

TABLE 3. Value effect controlled by distress risk and size

This table reports statistics of triple-sorted portfolios of stocks ranked on their market capitalization, book-to-market ratios and distress risk for the 1,500 largest U.S. stocks from September 1991 until December 2009. Each month, stocks are sorted into terciles based on their market capitalization. Then, for each size portfolio, stocks are sorted into terciles based on their distress risk as measured by debt-to-assets ratio, distance-to-default, credit spread or credit rating. Next, the small-, mid- and large-cap portfolios with similar risk are merged. Finally, for each tercile portfolio stocks are further sorted into quintiles based on their book-to-market ratio (B/M). Portfolio returns are computed by weighting equally the firms. Panel 1 reports median risk characteristics and Panel 2 annualized returns.

	High B/M	2	3	4	Low B/M
Panel 1. Risk					
Panel 1A. Debt-to-assets					
Low risk	0.10	0.10	0.08	0.07	0.04
Mid	0.28	0.27	0.27	0.26	0.26
High risk	0.43	0.43	0.44	0.44	0.55
High-Low	0.33	0.33	0.35	0.37	0.51
Panel 1B. Distance-to-default					
Low risk	11.2	11.9	12.8	13.5	14.5
Mid	6.5	6.8	7.1	7.5	7.5
High risk	3.0	3.5	3.7	3.8	3.5
High-Low	-8.2	-8.5	-9.1	-9.6	-11.0
Panel 1C. Credit spread					
Low risk	129	118	106	88	77
Mid	200	161	158	150	149
High risk	336	274	268	231	292
High-Low	207	156	162	143	215
Panel 1D. Credit rating					
Low risk	A-	A-	A	A+	A+
Mid	BBB	BBB	BBB	BBB+	BBB+
High risk	BB	BB+	BB+	BB	BB
High-Low	-	-	-	-	-

TABLE 3 (Continued). Value effect controlled by distress risk and size

	High B/M	2	3	4	Low B/M
Panel 2. Annualized returns					
Panel 2A. Debt-to-assets					
Low risk	12.8%	9.7%	10.2%	3.3%	5.0%
Mid	16.2%	10.9%	10.5%	8.0%	9.6%
High risk	12.4%	10.5%	10.1%	7.3%	9.8%
High-Low	-0.5%	0.7%	-0.2%	4.0%	4.7%
Panel 2B. Distance-to-default					
Low risk	13.8%	11.5%	11.1%	8.2%	7.1%
Mid	16.1%	10.5%	11.0%	8.6%	12.0%
High risk	12.9%	12.5%	8.3%	8.0%	5.6%
High-Low	-0.9%	1.1%	-2.8%	-0.2%	-1.5%
Panel 2C. Credit spread					
Low risk	16.0%	12.4%	10.2%	10.4%	9.3%
Mid	13.0%	13.3%	11.5%	10.0%	10.7%
High risk	12.8%	11.0%	5.4%	6.1%	6.7%
High-Low	-3.2%	-1.4%	-4.8%	-4.4%	-2.6%
Panel 2D. Credit rating					
Low risk	14.7%	15.9%	9.6%	11.5%	9.0%
Mid	15.9%	15.5%	10.9%	9.7%	9.1%
High risk	15.1%	9.1%	6.9%	6.9%	8.4%
High-Low	0.4%	-6.9%	-2.7%	-4.6%	-0.6%

TABLE 4. Value effect during different states of the business cycle

This table reports return characteristics of stocks during economic expansions (Panel 1) and recessions (Panel 2) based on the NBER's Business Cycle indicator. The size-neutral risk portfolios are constructed using the procedure outlined in Table 3. Portfolio returns are computed by weighting equally the firms.

