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Two Essays on Asset Pricing

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ABSTRACT

I examine two different types of market data. First, I examine how distress risk is priced. Previous literature finds mixed results when examining if distress risk is priced in the cross section of returns, depending on whether firm specific or market-wide distress risk proxies are used. We use factor mimicking portfolios to create systematic distress risk factors from idiosyncratic variables. We find that distress risk is priced in the cross section of returns when considered as a systematic risk. We then use a Daniel and Titman (1997) style test to determine if positive returns associated with the loadings on the distress factors are best represented as systematic risk factors or shared characteristics but do not find consistent evidence in support of either theory. Second, I examine how goodwill impairment write-offs are priced. Prior studies find a negative stock price reaction after goodwill impairment write-offs both in the short term and in the long term. In 2002 the FASB rules for accounting for goodwill changed. We examine data from after the rule changes and find that investors continue to perceive goodwill write-offs as negative events in the short term, but contrary to previous studies, we find that investors perceive goodwill write-offs as positive news in the long term. We find that the overall firm performance improves significantly post event. However, firm operating performance only slightly improves after the write-off. The overall firm performance improvements are due to decreased non-recurring charges in the years subsequent to the write-off.

CHAPTER ONE

IS SYSTEMATIC DISTRESS RISK PRICED?

1.1 Introduction

Fama and French (1993) create two systematic factors, SMB and HML, based on size and book to market equity (BTM),and suggest that these are proxies for systematic distress risk factors that capture common variation in returns. However, several studies examine if distress risk is priced and find that distress risk is not priced in the cross section of returns. These studies use idiosyncratic measures of distress risk. We examine distress risk using systematic distress factors and find that it is indeed priced.

Fama and French (1992, 1993) show that small firms command a premium and firms with higher levels of BTM command a premium. Chan and Chen (1991) suggest that the size premium is due to the "marginal" nature of small firms, making them more likely to default. They posit that the return premium associated with size is due to this increased level of distress likelihood. However, Dichev (1998), Griffin and Lemon (2002), and Campbell, Hilscher, and Szilagyi (2008) examine the relation between distress risk and future returns and find that bearing distress risk is not rewarded with higher expected returns. On the other hand, Kapadia (2011) provides evidence that a premium for bearing distress risk does exist in the cross section of returns and that SMB and HML are indeed proxies for aggregate distress risk. Yet Daniel and Titman (1997) and Griffin and Lemon (2002) provide evidence that size and BTM are not proxies for systematic risk of any kind. They suggest that the return differential for SMB and HML is not due to the covariance of stocks with these factors, but instead is due to stocks with shared characteristics moving together. Dichev (1998), Griffin and Lemon (2002), and

Campbell, Hilscher, and Szilagyi (2008) use bankruptcy prediction models as the distress risk proxy. These bankruptcy prediction models are based on firm specific characteristics. Therefore, these models may be examining idiosyncratic distress risk which according to traditional asset pricing theory should not be priced since it can be diversified away. Kapadia (2011) examines aggregate distress risk, and since asset pricing theory expects systematic risk to be priced, it is not surprising that he finds a distress risk premium.

We attempt to add clarity to this puzzle by using both firm-specific and macroeconomic variables as distress risk proxies. We create factor mimicking portfolios for firm-specific variables in order to make the risk systematic. We test our factors singularly and jointly to determine which factors are priced and which combination of factors provides the best model for pricing distress risk in the cross section of returns. We then test if our factor model subsumes SMB and HML or if SMB and HML provide additional explanatory power. Finally, we employ a test similar to Daniel and Titman (1997) to examine if our priced distress factors are a result of covariance of the stock returns with systematic distress risks or if the positive returns are related to the co-movement of stocks with shared characteristics.

Distress risk is the likelihood that a firm will not be able to meet its obligations to its debtors and will therefore fail. Since owning stock represents a residual claim investors generally lose their entire investment when a firm fails. Some firms are considered to have a higher probability of failure than others. Norden and Weber (2009) show that there is a negative relation between credit default swap (CDS) prices and the cross-section of stock returns; as the stock return declines, the CDS price increases, and vice versa. The CDS price is a measure of a firm's probability of default on their bonds. This can also be viewed as measures of a firm's distress risk. As the probability of default increases, the CDS becomes more expensive. Conversely, as the probability of default increases, the stock price decreases, which implies that if the distress risk were to be removed and the stock's price were allowed to return to equilibrium, then the stock price would increase and yield a positive return for any investors willing to carry the additional risk. But the simple fact that there is a significant negative relation between stock prices and CDS prices suggests that distress risk is priced in the cross-section of returns.

From the 1960s through today, the failure rates of firms varies significantly by year. Kapadia (2011) shows that firm failure rates are high during recessions. These facts suggest that there are economy wide factors that contribute to firm failures. Moreover, Campbell, Hilscher, and Szilagyi (2008) find that the returns of distressed firms are lower when the implied market volatility increases. This also suggests that distressed firms are vulnerable to market-wide risk. We hypothesize that some firms are more sensitive to these market-wide risk factors than other firms and therefore carry a greater level of systematic distress risk. Asset pricing theory states that investors who have firms with this increased level of systematic risk in their portfolios should be rewarded with higher expected returns for bearing this risk. Thus, systematic distress risk represents a risk that theoretically should be priced in the cross-section of stock returns.

The traditional CAPM of Sharpe (1964) and Lintner (1965) states that the market proxy captures all systematic risk a firm bears. However, Fama and French (1992,1993) show with their three factor model, which outperforms the CAPM, that there are factors involved in the cross-section of asset pricing other than the systematic risk proxied by the market factor. They suggest that these factors, represented by size and book to market equity (BTM) are due to distress risk. Thus, if their hypothesis is true and SMB and HML represent the premium associated with stock returns' covariance with systematic distress risk, then distress risk is priced in the cross section of returns.

Kapadia (2011) supports this theory by showing that aggregate distress risk is priced and that the empirically motivated factors, size and BTM could indeed proxy for aggregate distress risk. He finds that SMB and HML can predict future business failure rates. He uses tracking portfolios that are created by projecting the growth rate of future business failures onto a set of basis assets. This allows the use of information already priced in current returns to forecast future business failure rates. These tracking portfolios are thus designed to be maximally correlated with future changes in aggregate distress risk factors and also serve as hedging portfolios. The tracking portfolios are expected to have higher returns when business failure rates are expected to increase. He finds that the tracking portfolios have low average returns and significant negative alphas using the CAPM, which suggests that there is a positive premium associated with the aggregate distress risk factor. He further finds that a factor model consisting of solely the market and a distress factor based on his tracking portfolio does as accurate a job pricing returns as the three factor model of Fama and French (1992, 1993), thus providing evidence that SMB and HML are indeed proxies for distress risk.

However, neither Dichev (1998) nor Campbell, Hilscher, and Szilagyi (2008) find that distress risk is priced. Dichev (1998) tests if distress risk is priced by using the Altman (1968) Z-score and Ohlson (1980) O-score to proxy for distress risk. Both the Z-score and the O-score are measures of the probability of bankruptcy based on individual firm characteristics. Dichev (1998) uses subsequent realized returns to proxy for systematic risk. He sorts stocks into deciles based on their Z-score or O-score and measures the subsequent returns by decile. If distress risk is priced then there should be a positive correlation between firms with higher bankruptcy likelihood and future returns, and a monotonic pattern of returns should be evident across the deciles. Using data from 1981 to 1995, he does not find evidence of this relation. In fact he finds the opposite, firms with higher bankruptcy risk earn lower than average returns, however, this pattern is not monotonic across all deciles. No clear pattern emerges using either measure. In addition he examines the relation between BTM and the bankruptcy risk scores and does not find a monotonic relation here either, again suggesting the BTM does not proxy for risk of default.

Campbell, Hilscher, and Szilagyi (2008) create their own measure for predicting default and use this as their proxy for distress risk. Their model is similar to the Altman (1968) Z-score and Ohlson (1980) O-score models but contains some differences in the scaling of key variables and uses a dynamic logit process. However, consistent with Dichev (1998) they also find that financially distressed firms have low average future returns. And they find that the portfolios consisting of the higher probabilities of distress have high market betas and high loadings on SMB and HML and thus negative alphas, again suggesting that distress risk is not priced.

A key difference between these two studies and the Kapadia (2011) paper is that the studies using bankruptcy prediction models for distress proxies are relying on proxies based on individual firm characteristics, while Kapadia (2011) uses a distress proxy based on changes in aggregate distress or a market-wide measure. Traditional asset pricing theory states that firm specific or idiosyncratic risk should not be priced as it can be diversified away. Thus, Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008) may be testing idiosyncratic distress risk while Kapadia (2011) is measuring systematic distress risk. Our analysis considers both systematic and unsystematic measures of distress risk, the former is constructed by converting unsystematic distress risk measures into systematic measures.

We use nine systematic risk factors. We use six unsystematic risk factors from the Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008) studies. Following Fama and French (1993), we convert these unsystematic measures to systematic measure by creating six factor mimicking portfolios based on these firm characteristics. We also examine changes in three different macroeconomic variables.

For our firm-specific distress risk proxies we use the Altman (1968) Z- score and Ohlson (1980) O-score from the Dichev (1998) paper as two of our variables. This score represents the probability of bankruptcy and also represents the general health of the firm. Dichev (1998) shows that these measures have predictive capability for determining default risk. Both are reduced form models; the Altman Z-score uses multiple discriminant analysis, and the Ohlson O-score is a conditional logit model. We do not use the Campbell, Hilscher, and Szilagyi (2008) model for a distress proxy since it too is a reduced form model using a logit process, but instead we incorporate variables from their two key model changes for profitability and leverage. Campbell, Hilscher, and Szilagyi (2008) scale their profitability and leverage variables by total assets at market value instead of the traditional total book assets. They suggest that since market prices incorporate new information more quickly than accounting variables, scaling by total assets at market value allows their profitability and leverage variables to have greater explanatory power.

We therefore use two variables for leverage. The first is total liabilities scaled by total assets and the second is the Campbell, Hilscher, and Szilagyi (2008) version, total liabilities scaled by the sum of total book assets and market equity. We similarly use two variables for profitability. The first is the ratio of net income to total assets and the second is the Campbell, Hilscher, and Szilagyi (2008) version, the ratio of net income to the sum of total book assets and market equity. This gives us a total of six firm-specific risk proxies; the Ohlson O-score, the Altman Z-score, total liabilities scaled by book assets, total liabilities scaled by the sum of book assets and market equity, net income scaled by book assets, and net income scaled by the sum of book assets and market equity. These six unsystematic risk factors are used to create six systematic factor mimicking portfolios.

For our three market-wide distress risk variables we do not use the tracking portfolio of Kapadia (2011). However, we use macro-economic variables that Kapadia suggests are associated with distress risk. Our macro-economic distress risk proxies are change in GDP growth, the risk free rate, and change in amount of credit available for businesses.

Kapadia (2011) shows a strong negative correlation (-.56) between GDP growth and his business failure rate growth measure, and a negative correlation (-.44) between GDP growth and his liability growth measure. This suggests that GDP growth rate is related, at least in part, to aggregate distress.

Kapadia (2011), as well as Altman (1993), finds that a higher risk free rate is associated with greater future defaults, so we use this as our second market-wide distress proxy. This is intuitively appealing as increased costs of credit should impact firms that rely on credit negatively causing a greater number of defaults.

The third macro-economic distress proxy that we use is the availability of credit. Kapadia (2011) shows that failure rates are higher during bad economic times. Bernanke, Gertler, and Gilchrist (1996) suggest that changes in the credit-market conditions can impact the business cycle and that not all firms are impacted the same by changes in the credit-market conditions. Credit availability lessens during economic contractions. Therefore, we use availability of credit to proxy for distress risk associated with changes in the business cycle. This is also intuitively pleasing as the tightening of credit should negatively impact firms that rely on obtaining additional credit to cover their debt obligations causing an increase in defaults.

Our nine systematic risk factors are thus based on firm-specific based distress factors (six proxies) and macroeconomic based distress factors (three proxies). We create six factor mimicking portfolios from the firm-specific measures and examine changes in the three macroeconomic variables. We test these factors, both separately and jointly, to determine which factors are priced in the cross section of returns and which factors subsume the explanatory power of other factors. We next add HML and SMB to our factor model to determine if we are capturing the same information as these proxies capture or if they offer explanatory power beyond our distress proxies. Having shown which distress proxies are priced, the next piece of the puzzle is to determine whether our distress proxies are best represented as systematic distress risk factors or shared characteristics.

While Kapadia (2011) shows that SMB and HML are proxies for aggregate distress risk, prior literature disputes this claim. Griffin and Lemon (2002) explore if book-to-market equity is a proxy for distress risk and/or how it relates to distress risk. Griffin and Lemon (2002) specifically examine the relation between BTM, distress risk and expected returns. Using the Ohlson (1980) O-score as their proxy for distress risk, they find that the O-score does not contain information about distress risk beyond that already contained in the book-to-market equity factor. This paper does not provide evidence in support of BTM being a proxy for systematic distress risk. Instead, it suggests that the premium for BTM is due to the characteristics of the stocks and not covariance with a systematic distress factor.

Daniel and Titman (1997) find evidence that there is no risk factor associated with a firm's level of BTM and that it therefore cannot be a proxy for any type of systematic risk. They further suggest that neither SMB nor HML has a return premium associated with it. Instead they claim that stocks with similar characteristics move together. So, stocks with high levels of BTM covary with other stocks that have high levels of BTM, perhaps because they are in the same industry or are from the same geographical areas. They show this by examining portfolios with similar characteristics but different factor loadings on the Fama and French (1993) factors. They check for differing returns and find none. Once firm characteristics are controlled for, there is no premium associated with the loadings on SMB and HML.

We follow the methodology of Daniel and Titman (1997). Using our priced distress variables as the factors, we test if portfolios that consist of stocks with similar characteristics but different factor loadings have different returns. Since we have made the idiosyncratic characteristics into systematic risk factors, we examine differentiation between the returns with different factor loadings yet similar levels of the characteristic being tested for these variables. Our goal is to determine if the distress proxy is based on firm-specific characteristics or systematic risk that cannot be diversified away.

Our paper is similar to Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008) since we test if distress risk is priced using bankruptcy prediction models, and our paper is similar to Kapadia (2011) since we use aggregate distress proxies to determine if distress risk is priced. However, our main contribution to the existing literature is that by using factor mimicking portfolios to create systematic factors for the firm specific distress variables we show that distress risk is priced in the cross-section of returns. We also examine if the priced factors are due to covariance with systematic risk or if the premium is due to co-movement of stocks with similar characteristics.

The rest of the paper is organized as follows; section two specifies our data, defines our distress risk proxies, and identifies our hypotheses; section three outlines our methodology; section four presents our empirical results; and section five concludes.

1.2 Data and Hypothesis

1.2.1 Data

Our sample is from fiscal years 1965- 2011. We use all stocks listed on the NYSE, AMEX, or NASDAQ with the exception of financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999). Consistent with Fama and French (1993), we remove ADRs, REITs, and UITs using the appropriate share codes from CRSP. We obtain stock returns, number of shares outstanding, and month-end stock prices to calculate firm size from the Center for Research in Security Prices (CRSP). Accounting data is obtained from Compustat. To avoid survivor bias, firms must be listed in Compustat for at least two years to be included. Data for credit availability is obtained from the Flow of Funds document from the Federal Reserve website, and GDP data is obtained from the U.S. Bureau of Economic Analysis website. One month Treasury bill monthly rate data is taken from Wharton Research Data Services (WRDS), which obtains the data from Kenneth French's website.

1.2.2 Distress Risk Proxies

We use both economy wide variables and idiosyncratic firm characteristics as distress risk proxies. The idiosyncratic distress risk characteristics are proxies for leverage, firm health, (this is measured by both the Ohlson (1980) O-score and the Altman (1968) Z-score) and firm performance. The economy wide elements are proxies for the cost of credit, the availability of credit, and the general economic conditions.

We define leverage in two ways: total liabilities scaled by total book assets, and total liabilities scaled by the sum of total book assets and total market capital. Total market capital is the absolute value of the firm's price times the number of shares outstanding. Both of these are scaled to be in millions of dollars. This proxy is a measure of the firm's level of debt. The higher the relative debt level, the harder it will be for the firm to meet its debt obligations.

The O-score is a measure of a firm's probability of default. Thus, the higher the O-score value, the greater the probability of default. We use this as a proxy for the firm's overall health, so the lower the O-score, the healthier the firm. We calculate the O-score using the following formula:

$$
\begin{aligned}
&-1.32 - 0.407 \text{ x } \log(total\ assets) + 6.03\ \times \frac{(total\ liabilities)}{(total\ assets)} - 1.43 \\
&\times \frac{(working\ capital)}{(total\ assets)} + 0.076\ \times \frac{(current\ liabilities)}{(current\ assets)} - 1.72 \\
&\times (1\ if\ total\ liabilities > total\ assets, 0\ otherwise) - 2.37 \\
&\times \frac{(net\ income)}{(total\ assets)} - 1.83\ \times \frac{(funds\ from\ operations)}{(total\ liabilities)} + .285 \\
&\times (1\ if\ a\ net\ loss\ for\ the\ last\ two\ years,\ \ 0\ otherwise) - .521 \\
&\times \frac{(net\ income_t) - (net\ income_{t-1})}{|net\ income_t| + |net\ income_{t-1}|}
\end{aligned}
\tag{1}
$$

where total assets, total liabilities, current liabilities, current assets, and net income are taken directly from Compustat. Working capital is defined as current assets minus current liabilities. Funds from operations are defined as pre-tax income plus depreciation and amortization.

The other measure of a firm's health that we use is the Altman (1968) Z- score. This is a default measure similar to the Ohlson's O-score, but instead of measuring probability of default it measures the likelihood that a firm will not default, in other words it measures the firm's health. Thus, the higher the Z- score, the healthier the firm. The Z-score is calculated using the following formula:

$$1.2 \times \frac{(working\ capital)}{(total\ assets)} + 1.4 \times \frac{(retained\ earnings)}{(total\ assets)} + 3.3 \times \frac{(earnings\ before\ interest\ and\ taxes)}{(total\ assets)} + 0.6 \times \frac{(market\ value\ of\ equity)}{(book\ value\ of\ total\ liabilities)} + \frac{(sales)}{(total\ assets)} \tag{2}$$

where total assets, retained earnings, earnings before interest and taxes, market value of equity, book value of total liabilities, and sales are all taken directly from Compustat. Working capital is defined as current assets minus current liabilities. The firm's health is critical to the firm's ongoing ability to continue to meet its debt obligations.

Firm performance is measured in two ways. We use the ratio of net income to total assets, and the ratio of net income to the sum of total book assets and market equity. This proxy provides information regarding the firm's current success at generating profits and thus the immediate ability to meet its debt obligations.

Cost of credit is proxied by the one month U.S. Treasury bill rate. This variable is a proxy for the aggregate cost of credit. As credit costs increase, a firm's debt costs will increase. While firms will generally pay a much higher interest rate to obtain credit than the one month U.S. Treasury bill rate, this serves as a good proxy for changes in aggregate credit costs.

We use quarterly data for credit market instruments (liabilities) from the Flow of Funds Accounts of the United States (document Z.1) for nonfinancial corporate businesses to proxy for credit availability. We calculate the quarterly rate of change, which provides us with a stationary data set for the proxy. As credit is harder to obtain, firms that rely on credit will have increased distress probabilities.

General economic conditions are proxied by the quarterly percent change from the preceding period in real gross domestic product (GDP). This proxy provides information about the aggregate economic conditions. As the entire economy weakens, firms will have a harder time generating profits and thus a harder time covering their debt obligations.

1.2.3 Hypotheses

Our main hypothesis is that distress risk is priced in the cross-section of returns. We expect to see a relation between our distress proxies based on macroeconomic variables and returns since the macroeconomic variables represent market-wide or systematic risk. However, previous literature shows that the proxies based on firm-specific variables are not priced in the cross-section of returns and are therefore not representative of systematic risk. Surprisingly, both Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008) find a partial relation between distress risk and price, but the relation is the opposite of expectations; higher bankruptcy risk is associated with lower than average returns. We transform the distress proxies based on idiosyncratic firm characteristics into systematic risk proxies via factor mimicking portfolios following Fama and French (1993) in order to establish if these characteristics are indeed representative of shared risk factors. Our expectation is that they are, however it is possible that they may simply proxy for the macroeconomic based distress risk factors. Thus, our multivariate tests should determine which variables do the best job of representing systematic distress risk.

As previously identified by Daniel and Titman (1997), if firms that have shared characteristics have stock returns that move together, than it would be feasible that a premium would appear to be associated with an idiosyncratic distress proxy when the distress proxy is not representative of systematic risk. For example, if firms that have the same likelihood of default have returns that move together, this would appear as a distress risk premium that could be captured by a default probability model. We address this potentiality with a test based on Daniel and Titman (1997) discussed in more detail later.

Our three macro-economic based proxies are proxies for cost of credit, availability of credit, and general economic conditions. The cost of credit is relevant to all firms that rely on credit for funding all or part of their operations. The greater the cost of credit, the more difficult it is for firms to cover their debt obligations. Since firms have different capital structures and differ in their reliance on credit, we expect that firms will differ in their covariance with this macroeconomic variable. As credit costs increase, firms that rely on credit will have an increase in their default probability. Therefore we expect that firms with higher sensitivities to the cost of credit proxy will have lower prices and therefore higher expected returns.

The availability of credit is relevant to all firms that rely on obtaining additional credit for ongoing operations. Firms that have little, or no need for credit will not be sensitive to changes in credit availability. However, firms that rely heavily on additional credit will covary closely with changes in the credit availability. As credit conditions tighten, these firms will have an increased probability of default and their prices will decrease. Thus, we expect that firms that have higher sensitivities to this proxy will have lower prices and therefore higher returns.

The final macroeconomic distress proxy that we test is the change in GDP rate. As the GDP rate decreases, this is indicative of tougher times for all firms. All firms would have a tougher time generating profits but firms that are closer to bankruptcy would be more vulnerable to a contracting economy. Thus, we expect that firms which have higher sensitivities to this factor will have lower prices and higher returns. This hypothesis is consistent with Kapadia (2011) who finds a strong positive correlation between GDP growth rate and lagged market returns. This hypothesis is also consistent with Vassalou (2003) who finds that in a factor pricing model news about future GDP growth subsumes the explanatory power of SMB and HML

Our hypothesis for the systematic distress risk proxies based on the factor mimicking portfolios created from the default probability models (O-score and Z-score) is that the greater the level of sensitivity to the default probability the higher the return. Since the O-score measures probability of default, we expect that firms with a higher sensitivity to this factor mimicking portfolio have higher expected returns. The Z-score on the other hand, is a measure of the firm's health, thus, we expect that firms with lower expected returns will load positively on this factor and firms with greater distress risk and consequently higher returns will load more negatively. This is not consistent with the Dichev (1998) or the Campbell, Hilscher, and Szilagyi (2008) studies. However, they use sorts based on the idiosyncratic firm characteristic and do not create factors representing sensitivity to shared risk. It is also inconsistent with Kapadia (2011) who finds that firms with elevated default likelihood are not sensitive to aggregate distress risk. Kapadia (2011) suggests that this is due to the inability of default probability models to incorporate the varying costs of distress.

Our expectations for the systematic distress risk proxies created from factor mimicking portfolios based on profitability are that firms that have greater sensitivities to profitability will have lower returns. The more profitable a firm is, the less they need to rely on outside financing and the more likely they are to be able to fulfill all debt obligations using internally generated funds. Thus, they have less distress risk. We do not expect that both profitability proxies will be significant in our multivariate regressions. We expect that one will subsume the other since they are two different methods of measuring the same thing. We determine which of these methods does a superior job pricing distress risk.

Our hypothesis for the distress proxies created from the level of leverage is that firms that have higher loadings on this factor will have higher returns. Firms that utilize greater levels of leverage in their capital structure have more onerous debt obligations and will consequently have a tougher time fulfilling those obligations. Thus, we expect that firms with greater sensitivities to leverage will have greater probabilities of distress and therefore higher levels of distress risk and higher expected returns. Again, we do not expect that both leverage proxies will be significant in out multivariate regressions. One should subsume the explanatory power of the other since they measure the same phenomenon.

Our final test is a Daniel and Titman (1997) type of test to determine if each of our priced distress risk proxies is indicative of systematic risk or if its premium is due to co-movement of stocks with common characteristics. Our hypothesis is that the relation of returns with each of the priced macroeconomic based distress risk proxies is due to systematic risk. The macroeconomic based variables are not based on firm specific characteristics so it is unlikely that return premiums based on sensitivity to macroeconomic based distress proxies are due to co-movement of stocks with shared characteristics.

Our hypothesis is that the relation of returns with each of the priced firm-specific based factor mimicking portfolios is that they too are due to systematic risk. The firm-specific based variables are based on idiosyncratic characteristics, however if our factor mimicking portfolios show that these distress proxies are priced, then if stocks are rationally priced, these proxies must represent some shared undiversifiable risk.