	High B/M	2	3	4	Low B/M
Panel 1. Expansions					
Panel 1A. Debt-to-assets					
Low risk	17.9%	13.6%	13.6%	7.8%	10.2%
Mid	20.9%	14.6%	14.7%	12.3%	13.5%
High risk	16.7%	14.9%	14.4%	11.9%	14.4%
High-Low	-1.2%	1.2%	0.7%	4.1%	4.2%
Panel 1B. Distance-to-default					
Low risk	17.6%	14.9%	14.7%	12.2%	11.1%
Mid	19.5%	13.9%	15.5%	12.6%	16.0%
High risk	17.9%	17.9%	13.6%	13.2%	11.8%
High-Low	0.3%	3.0%	-1.1%	0.9%	0.7%
Panel 1C. Credit spread					
Low risk	19.3%	16.5%	14.4%	15.4%	13.1%
Mid	18.8%	18.4%	16.7%	14.7%	14.9%
High risk	18.4%	16.7%	12.9%	12.1%	13.6%
High-Low	-0.9%	0.2%	-1.5%	-3.3%	0.5%
Panel 1D. Credit rating					
Low risk	19.4%	19.5%	13.7%	16.2%	12.3%
Mid	19.9%	19.4%	16.4%	14.1%	13.5%
High risk	20.0%	14.9%	12.6%	13.0%	14.4%
High-Low	0.6%	-4.6%	-1.1%	-3.2%	2.1%

TABLE 4 (Continued). Value effect during different states of the business cycle

	High B/M	2	3	4	Low B/M
Panel 2. Recessions					
Panel 2A. Debt-to-assets					
Low risk	-16.3%	-13.4%	-10.4%	-22.7%	-24.5%
Mid	-11.6%	-11.0%	-14.5%	-17.4%	-13.9%
High risk	-13.3%	-15.4%	-15.2%	-19.4%	-17.4%
High-Low	3.1%	-1.9%	-4.8%	3.3%	7.1%
Panel 2B. Distance-to-default					
Low risk	-9.2%	-9.2%	-11.0%	-15.8%	-16.9%
Mid	-4.6%	-10.1%	-15.2%	-15.5%	-11.9%
High risk	-15.8%	-18.1%	-22.3%	-21.7%	-28.4%
High-Low	-6.6%	-8.9%	-11.3%	-6.0%	-11.5%
Panel 2C. Credit spread					
Low risk	-4.5%	-12.1%	-15.1%	-18.4%	-13.6%
Mid	-19.7%	-16.1%	-18.4%	-17.2%	-13.9%
High risk	-19.4%	-21.2%	-34.2%	-27.4%	-30.3%
High-Low	-14.8%	-9.1%	-19.1%	-9.1%	-16.7%
Panel 2D. Credit rating					
Low risk	-12.9%	-5.8%	-14.6%	-15.8%	-11.3%
Mid	-8.1%	-8.0%	-20.2%	-16.0%	-16.9%
High risk	-13.7%	-23.8%	-25.0%	-26.7%	-25.2%
High-Low	-0.8%	-18.0%	-10.4%	-10.9%	-13.9%

TABLE 5. Fama-MacBeth regression results for the relation value effect and distress risk characteristics

This table reports Fama-MacBeth regression results of stock returns regressed on book-to-market ratios while controlling for market beta, intermediate-term return momentum, short-term return reversal and industries for the 1,500 largest U.S. stocks from September 1991 until December 2009. Each month the following regression is performed:

(3) $r_{i,t} = a_t + b1_t BM_{i,t} + b2_t BETA_{i,t} + b3_t MOM_{i,t} + b4_t REV_{i,t} + \delta_t Z_i + \varepsilon_{i,t}$

where $r_{i,t}$ is the return of stock i in month t, $BM_{i,t}$ is the normalized book-to-market ratio of stock i in month t, $BETA_{i,t}$ is the normalized market beta of stock i in month t estimated using a three-year rolling window using weekly returns and the BMI index as proxy for the market return, $MOM_{i,t}$ is the normalized 11-month one-month lagged past return of stock i in month t, $REV_{i,t}$ is the normalized return of stock i over the past month in month t, and Z_i is a vector containing industry dummies for stock i based on the MSCI/S&P GICS level 1 classification of ten industries. The base case regression in Equation (3) is augmented with our four alternative proxies for distress risk. Panel 1 of Table 5 presents the average coefficient estimates of the different regression models together with their *t*-values computed using Fama-MacBeth standard errors. In addition, the table shows the average adjusted R-squared values of the regressions. Panel 2 presents the results of regressions where the regression models are augmented with the logarithm of market capitalizations (normalized).

	(1)	(2)	(3)	(4)	(5)
Panel 1. Excluding market capitalization as control variable					
Constant	0.84%	0.86%	0.83%	0.82%	0.83%
	2.69	2.82	2.62	2.59	2.60
BM	0.13%	0.13%	0.13%	0.13%	0.13%
	2.42	2.19	2.58	2.55	2.58
MOM	0.07%	0.07%	0.07%	0.07%	0.07%
	0.67	0.66	0.69	0.68	0.70
BETA	-0.03%	-0.05%	-0.04%	-0.05%	-0.05%
	-0.27	-0.43	-0.43	-0.49	-0.46
REV	-0.19%	-0.20%	-0.21%	-0.21%	-0.21%
	-3.22	-3.36	-3.52	-3.51	-3.54
Z	yes	yes	yes	yes	yes
Debt-to-assets		-0.03%			
		-0.52			
Distance-to-default			0.02%		
			0.32		
Credit spread				-0.03%	
				-0.43	
Credit rating					-0.02%
					-0.24
Adj. R2	17.25%	17.55%	18.08%	18.06%	18.08%

TABLE 5 (Continued). Fama-MacBeth regression results for the relation value effect and distress risk characteristics

	(1)	(2)	(3)	(4)	(5)
Panel 2. Including market capitalization as control variable					
Constant	0.85%	0.89%	0.86%	0.84%	0.85%
	2.68	2.89	2.72	2.67	2.68
BM	0.10%	0.08%	0.10%	0.10%	0.10%
	1.96	1.55	2.03	1.95	1.98
Market cap	-0.09%	-0.12%	-0.17%	-0.16%	-0.18%
	-1.39	-1.84	-3.11	-2.77	-2.98
MOM	0.05%	0.05%	0.06%	0.07%	0.07%
	0.54	0.55	0.58	0.69	0.72
BETA	-0.06%	-0.07%	-0.04%	-0.04%	-0.04%
	-0.57	-0.63	-0.38	-0.44	-0.37
REV	-0.20%	-0.20%	-0.21%	-0.21%	-0.21%
	-3.47	-3.50	-3.46	-3.51	-3.51
Z	yes	yes	yes	yes	yes
Debt-to-assets		-0.06%			
		-1.37			
Distance-to-default			-0.03%		
			-0.66		
Credit spread				-0.12%	
				-1.81	
Credit rating					-0.13%
					-1.81
Adj. R2	17.92%	18.09%	18.34%	18.27%	18.31%

TABLE 6. Size effect controlled by distress risk

This table reports statistics of triple-sorted portfolios of stocks ranked on their market capitalization and each of our four measures of distress risk for the 1,500 largest U.S. stocks from September 1991 until December 2009. Each month, stocks are sorted into quintiles based on their market capitalization. Then, for each size portfolio, stocks are further sorted into terciles based on their market capitalization. Then, for each size sub-portfolio stocks are sorted into terciles based on their debt-to-assets ratio, distance-to-default, credit spread or credit rating. Finally, the small-, mid- and large-cap portfolios with similar risk are merged. Portfolio returns are computed by weighting equally the firms. Panel 1 reports median risk characteristics and Panel 2 annualized returns.

	Small	2	3	4	Large
Panel 1. Risk					
Panel 1A. Debt-to-assets					
Low risk	0.04	0.06	0.08	0.10	0.10
Mid	0.26	0.27	0.28	0.27	0.25
High risk	0.47	0.46	0.46	0.43	0.40
High-Low	0.43	0.40	0.38	0.33	0.30
Panel 1B. Distance-to-default					
Low risk	10.2	10.8	11.5	13.1	15.9
Mid	5.3	6.0	6.8	8.0	10.1
High risk	2.5	2.9	3.4	4.3	6.1
High-Low	-7.6	-7.9	-8.1	-8.8	-9.7
Panel 1C. Credit spread					
Low risk	176	133	112	91	68
Mid	281	202	162	130	96
High risk	450	333	252	198	134
High-Low	274	200	140	107	66
Panel 1D. Credit rating					
Low risk	BBB+	A-	A	A	AA-
Mid	BB+	BBB-	BBB	BBB+	A
High risk	BB-	BB	BB+	BBB-	BBB+
High-Low	-	-	-	-	-