We make no assumptions about whether the size and BTM factors are proxies for distress risk. Although we do hypothesize that if size and BTM do indeed proxy solely for systematic distress risk, then our factor model will subsume their explanatory power.

1.3Methodology

1.3.1 Factor Mimicking Portfolios

We make factors for each of our idiosyncratic distress risk variables by creating factor mimicking portfolios following Fama and French (1993). The factor is the average premium that the risk or characteristic commands. We create our portfolios based on size and then the variable of interest to ensure that we have portfolios that contain stocks from firms of different sizes.

We measure the level of our variable being tested for all firms in our sample at the end of each fiscal year *t*-1. Size measurements used in the construction of our variables are taken at the end of December of year *t*-1. Consistent with Fama and French (1993) we require that firms be listed on Compustat for at least two years to be included in the factor mimicking portfolio in order to avoid survival bias. We winsorize the data at the 1% and 99% to remove extreme outliers. The summary statistics for our six idiosyncratic variables are shown in Table 1. We then follow the Fama and French (1993) sorting procedure to create the factor mimicking portfolios.

We start by sorting stocks into two size groups, big and small for each year based on the annual median size. We sort all stocks into the size groups based on NYSE breakpoints measured at the end of June of year *t*. Using only NYSE stocks ensures a more even distribution of stocks across both groups. We then place all stocks into their appropriate group, S or B, for small or big respectively using size measured at the end of June of year *t*.

Table 1: Summary Statistics for Idiosyncratic Variables

Accounting data is from Compustat. Size data is from CRSP. This data is for all U.S. firms listed on the NYSE, AMEX, or NASDAQ, excluding financial firms, utilities, ADRs, REITs, and UITs. The data is for fiscal years 1965 to 2012. Firms must be listed in Compustat for at least two years to be included. All accounting data is obtained at the end of fiscal year *t*-1 and market equity is measured at the end of December in year *t*-1. O-score is a measure of default probability from the Ohlson (1980) model. Higher values of the O-score represent a higher probability of default. Z-score is a measure of default probability from the Altman (1968) model. Higher values of Z-score represent a lower probability of default. Leverage1 is defined as total liabilities scaled by total assets. Leverage2 is total liabilities scaled by the sum of total book assets and market equity. Performance1 is defined as the ratio of net income to total assets, and Performance2 is the ratio of net income to the sum of total book assets and market equity. All variables are Winsorized at 1% and 99%. Stars are used to indicate statistical significance level for the t-statistic. Three stars indicate significance at the 1% level, two stars indicate significance at the 5% level, and one stat indicates significance at the 10% level.

	Number of Observations	**Mean**	**T-statistic**		**Standard Deviation**	**P5**	**P50**	**P95**
O-score	109579	-1.3963	-169.87	***	2.72	-5.59	-1.51	3.03
Z-score	107869	5.3060	259.11	***	6.73	0.41	3.66	15.95
Leverage1	109647	0.4643	704.84	***	0.22	0.12	0.46	0.83
Leverage2	108038	0.2612	473.28	***	0.18	0.03	0.23	0.61
Performance1	109603	0.0111	21.84	***	0.17	-0.31	0.05	0.16
Performance2	108038	0.0062	30.28	***	0.07	-0.12	0.02	0.06

After doing the sort on size, we further sort the size portfolios into three additional groupings based on the level of the variable being tested. All accounting data is obtained at the end of the fiscal year *t-1*. This gives us six portfolios with differing levels of size and our distress variable.

For the firm-specific characteristic FMPs, a stock will remain in the same size and distress variable portfolio for an entire year. Monthly returns are measured from July of year *t* to June of year *t+1*. Each year the portfolios are recalculated based on new levels of size and the distress variable. Every month the value-weighted returns are calculated for each portfolio. Weights are calculated using size measured in June of year *t*. The factor is simply the average premium that each variable commands. We want to ensure that we have a mix of small and large stocks and are not simply capturing the size premium, so we take a simple average of the value-weighted returns from the two portfolios that have a high distress proxy level or sensitivity minus value-weighted returns from the two portfolios that have a low distress proxy level or sensitivity using the following equation

$$[(SH + BH)/2] - [(SL + BL)/2] \tag{3}$$

where S and B refer to the size portfolios small and big, respectively, and H and L refer to the portfolios with high and low, respectively, factor loadings on the distress proxy being evaluated.

By creating a factor mimicking portfolio based on our firm-specific distress proxies we can capture variation in returns related to the variable being evaluated. The factor mimicking portfolio provides the average return associated with each of our firm-specific distress proxies and allows this variable to be treated as a shared risk. Following Fama and French (1993) we use a time-series regression of monthly returns on the factor mimicking portfolio to obtain the stock's sensitivity to this shared risk factor. The sensitivity, or factor loading, allows us to treat the idiosyncratic firm characteristic variable as if it were a systematic risk.

1.3.2 The Macro-Economic Variables

For the macro-economic variables, we have no need to create factor mimicking portfolios as these already impact firms systematically. We simply employ the macro-economic variable in a regression using the following formula.

$$R_{it}- R_{f,t} = \alpha_i + \beta_i(MKT_t-R_f) + \lambda_i FCT_t + \varepsilon_{i,t} \tag{4}$$

where R_{it}- R_{f} ,is the monthly excess return on the portfolio, $MKT-Rf_t$ is the monthly market factor, β_i is the estimated sensitivity of the stock to the market factor, FCT_t is the macro-economic variable we are testing, and λ_i is the coefficient estimate or loading on the macro-economic variable. For the macro-economic variables where we only have quarterly changes, we run the regression monthly and update the returns and market factor monthly, but the macro-economic variable's value is only updated quarterly.

1.3.3 The Dependent Variables

Once we have created factors for each of our distress risk variables, we then test how well each of these factors performs pricing stocks. We test them singularly and in combination to determine the best model. We use a time-series average approach again following Fama and French (1993). Our portfolios to be tested, the dependent variables, are excess monthly returns from the 25 portfolios that Fama and French (1993) create based on size and BTM, however our portfolios exclude financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999)[1].

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[1] I replicated the creation of twenty-five portfolios split on size and BTM as described by Fama and French (1993) and compared my results to theirs. I then used this SAS code but removed financial firms and utilities and adjusted the dates. While my results did not match theirs perfectly it was close enough to feel confident that my code was correct.

These portfolios represent a disperse mix of size and BTM stocks. Tables 2 and 3 display the summary statistics for our 25 portfolios. We then perform monthly regressions using the monthly factors from the factor mimicking portfolios and the market factor as the explanatory variables.

1.3.4 Performance Tests

We measure how well our factors perform by examining the significance of the coefficient estimate on our distress factor. It should be significantly different from zero and be of the sign expected by our hypotheses. We run both univariate regressions and multivariate regressions. We use the adjusted R-squared values of our regression to determine which set of factors offers the best fitting model. In addition to the coefficient estimates and R square values, we also examine the intercepts of each regression. If the factors from the factor mimicking portfolios are doing a good job pricing the disparate portfolios then the intercepts should be close to zero.

We then add SMB and HML to our model and test if they add any explanatory power, and if their coefficient estimates remain significant with the distress proxies in the model. We test different combinations of factors to determine the best factor model for pricing stock returns.

1.3.5 Risk vs. Characteristic Testing

We then test if each of these priced distress factors is truly acting as a proxy for distress risk or if they are representative of co-movement of stocks with similar characteristics. We follow the procedure of Daniel and Titman (1997). If our distress factors are proxies for systematic distress risk then we expect that stocks with high levels of the distress proxy (the firm characteristic), that also have a low loading on the distress factor (the factor mimicking portfolio) should have a low average return. However, if the co-movement of prices with our distress factors is due to firm

Table 2: Descriptive Statistics for 25 Portfolios Formed on Size and BTM

These portfolios are comprised of all stocks on the NYSE, NASDAQ, and AMEX from fiscal years 1965 to 2011.We exclude financial firms, utilities, ADRs, REITs, and UITs. Firms must be listed on Compustat for at least two years to be included. Book value data is from Compustat and is measured at the end of fiscal year *t* -1. Market equity data is taken from CRSP and is measured at the end of December of year t-1 for BTM and is measure at the end of June of year *t* for size. Stocks are split into quintiles based on size and quintiles based on their BTM level. Breakpoints for the quintiles are based solely on NYSE stocks. The 25 portfolios are created as the combination of the independent sorts on BTM and size. Stocks remain in a portfolio for an entire year.

	Book to Market Equity Quintiles									
Size Quintile	Low	2	3	4	High	Low	2	3	4	High
	Average of annual averages of firm size					Average of annual BE ratios for portfolio				
Small	72.9	71.9	70.5	65.1	49.5	0.23	0.48	0.69	0.96	1.93
2	286.3	286.4	284.1	281.3	275.3	0.25	0.48	0.69	0.95	1.82
3	660.2	651.7	660.5	647.2	655.3	0.24	0.47	0.68	0.95	1.64
4	1651.5	1631.3	1573.4	1572.5	1582.9	0.24	0.47	0.68	0.94	1.58
Big	15302.2	12262.7	10457.2	9689.8	8944.5	0.24	0.47	0.68	0.94	2.42
	Average of annual percent of market value in portfolio					Average of annual number of firms in portfolio				
Small	0.44	0.37	0.39	0.45	0.58	193	163	179	227	373
2	0.77	0.63	0.64	0.61	0.50	97	80	80	77	64
3	1.47	1.24	1.08	0.88	0.69	79	67	57	47	35
4	3.53	2.68	2.09	1.78	1.17	76	57	45	37	23
Big	34.88	16.41	11.22	9.65	5.86	84	52	36	28	18

Table 3: Return data for 25 portfolios Formed on Size and BTM

These portfolios are comprised of all stocks on the NYSE, NASDAQ, and AMEX from fiscal years 1965 to 2011.We exclude financial firms, utilities, ADRs, REITs, and UITs. Firms must be listed on Compustat for at least two years to be included. Book value data is from Compustat and is measured at the end of fiscal year *t* -1. Market equity data is taken from CRSP and is measured at the end of December of year t-1 for BTM and is measured at the end of June of year *t* for size. Stocks are split into quintiles based on size and quintiles based on their BTM level. Breakpoints for the quintiles are based solely on NYSE stocks. The 25 portfolios are created as the combination of the independent sorts on BTM and size. Stocks remain in a portfolio for an entire year. Value weighted monthly returns (in percent) are calculated for each portfolio from July of year *t* to June of year *t* +1. Mean returns for each portfolio are shown in the upper left panel and standard deviations are shown in the upper right panel, The t-statistics and significance level for the mean returns are shown in the lower left panel. The stars indicate statistical significance, with three stars indicating significance at the 1% level, two stars at the 5% level, and one star indicates significance at the 10% level.

	Book to Market Equity Quintiles										
Size Quintile	Low	2	3	4	High	Size Quintile	Low	2	3	4	High
	Means						Standard Deviations				
Small	0.78	1.11	1.18	1.24	1.49	Small	8.80	7.66	7.04	6.54	6.61
2	0.60	0.96	0.91	1.04	1.07	2	8.05	6.93	6.42	6.37	6.63
3	0.53	0.84	0.95	1.03	1.13	3	7.49	6.41	6.07	5.99	6.27
4	0.62	0.67	0.74	0.87	0.95	4	6.68	5.88	5.74	6.13	6.51
Big	0.42	0.61	0.55	0.53	0.81	Big	5.01	4.74	4.91	5.01	5.62
	t- statistics for Means										
Small	2.09 **	3.45 ***	3.97 ***	4.50 ***	5.35 ***						
2	1.76 *	3.28 ***	3.37 ***	3.89 ***	3.84 ***						
3	1.69 *	3.12 ***	3.72 ***	4.07 ***	4.27 ***						
4	2.19 **	2.73 ***	3.06 ***	3.37 ***	3.48 ***						
Big	2.00 **	3.05 ***	2.68 ***	2.54 **	3.43 ***						

characteristics, then we expect that stocks with high levels of the distress proxy that also have a low loading on the distress factor should have high average returns because the factor loading should be irrelevant. We test this by creating portfolios that have similar levels of the distress proxy characteristic but different distress factor loadings.

We start by sorting all stocks into three groupings based on the firm-specific characteristic being tested and three size groupings, yielding nine groups. Again, we use only NYSE stocks to determine our distress proxy and size breakpoints to ensure an even distribution of stocks across portfolios. We create breakpoints at 33.3% and 66.6% to give us three portfolios based on our distress proxy, L, M, and H, and three portfolios based on size, S, M, and B. We measure size at the end of June of year *t* and the distress proxy at the end of year *t-1.* Stocks remain in the same portfolio from July of year *t* to June of year *t+1.* We then create nine portfolios based on the independent sorts on the distress proxy and size. These are our characteristic-based portfolios.

In order to obtain different factor loadings for stocks with similar characteristics, we then split each of our nine characteristic portfolios into five sub-portfolios based on the individual stock's pre-formation factor loading on the distress factor being tested. We use the following regression equation to obtain the coefficient estimates for the distress factor.

$$R_{it} - R_{f,t} = \alpha_i + \beta_i(MKT_t - R_f) + \lambda_i FCT_t + \Upsilon_i SMB_t + \pi_i HML_t + \varepsilon_{i,t} \qquad (5)$$

where R_{it} is the monthly return of stock *i* at time *t,* R_f is the risk free rate, α is the intercept, β is the coefficient estimate on the market factor, λ is the coefficient estimate on the distress factor, Υ is the coefficient estimate on the SMB factor, and π is the coefficient estimate on the HML factor. We run this regression for each stock in the nine portfolios for the period -42 to -7 months prior to June of year *t*. We require that each of the observations used have 36 months of data for the preformation factor loadings. We put the stocks into five sub-portfolios based on the coefficient estimate for the distress factor, λ so that each of the nine portfolios based on the distress proxy and size is sorted in to five sub-portfolios based on the pre-formation distress factor loading, giving us a group of portfolios that have common characteristics but have different factor loadings. This gives us a total of 45 portfolios, five for each three-way sort.

We calculate a monthly value-weighted return for each of the 45 portfolios and then obtain the time-series mean return. If the distress factor we are testing is truly a proxy for systematic risk then the factor loadings matter and should compensate for the returns. We expect to see a monotonic pattern of returns across our five sub-portfolios for each of our nine portfolios. The portfolios with the lowest pre-formation factor loadings should have the lowest returns. However, if the distress factor is simply representative of common characteristics, then the factor loadings should not matter. The stocks that are sorted based on the characteristic level should all move together and the factor loading sorts become irrelevant. If this is the case, then there should be no discernible pattern among the returns of the five sub-portfolios.

Using the full time-series of returns post-formation, we estimate a regression of the monthly excess return for each of the 45 portfolios on the market factor, SMB, HML, and our distress factor. By design, there should be a monotonic, or near monotonic, pattern of the coefficient estimate on our distress factors across the five characteristic based portfolios based on the pre-formation factor loadings. This allows us to have portfolios that have the same level of the distress proxy yet have different factor loadings on the distress proxy factor. We examine the intercepts from the regression. If the factor loadings are relevant than the intercepts should be indistinguishable from zero, but if the factor loadings are not relevant then the intercepts of the low factor loading portfolios should be positive and the intercepts of the high factor loading portfolios should be negative.

We then create our “long-short” portfolios for our primary test of risk versus characteristics. Within each of the nine portfolios, we go long the lowest two loading portfolios, portfolios one and two, and we short the highest two loading portfolios, portfolios four and five. We calculate this by summing the monthly value-weighted excess returns from portfolios four and five and subtracting this from the summation of the monthly value-weighted returns from portfolios one and two. We calculate the mean returns for each of the nine long-short portfolios. We also combine the nine portfolios to form one characteristic balanced portfolio by taking an equal-weighted average of the nine long-short portfolio returns.

We expect that the average returns from these long-short portfolios are indistinguishable from zero if characteristics dominate the covariance with the distress proxy. Within each of the nine portfolios the characteristics are similar and only the factor loadings differ from the low to the high portfolios. If only the characteristics are relevant to returns and the factor loadings are irrelevant, then the long portfolio should have the same mean return as the short portfolio making the long-short portfolio mean return zero. Conversely, if the distress factors proxy for systematic risk, then the factor loadings are relevant to returns and the long portfolio should have returns that are different from the short portfolio returns, making the mean return for the long-short portfolio statistically different from zero. The two high loading portfolios, which we short, should have higher returns than the two portfolios that load the lowest on the distress proxy, which we long, thus our long-short portfolio should have negative returns if the factors are relevant.

We estimate a regression of the returns from our nine long-short portfolios and our characteristic-balanced portfolio on our distress proxy, SMB, HML, and the market factor. We examine the regression intercepts. If the distress factor is due to systematic risk, then the factor loading matters and we should see an intercept that is statistically indistinguishable from zero. However, if the covariance with the distress factor is due to shared characteristics and not systematic risk, we expect that the intercepts will be positive.

We perform this test for the distress factors that we determine to be priced in the cross section of returns to determine which of these factors are indeed proxies for systematic distress risk, and which factors appear priced due to stocks with common characteristics moving together. Again, our expectation is that all our priced distress proxies are representative of systematic risk and not due co-movement of stocks with similar characteristics.

1.4 Results

1.4.1 Are The Distressed FMPs Priced?

We begin by examining which of our distress proxies are priced in the cross section of returns. We estimate regressions of the time series mean returns from twenty-five portfolios on our distress FMP and the market factor and examine the coefficient estimates on our distress factor, the regression intercepts, and the R-square value of the regression. If the distress proxy is priced, we expect that our coefficient estimates for the distress factor are significant and we expect that the regression intercepts are statistically indistinguishable from zero. We start with the O-score factor.

The O-score FMP regressions, results shown in Table 4 have coefficient estimates that are significantly different from zero at the 1% level for the majority of the portfolios. Only three

Table 4: Regression Results for O-score FMP

This table shows the results from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the O-score factor mimicking portfolio for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t\text{- }Rf_{,t} = \alpha + \gamma\ (MKT_t\text{-}Rf_t) + \delta FCT_t + \varepsilon_{i,}$$

Where δ is the estimated coefficient on the O-score factor mimicking portfolio and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R squares. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles				
	Low	2	3	4	High		Low	2	3	4	High
Size Quintile	δ					Size Quintile	t(δ)				
Small	1.09	0.97	0.97	0.92	1.07	Small	9.32 ***	10.42 ***	11.31 ***	11.50 ***	11.69 ***
2	0.59	0.68	0.69	0.77	0.88	2	6.07 ***	10.04 ***	9.82 ***	9.55 ***	8.73 ***
3	0.43	0.48	0.54	0.62	0.79	3	5.52 ***	6.77 ***	8.96 ***	8.82 ***	9.30 ***
4	0.14	0.37	0.37	0.50	0.66	4	2.13 **	6.77 ***	5.57 ***	5.14 ***	7.04 ***
Big	-0.33	-0.12	-0.05	0.13	0.38	Big	-6.16 ***	-3.30 ***	-0.79	1.66 *	4.80 ***
	α						t (α)				
Small	-0.02%	0.40%	0.51%	0.62%	0.87%	Small	-0.11	2.45 **	3.57 ***	4.68 ***	6.28 ***
2	-0.15%	0.29%	0.29%	0.43%	0.45%	2	-0.88	2.21 **	2.43 **	3.53 ***	3.24 ***
3	-0.17%	0.22%	0.36%	0.45%	0.53%	3	-1.14	1.98 **	3.26 ***	3.90 ***	4.10 ***
4	-0.01%	0.09%	0.18%	0.28%	0.34%	4	-0.11	1.03	1.81 *	2.44 **	2.54 **
Big	-0.02%	0.16%	0.13%	0.09%	0.33%	Big	-0.26	2.38 **	1.21	0.81	2.39 **
	R^2										
Small	0.70	0.73	0.76	0.76	0.74						
2	0.75	0.80	0.80	0.79	0.75						
3	0.77	0.83	0.82	0.80	0.76						
4	0.82	0.86	0.82	0.80	0.75						
Big	0.86	0.88	0.74	0.72	0.65						

portfolios have coefficient estimates that are not significant at the 1% level. The coefficient estimates on the O-score FMPs follow a perfectly monotonic pattern with respect to size. The smallest firms have the highest loadings on the O-score FMP in every BTM level and the largest firms have the lowest loadings. Since our twenty-five portfolio returns follow a pattern where the smallest firms have the largest returns and the largest firms have the smallest returns, the results are consistent with our hypothesis that the portfolios that load higher on the O-score distress risk proxy will have higher returns. It is also supportive of size being a proxy for distress risk and consequently that the Fama and French (1993) SMB factor is a proxy for distress risk.

There is also a pattern with respect to BTM levels. For all but the smallest firms, this pattern is monotonic, where the firms with the highest BTM levels and therefore the highest returns have the highest coefficient estimates on the O-score FMP. Again, this is consistent with our hypothesis that distress risk is priced.

The R-square values range from 65% to 88%. This suggests that 65% to 88% of the variation in the portfolio returns is captured by our model. Eight of the twenty-five portfolios have values for the intercept that are statistically different from zero at the 1% significance level. This suggests that some portfolios exhibit a bias not captured by our model, but the majority of the portfolios do not. These results are all consistent with our hypothesis that distress risk, as proxied by the O-score FMP is priced in returns.

The results for the Z-score FMP, shown in Table 5, are also consistent with our hypothesis that distress risk is priced. The majority (eighteen out of twenty-five) of the portfolios have coefficient estimates on the Z-score FMP that are statistically significant at the 1% level. There is a perfectly monotonic pattern with respect to BTM. The firms with higher BTM levels have more negative coefficient estimates in every size category, and the firms with the lower BTM

Table 5: Regression Results for Z-score FMP

This table shows the results from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the Z-score factor mimicking portfolio for fiscal years 1965 to 201, 564 months. The following regression is estimated:

$$R_t\text{- } Rf_{,t} = \alpha + \gamma\ (MKT_t\text{-}Rf_t) + \delta FCT_t + \varepsilon_{i,}$$

Where δ is the estimated coefficient on the Z-score factor mimicking portfolio and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R squares. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles				
	Low	2	3	4	High
Size Quintile			δ		
Small	-0.13	-0.25	-0.37	-0.43	-0.63
2	0.14	-0.14	-0.36	-0.48	-0.64
3	0.20	-0.16	-0.36	-0.52	-0.66
4	0.26	-0.24	-0.35	-0.51	-0.59
Big	0.34	-0.02	-0.34	-0.50	-0.58
			α		
Small	0.08%	0.51%	0.64%	0.75%	1.04%
2	-0.12%	0.36%	0.40%	0.56%	0.61%
3	-0.16%	0.28%	0.45%	0.57%	0.69%
4	-0.04%	0.16%	0.26%	0.39%	0.48%
Big	-0.09%	0.16%	0.17%	0.17%	0.44%
			R^2		
Small	0.63	0.66	0.69	0.70	0.69
2	0.72	0.76	0.77	0.77	0.74
3	0.77	0.81	0.81	0.81	0.77
4	0.83	0.86	0.83	0.83	0.77
Big	0.87	0.88	0.78	0.80	0.71

	Book-to-Market Equity Quintiles									
	Low		2		3		4		High	
Size Quintile					t(δ)					
Small	-1.01		-2.37	**	-4.33	***	-5.94	***	-7.79	***
2	1.50		-2.00	**	-5.89	***	-7.24	***	-9.02	***
3	2.42	**	-2.51	**	-6.86	***	-10.01	***	-10.41	***
4	4.03	***	-5.66	***	-7.17	***	-8.36	***	-9.47	***
Big	8.68	***	-0.77		-6.36	***	-10.68	***	-10.67	***
					t (α)					
Small	0.37		2.75	***	3.88	***	5.03	***	6.72	***
2	-0.67		2.50	**	3.08	***	4.31	***	4.27	***
3	-1.06		2.36	**	3.99	***	5.05	***	5.40	***
4	-0.32		1.66	*	2.64	***	3.61	***	3.63	***
Big	-1.22		2.25	**	1.70	*	1.77	*	3.51	***

levels have more positive coefficient estimates in every size category. The returns from our twenty-five portfolios follow BTM. The firms with the highest BTM have the highest returns and the firms with the lowest BTM have the lowest returns. Thus, our Z-score distress proxy has a perfectly monotonic pattern with respect to returns. The higher return stocks load more negatively and the lower returns stocks load positively. This is the opposite of the O-score variable but since higher Z-score indicate healthier firms, this is expected.

There is also a pattern with respect to size. The portfolios comprised of smaller firms have more negative loadings on the Z-score FMP than the portfolios comprised of larger firms. This is a monotonic pattern within two of the BTM categories but not across all portfolios. Again, the firms with the higher returns have more negative loadings on the Z-score FMP than the firms with lower returns.

There are seven of the twenty-five portfolios where the coefficient estimate on the Z-score factor is not significant at the 1% level. Four of these are significant at the 5% level, leaving only three portfolios where the estimate for the distress factor coefficient is not significant at an acceptable level, indicating that the Z-score factor is not always relevant.