TABLE 6 (Continued). Size effect controlled by distress risk

	Small	2	3	4	Large
Panel 2. Annualized returns					
Panel 2A. Debt-to-assets					
Low risk	9.8%	4.9%	7.6%	12.2%	9.0%
Mid	10.4%	12.6%	10.6%	10.5%	9.5%
High risk	12.6%	11.4%	11.0%	8.6%	8.0%
High-Low	2.8%	6.5%	3.4%	-3.6%	-1.0%
Panel 2B. Distance-to-default					
Low risk	11.5%	9.6%	10.9%	11.2%	9.7%
Mid	13.4%	12.0%	12.5%	11.4%	9.4%
High risk	10.6%	11.6%	8.2%	9.2%	7.4%
High-Low	-0.9%	2.0%	-2.7%	-2.0%	-2.3%
Panel 2C. Credit spread					
Low risk	11.9%	13.8%	12.6%	11.5%	8.2%
Mid	15.9%	13.0%	11.6%	11.5%	8.9%
High risk	6.4%	9.4%	7.2%	10.2%	7.3%
High-Low	-5.5%	-4.4%	-5.4%	-1.3%	-0.9%
Panel 2D. Credit rating					
Low risk	15.5%	12.6%	13.0%	11.8%	9.4%
Mid	13.3%	14.4%	10.9%	13.1%	10.7%
High risk	11.5%	8.1%	10.7%	5.8%	7.6%
High-Low	-4.0%	-4.5%	-2.3%	-5.9%	-1.8%

TABLE 7. Size effect during different states of the business cycle

This table reports return characteristics of stocks during economic expansions (Panel 1) and recessions (Panel 2) based on the NBER's Business Cycle indicator. The size-neutral risk portfolios are constructed using the procedure outlined in Table 6. Portfolio returns are computed by weighting equally the firms.

	Small	2	3	4	Large
Panel 1. Expansions					
Panel 1A. Debt-to-assets					
Low risk	13.6%	8.5%	12.4%	17.0%	14.2%
Mid	14.2%	17.0%	14.2%	14.5%	14.3%
High risk	16.4%	16.1%	15.4%	14.0%	12.4%
High-Low	2.9%	7.6%	3.0%	-3.0%	-1.9%
Panel 1B. Distance-to-default					
Low risk	15.0%	13.1%	14.9%	14.6%	13.6%
Mid	16.8%	15.8%	16.3%	16.2%	14.5%
High risk	15.4%	17.4%	13.0%	14.7%	13.1%
High-Low	0.4%	4.4%	-1.9%	0.2%	-0.5%
Panel 1C. Credit spread					
Low risk	16.5%	16.5%	16.1%	15.6%	12.0%
Mid	21.4%	18.0%	17.5%	17.2%	13.5%
High risk	10.8%	15.6%	15.0%	16.9%	13.7%
High-Low	-5.6%	-0.9%	-1.1%	1.3%	1.7%
Panel 1D. Credit rating					
Low risk	18.8%	16.2%	16.7%	17.0%	14.1%
Mid	16.2%	19.0%	15.4%	18.3%	15.8%
High risk	18.3%	13.1%	16.1%	12.4%	13.1%
High-Low	-0.5%	-3.1%	-0.5%	-4.5%	-0.9%

TABLE 7 (Continued). Size effect during different states of the business cycle

	Small	2	3	4	Large
Panel 2. Recessions					
Panel 2A. Debt-to-assets					
Low risk	-12.6%	-16.9%	-20.1%	-15.4%	-20.9%
Mid	-12.2%	-13.5%	-11.2%	-13.4%	-18.3%
High risk	-10.3%	-16.1%	-14.9%	-21.7%	-17.8%
High-Low	2.3%	0.8%	5.2%	-6.3%	3.1%
Panel 2B. Distance-to-default					
Low risk	-9.6%	-11.3%	-13.3%	-9.3%	-13.7%
Mid	-7.1%	-10.8%	-10.7%	-16.3%	-19.8%
High risk	-17.4%	-21.0%	-19.6%	-22.0%	-24.8%
High-Low	-7.8%	-9.6%	-6.4%	-12.7%	-11.1%
Panel 2C. Credit spread					
Low risk	-14.9%	-3.2%	-8.3%	-13.2%	-14.6%
Mid	-15.8%	-15.8%	-21.7%	-20.7%	-17.8%
High risk	-19.2%	-25.1%	-33.5%	-26.5%	-27.6%
High-Low	-4.3%	-21.9%	-25.2%	-13.4%	-13.0%
Panel 2D. Credit rating					
Low risk	-4.6%	-9.3%	-9.4%	-18.1%	-17.8%
Mid	-4.5%	-12.6%	-15.4%	-16.7%	-18.8%
High risk	-25.5%	-20.7%	-20.3%	-30.0%	-23.4%
High-Low	-20.9%	-11.5%	-11.0%	-11.8%	-5.6%

TABLE 8. Summary statistics and correlations of SMB and HML distress-risk neutral factors

This table presents return and risk characteristics (Panel 1) of the market factor and of the SMB and HML factor with and without distress risk neutrality imposed for each of our four measures of distress risk (Panel 1). The SMB and HML factors are constructed on the 1,500 largest US stocks over the period September 1991 until December 2009 using the methodology as outlined on the webpage of Kenneth French. The risk-neutral factors are constructed by performing a triple sort, where stocks are first sorted into distress risk terciles and next on market capitalization and book-to-price. Panel 2 shows the correlations between factors.

	RMRF	SMB	SMB Debt-to-assets neutral	SMB Distance-to-default neutral	SMB Credit spread neutral	SMB Credit rating neutral	HML	HML Debt-to-assets neutral	HML Distance-to-default neutral	HML Credit spread neutral	HML Credit rating neutral
Panel 1. Summary statistics											
Return (annualized)	4.75%	2.00%	2.16%	2.99%	3.29%	3.70%	3.40%	3.58%	3.49%	3.16%	3.67%
Volatility (annualized)	15.46%	8.71%	9.05%	7.01%	6.67%	8.15%	14.49%	11.71%	11.20%	10.79%	10.75%
Sharpe ratio	0.31	0.23	0.24	0.43	0.49	0.45	0.23	0.31	0.31	0.29	0.34
5th Percentile	-7.78%	-3.82%	-3.80%	-2.63%	-2.74%	-3.04%	-5.15%	-4.83%	-4.55%	-4.87%	-4.46%
25th Percentile	-2.20%	-1.60%	-1.46%	-1.10%	-0.85%	-1.03%	-1.37%	-1.04%	-1.08%	-0.90%	-1.14%
Debt-to-assets		0.00	0.00	-0.04	0.04	0.03	0.09	0.00	0.04	-0.01	0.00
Distance-to-default		-2.8	-2.7	-0.5	-1.8	-1.6	-2.2	-1.8	-0.8	-1.3	-1.6
Credit spread		145	145	85	31	48	-9	-14	-15	7	19
Credit rating (top / bottom)		BB+ / A-	BB+ / BBB+	BBB- / BBB+	BBB / BBB+	BBB / BBB+	BBB / BBB-	BBB / BBB	BBB / BBB	BBB+ / BBB+	BBB / BBB
Panel 2. Correlations											
RMRF	1.00										
SMB	0.26	1.00									
SMB Debt-to-assets neutral	0.34	0.96	1.00								
SMB Distance-to-default neutral	0.05	0.83	0.86	1.00							
SMB Credit spread neutral	-0.17	0.51	0.53	0.71	1.00						
SMB Credit rating neutral	-0.21	0.43	0.47	0.72	0.81	1.00					
HML	-0.08	-0.12	-0.03	0.17	0.39	0.60	1.00				
HML Debt-to-assets neutral	0.04	0.02	0.09	0.19	0.35	0.51	0.92	1.00			
HML Distance-to-default neutral	-0.15	-0.13	-0.07	0.12	0.37	0.56	0.94	0.93	1.00		
HML Credit spread neutral	0.06	0.00	0.08	0.21	0.32	0.55	0.86	0.83	0.82	1.00	
HML Credit rating neutral	0.04	0.04	0.12	0.26	0.37	0.61	0.91	0.89	0.88	0.92	1.00