The R squares range from 63% to 88%, which indicates the majority of the variation in the portfolio returns, is explained using the distress factor and the market factor. The majority of the intercept values are statistically different from zero. This indicates that there is a bias that is not accounted for by the Z-score and market factor.

It is interesting to note that the intercept values increase in magnitude and in statistical significance as the portfolios move from lower BTM to higher BTM levels. This suggests that this model does a better job pricing lower BTM firms than it does higher BTM firms. With the higher level BTM firms the model does not appear to capture everything impacting the stock price.

The results for the Z-score FMP are also consistent with our hypothesis that distress risk is priced in returns, although the high numbers of intercept values that are not zero suggest that this model is not as robust as the O-score FMP model.

The results for the performance1 variable, shown in Table 6, are also consistent with distress risk being priced. The performance1 FMP has coefficient estimates significantly different from zero at the 1% level for nineteen of the twenty-five portfolios and significantly different from zero at the 5% level in twenty-one out of the twenty-five portfolios. There is a perfectly monotonic pattern with respect to size. The smaller firms, which are the firms with the higher returns, load more negatively on the performance1 FMPs and the larger firms, which are the firms with lower returns, load more positively on the performance1 FMP. The highest BTM firms have more negative loadings than the lowest BTM firms; however the pattern is not monotonic across the portfolios.

The adjusted R square values range from 64% to 88%. Similar to the Z-score, many of the intercept values are statistically different from zero and again the intercepts have higher t-stats the higher the BTM level. Once again, we see that the distress factor is significant and that the model using the distress factor and market factor captures a majority of the variation in the returns however, there is a bias not captured by the model that is represented by the non-zero intercepts.

The results for the regression using the performance2 FMP are shown in Table 7. The performance2 FMP does not have coefficient estimates that are significant at the 1% level for the

Table 6: Regression Results for PERFORMANCE1 FMP

This table shows the results from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the Performance1(ratio of net income to total assets) factor mimicking portfolio, for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t- Rf_{,t} = \alpha + \gamma(MKT_t-Rf_t) + \delta FCT_t + \varepsilon_{i,}$$

Where δ is the estimated coefficient on the Performance1 factor mimicking portfolio, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R squares. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
Size Quintile			δ			Size Quintile					t(δ)					
Small	-0.75	-0.62	-0.64	-0.55	-0.63	Small	-6.59	***	-7.24	***	-10.00	***	-8.81	***	-7.73	***
2	-0.35	-0.37	-0.30	-0.38	-0.48	2	-3.57	***	-6.05	***	-4.63	***	-5.47	***	-5.25	***
3	-0.25	-0.20	-0.20	-0.33	-0.42	3	-3.33	***	-3.67	***	-3.16	***	-4.38	***	-4.73	***
4	-0.12	-0.08	-0.12	-0.28	-0.37	4	-1.84	*	-1.44		-1.77	*	-3.65	***	-3.82	***
Big	0.23	0.12	-0.02	-0.15	-0.24	Big	6.63	***	3.77	***	-0.34		-2.02	**	-2.24	**
			α								t (α)					
Small	0.17%	0.57%	0.68%	0.77%	1.05%	Small	0.83		3.22	***	4.39	***	5.26	***	6.63	***
2	-0.05%	0.40%	0.39%	0.55%	0.59%	2	-0.29		2.82	***	2.95	***	4.03	***	3.81	***
3	-0.10%	0.28%	0.43%	0.55%	0.66%	3	-0.64		2.42	**	3.60	***	4.39	***	4.59	***
4	0.02%	0.13%	0.23%	0.36%	0.45%	4	0.13		1.37		2.15	**	2.98	***	3.12	***
Big	-0.08%	0.14%	0.13%	0.12%	0.39%	Big	-0.96		1.98	**	1.17		1.08		2.74	***
			R^2													
Small	0.69	0.71	0.74	0.72	0.69											
2	0.74	0.78	0.76	0.75	0.71											
3	0.77	0.81	0.79	0.77	0.72											
4	0.82	0.85	0.81	0.79	0.73											
Big	0.86	0.88	0.74	0.73	0.64											

Table 7: Regression Results for PERFORMANCE2 FMP

This table shows the results from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the Performance2 (ratio of net income to the sum of total book assets and market equity) FMP, for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t - Rf_{,t} = \alpha + \gamma(MKT_t - Rf_t) + \delta FCT_t + \varepsilon_{i,}$$

Where δ is the estimated coefficient on the Performance2 factor mimicking portfolio, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R squares. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles				
	Low	2	3	4	High
Size Quintile			δ		
Small	-0.84	-0.56	-0.49	-0.31	-0.29
2	-0.56	-0.35	-0.11	-0.11	-0.12
3	-0.47	-0.12	0.01	-0.02	-0.06
4	-0.37	0.00	0.08	0.03	-0.02
Big	-0.05	0.17	0.15	0.17	0.12
			α		
Small	0.08%	0.49%	0.60%	0.70%	0.96%
2	-0.09%	0.35%	0.35%	0.49%	0.52%
3	-0.12%	0.26%	0.40%	0.50%	0.60%
4	0.01%	0.12%	0.21%	0.32%	0.40%
Big	-0.05%	0.15%	0.12%	0.10%	0.36%
			R^2		
Small	0.71	0.70	0.71	0.68	0.63
2	0.76	0.77	0.75	0.73	0.67
3	0.79	0.81	0.78	0.75	0.69
4	0.85	0.85	0.81	0.77	0.70
Big	0.84	0.89	0.75	0.73	0.63

	Book-to-Market Equity Quintiles									
	Low		2		3		4		High	
Size Quintile					t(δ)					
Small	-7.89	***	-6.20	***	-6.72	***	-4.60	***	-3.60	***
2	-6.41	***	-5.32	***	-1.75	*	-1.58		-1.40	
3	-7.21	***	-2.20	**	0.17		-0.25		-0.74	
4	-6.96	***	0.07		1.20		0.50		-0.20	
Big	-1.16		4.65	***	2.34	**	2.67	***	1.28	
					t (α)					
Small	0.40		2.78	***	3.73	***	4.55	***	5.75	***
2	-0.55		2.50	**	2.59	***	3.51	***	3.26	***
3	-0.88		2.19	**	3.33	***	3.90	***	4.01	***
4	0.05		1.27		2.00	**	2.57	***	2.69	***
Big	-0.54		2.26	**	1.16		0.88		2.54	**

majority of the portfolios. Only eleven of the twenty-five portfolios had coefficient estimates on the performance 2 FMP that were statistically significant at the 1% level. Fourteen of the portfolios had coefficient estimates at a 10% or better significance level. However, once again there is a perfectly monotonic pattern where the smaller stock portfolios load more negatively on the performance2 factor and the larger stock portfolios load more positively.

The intercept values are significantly different from zero, at the 5% level for the majority (seventeen out of twenty-five) of the portfolios. This is not a strong model as the performance1 based model since the distress factor lacks significance and we have a bias represented by the intercepts.

The results for the leverage1 FMP, shown in Table 8, are again consistent with the hypothesis that distress risk is priced. The coefficient estimates for this FMP are significantly different from zero at the 1% level for eighteen out of the twenty-five portfolios. Four of the five portfolios that consist of the smallest size firms have statistically insignificant coefficient estimates.

Similar to the Z-score, there is a perfectly monotonic pattern with respect to BTM. The firms with higher levels of BTM load more positively on this FMP and the firms with the lowest BTM levels load more negatively. Again, this means that the higher return firms load positively on the leverge1 FMP and the lower returns firms load more negatively.

The R-square values range from 64% to 88%. Twelve of the intercept values are statistically indistinguishable from zero at the 1% level. The intercepts are indistinguishable from zero for the portfolios with low BTM levels. The intercepts are positive and significant for the high BTM portfolios. This suggests that for the portfolios with high BTM levels, there is a bias that is omitted by the model.

Table 8: Regression Results for LEVERAGE1 FMP

This table shows the results from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the Leverage1 (total liabilities scaled by total book assets) FMP, for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t - Rf_{,t} = \alpha + \gamma\ (MKT_t - Rf_t) + \delta FCT_t + \varepsilon_{i,}$$

Where δ is the estimated coefficient on the Leverage1 factor mimicking portfolio, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R squares. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
Size Quintile			δ			Size Quintile					t(δ)					
Small	-0.34	-0.10	0.04	0.22	0.43	Small	-1.95	*	-0.71		0.40		1.88	*	3.57	***
2	-0.40	-0.03	0.29	0.38	0.51	2	-3.45	***	-0.32		3.61	***	3.65	***	5.49	***
3	-0.37	0.11	0.32	0.40	0.51	3	-4.16	***	1.33		4.97	***	6.26	***	6.83	***
4	-0.43	0.23	0.33	0.39	0.47	4	-6.24	***	4.86	***	6.29	***	4.83	***	6.35	***
Big	-0.25	0.08	0.18	0.33	0.52	Big	-3.86	***	2.00	**	2.75	***	5.72	***	9.44	***
			α								t (α)					
Small	0.07%	0.48%	0.59%	0.69%	0.95%	Small	0.32		2.59	***	3.49	***	4.48	***	5.89	***
2	-0.10%	0.34%	0.34%	0.49%	0.51%	2	-0.56		2.37	**	2.64	***	3.65	***	3.45	***
3	-0.13%	0.25%	0.40%	0.49%	0.59%	3	-0.88		2.17	**	3.48	***	4.16	***	4.34	***
4	0.00%	0.12%	0.21%	0.31%	0.39%	4	0.04		1.28		2.09	**	2.73	***	2.83	***
Big	-0.04%	0.15%	0.12%	0.10%	0.35%	Big	-0.55		2.21	**	1.17		0.90		2.75	***
			R^2													
Small	0.64	0.65	0.67	0.67	0.65											
2	0.74	0.75	0.76	0.75	0.71											
3	0.78	0.80	0.80	0.78	0.74											
4	0.85	0.86	0.83	0.80	0.74											
Big	0.86	0.88	0.75	0.75	0.69											

The results for the second leverage FMP, shown in Table 9, are very similar to the leverage1 results. The coefficient estimates for the leverage2 FMPs are significantly different from zero at the 1% level for nineteen of the twenty five portfolios. The same monotonic pattern across BTM portfolios exists where the higher BTM firms load more positively on the leverage2 FMP and the lower BTM firms load more negatively. The R-square values range from 63% to 88%. The intercept values are not significantly different from zero for the low BTM firms but are statistically different from zero for the higher BTM firms. Once again, the majority of the intercepts are statistically different from zero indicating an omitted bias.

1.4.2 Are The Macro-Economic Distress Variables Priced?

None of the three macro-economic variables, GDP, credit availability, and cost of credit have significant explanatory power for pricing the returns of the twenty-five portfolios. The results are shown in Tables 10, 11, and 12 respectively. For the most part, the estimated coefficients for these variables were not statistically different from zero.

The few exceptions were for the availability of credit where three of the portfolios had coefficient estimates for the credit variable at the 1% significance level. Since we include the market factor in our test models, it is likely that the market factor is subsuming these macro-economic variables. The market factor captures systematic market movements which are often the result of economic conditions. The three macro-economic factors we use are also indicators of economic conditions.

Table 9: Regression Results for LEVERAGE2 FMP

This table shows the results from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the Leverage2 (total liabilities scaled by the sum of total book assets and total market capital) FMP, for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t\text{-} Rf_{,t} = \alpha + \gamma\ (MKT_t\text{-}Rf_t) + \delta FCT_t + \varepsilon_{i,}$$

Where δ is the estimated coefficient on the Leverage2 factor mimicking portfolio, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R squares. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
Size Quintile			δ			Size Quintile					t(δ)					
Small	-0.21	0.02	0.15	0.29	0.50	Small	-1.73	*	0.18		1.76	*	3.68	***	5.85	***
2	-0.29	0.03	0.30	0.42	0.57	2	-3.42	***	0.45		4.99	***	6.14	***	8.75	***
3	-0.25	0.14	0.33	0.45	0.54	3	-3.23	***	2.24	**	7.26	***	9.58	***	10.32	***
4	-0.31	0.18	0.32	0.43	0.51	4	-5.04	***	5.29	***	7.70	***	7.87	***	8.95	***
Big	-0.24	0.06	0.18	0.36	0.50	Big	-5.24	***	1.80	*	3.44	***	9.23	***	10.10	***
			α								t (α)					
Small	0.03%	0.48%	0.61%	0.74%	1.04%	Small	0.15		2.60	***	3.66	***	4.91	***	6.69	***
2	-0.15%	0.35%	0.39%	0.55%	0.61%	2	-0.85		2.40	**	3.07	***	4.38	***	4.41	***
3	-0.17%	0.28%	0.45%	0.57%	0.68%	3	-1.15		2.37	**	4.11	***	5.15	***	5.42	***
4	-0.05%	0.15%	0.26%	0.38%	0.47%	4	-0.45		1.60		2.70	***	3.64	***	3.69	***
Big	-0.08%	0.16%	0.15%	0.16%	0.43%	Big	-1.06		2.35	**	1.46		1.56		3.54	***
			R^2													
Small	0.63	0.65	0.67	0.69	0.69											
2	0.74	0.75	0.77	0.77	0.76											
3	0.77	0.81	0.82	0.81	0.78											
4	0.85	0.86	0.84	0.83	0.78											
Big	0.87	0.88	0.76	0.78	0.72											

Table 10: Regression Results for GDP

This table shows the results from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the GDP variable defined as the percent change in the quarterly real gross domestic product rate, for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t - Rf_{,t} = \alpha + \gamma\ (MKT_t - Rf_t) + \delta GDP_t + \varepsilon_{i,}$$

Where δ is the estimated coefficient on the GDP proxy, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R squares. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles				
	Low	2	3	4	High		Low	2	3	4	High
Size Quintile			δ			Size Quintile			t(δ)		
Small	-0.0011	-0.0006	-0.0006	-0.0003	0.0000	Small	-1.50	-0.95	-0.96	-0.54	0.06
2	-0.0011	-0.0005	-0.0010	-0.0005	-0.0005	2	-2.01 **	-0.92	-2.04 **	-0.92	-0.76
3	-0.0005	-0.0006	-0.0006	-0.0001	-0.0007	3	-0.97	-1.51	-1.32	-0.33	-1.27
4	-0.0006	-0.0008	-0.0006	-0.0003	0.0002	4	-1.62	-2.31 **	-1.65 *	-0.56	0.29
Big	0.0003	0.0000	0.0000	0.0001	0.0004	Big	1.20	-0.19	0.02	0.13	0.85
			α						t (α)		
Small	0.37%	0.65%	0.76%	0.78%	0.95%	Small	1.16	2.33 **	2.98 ***	3.29 ***	3.50 ***
2	0.20%	0.47%	0.63%	0.62%	0.65%	2	0.82	2.24 **	3.09 ***	2.82 ***	2.50 **
3	0.00%	0.42%	0.57%	0.54%	0.79%	3	0.00	2.61 ***	3.24 ***	2.88 ***	3.50 ***
4	0.17%	0.34%	0.39%	0.40%	0.35%	4	0.99	2.43 **	2.42 **	1.90 *	1.56
Big	-0.14%	0.17%	0.12%	0.09%	0.23%	Big	-1.12	1.62	0.80	0.47	1.12
			R^2								
Small	0.63	0.65	0.67	0.66	0.62						
2	0.72	0.75	0.75	0.72	0.67						
3	0.76	0.80	0.78	0.75	0.69						
4	0.82	0.85	0.80	0.77	0.70						
Big	0.84	0.88	0.74	0.72	0.63						

Table 11: Regression Results for Credit Availability

This table shows the results from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the credit availability variable defined as the quarterly rate of change in credit market instruments, from fiscal years1965 to 2011, 564 months. The following regression is estimated:

$$R_t - Rf_{,t} = \alpha + \gamma(MKT_t - Rf_t) + \delta CREDIT_t + \varepsilon_{i,}$$

Where δ is the estimated coefficient on the CREDIT proxy, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R squares. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
Size Quintile			δ			Size Quintile					t(δ)					
Small	-0.35	-0.23	-0.34	-0.33	-0.35	Small	-1.97	**	-1.45		-2.58	***	-2.60	***	-2.30	**
2	-0.26	-0.22	-0.31	-0.16	-0.25	2	-1.88	*	-1.79	*	-2.77	***	-1.24		-1.69	*
3	-0.22	-0.13	-0.10	-0.24	-0.21	3	-1.87	*	-1.36		-1.02		-2.28	**	-1.50	
4	-0.12	-0.17	-0.18	-0.08	-0.21	4	-1.32		-2.30	**	-2.19	**	-0.72		-1.77	*
Big	-0.01	0.01	0.11	0.09	0.06	Big	-0.21		0.22		1.34		0.89		0.49	
			α								t (α)					
Small	0.77%	0.93%	1.27%	1.37%	1.66%	Small	1.81	*	2.58	***	3.93	***	4.42	***	4.35	***
2	0.43%	0.79%	0.97%	0.82%	1.03%	2	1.32		2.77	***	3.53	***	2.52	**	2.75	***
3	0.31%	0.53%	0.60%	0.99%	1.01%	3	1.08		2.23	**	2.59	***	3.62	***	2.95	***
4	0.24%	0.47%	0.58%	0.48%	0.81%	4	1.07		2.74	***	2.75	***	1.63		2.75	***
Big	-0.02%	0.13%	-0.10%	-0.08%	0.23%	Big	-0.11		0.92		-0.50		-0.31		0.72	
			R^2													
Small	0.63	0.65	0.67	0.67	0.62											
2	0.72	0.75	0.75	0.72	0.67											
3	0.76	0.80	0.78	0.75	0.69											
4	0.82	0.85	0.81	0.77	0.70											
Big	0.84	0.88	0.74	0.72	0.63											

Table 12: Regression Results for Cost of Credit

This table shows the results from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the cost of credit variable proxied by the monthly risk free rate, for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t \text{- } Rf_{,t} = \alpha + \gamma \ (MKT_t\text{-}Rf_t) + \delta RF_t + \varepsilon_{i,}$$

Where δ is the estimated coefficient on the RF proxy, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R squares. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles				
	Low	2	3	4	High		Low	2	3	4	High
Size Quintile			δ			Size Quintile			t(δ)		
Small	-0.69	-0.32	-0.85	-0.81	-1.33	Small	-1.05	-0.54	-1.55	1.49	-2.03 **
2	-0.52	-0.63	-0.81	-0.26	-0.70	2	-0.95	-1.34	-1.72 *	-0.50	-1.10
3	-0.49	-0.14	0.21	-0.48	-0.48	3	-1.00	-0.35	0.50	-1.03	-0.78
4	-0.31	-0.12	-0.67	-0.16	-0.56	4	-0.79	-0.38	-1.69 *	-0.30	-0.97
Big	-0.11	0.02	0.05	0.00	0.11	Big	-0.32	0.06	0.12	0.01	0.21
			α						t (α)		
Small	0.36%	0.62%	0.96%	1.04%	1.53%	Small	1.01	2.06 **	3.30 ***	3.76 ***	4.52 ***
2	0.12%	0.61%	0.69%	0.60%	0.82%	2	0.43	2.49 **	2.85 ***	2.16 **	2.41 **
3	0.08%	0.31%	0.31%	0.70%	0.80%	3	0.30	1.48	1.45	2.80 ***	2.65 ***
4	0.13%	0.17%	0.50%	0.39%	0.64%	4	0.62	1.02	2.47 **	1.37	2.19 **
Big	0.00%	0.15%	0.10%	0.10%	0.31%	Big	0.00	1.14	0.50	0.45	1.12
			R^2								
Small	0.62	0.65	0.67	0.66	0.62						
2	0.72	0.75	0.75	0.72	0.67						
3	0.76	0.80	0.78	0.75	0.69						
4	0.82	0.85	0.80	0.77	0.70						
Big	0.84	0.88	0.74	0.72	0.63						

1.4.3 Testing the Best Model

We have two versions of the leverage variables and two versions of the performance variables. Our hypothesis is that one version of these variables will provide stronger results than the other. We run a regression with both variations of the leverage distress proxy to determine if one of the variables subsumes the other. The leverage2 has coefficient estimates that are significant at the 1% level for sixteen of the portfolios, while the leverage1 variable has significant coefficient estimates for only five of the portfolios. This suggests that of the two leverage variables, leverage2 is a better distress proxy. Likewise, we run a regression with both variations of the performance distress proxy. Our results are not as clear here, but we find that the performance1 FMP has coefficient estimates that are significant at the 1% level for twenty-two of the portfolios and the performancce2 FMP has significant coefficients for only nineteen of the portfolios.[2] Thus we use leverage2 and performance1 in further tests.

Thus, our results are strongest for the O-score, Z-score, performance1, and leverage2 FMPs. We estimate multivariate regressions with the following combinations of these variables: O-score and performance1; O-score and leverage2; O-score and Z-score; Z-score and performance1; and Z-score and leverage2.[3] The R-square values from the combination of O-score and leverage2 are 72% - 89%, which are the highest R-square values from any of our combinations. This model with O-score, LEV2, and the market factor has the greatest number of significant coefficient estimates on the distress factors of any of the models we examine. The results are shown in Table 13.

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[2] Results for the regressions for both leverage proxies and both performance proxies are available upon request.

[3] Results for the all the regressions mentioned in this paragraph are not included here for brevity's sake but are available upon request.

Combinations with three FMPs do not offer much greater explanatory power than the combination of O-score and leverage2.[4] The R-square values are only slightly greater but the estimated coefficients do not remain significant for all three variables. The intercepts remain significantly different from zero at the 1% level for thirteen of the twenty-five portfolios. However, no other model that we analyze has intercept values that are indistinguishable from zero. The model with O-score and performance1 has only eleven portfolios with significant intercepts but in this model the coefficient estimates on the performance1 distress factor are insignificant on all but two portfolios. Thus, our strongest model consists of O-score and Lev2.

1.4.4 Are SMB and HML Proxies for Distress?

We add SMB and HML to our strongest model and examine which factors remain significant. If HML and SMB are indeed proxies for distress, then we expect that either the O-score FMP or the leverage2 FMP will not remain significant, or that the SMB and HML factors will not be significant. If the SMB and HML factors are not proxies for distress risk (or a distress characteristic) then we expect that all the factors will remain significant in our regression. The results are shown in Table 14.

We find an increase in the R-square values compared to the model with just O-score and leverage2. The R-square values increase from 72% - 89% to 78% - 95%. However, the O-score FMP no longer has coefficient estimates that are statistically significantly different from zero at the 1% significance level for twenty-one of the twenty-five portfolios. When using a 5% significance level seven of the twenty-five portfolios have significant coefficient estimates for the O-score FMP. The leverage2 FMP has coefficient estimates that are not significantly different from zero at the 1% significance level for twenty-one of the twenty-five portfolios also.

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[4] The results for these regressions are not shown but are available upon request.

Table 13: Regression Results for O-score and LEVERAGE2 FMPs

This table shows the result from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return, the O-score FMP, and the leverage2 FMP, for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_{t}\text{- }Rf_{,t} = \alpha + \beta(MKT_{t}-Rf_{t}) + \gamma Oscore_{t,} + \delta LEV2_{t} + \varepsilon_{i,}$$

Where γ is the estimated coefficient on the O-score FMP, δ is the estimated coefficient on the leverage2 FMP, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R square values. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
Size Quintile	γ					Size Quintile	t(γ)									
Small	1.60	1.23	1.11	0.90	0.89	Small	12.77	***	10.92	***	11.46	***	9.77	***	9.89	***
2	1.04	0.84	0.59	0.58	0.57	2	9.23	***	9.94	***	8.35	***	7.65	***	7.08	***
3	0.79	0.47	0.38	0.36	0.49	3	7.79	***	6.09	***	5.47	***	5.71	***	6.89	***
4	0.49	0.30	0.17	0.22	0.36	4	5.55	***	4.07	***	2.41	**	2.97	***	4.08	***
Big	-0.19	-0.21	-0.24	-0.18	0.01	Big	-2.88	***	-4.35	***	-3.28	***	-3.00	***	0.19	
	δ						t(δ)									
Small	-0.68	-0.34	-0.18	0.03	0.24	Small	-6.69	***	-3.80	***	-2.50	**	0.47		3.72	***
2	-0.60	-0.21	0.12	0.25	0.41	2	-6.63	***	-3.00	***	2.27	**	4.11	***	7.72	***
3	-0.48	0.00	0.22	0.34	0.40	3	-6.12	***	0.08		4.05	***	7.06	***	8.32	***
4	-0.46	0.09	0.27	0.37	0.40	4	-6.61	***	1.88	*	5.21	***	7.02	***	6.59	***
Big	-0.18	0.12	0.25	0.42	0.49	Big	-3.70	***	3.18	***	4.90	***	8.91	***	8.79	***
	α						t (α)									
Small	-0.17%	0.33%	0.48%	0.63%	0.92%	Small	-0.94		2.10	**	3.36	***	4.72	***	6.77	***
2	-0.27%	0.24%	0.32%	0.48%	0.54%	2	-1.85	*	1.89	*	2.67	***	4.08	***	4.15	***
3	-0.27%	0.22%	0.41%	0.52%	0.62%	3	-1.98	**	1.96	**	3.80	***	4.86	***	5.19	***
4	-0.11%	0.11%	0.24%	0.36%	0.43%	4	-1.05		1.24		2.50	**	3.45	***	3.45	***
Big	-0.06%	0.19%	0.18%	0.18%	0.43%	Big	-0.77		2.85	***	1.79	*	1.81	*	3.51	***

Table 13- continued

	Book-to-Market Equity Quintiles				
	Low	2	3	4	High
			R^2		
Small	0.75	0.75	0.76	0.76	0.75
2	0.80	0.81	0.80	0.81	0.78
3	0.81	0.83	0.83	0.83	0.80
4	0.87	0.87	0.84	0.84	0.79
Big	0.87	0.89	0.76	0.79	0.72

When using the 5% significance level ten of the twenty-five portfolios have significant coefficient estimates for the leverage2 FMP. SMB has coefficient estimates that are significantly different from zero in all but two of the portfolios and. HML also has coefficient estimates that are significantly different from zero in all but seven of the portfolios.