TABLE 9. Pricing errors for 5x5 portfolios sorted on size and value

This table reports regression results of the 5x5 double-sorted portfolios on market capitalization and book-to-price from the webpage of Kenneth French on the one-factor CAPM model

(4) $r_{i,t} = a + bRMRF_t + \varepsilon_{i,t}$

and the three-factor Fama-French model

(5) $r_{i,t} = a + bRMRF_t + sSMB_t + hHML_t + \varepsilon_{i,t}$.

where $r_{i,t}$ is the return of portfolio *i* at time *t* in excess of the risk-free rate. $RMRF_t$, SMB_t, and HML_t are the returns on Fama and French (1993) factors for respectively market, size, and value at time *t*. The SMB and HML factors are constructed on the 1,500 largest US stocks over the period September 1991 until December 2009 using the methodology as outlined on the webpage of Kenneth French. The risk-neutral factors are constructed by performing a triple sort, where stocks are first sorted into distress risk terciles and next on market capitalization and book-to-price. The table reports the average annualized returns, regression intercepts and their associated *t*-value and adjusted R-squared values. In addition the average and median absolute intercepts and t-values are shown (pricing errors) and adjusted R-squared values.

	Return	CAPM a	CAPM t(a)	CAPM Adj. R2	Fama-French a	Fama-French t(a)	Fama-French Adj. R2	Fama-French risk-neutral (Debt-to-assets) a	t(a)	Adj. R2	Fama-French risk-neutral (Distance-to-default) a	t(a)	Adj. R2	Fama-French risk-neutral (Credit spread) a	t(a)	Adj. R2	Fama-French risk-neutral (Credit rating) a	t(a)	Adj. R2
Small / Low B/M	-0.56%	-7.69%	-1.71	54%	-7.42%	-2.75	80%	-7.51%	-2.22	75%	-8.29%	-2.46	70%	-7.13%	-1.46	57%	-7.57%	-1.66	58%
Small / Value2	11.15%	3.44%	0.89	51%	2.79%	1.09	81%	2.99%	1.05	77%	1.56%	0.55	72%	2.48%	0.56	54%	1.85%	0.47	56%
Small / Value3	12.87%	5.09%	1.59	57%	3.60%	1.67	81%	3.94%	1.93	81%	2.21%	1.16	78%	2.90%	0.90	61%	2.22%	0.85	65%
Small / Value4	15.93%	8.28%	2.29	53%	6.20%	2.40	77%	6.70%	2.62	76%	4.65%	2.10	75%	5.27%	1.61	59%	4.56%	1.68	65%
Small / High B/M	17.17%	9.12%	2.28	56%	5.90%	2.37	80%	6.45%	2.57	80%	4.34%	1.77	76%	5.03%	1.62	66%	4.49%	1.67	70%
Size2 / Low B/M	4.37%	-3.71%	-1.17	65%	-3.70%	-2.22	90%	-3.66%	-1.57	86%	-4.56%	-1.95	82%	-4.26%	-1.34	70%	-4.03%	-1.33	70%
Size2 / Value2	9.52%	1.46%	0.54	68%	-0.28%	-0.20	91%	0.05%	0.03	89%	-1.65%	-1.09	88%	-1.43%	-0.63	76%	-1.33%	-0.63	77%