The intercept values are not statistically different from zero at the 1% significance level for twenty of the twenty-five portfolios. However, for the smallest size firms, the three with the largest BTM values all have intercepts that are significantly different from zero and for the largest firm, the two firms with the lowest BTM values have intercepts that are significantly different from zero.

If the premiums captured by SMB and HML are due to distress risk and only distress risk, then we expect that our distress proxies O-score and LEV2 would subsume the explanatory power of SMB and HML. Since SMB and HML have coefficient estimates that remain significant and the O-score and leverage2 factors do not, it appears that SMB and HML subsume the O-score and leverage2 factors. However, in this model there are three more intercept values

Table 14: Regression Results for O-score, LEVERAGE2, SMB, and HML FMPs

This table shows the result from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the O-score FMP, the leverage2 FMP, SMB, and HML for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t - Rf_{,t} = \alpha + \beta(MKT_t - Rf_t) + \gamma Oscore_{t,} + \delta LEV2_t + \lambda SMB_t + \pi HML_t + \varepsilon_{i,}$$

Where γ is the estimated coefficient on the O-score FMP, δ is the estimated coefficient on the leverage2 FMP, λ is the estimated coefficient on SMB, π is the estimated coefficient on HML, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R square values. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
Size Quintile	γ					Size Quintile	t(γ)									
Small	0.43	0.13	0.14	-0.02	0.02	Small	4.86	***	1.77	*	1.95	*	-0.50		0.30	
2	0.08	-0.01	-0.14	-0.14	-0.16	2	0.99		-0.12		-2.48	**	-2.62	***	-2.81	***
3	0.01	-0.14	-0.15	-0.08	0.04	3	0.16		-1.92	*	-2.10	**	-1.18		0.64	
4	0.10	0.02	-0.08	0.04	0.14	4	1.17		0.29		-1.06		0.50		1.61	
Big	-0.07	-0.17	-0.01	0.02	0.19	Big	-1.53		-3.09	***	-0.11		0.25		2.48	**
	δ						t(δ)									
Small	-0.17	-0.03	-0.01	0.02	0.14	Small	-1.30		-0.28		-0.16		0.41		2.43	**
2	-0.03	0.00	0.15	0.17	0.17	2	-0.37		0.06		2.56	**	3.63	***	3.02	***
3	0.02	0.14	0.20	0.15	0.11	3	0.19		1.91	*	2.99	**	2.22	**	1.61	
4	-0.08	0.17	0.17	0.13	0.08	4	-0.98		2.79	***	2.47	**	1.84	*	0.97	
Big	0.12	0.14	0.16	0.07	-0.05	Big	2.47	**	2.48	**	1.62		0.98		-0.57	
	λ						t(λ)									
Small	1.23	1.19	1.07	1.06	1.03	Small	18.76	***	23.16	***	24.37	***	35.32	***	30.11	***
2	0.99	0.93	0.84	0.85	0.89	2	22.92	***	30.66	***	20.30	***	30.16	***	25.88	***
3	0.79	0.68	0.61	0.56	0.58	3	17.59	***	18.35	***	16.15	***	15.52	***	14.10	***
4	0.37	0.30	0.31	0.26	0.32	4	10.15	***	7.97	***	7.26	***	7.23	***	6.32	***
Big	-0.20	-0.05	-0.24	-0.16	-0.09	Big	-6.26	***	-1.75	*	-4.78	***	-4.30	***	-1.50	

Table 14 - continued

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
			π								t(π)					
Small	-0.33	-0.06	0.11	0.36	0.48	Small	-2.05	**	-0.45		1.27		5.72	***	6.75	***
2	-0.50	-0.01	0.24	0.38	0.62	2	-5.76	***	-0.12		3.93	***	7.82	***	13.17	***
3	-0.46	0.03	0.22	0.46	0.60	3	-5.10	***	0.42		3.84	***	7.90	***	9.59	***
4	-0.43	-0.02	0.24	0.43	0.57	4	-6.66	***	-0.27		3.92	***	7.12	***	7.83	***
Big	-0.49	-0.04	0.05	0.45	0.75	Big	-12.40	***	-0.90		0.49		6.81	***	6.48	***
			β								t(β)					
Small	1.03	0.98	0.94	0.93	0.92	Small	27.89	***	33.26	***	36.54	***	45.33	***	38.26	***
2	1.12	1.05	1.05	1.04	1.07	2	41.65	***	47.50	***	44.11	***	54.89	***	48.69	***
3	1.13	1.10	1.07	1.06	1.06	3	43.16	***	49.48	***	44.51	***	43.71	***	41.33	***
4	1.13	1.09	1.09	1.16	1.16	4	40.36	***	42.39	***	38.62	***	35.95	***	35.16	***
Big	0.99	1.01	0.99	1.03	1.07	Big	52.64	***	55.30	***	31.49	***	37.31	***	31.75	***
			α												t (α)	
Small	-0.12%	0.21%	0.27%	0.27%	0.50%	Small	-0.77		1.58		2.71	***	3.57	***	6.07	***
2	-0.10%	0.13%	0.06%	0.14%	0.04%	2	-0.93		1.56		0.77		1.95	*	0.50	
3	-0.09%	0.11%	0.19%	0.17%	0.18%	3	-0.76		1.31		2.19	**	1.85	*	1.80	*
4	0.10%	0.08%	0.05%	0.06%	0.04%	4	1.01		0.88		0.59		0.59		0.34	
Big	0.26%	0.22%	0.18%	-0.07%	-0.02%	Big	3.85	***	3.24	***	1.39		-0.77		-0.12	
			R^2													
Small	0.90	0.92	0.93	0.95	0.93											
2	0.93	0.94	0.93	0.94	0.93											
3	0.92	0.91	0.90	0.90	0.88											
4	0.91	0.89	0.87	0.87	0.83											
Big	0.91	0.89	0.78	0.83	0.79											

that are significantly different from zero (at the 10% significance level) than there are in a model with only SMB, HML , and the market factor.[5] Since including our two distress proxies introduces bias into the results, we cannot conclude that our O-score and LEV2 proxies contain exactly the same information as SMB and HML. Although the fact that the explanatory power of the O-score and Lev2 factors is subsumed by SMB and HML and the additional bias is minimal (only significant at the 10% level) it can be construed that the information contained in SMB and HML is quite similar to that in our two distress based factors.

We also examine a model consisting of our O-score and Z-score FMPs and SMB and HML shown in Table 15. The R-square values of 79% - 95% are very similar to the values of the previous model. Again we find SMB and HML subsume the explanatory power of the O-score FMP. Only two of the estimated O-score FMP coefficients are statistically significant at the 1% level, and four at the 5% level. More of the Z-score coefficients remain significant with seven of the twenty-five significant at the 1% level and thirteen at the 5% level. The SMB factor coefficients remain significant for all but two portfolios and the HML factor coefficients remain significant at the 1% level for all but seven of the portfolios and two of them are significant at the 5% level.

The intercept values are statistically different from zero at the 5% level for eight of the portfolios indicating that there is a bias. Similar to the previous model the smallest size firms with the higher BTM levels have intercept values significantly different from zero and the largest size firms with the lower BTM values have intercept values significantly different from zero.

It is interesting that the Z-score factor remains more significant in our combined model than the O-score factor. In the models with only one of our distress factors, the Z-score had slightly

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[5] We exclude financial firms and utilities in our SMB and HML factors so our results are slightly different than those shown in Fama and French (1993).

less robust results as measured by the significance of the coefficient estimates. Sine it performs better than the O-score factor in the combined model, we estimate a model with Z-score, LEV2, SMB, HML, and the market factor to determine if that is our strongest multivariate model. The results are shown in Table 16.

The R-square values increase to 79-95%. The Z-score and Lev2 FMP coefficient estimates have more significance than the O-score and Lev2 FMPS in the previous model. However, SMB and HML continue to have more significant coefficient estimates. And again, more alpha values are significantly different from zero in this model than in a model with SMB, HML, and the market factor alone, indicating that the inclusion of the Z-score and Lev2 factors introduces bias. The fact that the Z-score FMP remains significant in thirteen of the portfolios and the Lev2 FMP remains significant in fourteen of the portfolios suggests that there is information in these distress proxies that is not captured by SMB or HML.

Finally we examine a model consisting of all four of our strongest distress factors, O-score, Z-score, performance1, and leverage2, with SMB and HML. Results are shown in Table 17. Our R-square values are 79% to 95%. Once again it appears that SMB and HML subsume the other distress factors.

The O-score factor coefficients are not significant at the 1% level for any portfolio and only three portfolios have significant coefficients at the 5% level. The Z-score factor is more robust with eight portfolios that have significant coefficient estimates at the 1% level and ten at the 5% level. The performance1 FMP has four portfolios where the coefficient remains significant at the 1% level and seven at the 5% level. The leverage2 FMP coefficient remains significant at the 1% level in only two portfolios and in six portfolios at the 5% level. On the other hand, the SMB coefficient remains significant in twenty-three of the twenty-five portfolios at both the 5% and

Table 15: Regression Results for O-score, Z-score, SMB, and HML FMPs

This table shows the result from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the O-score FMP, the Z-score FMP, SMB, and HML for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t - Rf_{,t} = \alpha + \beta(MKT_t - Rf_t) + \gamma Oscore_{t,} + \delta Zscore_t + \lambda SMB_t + \pi HML_t + \varepsilon_{i,}$$

Where γ is the estimated coefficient on the O-score FMP, δ is the estimated coefficient on Z-score FMP, λ is the estimated coefficient on SMB, π is the estimated coefficient on HML, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R square values. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles				
	Low	2	3	4	High		Low	2	3	4	High
Size Quintile			γ			Size Quintile			t(γ)		
Small	0.098	-0.059	-0.034	-0.080	-0.001	Small	0.97	-0.65	-0.50	-1.45	-0.02
2	-0.070	-0.070	-0.138	-0.125	-0.127	2	-0.89	-1.33	-1.96 **	-1.85 *	-1.77 *
3	-0.004	-0.100	-0.109	-0.096	0.012	3	-0.05	-1.20	-1.26	-1.29	0.15
4	0.029	-0.012	-0.077	0.010	0.146	4	0.36	-0.15	-0.95	0.11	1.59
Big	0.016	-0.151	-0.255	-0.161	0.149	Big	0.25	-2.58 ***	-3.16 ***	-2.41 **	1.61
			δ						t(δ)		
Small	-0.427	-0.301	-0.290	-0.112	-0.145	Small	-3.00 ***	-2.22 **	-3.53 ***	-1.70 *	-1.95 *
2	-0.222	-0.109	-0.117	-0.121	-0.092	2	-2.57 ***	-2.12 **	-1.98 **	-2.07 **	-1.50
3	-0.043	-0.049	-0.100	-0.146	-0.147	3	-0.40	-0.77	-1.59	-2.67 ***	-1.98 **
4	-0.049	-0.199	-0.136	-0.157	-0.062	4	-0.78	-2.89 ***	-1.88 *	-2.36 **	-0.73
Big	0.053	-0.077	-0.543	-0.355	-0.026	Big	1.07	-1.34	-5.28 ***	-5.59 ***	-0.22
			λ						t(λ)		
Small	1.277	1.220	1.099	1.072	1.031	Small	20.72 ***	24.27 ***	25.59 ***	34.80 ***	27.32 ***
2	1.013	0.941	0.843	0.848	0.887	2	24.34 ***	31.62 ***	18.01 ***	28.70 ***	21.89 ***
3	0.793	0.673	0.606	0.558	0.580	3	16.81 ***	17.12 ***	13.98 ***	14.17 ***	13.11 ***
4	0.378	0.309	0.312	0.267	0.321	4	10.40 ***	7.50 ***	6.59 ***	7.58 ***	6.15 ***
Big	-0.210	-0.052	-0.211	-0.132	-0.082	Big	-6.01 ***	-1.72 *	-4.46 ***	-3.94 ***	-1.38

Table 15 - continued

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
			π								t(π)					
Small	-0.678	-0.235	-0.042	0.320	0.513	Small	-5.51	***	-2.10	**	-0.55		5.66	***	7.58	***
2	-0.630	-0.058	0.296	0.453	0.713	2	-9.26	***	-1.37		4.93	***	9.85	***	14.06	***
3	-0.472	0.112	0.330	0.499	0.615	3	-5.49	***	1.98	**	7.00	***	9.81	***	10.42	***
4	-0.513	0.017	0.305	0.454	0.600	4	-10.47	***	0.31		5.10	***	8.75	***	8.73	***
Big	-0.376	0.027	-0.097	0.325	0.702	Big	-8.72	***	0.61		-1.12		6.39	***	6.39	***
			β								t(β)					
Small	1.028	0.982	0.945	0.933	0.927	Small	33.03	***	39.92	***	40.20	***	46.98	***	38.78	***
2	1.122	1.055	1.051	1.043	1.073	2	44.05	***	48.44	***	42.97	***	53.71	***	46.76	***
3	1.129	1.105	1.075	1.070	1.061	3	44.22	***	49.12	***	43.24	***	43.79	***	41.63	***
4	1.124	1.093	1.096	1.164	1.158	4	40.64	***	41.10	***	37.44	***	35.50	***	34.57	***
Big	0.993	1.017	1.005	1.037	1.066	Big	50.80	***	54.48	***	35.53	***	40.36	***	32.17	***
			α								t (α)					
Small	0.15%	0.35%	0.39%	0.31%	0.48%	Small	1.04		2.81	***	4.08	***	4.13	***	5.74	***
2	0.00%	0.17%	0.03%	0.09%	-0.02%	2	0.05		2.10	**	0.33		1.26		-0.21	
3	-0.08%	0.06%	0.12%	0.15%	0.18%	3	-0.71		0.69		1.40		1.68	*	1.81	*
4	0.17%	0.07%	0.01%	0.05%	0.02%	4	1.81	*	0.74		0.15		0.54		0.18	
Big	0.18%	0.18%	0.31%	0.03%	0.02%	Big	2.55	**	2.53	**	2.75	***	0.38		0.17	
			R^2													
Small	0.91	0.93	0.93	0.95	0.93											
2	0.93	0.94	0.92	0.93	0.93											
3	0.92	0.91	0.90	0.90	0.88											
4	0.91	0.89	0.87	0.87	0.83											
Big	0.91	0.89	0.82	0.84	0.79											

Table 16: Regression Results for Z-score, LEVERAGE2, SMB, and HML FMPs

This table shows the result from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the Z-score FMP, LEV2 FMP, SMB, and HML for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t - Rf_{,t} = \alpha + \beta(MKT_t - Rf_t) + \gamma Zscore_{t,} + \delta LEV2_t + \lambda SMB_t + \pi HML_t + \varepsilon_{i,}$$

Where γ is the estimated coefficient on the Z-score FMP, δ is the estimated coefficient on LEV2 FMP, λ is the estimated coefficient on SMB, π is the estimated coefficient on HML, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R square values. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles				
	Low	2	3	4	High		Low	2	3	4	High
Size Quintile			γ			Size Quintile			t(γ)		
Small	-0.72	-0.40	-0.38	-0.10	-0.08	Small	-6.92 ***	-3.83 ***	-4.67 ***	-1.83 *	-1.28
2	-0.29	-0.12	0.01	0.02	0.06	2	-3.95 ***	-2.01 **	0.16	0.39	1.01
3	-0.04	0.08	0.07	-0.05	-0.11	3	-0.46	1.18	1.13	-0.73	-1.68 *
4	-0.13	-0.13	-0.02	-0.11	-0.07	4	-2.23 **	-1.69 *	-0.24	-1.75 *	-0.90
Big	0.15	0.06	-0.50	-0.36	-0.13	Big	3.34 ***	1.14	-5.01 ***	-5.67 ***	-1.37
			δ						t(δ)		
Small	-0.42	-0.20	-0.17	-0.04	0.10	Small	-6.28 ***	-3.14 ***	-2.61 ***	-0.91	1.91 **
2	-0.16	-0.06	0.11	0.14	0.16	2	-2.54 **	-1.03	1.63	2.84 ***	2.41 **
3	0.00	0.13	0.19	0.10	0.07	3	0.00	1.74 *	2.55 **	1.28	0.97
4	-0.12	0.11	0.14	0.08	0.09	4	-1.46	1.71 *	1.87 *	1.06	1.05
Big	0.17	0.12	-0.11	-0.11	-0.06	Big	3.24 ***	2.19 **	-1.24	-1.74 *	-0.81
			λ						t(λ)		
Small	1.32	1.21	1.09	1.05	1.03	Small	28.80 ***	35.98 ***	28.48 ***	36.14 ***	34.34 ***
2	1.00	0.92	0.80	0.81	0.84	2	31.05 ***	35.23 ***	20.92 ***	32.71 ***	25.48 ***
3	0.79	0.64	0.57	0.53	0.58	3	20.53 ***	19.03 ***	16.46 ***	16.03 ***	15.43 ***
4	0.39	0.30	0.28	0.27	0.36	4	11.86 ***	7.48 ***	6.46 ***	7.08 ***	6.95 ***
Big	-0.21	-0.10	-0.29	-0.18	-0.03	Big	-7.56 ***	-3.88 ***	-7.21 ***	-5.66 ***	-0.70

Table 16 – continued

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
			π								t(π)					
Small	-0.47	-0.13	0.04	0.34	0.46	Small	-3.40	***	-1.04		0.53		5.28	***	6.31	***
2	-0.55	-0.03	0.25	0.39	0.64	2	-6.76	***	-0.52		3.87	***	7.35	***	12.30	***
3	-0.47	0.05	0.24	0.45	0.58	3	-4.92	***	0.69		4.22	***	7.80	***	9.43	***
4	-0.46	-0.04	0.24	0.41	0.55	4	-7.48	***	-0.63		3.76	***	6.72	***	7.58	***
Big	-0.46	-0.03	-0.03	0.39	0.73	Big	-10.87	***	-0.50		-0.32		6.62	***	6.01	***
			β								t(β)					
Small	1.06	0.99	0.95	0.92	0.92	Small	30.24	***	32.81	***	40.20	***	46.66	***	38.32	***
2	1.12	1.05	1.03	1.02	1.05	2	43.52	***	49.05	***	44.72	***	54.67	***	47.63	***
3	1.13	1.08	1.05	1.05	1.06	3	41.88	***	50.81	***	45.04	***	43.56	***	41.82	***
4	1.13	1.09	1.08	1.16	1.17	4	43.33	***	47.36	***	40.53	***	38.78	***	37.52	***
Big	0.99	0.99	0.98	1.02	1.09	Big	53.89	***	51.75	***	31.63	***	38.76	***	32.43	***
			α								t (α)					
Small	0.02%	0.29%	0.34%	0.29%	0.52%	Small	0.16		2.18	**	3.59	***	3.69	***	6.11	***
2	-0.05%	0.14%	0.05%	0.13%	0.02%	2	-0.48		1.79	*	0.61		1.71	*	0.25	
3	-0.08%	0.09%	0.17%	0.17%	0.20%	3	-0.69		1.06		1.97	**	1.87	*	2.03	**
4	0.13%	0.10%	0.05%	0.08%	0.06%	4	1.32		1.10		0.55		0.79		0.50	
Big	0.24%	0.20%	0.26%	-0.02%	0.02%	Big	3.37	***	2.81	***	2.14	**	-0.18		0.12	
			R^2													
Small	0.92	0.93	0.93	0.95	0.93											
2	0.93	0.94	0.92	0.93	0.93											
3	0.92	0.91	0.90	0.90	0.88											
4	0.91	0.89	0.87	0.87	0.83											
Big	0.92	0.89	0.81	0.84	0.79											

Table 17: Regression Results for O-score, Z-score, PERFORMANCE1, LEVERAGE2, SMB, and HML FMPs

This table shows the result from a regression of excess stock returns from the 25 portfolios formed on size and BTM on the excess market return and the O-score FMP, the Z-score FMP, performance1 FMP, leverage2 FMP, SMB, and HML for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_t - Rf_{,t} = \alpha + \beta(MKT_t - Rf_t) + \gamma Oscore_{t,} + \delta Zscore_t + \lambda PER1_t + \pi LEV2_t + \Delta SMB_t + \xi HML_t + \varepsilon_{i,}$$

Where γ is the estimated coefficient on the O-score FMP, δ is the estimated coefficient on Z-score FMP, λ is the estimated coefficient on the perfroamcne1 FMP, π is the estimated coefficient on the leverage2 FMP, Δ is the estimated coefficient on SMB, ξ is the estimated coefficient on HML, and α is the intercept. The t-statistics are shown on the right, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). R-square values are adjusted R square values. These regressions are corrected for heteroskedasticity.

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles				
	Low	2	3	4	High		Low	2	3	4	High
Size Quintile			γ			Size Quintile			t(γ)		
Small	0.08	-0.06	-0.07	-0.09	-0.07	Small	0.75	-0.62	-0.85	-1.46	-0.94
2	-0.04	-0.03	-0.05	-0.09	-0.14	2	-0.38	-0.45	-0.64	-1.41	-1.96 *
3	-0.04	-0.06	-0.02	-0.08	0.04	3	-0.44	-0.75	-0.28	-1.01	0.53
4	0.00	0.14	0.01	0.01	0.12	4	-0.04	2.00 **	0.19	0.08	1.12
Big	-0.02	-0.11	-0.20	-0.15	0.16	Big	-0.41	-1.89 *	-2.06 **	-2.11 **	1.51
			δ						t(δ)		
Small	-0.58	-0.37	-0.32	-0.12	-0.05	Small	-4.40 ***	-3.00 ***	-3.90 ***	-1.69 *	-0.62
2	-0.31	-0.17	-0.15	-0.09	-0.01	2	-3.51 ***	-2.52 **	-2.11 **	-1.47	-0.16
3	-0.01	-0.03	-0.10	-0.12	-0.15	3	-0.05	-0.39	-1.45	-1.74 *	-1.90 *
4	-0.07	-0.29	-0.16	-0.12	-0.01	4	-0.91	-3.80 ***	-1.96 **	-1.43	-0.10
Big	0.16	-0.06	-0.63	-0.40	-0.07	Big	2.82 ***	-0.99	-5.54 ***	-5.22 ***	-0.54
			λ						t(λ)		
Small	-0.14	-0.06	-0.10	-0.02	-0.07	Small	-2.28 **	-1.24	-1.49	-0.56	-1.43
2	0.01	0.05	0.17	0.10	0.02	2	0.23	1.12	2.80 ***	2.33 **	0.39
3	-0.06	0.10	0.19	0.05	0.07	3	-1.03	1.85 *	3.49 ***	1.00	1.13
4	-0.08	0.26	0.18	0.02	-0.02	4	-1.52	4.43 ***	2.88 ***	0.27	-0.25
Big	-0.01	0.10	0.07	-0.01	0.00	Big	-0.32	2.28 **	0.96	-0.24	-0.04

Table 17 – continued

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
			π								t(π)					
Small	-0.36	-0.16	-0.11	-0.02	0.14	Small	-4.53	***	-2.26	**	-1.81	*	-0.40		2.52	**
2	-0.16	-0.08	0.04	0.11	0.16	2	-2.31	**	-1.19		0.59		1.84	*	2.40	**
3	0.03	0.10	0.11	0.08	0.03	3	0.37		1.15		1.52		1.06		0.46	
4	-0.08	-0.02	0.06	0.07	0.09	4	-0.90		-0.40		0.78		0.84		0.90	
Big	0.18	0.08	-0.12	-0.09	-0.08	Big	3.35	***	1.58		-1.31		-1.22		-1.04	
			Δ								t(Δ)					
Small	1.25	1.21	1.09	1.07	1.03	Small	20.68	***	23.50	***	23.91	***	34.90	***	28.80	***
2	1.01	0.94	0.86	0.86	0.89	2	23.61	***	31.57	***	23.81	***	30.28	***	26.72	***
3	0.79	0.69	0.63	0.57	0.59	3	16.74	***	19.80	***	18.59	***	16.15	***	14.75	***
4	0.37	0.34	0.33	0.27	0.32	4	9.99	***	9.73	***	8.35	***	7.58	***	6.23	***
Big	-0.21	-0.04	-0.21	-0.14	-0.08	Big	-7.16	***	-1.41		-4.51	***	-3.84	***	-1.41	
			ξ								t(ξ)					
Small	-0.48	-0.15	0.02	0.33	0.45	Small	-3.21	***	-1.09		0.26		5.03	***	5.89	***
2	-0.55	-0.02	0.27	0.39	0.63	2	-6.46	***	-0.42		4.08	***	7.33	***	11.75	***
3	-0.48	0.06	0.26	0.45	0.59	3	-4.77	***	0.76		4.57	***	7.50	***	9.01	***
4	-0.47	0.01	0.26	0.41	0.56	4	-7.21	***	0.17		3.98	***	6.56	***	7.07	***
Big	-0.47	-0.02	-0.04	0.37	0.74	Big	-10.64	***	-0.46		-0.42		6.17	***	5.93	***

Table 17 – continued

	Book-to-Market Equity Quintiles						Book-to-Market Equity Quintiles									
	Low	2	3	4	High		Low		2		3		4		High	
			β								t (β)					
Small	1.03	0.99	0.95	0.93	0.92	Small	34.19	***	38.91	***	38.96	***	46.42	***	38.94	***
2	1.13	1.06	1.05	1.04	1.07	2	44.22	***	48.62	***	42.41	***	53.89	***	47.94	***
3	1.13	1.10	1.08	1.07	1.06	3	43.89	***	48.65	***	44.52	***	43.32	***	42.47	***
4	1.12	1.10	1.10	1.16	1.15	4	41.62	***	42.47	***	38.95	***	36.40	***	34.18	***
Big	0.99	1.02	1.01	1.04	1.07	Big	52.46	***	56.35	***	33.93	***	40.62	***	31.19	***
			α								t (α)					
Small	0.04%	0.31%	0.37%	0.30%	0.54%	Small	0.30		2.20	**	3.78	***	3.82	***	6.09	***
2	-0.05%	0.14%	0.02%	0.12%	0.03%	2	-0.45		1.70	*	0.20		1.53		0.38	
3	-0.06%	0.08%	0.13%	0.17%	0.18%	3	-0.49		0.85		1.49		1.80	*	1.76	*
4	0.15%	0.03%	0.01%	0.08%	0.05%	4	1.46		0.26		0.10		0.73		0.41	
Big	0.24%	0.19%	0.27%	0.01%	0.00%	Big	3.34	***	2.73	***	2.19	**	0.06		-0.01	
			R^2													
Small	0.92	0.93	0.93	0.95	0.93											
2	0.93	0.94	0.93	0.94	0.93											
3	0.92	0.91	0.91	0.90	0.89											
4	0.91	0.89	0.87	0.87	0.83											
Big	0.92	0.89	0.82	0.84	0.79											

1% level. The HML coefficient remains significant at the 1% and 5% level for eighteen for the portfolios.

The intercept values follow the pattern of the previous two models. There are seven portfolios where the intercept is significantly different from zero at the 5% level. The smallest size firms with the higher BTM levels have intercept values significantly different from zero and the largest size firms with the lower BTM values have intercept values significantly different from zero.

1.4.5 Risk vs. Characteristics

O-score, Z-score, leverage2, and performance1 are our strongest systematic distress FMPs. Each of these variables shows statistically significant coefficient estimates when used in a regression with only the market factor, suggesting that these distress risk proxies are indeed priced in the cross section of stock returns. However, they appear to be subsumed by SMB and HML when SMB and HML are added to the model. This suggests that using the Daniel and Titman (1997) method of determining if these factors proxy for a systematic risk or are indicative of characteristics may not give us strong results. The goal is to create portfolios that have the same level of size and the distress variable yet have different loadings on the distress factor. To accomplish this, we create nine portfolios based on three size levels and three levels of the distress proxy. We then use thirty-six months of data preformation to split each of these nine portfolios into five sub-portfolios based on the preformation loadings on the distress factor. If size and BTM are subsuming the explanatory power of the distress variable then our preformation loadings on the distress factor may not provide the dispersion required post-formation. In other words, if our pre-formation factor loadings are not representative of post-formation factor loadings on the distress proxy then we do not have portfolios with similar characteristics yet different factor loadings and our test results are not valid. In the previous model using our four strongest distress factors and SMB and HML, we see some portfolios where the distress factor is not subsumed. Therefore we optimistically run the test on all four of the distress variables, O-score, Z-score, performance1, and leverage2, but cannot expect strong results.

We start with the O-score variable. We examine the coefficient estimates of the monthly excess returns for each of the forty-five portfolios on the excess market returns, SMB, HML, and the O-score FMP. In order for our test to have any validity, we must show that the post-formation factor loadings on the O-score FMP have dispersion across the five sub-portfolios. We need to see a monotonic pattern based on our ex-ante factor loadings. While the pattern is not perfectly monotonic, we do show differences across the factor loadings. This is shown in Table 18.

We do not obtain the perfectly monotonic pattern that we require in the post-formation factor loadings on the distress factor, but we do have a pattern going from lowest loading to highest loading. We examine the mean returns, shown as a percent, across the five sub-portfolios. The results are shown in Table 19. If the distress FMP is a proxy for systematic risk, we expect the factor loading to be relevant and the returns should follow a pattern similar to the coefficient estimates. The highest returns should be for the portfolios with the highest loading on the distress factor and the lowest returns on the portfolios with the lowest loading on the distress factor. The portfolio with the lowest factor loading has the highest returns and the portfolio with the highest factor loadings has the highest returns. Since the O-score is an indication of distress probability, we expect that the portfolio that loads the highest on this factor would have the highest return, so these results are the reverse of what we expect. There is no pattern across the portfolios. Returns do not appear to be associated with the factor loading. This suggests that the factor loadings are

Table 18: Coefficient Estimates for Regression Using Portfolios Formed from Predicted O-Score FMP Loadings

This table shows the result from a time series regression of excess stock returns from the 45 portfolios formed on size and O-score characteristics, then split into sub-portfolios based on predicted O-score FMP loadings. These are the estimated coefficients from a regression of the portfolios on, the O-score FMP, SMB, and the excess market return for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_{o,sz,fl} - R_f = \alpha + \beta_{OSCORE} * \tilde{R}_{OSCORE} + \beta_{SMB} * \tilde{R}_{SMB} + \beta_{HML} * \tilde{R}_{HML} + \beta_{(MKT-RF)} * \tilde{R}_{(MKT-RF)} + e$$

Where α is the intercept, β_{OSCORE} is the estimated coefficient on the O-score FMP, β_{SMB} is the estimated coefficient on SMB, and $\beta_{(MKT-RF)}$ is the estimated coefficient on the excess market return. The last line of each section shows the mean coefficient for each factor loading level. The right hand column shows the corresponding t-stats, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%).

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio				
O-score level	Size	1	2	3	4	5	1	2	3	4	5
				α					t (α)		
1	1	0.16	0.01	0.11	0.10	0.04	1.32	0.06	1.24	0.97	0.34
1	2	0.04	-0.13	0.14	0.03	0.19	0.27	-1.28	1.38	0.27	1.62
1	3	0.27	0.20	-0.01	0.18	0.22	1.64	1.62	-0.10	2.02 **	1.95 *
2	1	0.20	0.17	0.09	0.18	-0.17	1.71 *	1.76 *	0.89	1.66 *	-1.51
2	2	-0.10	0.07	0.19	0.04	0.20	-0.73	0.68	1.74 *	0.31	1.50
2	3	0.18	0.12	0.15	-0.02	0.18	1.23	0.98	1.52	-0.18	1.34
3	1	0.23	0.13	0.15	0.24	0.23	1.97 **	1.47	1.68 *	2.33 **	1.61
3	2	0.25	0.17	-0.07	0.00	-0.38	1.50	1.33	-0.64	0.02	-2.24 **
3	3	0.20	-0.16	0.19	0.43	-0.32	1.10	-0.97	1.18	2.44 **	-1.42
	Average	0.16	0.06	0.10	0.13	0.02	1.11	0.63	0.99	1.09	0.35

Table 18- continued

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
O-score level	Size	1	2	3	4	5	1		2		3		4		5	
				β_{OSCORE}							t (β_{OSCORE})					
1	1	-28.00	-29.75	-33.78	-23.69	8.47	-4.09	***	-5.51	***	-6.37	***	-4.21	***	1.30	
1	2	-44.58	-30.11	-23.38	-18.59	3.50	-5.57	***	-5.07	***	-3.97	***	-3.16	***	0.51	
1	3	-39.46	8.09	-12.00	-8.90	24.05	-4.20	***	1.15		-2.25	**	-1.70	*	3.64	***
2	1	-17.02	-24.11	-17.73	-14.92	11.44	-2.59	***	-4.39	***	-3.15	***	-2.45	**	1.73	*
2	2	-28.41	-11.84	-9.32	-10.99	-1.47	-3.56	***	-1.96	*	-1.50		-1.68	*	-0.19	
2	3	-9.46	16.11	-1.48	2.70	28.26	-1.12		2.37	**	-0.25		0.44		3.75	***
3	1	4.78	6.06	7.26	19.09	52.64	0.70		1.17		1.45		3.28	***	6.50	***
3	2	23.38	0.56	22.13	10.69	53.38	2.48	**	0.07		3.30	***	1.32		5.51	***
3	3	44.08	22.98	13.42	40.46	52.53	4.13	***	2.41	**	1.45		4.02	***	4.08	***
Average		-10.52	-4.67	-6.10	-0.46	25.87	-1.54		-1.08		-1.25		-0.46		2.98	
				β_{SMB}							t (β_{SMB})					
1	1	111.75	93.78	91.53	91.48	99.54	25.59	***	27.24	***	27.09	***	25.54	***	24.01	***
1	2	84.58	71.11	64.23	57.27	64.70	16.59	***	18.80	***	17.13	***	15.26	***	14.94	***
1	3	16.57	-18.32	-19.55	-21.03	-33.37	2.77	***	-4.08	***	-5.76	***	-6.31	***	-7.93	***
2	1	105.72	93.75	96.76	92.73	96.97	25.22	***	26.80	***	26.96	***	23.86	***	23.04	***
2	2	73.88	50.68	48.47	55.87	58.74	14.54	***	13.17	***	12.24	***	13.43	***	12.18	***
2	3	3.87	-11.24	-9.27	-2.65	-5.50	0.72		-2.59	***	-2.51	**	-0.68		-1.14	
3	1	116.03	98.48	95.19	110.75	123.76	26.70	***	29.92	***	29.90	***	29.87	***	23.99	***
3	2	61.57	48.70	58.37	48.67	67.25	10.25	***	10.24	***	13.68	***	9.45	***	10.89	***
3	3	0.76	0.58	-7.22	-7.53	6.65	0.11		0.10		-1.23		-1.18		0.81	
Average		63.86	47.50	46.50	47.28	53.19	13.61		13.29		13.06		12.14		11.20	

Table 18 - continued

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
O-score level	Size	1	2	3	4	5	1		2		3		4		5	
				β_{HML}							$t(\beta_{HML})$					
1	1	13.52	34.33	38.95	33.32	0.17	3.18	***	10.25	***	11.84	***	9.56	***	0.04	
1	2	10.19	19.51	12.25	15.44	-9.87	2.05	**	5.30	***	3.36	***	4.23	***	-2.34	**
1	3	-37.16	-23.47	1.38	-3.14	-25.58	-6.38	***	-5.37	***	0.42		-0.97		-6.25	***
2	1	29.95	49.07	39.52	52.16	32.16	7.34	***	14.41	***	11.31	***	13.79	***	7.85	***
2	2	32.65	38.05	48.89	45.37	25.71	6.60	***	10.16	***	12.69	***	11.20	***	5.48	***
2	3	9.21	12.70	26.72	26.15	18.58	1.76	*	3.01	***	7.42	***	6.93	***	3.97	***
3	1	28.82	43.27	41.87	26.96	-9.22	6.81	***	13.51	***	13.51	***	7.47	***	-1.84	*
3	2	4.28	39.47	37.57	30.11	-6.00	0.73		8.53	***	9.04	***	6.00	***	-1.00	
3	3	7.44	23.37	15.57	-3.98	-1.91	1.12		3.95	***	2.72	***	-0.64		-0.24	
Average		10.99	26.26	29.19	24.71	2.67	2.58		7.08		8.03		6.40		0.63	
				β_{MKT}							$t(\beta_{MKT})$					
1	1	99.17	93.51	91.93	92.59	96.44	33.75	***	40.37	***	40.43	***	38.42	***	34.57	***
1	2	116.69	103.80	93.79	103.81	107.88	34.02	***	40.80	***	37.18	***	41.12	***	37.03	***
1	3	111.67	105.17	90.08	99.33	102.26	27.72	***	34.81	***	39.47	***	44.27	***	36.12	***
2	1	101.68	97.49	96.37	101.12	102.85	36.05	***	41.42	***	39.91	***	38.67	***	36.32	***
2	2	120.19	100.63	102.97	104.34	111.49	35.16	***	38.87	***	38.66	***	37.27	***	34.37	***
2	3	110.53	100.73	101.21	103.08	116.75	30.48	***	34.54	***	40.68	***	39.55	***	36.12	***
3	1	109.45	97.52	98.89	106.66	101.68	37.44	***	44.04	***	46.17	***	42.75	***	29.29	***
3	2	122.65	105.42	107.94	115.66	112.46	30.36	***	32.96	***	37.58	***	33.36	***	27.08	***
3	3	112.46	102.91	97.94	99.28	119.50	24.59	***	25.16	***	24.76	***	23.03	***	21.68	***
Average		111.61	100.80	97.90	102.87	107.92	32.17		37.00		38.32		37.60		32.51	

Table 19: Mean Returns for the O-score Factor Loading Portfolios

This table shows the time-series mean excess returns of value-weighted forty-five monthly factor portfolios. These portfolios are formed by splitting the stocks into three size levels and three O-score levels, with 1 being the smallest or lowest level and 3 being the highest. The intersection of these two sorts creates the nine characteristic based portfolios. These characteristic portfolios are each further divided into five sub-portfolios based on the pre-formation loading of the stock on the O-score FMP from -42 to -7 months prior to June of year *t*. The quintile with the lowest pre-formation factor loading is 1 and the quintile with the highest pre-formation factor loading is 5. The top panel shows the time series mean excess monthly portfolio returns. These are shown as a percent return. The last line shows the mean percent return by each factor loading level. The bottom panel shows the t-statistics for each of the time series mean returns. Statistical significance level is denoted by stars. Three stars indicate significance at the 1% level, two stars indicates significance at the 5% level, and one star indicates significance at the 10% level.

		Monthly Excess Mean Returns					*t*- statistics									
Char Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
O-score level	Size	1	2	3	4	5	1		2		3		4		5	
1	1	1.119	0.952	1.053	1.037	0.965	3.67	***	3.61	***	4.12	***	3.92	***	3.13	***
1	2	0.943	0.723	0.899	0.839	0.996	3.05	***	2.73	***	3.66	***	3.24	***	3.36	***
1	3	0.702	0.629	0.392	0.618	0.608	2.43	**	2.54	**	2.03	**	2.94	***	2.53	**
2	1	1.242	1.210	1.109	1.268	0.919	4.08	***	4.43	***	3.97	***	4.42	***	2.93	***
2	2	0.913	0.950	1.121	0.986	1.137	2.96	***	3.81	***	4.41	***	3.74	***	3.90	***
2	3	0.821	0.717	0.784	0.653	0.939	3.13	***	3.07	***	3.58	***	2.86	***	3.42	***
3	1	1.406	1.236	1.241	1.397	1.334	4.11	***	4.20	***	4.24	***	4.17	***	3.49	***
3	2	1.223	1.103	0.947	0.973	0.590	3.55	***	4.04	***	3.25	***	3.23	***	1.67	*
3	3	0.956	0.557	0.797	1.018	0.475	3.11	***	2.07	**	3.17	***	3.69	***	1.36	
	Average	1.036	0.897	0.927	0.977	0.885										

irrelevant and only the characteristics matter. However, since our preformation factor loadings do not give us the monotonic pattern of loading post formation, this test is not strong evidence.

We do have a difference in the factor loadings of the lowest loading portfolios and the highest loading portfolios so we create “long-short” portfolios and examine the results of these. We long the two lowest and short the two highest factor loading portfolios for each of our nine characteristic portfolios. Results are shown in Table 20.We expect that if the O-score FMP factor loadings are relevant and therefore indicative of systematic risk, a long short portfolio should have lower returns for portfolios one and two and higher returns for portfolios four and five, making the returns on the long-short portfolio negative. We also expect that if the distress factors represent systematic risk, than the factor loadings matter and the intercepts from the long-short portfolio should be indistinguishable from zero. However, if only characteristics matter then the loadings on the distress factor are irrelevant and our five sub-portfolios within each of the nine characteristic based portfolios should have the same returns making our long-short portfolio return indistinguishable from zero and the intercepts should be positive.

Only one of the returns for the characteristic balanced portfolios is significantly different from zero. Additionally the combined portfolio (an equal weighted combination of all the long-short portfolios) has a return that is statistically indistinguishable from zero. Four of the intercepts are negative but they lack statistical significance. The only intercept with significance at the 1% level is positive. Even with the large difference in estimated factor loadings on the O-score FMP between the lowest and highest loading portfolios, we get no conclusive evidence with our long-short portfolio. The evidence is neither supportive of risk nor characteristics.

We then employ the same tests on the Z-score, performance1, and leverage2 FMPs. The coefficient estimates for the Z-score FMP, shown in Table 21, provide evidence that the preformation factor loadings provide the dispersion pattern we desire across the first four factor loading portfolios, but not the fifth. The portfolios with the lowest factor loadings have the most negative Z-score coefficient and the portfolios with the highest factor loading have the most positive Z-score coefficient, again with the exception of the fifth or largest factor loading portfolio. This is true on average and across some of the nine portfolios but the pattern is not monotonic across all the portfolios.

Table 20: Regression Results for O-score Characteristic Balanced Portfolio

We create long-short portfolios for each of the nine major portfolios by summing the monthly value-weighted portfolio returns for portfolios four and five and subtracting them from the summation of the monthly value-weighted returns of portfolios one and two. The return for this portfolio is the mean time series monthly return as a percent. We then estimate a regression of these returns on the excess market returns, SMB, and the O-score FMP.

$$R_{CBP} - R_f = \alpha + \beta_{(MKT-RF)} * R_{(MKT-RF)} + \beta_{SMB} * R_{SMB} + \beta_{HML} * R_{HML} + \beta_{OSCORE} * R_{OSCORE} + e$$

Where $R_{CBP} - R_f$ is the monthly excess returns from the long-short portfolio, α is the intercept, $\beta_{(MKT-RF)}$ is the estimated coefficient on the excess market return, β_{SMB} is the estimated coefficient on SMB, and β_{OSCORE} is the estimated coefficient on the O-score FMP. The coefficient estimates are shown in the table below. The second panel shows the corresponding t-statistics for each, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). The last line shows the results for a combined portfolio that is constructed from an equal weighted average of the returns from the nine long-short portfolios. The R-square values are shown as a percent.

Characteristic-Balanced Portfolio								
O-Score	Size	Ret	α	β_{MKT}	β_{SMB}	β_{HML}	β_{OSCORE}	R^2
1	1	0.07	0.03	3.65	14.52	14.35	-42.53	2.52
1	2	-0.17	-0.31	8.80	33.72	24.13	-59.60	5.63
1	3	0.10	0.06	15.25	52.66	-31.90	-46.52	8.75
2	1	0.26	0.36	-4.80	9.78	-5.29	-37.66	3.5
2	2	-0.26	-0.26	4.99	9.95	-0.38	-27.79	1.19
2	3	-0.05	0.14	-8.57	0.78	-22.82	-24.31	3.36
3	1	-0.09	-0.10	-1.38	-19.99	54.35	-60.90	19.58
3	2	0.76	0.79	-0.05	-5.66	19.64	-40.13	2.68
3	3	0.02	-0.06	-3.41	2.22	36.69	-25.93	1.81
Combined Portfolio		0.07	0.07	1.61	10.89	9.86	-40.60	4.57

Table 20 – continued

		Characteristic-Balanced Portfolio: *t*- statistics											
O-Score	Size	Ret		α		β_{MKT}		β_{SMB}		β_{HML}		β_{OSCORE}	
1	1	0.34		0.14		0.71		1.89	*	1.92	*	-3.53	***
1	2	-0.82		-1.51		1.72	*	4.43	***	3.26	***	-4.99	***
1	3	0.31		0.18		1.85	*	4.30	***	-2.68	***	-2.42	**
2	1	1.25		1.68	*	-0.91		1.24		-0.69		-3.05	***
2	2	-1.20		-1.18		0.91		1.22		-0.05		-2.18	**
2	3	-0.20		0.52		-1.30		0.08		-2.39	**	-1.58	
3	1	-0.37		-0.44		-0.25		-2.47	**	6.89	***	-4.78	***
3	2	2.51	**	2.57	**	-0.01		-0.50		1.79	*	-2.26	**
3	3	0.05		-0.16		-0.34		0.15		2.54	**	-1.11	
Combined Portfolio		0.48		0.47		0.43		1.94	*	1.81	*	-4.62	***

Since we have the desired dispersion in our distress factor loadings across portfolios one through four, we examine the mean returns for these portfolios in Table 22. If the distress factors are proxies for systematic risk, we expect that the returns are greater for the portfolios with the higher loadings. We see a monotonic pattern across the portfolios where the portfolios that load lower on the distress proxy have lower returns and the portfolios that load higher on the distress proxy have higher returns for portfolios one through four. Interestingly portfolio five has the highest returns yet the post-formation loading on the highest preformation loading portfolio is not the highest. In other words, we do not have the highest factor loadings on portfolio five. Therefore we should not see the highest returns for this portfolio.

Even though we do not have a perfectly monotonic pattern across the coefficient loadings on the Z-score, we have a large difference in the loadings of the two lowest and two highest portfolios, so we examine our long- short, or characteristic balanced portfolio in Table 23.

Table 21: Coefficient Estimates for Regression Using Portfolios Formed from Predicted Z-Score FMP Loadings

This table shows the result from a time series regression of excess stock returns from the 45 portfolios formed on size and Z-score characteristics, then split into sub-portfolios based on predicted Z-score FMP loadings. These are the estimated coefficients from a regression of the portfolios on, the Z-score FMP, SMB, and the excess market return for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_{o,sz,fl} - R_f = \alpha + \beta_{ZSCORE} * \tilde{R}_{ZSCORE} + \beta_{SMB} * \tilde{R}_{SMB} + \beta_{HM\ L} * \tilde{R}_{HM\ L} + \beta_{(MKT-RF)} * \tilde{R}_{(MKT-RF)} + e$$

Where α is the intercept, β_{ZSCORE} is the estimated coefficient on the Z-score FMP, β_{SMB} is the estimated coefficient on SMB, and $\beta_{(MKT-RF)}$ is the estimated coefficient on the excess market return. The last line of each section shows the mean coefficient for each factor loading level. The right hand column shows the corresponding t-stats, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%).