Size2 / Value3	13.61%	5.66%	1.98	66%	3.09%	2.36	91%	3.61%	2.35	89%	1.60%	1.23	90%	1.51%	0.79	81%	1.62%	0.98	82%
Size2 / Value4	12.46%	4.70%	1.51	62%	1.71%	0.94	86%	2.25%	1.14	84%	0.14%	0.08	86%	0.18%	0.09	78%	0.03%	0.02	82%
Size2 / High B/M	13.06%	5.14%	1.30	58%	1.31%	0.53	85%	2.02%	0.75	83%	-0.49%	-0.20	83%	-0.56%	-0.21	78%	-0.60%	-0.23	80%
Size3 / Low B/M	5.21%	-3.06%	-1.13	70%	-2.42%	-2.08	93%	-2.35%	-1.50	90%	-2.75%	-1.64	87%	-3.24%	-1.36	76%	-2.65%	-1.16	77%
Size3 / Value2	10.48%	2.17%	0.94	77%	0.30%	0.23	90%	0.62%	0.45	89%	-0.71%	-0.50	89%	-1.06%	-0.63	86%	-0.71%	-0.42	86%
Size3 / Value3	13.09%	5.10%	1.92	71%	2.57%	1.63	87%	3.04%	1.79	85%	1.37%	0.85	87%	1.19%	0.73	86%	1.46%	0.83	85%
Size3 / Value4	12.07%	4.41%	1.42	63%	1.49%	0.95	81%	1.99%	1.09	79%	0.31%	0.18	81%	0.14%	0.08	80%	0.23%	0.13	81%
Size3 / High B/M	17.54%	9.53%	2.57	60%	5.98%	2.74	81%	6.44%	2.82	78%	4.69%	2.14	79%	4.79%	2.00	77%	4.87%	2.12	78%
Size4 / Low B/M	9.04%	0.31%	0.12	78%	1.30%	0.95	93%	1.25%	0.67	90%	1.30%	0.69	90%	0.86%	0.34	84%	1.17%	0.48	84%
Size4 / Value2	11.22%	2.95%	1.22	80%	1.04%	0.71	88%	1.34%	0.88	87%	0.14%	0.10	88%	-0.07%	-0.05	88%	0.27%	0.17	87%
Size4 / Value3	10.41%	2.42%	0.82	72%	-0.22%	-0.14	87%	0.12%	0.07	85%	-1.19%	-0.73	86%	-1.26%	-0.72	85%	-1.06%	-0.68	85%
Size4 / Value4	12.69%	4.75%	1.64	70%	2.46%	1.40	82%	2.77%	1.48	80%	1.69%	0.93	80%	1.63%	0.85	80%	1.69%	0.96	81%
Size4 / High B/M	10.28%	2.62%	0.77	61%	-0.83%	-0.45	83%	-0.38%	-0.18	80%	-1.82%	-0.92	81%	-1.35%	-0.69	80%	-1.66%	-0.88	82%
Large / Low B/M	7.86%	-0.29%	-0.18	87%	1.07%	0.94	93%	0.87%	0.76	92%	1.56%	1.27	91%	1.42%	1.07	90%	1.53%	1.21	91%
Large / Value2	10.43%	2.66%	1.63	79%	1.97%	1.57	88%	2.13%	1.54	85%	1.82%	1.40	84%	1.92%	1.41	82%	1.73%	1.29	82%
Large / Value3	8.58%	0.97%	0.45	73%	-0.58%	-0.47	88%	-0.43%	-0.29	84%	-0.94%	-0.67	83%	-0.54%	-0.39	82%	-0.75%	-0.53	83%
Large / Value4	8.13%	1.11%	0.37	58%	-1.16%	-0.78	84%	-0.85%	-0.43	77%	-1.73%	-0.91	77%	-1.29%	-0.67	75%	-1.55%	-0.79	76%
Large / High B/M	9.79%	2.60%	0.80	52%	0.42%	0.17	68%	0.43%	0.18	68%	-0.12%	-0.05	68%	0.49%	0.20	65%	0.47%	0.20	68%
Average abs pricing error		3.97%	1.25	66%	2.39%	1.27	85%	2.57%	1.21	83%	2.07%	1.02	82%	2.08%	0.82	76%	2.00%	0.85	77%
Median abs pricing error		3.44%	1.22	65%	1.71%	0.95	86%	2.13%	1.09	84%	1.60%	0.92	83%	1.42%	0.72	78%	1.55%	0.83	81%

TABLE 10. Pricing errors for decile portfolios sorted on dividend yield

This table reports regression results of the decile portfolios sorted on dividend yield from the webpage of Kenneth French on the one-factor CAPM model

(4) $r_{i,t} = a + bRMRF_t + \varepsilon_{i,t}$

and the three-factor Fama-French model

(5) $r_{i,t} = a + bRMRF_t + sSMB_t + hHML_t + \varepsilon_{i,t}$.

where $r_{i,t}$ is the return of portfolio *i* at time *t* in excess of the risk-free rate. $RMRF_t$, SMB_t, and HML_t are the returns on Fama and French (1993) factors for respectively market, size, and value at time *t*. The SMB and HML factors are constructed on the 1,500 largest US stocks over the period September 1991 until December 2009 using the methodology as outlined on the webpage of Kenneth French. The risk-neutral factors are constructed by performing a triple sort, where stocks are first sorted into distress risk terciles and next on market capitalization and book-to-price. The table reports the average annualized returns, regression intercepts and their associated *t*-value and adjusted R-squared values. In addition the average and median absolute intercepts and t-values are shown (pricing errors) and adjusted R-squared values.

		CAPM			Fama-French			Fama-French risk-neutral (Debt-to-assets)			Fama-French risk-neutral (Distance-to-default)			Fama-French risk-neutral (Credit spread)			Fama-French risk-neutral (Credit rating)		
	Return	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2	a	t(a)	Adj. R2
Low DY	6.51%	-1.94%	-1.10	85%	-1.39%	-0.80	85%	-1.57%	-0.88	85%	-1.24%	-0.72	85%	-1.30%	-0.72	85%	-0.92%	-0.53	85%
DY2	8.90%	0.74%	0.45	85%	0.68%	0.43	85%	0.65%	0.41	84%	0.70%	0.44	84%	0.47%	0.28	85%	0.91%	0.57	85%
DY3	8.56%	0.74%	0.47	74%	0.35%	0.24	79%	0.49%	0.32	77%	0.14%	0.10	76%	0.28%	0.18	75%	-0.02%	-0.01	75%
DY4	10.43%	3.02%	1.42	68%	2.45%	1.37	73%	2.69%	1.39	71%	2.18%	1.19	70%	1.64%	0.88	70%	1.55%	0.91	71%
DY5	8.26%	1.07%	0.42	60%	-0.12%	-0.07	72%	0.11%	0.05	68%	-0.61%	-0.30	68%	-1.05%	-0.48	68%	-0.99%	-0.49	68%
DY6	9.52%	2.64%	1.37	58%	1.97%	1.14	75%	2.17%	1.17	70%	1.84%	1.05	68%	1.84%	0.97	62%	1.68%	0.95	63%
DY7	9.29%	2.08%	0.88	63%	0.63%	0.39	80%	0.88%	0.44	74%	0.20%	0.11	75%	0.39%	0.20	71%	0.20%	0.11	71%
DY8	10.82%	3.78%	1.43	57%	1.80%	1.25	81%	2.15%	1.15	74%	1.35%	0.78	74%	1.49%	0.83	73%	1.39%	0.74	73%
DY9	10.10%	3.45%	1.09	48%	1.15%	0.58	75%	1.40%	0.63	70%	0.43%	0.21	72%	1.23%	0.64	72%	0.50%	0.25	72%
High DY	7.68%	2.04%	0.42	28%	-1.46%	-0.42	58%	-0.90%	-0.24	51%	-2.26%	-0.58	52%	-1.85%	-0.54	62%	-2.70%	-0.71	59%
Average abs pricing error		2.15%	0.90	62%	1.20%	0.67	76%	1.30%	0.67	72%	1.10%	0.55	73%	1.15%	0.57	72%	1.09%	0.53	72%
Median abs pricing error		2.06%	0.99	62%	1.27%	0.50	77%	1.15%	0.54	72%	0.97%	0.51	73%	1.27%	0.59	71%	0.96%	0.55	72%