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio				
Z-score level	Size	1	2	3	4	5	1	2	3	4	5
				α					t (α)		
1	1	0.39	0.53	0.28	0.36	0.36	2.58 **	4.41 ***	2.75 ***	3.09 ***	2.76 ***
1	2	0.08	0.02	0.15	0.28	0.35	0.40	0.13	1.16	2.18 **	2.38 **
1	3	0.01	0.18	-0.01	0.20	0.18	0.08	1.41	-0.09	1.49	1.20
2	1	0.12	0.11	0.13	0.19	0.36	1.01	1.06	1.39	2.00 **	3.39 ***
2	2	-0.10	0.10	0.05	0.23	0.19	-0.68	0.89	0.42	1.90 *	1.52
2	3	0.25	0.13	0.15	0.15	0.10	1.72 *	1.09	1.32	1.23	0.71
3	1	-0.01	-0.03	0.07	0.09	0.10	-0.08	-0.27	0.85	1.01	0.95
3	2	0.17	-0.03	0.005	0.05	0.07	1.38	-0.26	0.05	0.50	0.57
3	3	0.03	0.27	0.02	0.08	0.38	0.22	2.22 **	0.14	0.72	2.40 **
	Average	0.11	0.14	0.09	0.18	0.23	0.74	1.19	0.89	1.57	1.76

Table 21 – continued

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio				
Z-score level	Size	1	2	3	4	5	1	2	3	4	5
				β_{ZSCORE}					t (β_{ZSCORE})		
1	1	-58.63	-43.59	-37.69	-14.63	-26.53	-8.43 ***	-7.95 ***	-8.12 ***	-2.75 ***	-4.53 ***
1	2	-64.59	-52.43	-17.31	-33.40	-37.13	-6.99 ***	-8.00 ***	-2.98 ***	-5.71 ***	-5.61 ***
1	3	-35.47	-50.69	-17.19	-33.31	-43.75	-4.66 ***	-8.60 ***	-3.28 ***	-5.54 ***	-6.26 ***
2	1	-14.39	-8.67	-0.14	6.85	-16.41	-2.59 ***	-1.80 *	-0.03	1.55	-3.39 ***
2	2	-23.37	-5.43	3.01	-4.21	0.34	-3.45 ***	-1.06	0.61	-0.77	0.06
2	3	-33.57	-22.78	-13.56	-11.40	8.33	-5.05 ***	-4.13 ***	-2.59 ***	-2.00 **	1.29
3	1	-23.16	-3.43	6.36	7.24	0.16	-4.15 ***	-0.81	1.64	1.82 *	0.03
3	2	-3.68	9.08	7.69	7.30	16.70	-0.66	1.93 *	1.74 *	1.52	2.96 ***
3	3	-12.04	5.23	19.54	31.87	8.51	-1.80 *	0.94	4.04 ***	6.15 ***	1.18
	Average	-29.88	-19.19	-5.48	-4.85	-9.97	-4.20	-3.28	-1.00	-0.64	-1.59
				β_{SMB}					t (β_{SMB})		
1	1	120.66	105.31	92.44	105.33	107.05	25.64 ***	28.37 ***	29.42 ***	29.25 ***	27.01 ***
1	2	61.35	42.42	53.17	43.15	66.98	9.81 ***	9.56 ***	13.54 ***	10.90 ***	14.96 ***
1	3	-8.22	-23.14	-6.33	-16.93	-1.60	-1.60	-5.80 ***	-1.78 *	-4.16 ***	-0.34
2	1	101.07	94.53	87.90	81.13	105.09	26.87 ***	28.98 ***	30.47 ***	27.10 ***	32.10 ***
2	2	57.15	50.06	57.44	50.81	59.39	12.48 ***	14.47 ***	17.15 ***	13.73 ***	15.73 ***
2	3	-29.55	-23.39	-6.53	-10.32	-0.22	-6.57 ***	-6.27 ***	-1.84 *	-2.67 ***	-0.05
3	1	113.85	95.65	86.95	93.24	111.98	30.13 ***	33.25 ***	33.09 ***	34.57 ***	33.92 ***
3	2	67.63	61.76	53.75	59.77	75.01	17.85 ***	19.42 ***	17.94 ***	18.40 ***	19.62 ***
3	3	-10.63	-23.59	-17.12	-11.07	-1.22	-2.35 **	-6.28 ***	-5.23 ***	-3.16 ***	-0.25
	Average	52.59	42.18	44.63	43.90	58.05	12.47	12.86	14.75	13.77	15.86

Table 21 – continued

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
Z-score level	Size	1	2	3	4	5	1		2		3		4		5	
				β_{HML}							$t(\beta_{HML})$					
1	1	6.60	18.61	31.11	34.48	13.37	1.01		3.61	***	7.12	***	6.88	***	2.43	**
1	2	15.62	22.88	42.45	32.04	6.98	1.80	*	3.71	***	7.77	***	5.82	***	1.12	
1	3	26.11	-2.67	40.41	11.04	-9.10	3.65	***	-0.48		8.19	***	1.95	*	-1.38	
2	1	30.41	48.78	43.52	50.68	13.75	5.81	***	10.75	***	10.85	***	12.17	***	3.02	***
2	2	23.14	31.84	40.11	41.41	22.41	3.63	***	6.62	***	8.61	***	8.04	***	4.27	***
2	3	-2.20	7.91	4.58	4.89	17.09	-0.35		1.52		0.93		0.91		2.81	***
3	1	-25.34	11.54	22.70	21.21	0.36	-4.82	***	2.88	***	6.21	***	5.65	***	0.08	
3	2	-26.23	6.18	7.66	0.94	-12.91	-4.98	***	1.40		1.84	*	0.21		-2.43	**
3	3	-37.49	-28.61	-15.29	-21.42	-43.44	-5.96	***	-5.47	***	-3.36	***	-4.39	***	-6.40	***
	Average	1.18	12.94	24.14	19.47	0.95	-0.02		2.73		5.35		4.14		0.39	
				β_{MKT}							$t(\beta_{MKT})$					
1	1	107.13	104.88	100.75	101.35	105.55	30.68	***	38.09	***	43.21	***	37.94	***	35.89	***
1	2	115.05	114.95	109.34	110.81	117.73	24.81	***	34.91	***	37.53	***	37.74	***	35.45	***
1	3	119.25	95.68	103.71	107.70	106.28	31.22	***	32.32	***	39.42	***	35.66	***	30.29	***
2	1	105.05	100.75	94.07	90.80	99.06	37.65	***	41.63	***	43.95	***	40.88	***	40.78	***
2	2	116.18	105.90	100.08	104.81	106.24	34.19	***	41.27	***	40.26	***	38.16	***	37,92	***
2	3	109.22	101.54	97.05	92.60	105.42	32.75	***	36.67	***	36.87	***	32.32	***	32.48	***
3	1	94.25	94.18	89.30	88.84	102.05	33.62	***	44.13	***	45.81	***	44.39	***	41.67	***
3	2	103.33	100.34	98.92	96.56	107.74	36.77	***	42.53	***	44.51	***	40.06	***	37.98	***
3	3	108.44	99.51	100.82	99.29	106.16	32.32	***	35.68	***	41.50	***	38.18	***	29.33	***
	Average	108.65	101.97	99.34	99.20	106.25	32.67		38.58		41.45		38.37		35.48	

Table 22: Mean Returns for the Z-score Factor Loading Portfolios

This table shows the time-series mean excess returns of value-weighted forty-five monthly factor portfolios. These portfolios are formed by splitting the stocks into three size levels and three Z-score levels, with 1 being the smallest or lowest level and 3 being the highest. The intersection of these two sorts creates the nine characteristic based portfolios. These characteristic portfolios are each further divided into five sub-portfolios based on the pre-formation loading of the stock on the Z-score FMP from -42 to -7 months prior to June of year *t*. The quintile with the lowest pre-formation factor loading is 1 and the quintile with the highest pre-formation factor loading is 5. The top panel shows the time series mean excess monthly portfolio returns. These are shown as a percent return. The last line shows the mean percent return by each factor loading level. The bottom panel shows the t-statistics for each of the time series mean returns. Statistical significance level is denoted by stars. Three stars indicate significance at the 1% level, two stars indicates significance at the 5% level, and one star indicates significance at the 10% level.

							t- statistics									
Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
Z-score level	Size	1	2	3	4	5	1		2		3		4		5	
1	1	1.421	1.550	1.284	1.450	1.376	3.84	***	4.66	***	4.21	***	4.59	***	4.13	***
1	2	0.959	0.865	1.115	1.160	1.246	2.72	***	2.83	***	3.90	***	4.06	***	3.83	***
1	3	0.719	0.569	0.692	0.746	0.690	2.48	**	2.46	**	2.94	***	2.99	***	2.58	**
2	1	1.199	1.221	1.162	1.218	1.348	3.75	***	4.09	***	4.23	***	4.65	***	4.33	***
2	2	0.832	1.000	0.984	1.167	1.090	2.68	***	3.73	***	3.78	***	4.33	***	3.89	***
2	3	0.704	0.618	0.670	0.636	0.759	2.75	***	2.69	***	3.01	***	2.91	***	3.05	***
3	1	0.815	0.900	0.993	1.024	1.089	2.48	**	3.14	***	3.77	***	3.79	***	3.36	***
3	2	0.882	0.792	0.791	0.820	0.906	2.97	***	2.97	***	3.10	***	3.14	***	2.96	***
3	3	0.422	0.614	0.457	0.523	0.786	1.57		2.60	***	2.00	**	2.20	**	2.80	***
	Average	0.884	0.903	0.905	0.972	1.032										

Only three of the characteristic balanced portfolios have returns that are statistically different from zero. They are negative which suggests that the factor loadings are relevant; however the significance is weak, only at the 10% level for two of the three portfolios. The combined portfolio's return is not statistically different from zero, although it is negative. Only one of the portfolios has an intercept value that is statistically different from zero and it is only weakly significant.

Table 23: Regression Results for Z-score Characteristic Balanced Portfolio

We create long-short portfolios for each of the nine major portfolios by summing the monthly value-weighted portfolio returns for portfolios four and five and subtracting them from the summation of the monthly value-weighted returns of portfolios one and two. The return for this portfolio is the mean time series monthly return as a percent. We then estimate a regression of these returns on the excess market returns, SMB, and the Z-score FMP.

$$R_{CBP} - R_f = \alpha + \beta_{(MKT-RF)} * R_{(MKT-RF)} + \beta_{SMB} * R_{SMB} + \beta_{HML} * R_{HML} + \beta_{ZSCORE} * R_{ZSCORE} + e$$

Where $R_{CBP} - R_f$ is the monthly excess returns from the long-short portfolio, α is the intercept, $\beta_{(MKT-RF)}$ is the estimated coefficient on the excess market return, β_{SMB} is the estimated coefficient on SMB, and β_{ZSCORE} is the estimated coefficient on the Z-score FMP. The coefficient estimates are shown in the table below. The second panel shows the corresponding t-statistics for each, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%). The last line shows the results for a combined portfolio that is constructed from an equal weighted average of the returns from the nine long-short portfolios. The R-square values are shown as a percent.

Characteristic Portfolio		Characteristic-Balanced Portfolio						
Z-Score	Size	Ret	α	β_{MKT}	β_{ZSCORE}	β_{SMB}	β_{HML}	R^2
1	1	0.14	0.21	5.11	-61.06	13.60	-22.63	8.03
1	2	-0.58	-0.53	1.47	-46.48	-6.37	-0.53	3.22
1	3	-0.15	-0.19	0.94	-9.10	-12.83	21.50	1.61
2	1	-0.15	-0.32	15.94	-13.49	9.38	14.76	5.64
2	2	-0.42	-0.42	11.03	-24.94	-2.98	-8.84	2.41
2	3	-0.07	0.13	12.75	-53.27	-42.40	-16.27	5.6
3	1	-0.40	-0.22	-2.46	-34.00	4.28	-35.37	4.52
3	2	-0.05	0.02	-0.64	-18.60	-5.40	-8.08	0.82
3	3	-0.27	-0.16	2.49	-47.19	-21.93	-1.24	3.96
Combined Portfolio		-0.22	-0.16	5.18	-34.24	-7.18	-6.30	5.94

Table 23 – continued

Characteristic Portfolio		Characteristic-Balanced Portfolio: *t*- statistics					
Z-Score	Size	Ret	α	β_{MKT}	β_{ZSCORE}	β_{SMB}	β_{HML}
1	1	0.57	0.82	0.87	-5.24 ***	1.72 *	-2.06 **
1	2	-1.80 *	-1.57	0.19	-3.05 ***	-0.62	-0.04
1	3	-0.43	-0.53	0.12	-0.57	-1.18	1.42
2	1	-0.71	-1.52	3.31 ***	-1.41	1.44	1.63
2	2	-1.89 *	-1.79 *	2.08 **	-2.36 **	-0.42	-0.89
2	3	-0.23	0.39	1.72 *	-3.60 ***	-4.24 ***	-1.17
3	1	-2.12 **	-1.17	-0.56	-3.89 ***	0.72	-4.30 ***
3	2	-0.25	0.10	-0.13	-1.91 *	-0.82	-0.88
3	3	-0.85	-0.49	0.33	-3.17 ***	-2.18 **	-0.09
Combined Portfolio		-1.34	-0.99	1.38	-4.57 ***	-1.42	-0.89

This, again, suggests that the factor loadings are relevant. This evidence is very weak, but is supportive of the distress proxy representing a systematic risk.

The coefficient estimates for the performance1 FMPs, shown in Table 24, do not exhibit the pattern we expect to see. This suggests that the preformation factor loadings are not a good indicator of post formation factor loadings. There is dispersion between the lowest factor loading portfolios and the second to highest loading, but the highest factor loading portfolios have on average lower coefficient estimates than do any of the other portfolios with the exception of the lowest factor loading portfolio. This lack of a monotonic pattern of coefficient estimates for the performance1 FMP eliminates the ability to do any testing of risk or characteristic with this factor.

Likewise, the coefficient estimates for the leverage2, shown in Table 25, do not provide the dispersion we expect across the portfolios and the lack of a monotonic pattern of coefficient

Table 24: Coefficient Estimates for Regression Using Portfolios Formed from Predicted PERFORMANCE1 FMP Loadings

This table shows the result from a time series regression of excess stock returns from the 45 portfolios formed on size and Performance1 characteristics, then split into sub-portfolios based on predicted Performance1 FMP loadings. These are the estimated coefficients from a regression of the portfolios on, the Performance1 FMP, SMB, and the excess market return for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_{o,sz,fl} - R_f = \alpha + \beta_{PER1} * \tilde{R}_{PER1} + \beta_{SMB} * \tilde{R}_{SMB} + \beta_{HML} * \tilde{R}_{HML} + \beta_{(MKT-RF)} * \tilde{R}_{(MKT-RF)} + e$$

Where α is the intercept, β_{PER1} is the estimated coefficient on the Performance1 FMP, β_{SMB} is the estimated coefficient on SMB, and $\beta_{(MKT-RF)}$ is the estimated coefficient on the excess market return. The last line of each section shows the mean coefficient for each factor loading level. The right hand column shows the corresponding t-stats, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%).

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio				
PER1 level	Size	1	2	3	4	5	1	2	3	4	5
				α					t (α)		
1	1	0.40	0.11	0.30	0.21	0.31	2.64 ***	1.03	3.12 ***	2.18 **	2.84 ***
1	2	0.11	0.03	0.02	0.19	0.15	0.65	0.19	0.14	1.61	1.09
1	3	-0.17	-0.03	-0.11	-0.03	0.03	-0.92	-0.24	-0.83	-0.24	0.22
2	1	-0.01	0.04	0.09	-0.01	0.20	-0.07	0.46	0.98	-0.10	2.12 **
2	2	-0.05	0.10	-0.07	-0.20	0.09	-0.41	0.96	-0.70	-1.85 *	0.82
2	3	0.02	0.04	0.11	-0.01	0.35	0.15	0.38	1.00	-0.05	2.57 **
3	1	0.11	-0.07	0.04	-0.03	-0.07	0.82	-0.69	0.39	-0.36	-0.62
3	2	0.01	0.20	-0.08	0.02	0.04	0.10	2.10 **	-0.78	0.23	0.33
3	3	-0.01	0.06	0.22	0.21	0.36	-0.12	0.66	2.24 **	1.99 **	2.32 **
	Average	0.04	0.05	0.06	0.04	0.16	0.32	0.54	0.62	0.38	1.30

Table 24 – continued

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
PER1 level	Size	1	2	3	4	5	1		2		3		4		5	
				β_{PER1}							t ($\beta_{PER1)}$					
1	1	-66.77	-29.38	-17.56	-8.94	-25.33	-12.19	***	-7.64	***	-5.07	***	-2.60	***	-6.39	***
1	2	-50.89	-21.68	-11.85	-10.66	-37.39	-7.98	***	-4.14	***	-2.72	***	-2.44	**	-7.44	***
1	3	-58.84	-33.46	-15.37	-12.65	-43.17	-8.72	***	-6.32	***	-3.27	***	-2.63	***	-7.45	***
2	1	13.86	18.55	21.90	30.10	14.97	3.47	***	5.47	***	6.86	***	8.85	***	4.40	***
2	2	17.89	19.62	27.22	25.49	17.48	3.66	***	5.02	***	7.82	***	6.64	***	4.14	***
2	3	8.42	18.60	4.57	-12.46	-20.22	1.70	*	4.69	***	1.15		-2.93	***	-4.08	***
3	1	21.41	29.62	33.23	24.41	28.24	4.44	***	8.00	***	9.43	***	7.40	***	6.89	***
3	2	11.14	25.14	28.16	22.10	13.99	2.68	***	7.33	***	7.52	***	6.01	***	2.95	***
3	3	16.48	20.84	10.39	2.70	-3.18	3.73	***	5.94	***	2.93	***	0.72		-0.56	
	Average	-9.70	5.32	8.97	6.68	-6.07	-1.02		2.04		2.74		2.11		-0.84	
				β_{SMB}							t (β_{SMB})					
1	1	123.68	105.58	102.02	97.52	107.96	24.51	***	29.81	***	31.96	***	30.80	***	29.58	***
1	2	78.07	55.98	52.68	65.92	65.78	13.30	***	11.61	***	13.11	***	16.37	***	14.21	***
1	3	1.83	-14.98	-15.64	-12.37	-43.17	0.29		-3.08	***	-3.61	***	-2.79	***	0.44	
2	1	98.02	94.93	90.60	96.12	100.06	26.62	***	30.38	***	30.83	***	30.68	***	31.96	***
2	2	65.07	61.37	56.24	56.48	55.31	14.44	***	17.07	***	15.75	***	15.98	***	14.22	***
2	3	-3.06	-13.04	-13.62	-13.94	-5.85	-0.67		-3.57	***	-3.71	***	-3.56	***	-1.28	
3	1	107.63	91.71	96.28	92.57	103.52	24.26	***	26.89	***	29.67	***	30.47	***	27.42	***
3	2	61.24	57.95	62.75	65.40	71.62	16.02	***	18.34	***	18.20	***	19.30	***	16.37	***
3	3	-8.16	-11.89	-17.74	-24.85	-1.27	-2.01	**	-3.68	***	-5.44	***	-7.17	***	-0.24	
	Average	58.26	47.51	45.95	46.98	50.44	12.97		13.75		14.08		14.45		14.74	

Table 24 – continued

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
PER1 level	Size	1	2	3	4	5	1		2		3		4		5	
				β_{HML}							t (β_{HML})					
1	1	-16.79	23.63	41.43	36.49	27.62	-3.37	***	6.75	***	13.13	***	11.66	***	7.66	***
1	2	-18.18	27.19	30.06	27.59	9.54	-3.13	***	5.71	***	7.57	***	6.93	***	2.09	**
1	3	-3.46	17.81	35.66	31.33	-0.83	-0.56		3.70	***	8.32	***	7.16	***	-0.16	
2	1	34.89	44.21	47.51	49.67	42.08	9.59	***	14.32	***	16.36	***	16.04	***	13.60	***
2	2	35.06	47.15	46.85	45.90	38.70	7.87	**	13.27	***	13.27	***	13.15	***	10.07	***
2	3	-0.07	29.74	22.81	3.99	0.40	-0.02		8.24	***	6.28	***	1.03		0.09	
3	1	12.59	31.69	35.90	28.70	24.29	2.87	***	9.40	***	11.19	***	9.56	***	6.51	***
3	2	-8.46	9.94	29.47	22.69	9.72	-2.24	**	3.18	***	8.65	***	6.78	***	2.25	**
3	3	-22.59	-13.41	-16.04	-22.94	-30.06	-5.62	***	-4.20	***	-4.98	***	-6.70	***	-5.82	***
	Average	1.44	24.22	30.40	24.82	13.50	0.60		6.71		8.87		7.29		4.03	
				β_{MKT}							t (β_{MKT})					
1	1	100.63	101.65	101.52	102.31	101.49	28.48	***	40.98	***	45.42	***	46.14	***	39.70	***
1	2	117.23	118.98	110.59	105.98	111.08	28.52	***	35.25	***	39.29	***	37.57	***	34.25	***
1	3	121.19	103.29	114.74	105.63	113.58	27.83	***	30.27	***	37.79	***	34.07	***	30.38	***
2	1	107.00	98.17	94.07	94.71	96.23	41.50	***	44.86	***	45.70	***	43.17	***	43.89	***
2	2	118.49	106.48	108.57	99.81	108.36	37.55	***	42.28	***	43.40	***	40.33	***	39.78	***
2	3	112.07	108.69	99.90	107.71	104.30	35.16	***	42.48	***	38.85	***	39.32	***	32.63	***
3	1	104.74	95.30	91.30	93.04	105.30	33.71	***	39.91	***	40.17	***	43.72	***	39.82	***
3	2	107.41	101.56	103.40	100.07	106.54	40.12	***	45.91	***	42.82	***	42.17	***	34.78	***
3	3	106.38	101.59	95.33	99.77	102.54	37.33	***	44.86	***	41.75	***	41.11	***	28.01	***
	Average	110.57	103.97	102.16	101.00	105.49	34.47		40.76		41.69		40.84		35.92	

Table 25: Coefficient Estimates for Regression Using Portfolios Formed from Predicted LEVERAGE2 FMP Loadings

This table shows the result from a time series regression of excess stock returns from the 45 portfolios formed on size and Leverage2 characteristics, then split into sub-po4rtfolios based on predicted Leverage2 FMP loadings. These are the estimated coefficients from a regression of the portfolios on, the Leverage2 FMP, SMB, and the excess market return for fiscal years 1965 to 2011, 564 months. The following regression is estimated:

$$R_{o,sz,fl} - R_f = \alpha + \beta_{LEV2} * \tilde{R}_{LEV2} + \beta_{SMB} * \tilde{R}_{SMB} + \beta_{HML} * \tilde{R}_{HML} + \beta_{(MKT-RF)} * \tilde{R}_{(MKT-RF)} + e$$

Where α is the intercept, β_{LEV2} is the estimated coefficient on the Leverage2 FMP, β_{SMB} is the estimated coefficient on SMB, and $\beta_{(MKT-RF)}$ is the estimated coefficient on the excess market return. The last line of each section shows the mean coefficient for each factor loading level. The right hand column shows the corresponding t-stats, with significance indicated by stars (*** indicates significance at the 1% level, ** 5% and * 10%).

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
LEV2 Level	Size	1	2	3	4	5	1		2		3		4		5	
				α							t (α)					
1	1	0.10	0.06	0.08	-0.01	-0.17	0.76		0.63		0.98		-0.12		-1.35	
1	2	0.08	-0.09	-0.10	0.16	0.06	0.55		-0.86		-0.94		1.63		0.48	
1	3	0.18	0.26	0.16	0.20	0.19	1.10		2.27	**	1.53		1.70	*	1.37	
2	1	0.21	0.17	0.26	0.29	0.24	1.68	*	1.68	*	2.57	**	3.03	***	2.00	**
2	2	0.02	0.23	0.01	0.20	0.14	0.14		2.05	**	0.09		1.84	*	1.10	
2	3	-0.01	0.10	0.12	0.29	0.12	-0.11		0.88		1.11		2.56	**	0.95	
3	1	0.40	0.58	0.48	0.11	0.56	3.14	***	5.25	***	4.58	***	1.06		4.69	***
3	2	0.26	0.20	0.28	0.25	0.19	1.71	*	1.57		2.25	**	1.93	*	1.18	
3	3	0.21	0.09	0.32	0.07	0.35	1.40		0.69		2.66	***	0.50		2.31	**
	Average	0.16	0.18	0.18	0.17	0.19	1.15		1.57		1.65		1.57		1.41	

Table 25 – continued

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
LEV2 Level	Size	1	2	3	4	5	1		2		3		4		5	
				β_{LEV2}							t (β_{LEV2})					
1	1	-1.72	-16.06	-4.14	-3.38	-2.14	-0.30		-3.92	***	-1.15		-0.89		-0.39	
1	2	-18.54	-4.65	-14.37	-0.45	0.06	-2.90	***	-1.00		-3.27	***	-0.11		-0.96	
1	3	-7.77	-8.13	-6.95	6.27	5.89	-1.10		-1.68	*	-1.59		1.28		0.98	
2	1	11.76	1.50	16.36	14.23	12.75	2.16	**	0.35		3.82	***	3.46	***	2.55	**
2	2	14.97	18.29	5.49	20.87	11.72	2.59	***	3.75	***	1.17		4.59	***	2.19	**
2	3	23.64	8.85	19.17	10.33	5.37	3.92	***	1.88	*	4.17	***	2.15	**	0.98	
3	1	30.14	38.77	38.26	40.69	38.48	5.54	***	8.29	***	8.62	***	8.86	***	7.50	***
3	2	32.84	24.15	22.88	48.90	41.87	5.10	***	4.39	***	4.38	***	9.01	***	6.22	***
3	3	34.14	21.67	29.61	30.34	31.20	5.33	***	3.74	***	5.77	***	5.22	***	4.79	***
	Average	13.27	9.38	11.81	18.64	16.13	2.26		1.76		2.44		3.73		2.65	
				β_{SMB}							t (β_{SMB})					
1	1	120.66	101.77	91.37	95.00	109.18	29.55	***	35.11	***	35.85	***	35.27	***	28.33	***
1	2	83.90	60.47	64.23	58.00	54.90	18.56	***	18.43	***	20.65	***	19.25	***	14.36	***
1	3	-1.70	-5.12	-18.82	-24.99	-15.07	-0.34		-1.49		-6.08	***	-7.22	***	-3.56	***
2	1	99.65	85.85	88.97	93.35	104.95	25.90	***	28.38	***	29.39	***	32.07	***	29.64	***
2	2	47.53	49.10	48.12	54.02	56.10	11.62	***	14.23	***	14.48	***	16.78	***	14.79	***
2	3	-13.77	-18.66	-11.10	-16.10	-15.00	-3.22	***	-5.61	***	-3.41	***	-4.73	***	-3.86	***
3	1	101.21	89.87	85.09	98.42	110.51	26.30	***	27.16	***	27.12	***	30.29	***	30.45	***
3	2	58.38	50.43	47.69	58.74	74.80	12.82	***	12.97	***	12.91	***	15.30	***	15.71	***
3	3	-9.42	-14.76	-12.92	-3.56	14.73	-2.08	**	-3.60	***	-3.56	***	-0.86		3.20	***
	Average	54.05	44.33	42.51	45.88	55.01	13.23		13.95		14.15		15.13		14.34	

Table 25 – continued

Characteristic Portfolio		Factor Loading Portfolio					Factor Loading Portfolio									
LEV2 Level	Size	1	2	3	4	5	1		2		3		4		5	
				β_{HML}							$t(\beta_{HML})$					
1	1	-27.90	12.03	15.32	19.76	5.99	-4.09	***	2.49	**	3.60	***	4.39	***	0.93	
1	2	-32.79	-6.30	10.90	-2.06	-5.92	-4.35	***	-1.15		2.10	**	-0.41		-0.93	
1	3	-47.97	-35.86	-24.98	-28.06	-32.97	-5.76	***	-6.27	***	-4.83	***	-4.85	***	-4.66	***
2	1	24.58	44.38	26.58	27.83	31.91	3.83	***	8.79	***	5.26	***	5.73	***	5.40	***
2	2	25.04	28.83	41.33	17.59	18.04	3.67	***	5.00	***	7.45	***	3.27	***	2.85	***
2	3	-7.04	11.81	3.87	4.39	11.32	-0.99		2.13	**	0.71		0.77		1.75	
3	1	29.61	23.79	34.11	44.62	35.73	4.61	***	4.31	***	6.51	***	8.23	***	5.90	***
3	2	25.37	33.88	41.16	24.67	37.11	3.34	***	5.22	***	6.68	***	3.85	***	4.67	***
3	3	19.81	29.66	22.32	24.75	25.24	2.62	***	4.33	***	3.68	***	3.61	***	3.29	***
	Average	0.97	15.80	18.96	14.83	14.05	0.32		2.76		3.46		2.73		2.13	
				β_{MKT}							$t(\beta_{MKT})$					
1	1	98.78	92.57	90.60	90.32	106.30	32.06	***	42.33	***	47.11	***	44.44	***	36.56	***
1	2	114.22	104.22	99.43	96.55	109.84	33.49	***	42.10	***	42.36	***	42.47	***	38.08	***
1	3	109.73	100.96	102.87	94.60	108.29	29.17	***	39.04	***	44.01	***	36.19	***	33.88	***
2	1	108.72	93.17	88.79	94.77	105.53	37.44	***	40.82	***	38.87	***	43.15	***	39.50	***
2	2	115.63	98.29	103.36	96.36	106.54	37.46	***	37.74	***	41.22	***	39.66	***	37.22	***
2	3	103.72	96.93	92.89	99.69	103.51	32.19	***	38.64	***	37.87	***	38.80	***	35.32	***
3	1	107.46	98.08	105.86	104.81	108.88	37.01	***	39.28	***	44.71	***	42.75	***	39.76	***
3	2	117.25	105.36	109.14	108.61	121.43	34.13	***	35.92	***	39.17	***	37.50	***	33.80	***
3	3	118.28	106.83	105.71	107.74	119.19	34.62	***	34.51	***	38.60	***	34.72	***	34.32	***
	Average	110.42	99.60	99.85	99.27	109.95	34.17		38.93		41.55		39.96		36.49	

estimates for the leverage2 factor eliminates the ability to do any testing of risk versus characteristic with this factor.

The evidence from our Daniel and Titman (1997) tests are inconclusive. O-score results are slightly indicative of a characteristic based model and Z-score results are slightly indicative of a risk based model. However, the fact that SMB and HML generally subsume the explanatory power of our distress factors severely weakens our ability to test if the distress FMPs proxy for a systematic risk or if the firms with these characteristics move together.

1.5 Conclusion

The main contribution of this paper is the finding that once we convert the distress risk variables, O-score, Z-score, performance1, and leverage2 into systematic variables using factor mimicking portfolios, we find evidence that these variables are priced in the cross section of returns. The O-score and performance1 FMPs have perfectly monotonic patterns with respect to the portfolios formed on size. The Z-score and leverage2 FMPs have perfectly monotonic patterns with respect to BTM level. The returns in our twenty-five portfolios correspond to size and BTM levels, thus our distress proxy FMPs have a relation to returns. Firms that load more positively on the O-score and leverage2 FMPs have higher returns. Firms that load more negatively on the Z-score and performance1 FMPs have higher returns.

This is not consistent with the findings of Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008) who do not find monotonic patterns between distress risk proxies and returns. However, their distress proxies were idiosyncratic variables. We have converted our distress proxies into systematic factors, via the creation of factor mimicking portfolios. The fact that we find a relation between distress proxies and returns and the previous studies do not can be explained by the theory that only systematic risk should be rewarded since it cannot be diversified away.

Our systematic distress proxies do not do as good a job pricing the twenty-five portfolios formed on size and BTM as the SMB and HML factors. When HML and SMB are added to our factor model the coefficient estimates on the majority of our distress factors lose statistical significance. This suggests that while SMB and HML proxy for distress risk they contain more information than what is contained in the distress risk proxies. It is intriguing that the O-score and performance1 FMPs have a perfectly monotonic pattern with respect to size. It suggests that SMB is representing distress risk although it also contains information beyond just distress risk.

Our macroeconomic variables fail to offer any explanatory power beyond that already captured by the excess return on the market. Therefore, it is feasible that there is some level of distress risk already captured by the market variable.

While our evidence in strong in support of distress risk being priced in the cross section of returns, we get inconclusive results when testing if this is due our distress proxies representing a systematic risk or if stocks with these distress characteristics move together.

Previous literature suggests that SMB proxies for distress risk. Our findings contribute evidence in support of this. The O-score FMP has a perfectly monotonic pattern with respect to size which suggests that SMB does indeed proxy for distress risk however, since SMB and HML subsume our distress proxies there must be more information contained in SMB and HML than just distress. Further research opportunities exist to identify what other information is contained in these factors. Since small firms have greater returns, it may be that SMB does not proxy only for a risk but also for an opportunity. Small firms are more focused and therefore more volatile. SMB and HML may proxy for both distress risk and the increased volatility of small firms.

The relation between small firms and distress risk may be due to the fact that firms that have business plans that are no longer viable perform poorly and have their stock price drop. This is similar to Chan and Chen's (1991) idea of small firms being marginal firms. As the stock price of the firm decreases, they become smaller firms by definition. On the other hand, there are small firms that are not marginal firms and have viable business plans and generate strong revenues and earnings yet do not grow in size. The SMB and HML factors may carry information besides distress that is highly relevant to these firms. It would be interesting to examine if there is a difference in the returns related to distress risk for small firms that have seen significant stock price decreases versus small firms without price decreases. We would expect that in the firms with price decreases, firms moving from large firms to smaller firms, that the distress risk is stronger and that our distress proxy may not be subsumed by SMB and HML in these cases. However, for the firms moving from a small firm to a larger firm, firms that are newly listed, or firms that remain in the same size category for an extended period, the distress risk should be much less relevant and our distress proxy should not do a good job pricing these stocks.

CHAPTER TWO

ADMITTING MISTAKES PAYS: THE LONG TERM IMPACT OF GOODWILL IMPAIRMENT WRITE-OFFS ON STOCK PRICES

2.1 Introduction

How do investors perceive the writing-off of all, or part, of the goodwill value from a previous acquisition? Goodwill impairment write-offs have a significant negative short-term announcement impact on stock prices (Hirschey and Richardson, 2003; Bens , Heltzer, and Segal, 2011). Studies using data prior to 2002 find this negative effect continues in the long term after the announcement (Bartov, Lindahl, and Ricks, 1998; Hirschey and Richardson, 2003). In 2001 the accounting standards significantly changed for the treatment of goodwill on the balance sheet with the adoption of Rules SFAS 141 and SFAS 142. Goodwill must now be assessed annually to determine if its value on the balance sheet is accurate or if the goodwill has become an impaired asset. If it is determined to be impaired it must be written- off.

Previous long-term studies focus on stock returns prior to the rules changes, which may now be altered with the implementation of the new accounting rules. Prior to the rule change, write-offs were infrequent events that provided investors with ambiguous information (Bartov, Lindhal, and Ricks, 1998). With the advent of the new rules, goodwill must be assessed for impairment annually, making a goodwill impairment write-off a much more frequent event conveying more specific information. With the new rules an impairment write-off indicates that the value of the goodwill has declined using a fair value estimation of the reporting unit to which the goodwill is assigned. But there is not agreement regarding the efficacy of the rule changes in regards to the information conveyed by impairment write-offs. Lee (2011) finds that the accounting changes improve goodwill’s ability to predict future cash flows, yet Bens, Heltzer, and Segal (2011) find that the information content contained in goodwill impairment write-offs decreases after the implementation of the new rules.

We add to this literature by examining whether the new accounting rules for goodwill and the subsequent changes in information conveyed by goodwill impairments have impacted investors' reactions to goodwill impairments. Consistent with previous literature, we find that the short-term impact of goodwill impairments on stock returns continues to be negative. However, our primary objective is to examine the long-term impact of goodwill impairment write-offs and, using post rule change data, we find that since the adoption of Rules SFAS 141 and SFAS 142 the long-term impact of goodwill impairment write-offs on stock returns is positive and economically significant. Since the goodwill impairment write-off is a publicly announced event and the increase in returns is not an immediate effect, the long-term reaction represents a market inefficiency providing an excellent opportunity for investors.

We then examine if the positive investor reaction is justified by improved firm performance after a goodwill impairment write-off, or if it is due to earnings management by the firm. Since the new rules allow for very little discretion on the part of management regarding when and if to take the impairment, the firm is essentially forced to take the write-off. Our hypothesis is that since the firm must take a write-off that will negatively impact earnings, the firms use the opportunity to implement a "big bath" and take all foreseeable write-offs and write-downs at one time. While this causes a more negative impact to earnings in the short term, it eliminates potential negative earnings surprises in the future. Our findings support our "big bath" hypothesis.

Our findings show that the rule changes have made a significant difference to investors' perceptions of goodwill impairment write-offs. We show that the positive abnormal returns continue for approximately 250 days after the announcement and can be as much as 7.9% annually. We also find that the abnormal returns are related to the size of the impairment write-off in the short term. In the two-day window around the event, the size of the impairment is negatively related to the abnormal returns. However, in the long term, we do not find a strong correlation between the size of the impairment write-off and the abnormal return, but we do find a strong correlation between abnormal returns and firms' book-to-market equity values.

Goodwill is an intangible asset that represents the difference between what an acquiring firm pays for a target company during an acquisition and the book value of the target firm. FASB statement 141 states, "the excess of the cost of an acquired entity over the net of the amounts assigned to assets acquired and liabilities assumed shall be recognized as an asset referred to as goodwill."[6] Simply put, this is the amount a company pays for a firm during an acquisition above the book value of the target firm. This goodwill can be a substantial portion of the acquisition price. The mean goodwill to purchase price ratio is 55 percent (Shalev, 2009; Lys, Vincent, and Yehuda, 2011).With the adoption of rule SFAS 141, a firm that acquires another firm, regardless of whether the target firm is public or private, is required to list this goodwill as an intangible asset on the balance sheet. Thus, almost all acquisitions result in goodwill being brought onto the balance sheet.

Prior to the adoption of rule SFAS 142, goodwill was considered a "wasting" asset. This meant that the goodwill was expected to lose its value over time. Firms were required to expense a portion of the goodwill every year, which systematically reduced the amount of goodwill carried on the balance sheet. With the adoption of SFAS 142, goodwill is no longer considered a wasting asset. It can theoretically retain its value over an infinite period of time. With the adoption of SFAS 142, all firms with goodwill on the balance sheet are now required to perform an assessment of the goodwill on an annual basis. If the value of the existing goodwill does not match its book value, it must be deemed impaired and subsequently written off. This has made goodwill impairment write-offs much more common and frequent events. Under the prior rules a goodwill impairment write-off only occurred when there was reason to write-off the goodwill beyond the amount already being amortized. Thus, historically, impairment announcements were received by investors as negative news and had a negative impact on stock prices. Since the new rules eliminate this systematic write-down and instead require an annual assessment of the goodwill on the balance sheet, a goodwill impairment write-off has become a more frequent event that signals specific information.

With the new rules, a goodwill impairment is the result of a reduction in the value of the goodwill since the acquisition. If the acquisition was performing as expected, then the current goodwill value would not be less than the goodwill value at acquisition and an impairment need not be taken. Ergo, the goodwill impairment is an implicit public confirmation that the acquisition is not performing as well as expected. The write-off can be quite significant.[7] We find that the mean goodwill impairment write-off post rule change is 11% of the total company's assets. The goodwill may not be overvalued when initially recorded, but the acquired firm may lose value post acquisition (Churyk, 2005) or it may be that the initial overpayment for the target

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[6] See the Financial Accounting Standards Board, 2007, Business Combinations.

[7] Examples of substantial write-offs include Time Warner's $44.69B write-off in December of 2002 related to the AOL acquisition in 2000; Qwest's $8.48B write-off in December of 2002 related to the U.S. West acquisition in June of 2000; and Macy's Inc. $5.4B write-off in January of 2009 related to the May Department Stores acquisition of 2005.

firm causes the subsequent goodwill impairment (Li, Shroff, Venkataraman, and Zhang, 2011). Either way, the impairment write-off is an implicit acknowledgement by management that a mistake was made.

Prior literature shows a negative reaction in the short term to these mistake acknowledgements. Hirschey and Richardson (2003) find a negative abnormal return of -2.94% to -3.52% in the two-day window around the goodwill impairment announcement using data pre rule change. Bens, Heltzer, and Segal (2011) find a -3.3% abnormal return in the two-day window around the announcement using data from both pre rule change and post rule change. We test if the short-term negative market reaction persists after the rules changes even with the greater frequency of impairment write-offs. We find that impairment write-offs are still considered negative news to shareholders and that the market reaction is significantly negative in the short-term with a -1.76% abnormal return in the two-day window around announcement.

Prior literature also shows a negative reaction in the long term to goodwill impairment write-offs. Bartov, Lindhal and Ricks (1998) document a mean -12% cumulative abnormal return in the year following an asset write-down, although it should be noted that their study considers all types of asset write-offs and not just goodwill impairment write-offs. Hirschey and Richardson (2003) examine strictly goodwill impairment write-offs and they find a market adjusted cumulative abnormal return of -11.02% in the one-year period after the write-off announcement. They show that stock prices start declining prior to the write-off event and continue to decline for approximately 150 days after the event. Both of these studies use pre rule change data. Using only data from after the rule changes, we find that the long-term reaction to management's acknowledgement of the mistake is positive. We find that this positive reaction continues for as much as one year post the write-off event. Using matching firms to calculate buy and hold abnormal returns, we document a 10.86% abnormal return over 250 days post announcement and, using a risk-adjusted calendar time regression, we find a 7.92% abnormal return for twelve months beginning the month after the write-off. This post event abnormal return is greater than the negative abnormal return we find during the two-day window around the event[8]. We further find that systematic risk does not change after the write-off. Thus, our data suggests that the positive returns post-event are a market inefficiency that can be exploited.

The adoption of SFAS 141 and 142 have also led to an increase in the amount of goodwill carried on corporate balance sheets. Prior to the adoption of SFAS141 there was a great deal of discretion in how acquisitions were recorded. Rule SFAS 141 eliminates this discretion by defining specific purchase accounting rules for all business combinations, with the result that purchased goodwill is now recorded for virtually every acquisition. Thus, there now should be more goodwill impairment write-offs than before the rule changes. Hayn and Hughes (2006) find that not only has the number of write-offs increased, but the size of the write-off has grown as well. Prior to the rule change, roughly 33% of all firms had a positive goodwill balance. We find that since the rule change, the percent of firms with positive goodwill balances has been growing monotonically, with the exception of 2008[9]. In 2010, 57% of all firms had a positive goodwill balance. In 2002, the new rules SFAS 141 and 142 went into effect; consequently, goodwill as a percent of total assets increased 68% from 6.56% in 2001 to 11.03% in 2002[10].

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[8] Write-off announcements frequently occur at earnings releases. The post-announcement abnormal return cannot be a manifestation of post-earnings announcement drift because, with write-offs, the long term response (more than) reverses the initial reaction.

[9] 2008 was the year of the financial crisis and the stock market dropped significantly in value, decreasing firms' market caps and reducing firms' fair values for reporting units. Thus, goodwill impairment write-offs increased 350% versus the previous year. Additionally, most acquisition activity ceased. Consequently, goodwill balances in aggregate declined.

[10] Firms were required to make the transition to the new accounting rules in 2001. Fiscal year 2002 was completely under the new SFAS 142 guidelines.

Ideally the acquisition that is the source of the goodwill should create synergies that improve the overall performance of the acquiring firm. If this is true then the positive abnormal returns post write-off are justified by improved firm performance. Our findings show that the firm's operating performance improves only slightly after a goodwill impairment write-off. However, we find that the overall firm performance improves significantly. Since the operating performance sees little improvement but the overall firm performance shows substantial improvement, we examine the amount of non-recurring costs post event. Consistent with our "big bath" hypothesis we find that firms with goodwill impairments have an increase in nonrecurring costs (excluding the goodwill impairment) in the year of the impairment. We find that the level of nonrecurring costs significantly decreases in the years subsequent to the goodwill impairment leading to overall improvements in firm earnings in the two years post event.

With goodwill balances increasing, more firms are exposed to the potential of substantial future goodwill impairment write-offs. Our paper examines the long-term impact of the goodwill impairment write-offs using only data post rule change. We show that these write-offs have an economically significant positive effect on stock prices in the long term. We show evidence suggesting improved firm performance post event is due to earnings management. Since goodwill write-offs are publicly announced events, there is ample opportunity for investors to react to this management signal. Rational investors can anticipate the increase in stock prices post event and trade on the goodwill impairment announcement.

This study is developed in the following sections. In Section II we describe the data. We discuss the empirical methodology in Section III. In Section IV we present the empirical results. We conclude in Section V.

2.2 Data

Stock returns, number of shares outstanding, and month-end stock prices are obtained from the Center for Research in Security Prices (CRSP). Value weighted market returns are also obtained from CRSP. All accounting data, including goodwill and goodwill write-off amounts, is obtained from Compustat. The monthly risk free rate and the Fama French three factors; market (MKT), value (HML) and size (SMB), as well as the Carhart momentum factor (UMD) are obtained from Wharton Research Data Services (WRDS). The 49 Fama and French industry codes used in the matching BHAR calculations are obtained from Kenneth French's website.[11]

Our sample is from fiscal year 2002 through fiscal year 2011. We include only U.S. based firms, and only firms listed on the NYSE, AMEX, or NASDAQ. Financial firms (SIC codes 6000-6999) and utilities (SIC codes 4900-4999) are excluded. We obtain our sample by taking all firms listed in Compustat for fiscal years 2002 through 2011 that meet the above requirements and have a negative pre-tax goodwill impairment write-off[12]. This gives us 4,508 firm-quarter observations.

We eliminate observations where there are no lagged assets, where no earnings announcement date is available, where the CRSP and Compustat cusips (firm identifiers) do not match, or where the return data necessary for the size, abnormal returns, or momentum calculations are not available. This leaves a final sample of 3,209[13] firm-quarter observations.

Summary statistics are shown in table 1. All values are in millions of dollars, except for the percent of goodwill written off. Goodwill impairment write-offs are measured in the current

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[11] The address of Kenneth French's website is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[12] The Compustat variable for the quarterly pre-tax goodwill impairment write-off is GDWLIPQ.

[13] All data from Eastman Kodak Company is deleted to avoid any potential confidentiality concerns due to a previous affiliation of one of the authors with Eastman Kodak.

quarter. Assets, sales, and goodwill are measured at the quarter-end prior to the event. The percent of goodwill written off is the current quarter's impairment amount divided by the previous quarter's goodwill balance. Goodwill can be acquired and written off within the same quarter, thus allowing the write-off amount to be greater than the previous quarter's goodwill balance. If there is no goodwill balance from the previous quarter, the percent written off is set to zero. Size is measured ten days prior to the event and is the product of shares outstanding and price.

Table 26: Summary Statistics

Accounting data is from Compustat. Size data is from CRSP. This data is for all U.S. firms listed on the NYSE, AMEX, or NASDAQ, excluding financial firms and utilities that have a negative goodwill write-off taken between fiscal years 2002 and 2011. All dollar amounts are in millions. Assets, goodwill, and sales are measured the quarter end prior to the event. Impairment write-offs are for the current quarter. Size is measured ten days prior to the event.

	N	Mean	Median	Standard Deviation	Min	Max
Goodwill Impairment Write-off	3209	-\$168.79	-\$12.57	\$1,247	-\$0.001	-\$45,538
Percent of goodwill written-off	3109	7.62%	2.67%	12.68%	0.00%	326%
Goodwill	2888	\$858.55	\$90.73	\$3,594	\$0.00	\$81,688
Size	3204	\$2,495	\$231	\$9,703	\$0	\$208,000
Sales	3114	\$831.46	\$132.31	\$2,817	\$0.00	\$66,022
Assets	3109	\$3,832.61	\$598.62	\$13,752	\$2.06	\$282,913

In order to accurately attribute investor reaction to goodwill impairment write-off events, we search for any pre-announcements of the write-off. First, we scale the current quarter goodwill impairment write-off value by the previous quarter's total assets. We then search for pre-announcements for our sample firms that have a pre-tax goodwill impairment write-off with a total value of at least 5% of the previous quarter's total assets. This sample includes 1,948 firm-quarter observations. The LexisNexis™ Academic Universe database is used to search for related articles. Specifically, we look for any articles within a three-month window prior to the firm's quarterly earnings announcement date, where the earnings announcement date is for the quarter where the impairment charge was taken and is obtained from Compustat. The search is done using the firm name from Compustat and the following key words in conjunction with the firm name; goodwill impairment, and write off, or write-off, or write down, or write-down. All English news sources are searched within Lexis Nexis™.[14]

If a pre-announcement is found, we use that date as the event date. Otherwise, we use the earnings announcement date as the event date. Barring a pre-announcement, we assume that investors learn about the goodwill impairment write-off at the time of the earnings announcement. These write-offs are typically prominently addressed in the earnings announcement. For example, from the first page of the Valspar earnings announcement for the fourth quarter and fiscal year 2011[15] :

> Fourth-quarter adjusted net income per share in 2011 excludes a $3.82 per share non-cash impairment charge for goodwill and intangibles associated with the company's wood coatings and gelcoat product lines and a $0.13 per share restructuring charge. Fourth-quarter adjusted net income per share for 2010 excludes a $0.03 per share charge for fees related to the acquisition of Wattyl and a $0.02 per share restructuring charge. Including the after-tax non-cash impairment charge of $363.4 million, the reported net loss for the fourth quarter of 2011 was $295.7 million or $3.18 per share. Net income for the fourth quarter of 2010 was $51.3 million and reported earnings per share were $0.51.
>
> The fiscal year 2011 fourth quarter non-cash goodwill impairment charge was associated with the wood coatings and gelcoat product lines from the acquisition of Lilly Industries, Inc. in 2000. The action is a result of the company's annual impairment analysis of goodwill. The company concluded that the economic outlook for the end-markets served by these product lines, which are closely tied to U.S. housing starts, is not likely to change in the foreseeable future. Therefore, the carrying amount of these businesses exceeded their fair value.

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[14] We exclude announcements stating that a review of goodwill is underway; the announcement must indicate that there is an expected goodwill impairment write-off forthcoming for the quarter in question, but an amount need not be mentioned.

[15] Copied from the investors section of the Valspar website: http://investors.valspar.com/phoenix.zhtml?c=80086&p=irol-newsArticle&id=1632877

To calculate the short-term abnormal return for the firms with impairments we use a two-day window where day 0 is the announcement day, or the first trading day after the announcement if the announcement occurs on a non-trading day, and day 1 is one trading day after day 0. To calculate long-term cumulative and buy-and-hold abnormal returns we use either 125 days or 250 days after the two-day short-term window. Days refer to trading days only, so 125 trading days is approximately 6 months and 250 trading days is approximately 1 year.

2.3 Methodology

We investigate the long-term returns after the write-off event using three different methodologies: cumulative abnormal returns (CARs), buy-and-hold abnormal returns (BHARs) using matching firms, and risk-adjusted calendar time regressions. For the short term returns we only examine CARs.

2.3.1 CARs

We start by examining if a goodwill impairment write-off or announcement of an upcoming write-off has an immediate negative impact on the stock price. We only use data from after the implementation of the accounting rules changes. We run an event study and calculate a two-day cumulative abnormal return (CAR) by firm for all firms that have taken a goodwill impairment charge in the quarter. The CAR is the difference between the stock's return and the value weighted market return on the corresponding date. We define the event date as the announcement date of the write-off or the earnings announcement date if no pre-announcement is made.

We match our sample data to each individual firm's return data from CRSP based on the date of the event. The CAR is calculated by summing the abnormal returns over the time period of the event. The two-day CAR is the mean of the summed abnormal returns of all firms, as shown in equation 6.

$$\overline{CAR}\ (\mathrm{t}_1,\mathrm{t}_2) = \frac{1}{N}\sum_{i=1}^{N} CAR_{\mathrm{i}}\ (\mathrm{t}_1,\mathrm{t}_2) \tag{6}$$

Here, t_1 is the first day of the event study, day zero, and t_2 is the final day of the event study, day one. N is the total number of observations, and CAR_i is the CAR for firm *i*.

We use the same model for the long-term CAR studies. For example, in the 250 day study, t_1 is day 2 and t_2 is day 251. We examine the time periods both before and after the write-off event with the write-off event being day zero.

In order to determine if the size of the impairment write-off is correlated with the abnormal returns post event, we regress the short-term and long-term post-event CARs on the write-off amount while controlling for size and book-to-market (btm), year fixed effects, and industry fixed effects. Size is the log of the product of shares and price data from CRSP measured ten days prior to the event. Btm is the log of book equity divided by market equity where book equity is total assets minus total liabilities plus deferred tax credits minus preferred stock value as defined by Fama and French (2008). Industry is determined by the two digit Fama and French industry code. Dummy variables are used for each industry code and each year. Since the accounting values are obtained from Compustat and are only available quarterly, both the book and size values are from the end of the quarter immediately preceding the event. We obtain the coefficient estimates for the impairment size and examine if it is statistically significant. The null hypothesis is that the size of the write-off has zero effect on the abnormal return.

2.3.2 BHARs

For our next test, we calculate a BHAR using matching firms. We match the firms on three criteria; industry, size, and momentum. We then calculate the return on day t for both the event firm i ($R_{event\ firm\ i,t}$) and its matching firm ($R_{matchingfirm\ i,t}$). The BHAR for firm i is

$$BHAR_i = \prod_{t=2}^{T}(1 + R_{event\ firm\ i,t}) - \prod_{t=2}^{T}(1 + R_{matchingfirm\ i,t}) \tag{7}$$

Here, *t* is the starting day for the calculations. Since this is all after the two-day window around the event, we start with day 2. We calculate BHAR for T = 125 days (approximately 6 months) and T = 250 days (approximately 1 year) after the two-day announcement period.

We start with our sample of 3,209 firm-quarter observations. We obtain the SIC code for each firm from CRSP and convert this to the corresponding two-digit Fama and French industry code. We use all firms in CRSP, excluding financial firms and utilities that are listed on NYSE, AMEX, or NASDAQ as our universe of potential matches. We first assign each potential matching firm one of the 49 two-digit Fama and French industry codes based on the firm's SIC information in CRSP. The event firm is matched with all firms having the same two-digit Fama and French industry code which have not had a goodwill impairment write-off within the timeframe we are examining. For the 125 day analysis this would be within six months before or six months after the event date, and for the 250 day analysis, we exclude firms with impairment write-offs within one year before or one year after the event date.

Next we calculate the market capitalization for each of the event firms and each of the potential matches ten days prior to the event. We then reduce the pool of potential matches by requiring that the matching firm's size be within +/- 30 percent of the size of the event firm. We then calculate momentum for the sample firm as the cumulated continuously compounded return for days *t*-259 to *t*-10, where *t* is the event date. We calculate momentum returns for each of the potential matches in the same fashion. We then take the firm from the pool of potential matches that has the value for momentum that is closest to the event firm. This is our matching firm.

The buy and hold return is the cumulated continuously compounded return over day 2 through day 126 or from day 2 through day 251. If the event firm does not have a full complement of days post event, then we use what data is available. If the number of days in the matched firm buy-and-hold calculation is less than the number of days in the event firm's buy-and-hold calculation, we take the next best match, (the next closest momentum value with the same two digit industry code and size within +/- 30%) and use its returns starting from date *d*+1, where *d* is the day that the first matched firm's return data ends. We use data from the second matched firm to calculate a total buy and hold return for the two matched firms that uses the same number of days as the event firm. If the second matched firm does not have enough return data we go to the third match and so on until the buy and hold return data for the matching firm has the same number of days as the buy and hold data for the event firm.

We test if size is a factor for abnormal returns by assigning each firm to a size quintile and then calculating the mean and median BHAR for each size quintile. To obtain the size quintiles, we use all firms listed on the NYSE during the time frame October 2001[16] to December 2011. Consistent with our sample data, we limit these firms to U.S. firms only and exclude all financial firms and utilities. The breakpoints for these quintiles are used for determine in which quintile the sample firms reside. We obtain price and share data from CRSP for each of our sample firms at time *t*-10, or ten days prior to the event. It is at *t*-10 where the sort across NYSE firms is done, quintile breakpoints are formed, and firms are placed into quintiles. In other words, there is a separate sort for each event firm. This means that there are not an equal number of firms in each quintile.

We further test if the size of the impairment is correlated with the abnormal return by regressing the BHAR for both the 125 day interval and the 250 day interval on the impairment size while controlling for firm size, btm, and industry and year fixed effects. This is done in the same manner as described earlier for the CARs.

2.3.3 Calendar Time Regressions

The final method we use to determine abnormal returns is a risk-adjusted calendar time regression. This method creates monthly portfolios of all firms that had a goodwill impairment charge in the prior six (or twelve) calendar months. We adjust for risk using MKT,SMB, HML and UMD. We do this for both equal-weighted and value-weighted portfolios, and for both the total pool of firms and by quintiles based on size. The size quintiles are determined in the same manner as described in the BHAR analysis.

We run the calendar time regression on the total pool first and then on each of the quintile pools. We also estimate the regressions over two different time periods, using firms announcing write-offs in the prior six calendar months and, separately, with firms announcing write-offs in the prior twelve months. For both equal-weighted and value-weighted portfolios we estimate the regression

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[16] The new goodwill accounting rules went into effect beginning with fiscal year 2002. The first date of any firm in our sample is October 2001, which is part of their fiscal year 2002, and thus is under the auspices of the new rules. We therefore use this as our starting date in our size analysis.

$$(\text{RET} - \text{RF})_{p,t} = \alpha_p + \beta_p\text{MKT}_t + s_p\text{SMB}_t + h_p\text{HML}_t + u_p\text{UMD}_t + \varepsilon_{p,t} \quad (8)$$

where RET is the portfolio return, RF is the risk-free rate, $(\text{RET-RF})_{p,t}$ is the excess return for portfolio *p* in month *t*, and the intercept, α_p, is the portfolio abnormal return. We correct for potential autocorrelation and heteroskedasticity using robust standard errors.

We also assess whether a portfolio's risk changes after firms announce a goodwill impairment write-off. Specifically, we examine if factor loadings change after announcements. For both the six-month and twelve-month analyses, we expand the estimation period to an equivalent number of months before the write-off announcement. We compare pre and post write-off coefficients using a Wald test.

2.3.4 Operating Performance

We measure operating performance using both net income and operating income before depreciation[17]. Net income is the income or loss that results after all expenses and losses including extraordinary costs have been subtracted from all revenues. Operating income before depreciation is revenues less operating expenses. Operating expenses is cost of goods sold (COGS) and sales and general administrative (SG&A). If firms do not have data for both net income and operating income they are excluded from our sample.

We scale our net income measure by sales and then we scale by total assets to create two net income based performance measures. We scale operating income by sales and then by total assets to create two operating income based performance measures as well. When using total assets we add goodwill impairments back into the total asset number so that we do not skew the

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[17] The Compustat mnemonic for net income is NI, and operating income before depreciation is OIBDP.

performance measure by using a smaller denominator and making the performance appear to improve simply by removing assets.

We measure the median value for all firms with impairments from the year prior to the impairment to two years post impairment. Impairment firms are then placed into size quintiles and we calculate the performance by size.

Industry-adjusted values are calculated by sorting all firms using the Fama and French two digit industry code. The median performance measure for each industry is calculated by year. This is subtracted from the impaired firm median value. If an industry-year has a median value of zero, that industry- year observation is deleted.

An industry and performance-adjusted measure is created by using a matched firm, based on the same matching criteria as used for the BHAR calculations. This value is subtracted from the impaired firm performance measure.

The changes in performance across years are calculated using the median change. The statistical significance of the change is measured using a signed rank test.

2.3.5 Big Bath

Our hypothesis is that firms that are required to take a goodwill impairment write-off use the opportunity to take other nonrecurring charges at the same time instead of taking them in subsequent years when they should rightfully occur. If investors do not attach significance to the size of the event, but only to the event itself, it follows that a firm may “pull-forward” any anticipated future charges. This would allow subsequent years to have more positive results than they would otherwise.

We test this “big bath’ hypothesis by examining the amount of special items of costs taken by the firms with goodwill impairment write-offs. The category, special items of cost (SPI) represents costs that the firm incurs that are one-time or non-recurring costs. This includes items such as inventory write-downs, write-downs of other assets, restructuring charges, discontinued operation costs, and generally any significant non-recurring item.

We measure the absolute amount of SPI in the year of the goodwill impairment write-off as well as the two years prior to the impairment write-off and the two years subsequent to the impairment write-off. SPI is tracked in Compustat as a negative amount. Since SPI includes the goodwill impairment write-off, we add back in any goodwill impairment taken in the years we measure.

We obtain the median SPI value for all firms with goodwill impairment write-offs and the median SPI value by size quintiles for these firms. We examine the annual changes in the amount of SPI from two years prior to the impairment write-off to two years subsequent to the impairment write-off. We obtain the median difference and use the signed rank test statistic to designate statistical significance. A negative amount indicates that the SPI increased year-on-year, while a positive amount is indicative of a decrease in SPI. We obtain this annual change in SPI by size decile as well.

2.4 Results

2.4.1 CARs

CARs are presented for the announcement period, and the subsequent 125 and 250 trading days in Table 27, panel A. We start by examining if the new accounting rules for goodwill have changed investors’ perceptions of a goodwill impairment write-off. We examine short-term

CARs for firms that have taken an impairment write-off after the rule change. We find that the mean two-day CAR is -1.76% and the median is -1.38%, both of which are significant at the 1% level. This is consistent with results from studies done prior to the change in accounting rules. Thus, even with the new rules and the subsequent increase in frequency of goodwill impairment write-offs, investors still perceive write-offs as a negative event.

Our main objective is to test the long-term abnormal returns after the rule changes. Accordingly, our next step is to examine the long-term CARs of firms taking a goodwill write-off. We find that the mean (median) 125-day CAR is 18.53% (9.94%) and the mean (median) 250- day CAR is 28.6% (17.31%), and all are significant at the 1% level. These long-run results are both statistically and economically significant, and are contrary to results from previous studies prior to the rules changes. The post-event positive average CARs are several times greater than the initial negative response.

Table 27: CAR Results

Mean and median CAR values for all firms with goodwill impairment write-offs from fiscal year 2002 through fiscal year 2011 are reported in panel A. The t-statistic is given for the mean. The significance level of the median is from a Wilcoxon signed rank test. Panel B shows the results of an estimated regression of the mean CAR values on the write-off size scaled by assets lagged one quarter while controlling for size, btm, industry fixed effects using Fama and French two-digit industry codes, and year fixed effects. Standard errors are robust to heteroskedasticity.

CAR Period	**Total Number of Days**	**Number of Observations**	**Mean**	**t -Stat**	**Median**
Panel A					
0-1	2	3209	-0.0176	-7.70***	-0.0138 ***
2-126	125	3209	0.1853	17.70***	0.0994 ***
2-251	250	3209	0.2860	20.19***	0.1731 ***

*** significant at 1%, ** significant at 5%, * significant at 10%

Table 27 – continued

CAR Period	Total Number of Days		Number of Observations	Coefficient Estimate	t-Stat	
Panel B						
0-1	2	Intercept	2889	-0.1766	-2.28	**
		Write-off size	2889	-0.0715	-2.77	***
		Size	2889	0.0018	1.42	
		BtM	2889	0.0027	0.83	
2-126	125	Intercept	2889	-0.0589	-0.27	
		Write-off size	2889	0.2608	2.25	**
		Size	2889	-0.0396	-7.18	***
		BtM	2889	0.0563	4.13	***
2-251	250	Intercept	2889	0.0902	0.35	
		Write-off size	2889	0.3117	1.9	*
		Size	2889	-0.0570	-7.68	***
		BtM	2889	0.1018	5.28	***

*** significant at 1%, ** significant at 5%, * significant at 10%

We then examine if the size of the impairment write-off has an impact on the abnormal returns. We estimate a regression of the abnormal returns on the size of the impairment scaled by assets, lagged one quarter, while controlling for size, btm, year fixed effects, and industry fixed effects. We do this for the two-day CAR, and both the 125 and 250 trading days post-event CARs, as shown in panel B of Table 2. During the two-day window, the larger the relative sizes of the impairment, the more negative the abnormal returns. This is significant at the 1% level. But after the write-off, the larger the relative size of the write-off, the more positive the returns. The significance level decreases as the time period of the CAR increases. For the 125-day study the results are significant at the 5% level, but for the 250-day study the results are only significant at the 10% level. For the two-day event period the size of the firm has no significant effect on the amount of the abnormal return. However, firm size is inversely related to the abnormal returns in the 125-day and 250-day periods and for both it is significant at the 1% level. Similar to size, btm has no significant effect on the abnormal returns during the two-day announcement period. But btm does have a positive and significant, at the 1% level, relation to the abnormal returns post-event for both time periods.

Next we calculate the CARs prior to the write-off event, and consistent with prior literature we find that the days leading up to the write-off have negative abnormal returns. We chart the daily CARs from 250 days prior to the event to 250 days after in Figure 1. We find that the positive abnormal returns post-event are not only greater than the negative announcement period; they are also greater than the sum of the pre-event and event negative abnormal returns. These results cannot be due to post-earnings announcement- drift as the stock returns reverse, not continue, following earnings announcements.[18]

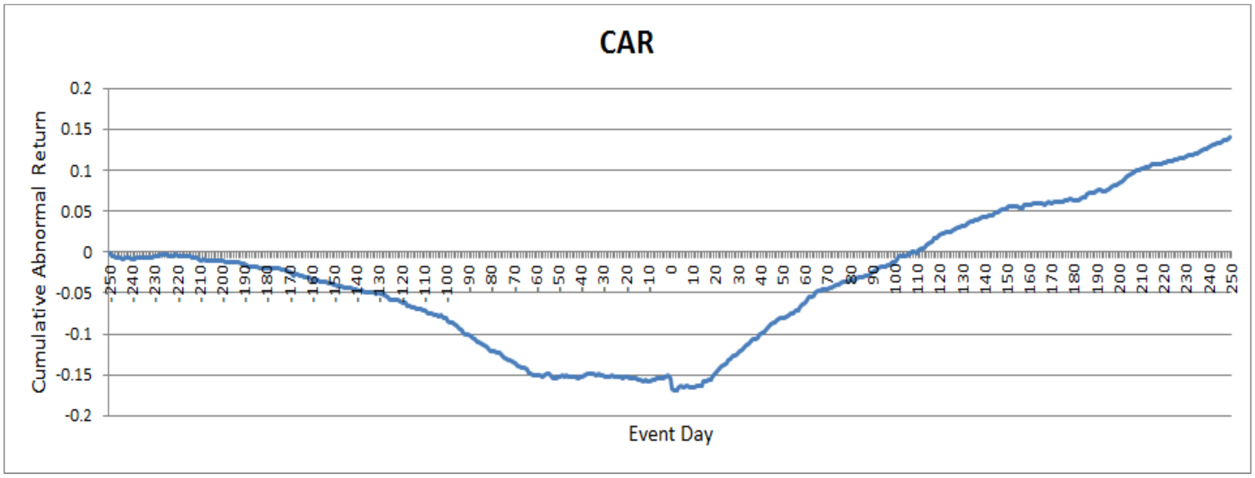

Figure 1: CAR Graph

This is the cumulative abnormal returns from 250 days prior to the write-off to 250 days after the write-off for all U.S. based firms listed on the NYSE, AMEX, or NASDAQ with a negative goodwill impairment write-off between fiscal year 2002 and 2011, excluding financial firms and utilities.

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[18] As mentioned earlier, most impairment write-offs are announced with earnings reports.

The CAR results are consistent with the idea that the rule changes have made a difference to investors' perception of goodwill impairment write-offs in the long term. Before the rules changes the post-event abnormal returns were negative. Now, not only are the abnormal returns positive, but the larger the write-off, the more positive the abnormal return.

2.4.2 BHARs

Next we examine the BHARs using matching firms. This is more representative of an investor's experience than the CARs. We perform both a 125 day (approximately six months) and a 250 day (approximately one year) analysis, with results provided in Table 28. The mean abnormal return for 125 days post event is 5.88% and significant at the 1% level. The mean abnormal return for 250 days post event is 10.86% and, again, significant at the 1% level. The median abnormal return for the 125-day period is 1.74% and significant at the 5% level, and the median abnormal return for the 250-day period is 2.1%, significant at the 1% level. These results suggest that, since the rule changes, after the initial negative announcement effect investors' perceive goodwill impairments as positive news. It takes some time for the market to incorporate this information and for the prices to adjust accordingly. Further, the positive post-event BHARs are several times larger than the negative CARs (Table 27) over the two-day announcement period.

We next test if the size of the firm significantly influences the BHARs. We assign each firm to a size quintile based on size quintile splits of NYSE listed stocks, using the size measured ten days prior to the event date. Table 29 shows the mean and median BHAR by size quintile. For the 125 day analysis, shown in panel A, the smaller firms tend to have the more positive results, but it is not a monotonic relation. However, the smallest quintile has a significantly positive

BHAR, and the largest quintile has a significantly negative BHAR, although the smallest quintile's BHAR is significant at the 1% level, while the largest quintile's BHAR is only significant at the 10% level. This is true for both the mean and median BHARs. The results for the 250-day study, shown in panel B, exhibit similar characteristics; there is not a monotonic relation, but the smallest quintile has a significantly positive BHAR, significant at the 1% level, and the largest quintile has a significantly negative BHAR, significant at the 5% level. This is true for both the mean and median BHARs. While our overall results are contrary to previous studies, it is interesting to note that the results for the largest quintile of firms are consistent with the continued negative performance identified in the previous studies using data prior to the rules changes.

Table 28: BHAR Results

Event firms are matched to firms that did not have an impairment write-off within six months (one year) before or after the event date. Firms are matched by two digit Fama and French industry code, size, and momentum. Size of the matching firm must be +/-30% of the size of the event firm. After the SIC and size criteria are met, the firm with the closest momentum, measured as returns from day *t*-259 to day *t*-10, is used as the matching firm. A buy-and-hold return is calculated for the event firm and for the matching firm from day *t*+2 to *t*+126 (251). If the event firm does not have the total complement of returns for the days required, the matching firm's buy-and-hold return is calculated using the same number of days as the event firm. If the matching firm does not have as many days of returns as the event firm, the second closest match is found and returns from it are used from day *d*+1, where *d* is the day of the last return for the first matching firm. If the second matching firm does not have returns for the full amount of days required a third matching firm is used and so on until the matching firm's buy-and –hold calculation is comprised of the same number of days as the event firm. The difference between the two is the BHAR. The mean and median returns are reported below. The t-statistic is provided for the mean and the significance value for the median return is from a Wilcoxon signed rank test.

BHAR Period	**Total Number of Days**	**Number of Observations**	**Mean**	**t -Stat**	**Median**
2-126	125	3074	0.0588	4.18***	0.0174**
2-251	250	3046	0.1086	4.74***	0.0210***

*** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

We create an arbitrage portfolio where we go long in the firms in the smallest quintile and short the firms in the largest quintile. For the 125-day study the mean (median) return of this arbitrage portfolio is 12.31% (4.88%) and is significant at the 1% (10%) level. The 250-day arbitrage portfolio yields a mean (median) return of 24.02% (9.69%) and is also significant at the 1% (5%) level. These returns are also economically significant.

Table 29: BHAR Results by Size Quintile

Firms are split into size quintiles based on size sorts of all stocks on the NYSE excluding utilities and financial firms. Separate sorts are done for each firm with size measured ten days prior to the event. Mean and median BHARs are calculated for each quintile. T-statistics are provided for the means, and significance values for the medians are from Wilcoxon signed rank tests. An arbitrage portfolio is calculated as the mean abnormal return from the smallest quintile of firms minus the mean abnormal return from the largest quintile of firms. Panel A has results for the 125 day analysis. Panel B has results for the 250 day analysis.

Quintile	Number of Observations	Mean BHAR	t- stat	Median BHAR
Panel A: 125 Day BHAR by size quintile				
1 smallest	1656	0.0926	4.00***	0.0295 ***
2	530	0.0095	.32	-0.0264
3	331	0.0626	2.33**	0.0641 ***
4	275	0.0373	1.56	0.0160
5 - Largest	282	-0.0305	-1.69*	-0.0193 *
1-5		0.1231	4.19***	0.0488 *

Quintile	Number of Observations	Mean BHAR	t- stat	Median BHAR
Panel B: 250 Day BHAR by size quintile				
1 smallest	1640	0.1738	4.53***	0.0493 ***
2	528	0.0691	1.60	-0.0185
3	330	0.0705	1.51	0.1052 ***
4	273	0.0149	.47	0.0207
5 - Largest	275	-0.0664	-2.21**	-0.0475 **
1-5		0.2402	4.93***	0.0969 **

*** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

We examine the effect of the size of the write-off on the BHAR, similar to our CAR analysis. We estimate a cross-sectional regression of BHARs on the size of the impairment write-off, firm size, and btm, while controlling for year and industry fixed effects. We use the two digit Fama and French industry code for the industry fixed effects. Results are shown in Table 30. For both the 125-day study, shown in panel A, and the 250-day study, shown in panel B, the coefficients on btm are positive and significant at the 5% level. This is consistent with our results from the CAR regressions, and suggests that firms with higher btm values (value firms) have more positive abnormal returns after an impairment write-off. However, contrary to the results from the CAR regressions, we find that when using the BHAR methodology the size of the write-off has no significant correlation with abnormal returns. Thus, the (more powerful) BHAR analysis suggests that the post-write-off positive response is more closely identified with the "event" of a write-off and not its magnitude. Another difference is the relation of firm size with abnormal returns is much weaker for BHARs than CARs. Thus, the overall BHAR results for firm size are somewhat mixed since portfolio results in Table 29 show highly significant differences while the regression results in Table 30 are more muted.

2.4.3 Calendar Time Regressions

Next we examine returns post event using risk-adjusted calendar time regressions. This approach corrects for any potential cross-sectional correlations between the event firms. We examine the returns for both equal-weighted portfolios and value- weighted portfolios. We expect the equal-weighted portfolios to have more positive abnormal returns then the value-weighted portfolios since the majority of firms taking impairments are small firms, and our CAR and BHAR analyses indicate that the size of the firm is inversely related to the abnormal return.

And the results, shown in Table 31, are consistent with both our previous analyses and our expectations.

Table 30: Regression of BHARs on Size of Impairment, Firm Size, and Book-to-Market

The abnormal returns from the matching buy-and-hold calculations are regressed on the size of the impairment write-off scaled by total assets lagged one quarter, while controlling for firm size, btm, industry fixed effects, and year fixed effects. Size is log of the size measured ten days prior to the event. Btm is log of btm measured at the end of the quarter directly preceding the impairment quarter. Industry fixed effects are measured using two digit Fama and French industry codes for each firm. Standard errors are robust to heteroskedasticity.

BHAR Period	**Total Number of Days**		**Number of Observations**	**Coefficient Estimate**	**t-Stat**	
Panel A: 125 Days Post Event						
2-126	125	Intercept	2777	-0.3935	-1.64	
		Write-off	2777	0.0506	0.34	
		Size	2777	-0.0051	-0.63	
		BtM	2777	0.0550	2.47	**

BHAR Period	**Total Number of Days**		**Number of Observations**	**Coefficient Estimate**	**t-Stat**	
Panel B: 250 Days Post Event						
2-251	250	Intercept	2751	-0.1549	-0.40	
		Write-off	2751	-0.3325	-1.21	
		Size	2751	-0.0235	-1.88	*
		BtM	2751	0.0769	2.31	**

*** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

The equal-weighted portfolios, shown in panel A, exhibit positive and significant abnormal returns (alphas) and the value-weighted portfolios, shown in panel B, do not.

The equal-weighted portfolios have annualized abnormal returns for the 6 months post event of 8.94% and 7.92% for the 12 month portfolio. The mean monthly raw returns[19] of the equal-weighted portfolios are also positive. The value-weighted portfolios do not have alphas significantly different from zero. The mean monthly raw returns are positive, but considerably smaller than the corresponding equal-weighted measures.

Table 31: Calendar Time Regression Results

Calendar time portfolios are constructed consisting of 6 months (12 months) of returns. The mean return is calculated for each month. The risk free rate is subtracted from the monthly mean return and regressed on the factors MKT, SMB, HML, and UMD. The intercept (alpha) and its t-statistic are presented in the first two columns. The annualized return is the alpha times 12. The mean monthly raw return is the mean of the monthly returns minus the risk free rate. Panel A shows the results using equal-weighted portfolios. Panel B has the same analysis using value-weighted portfolios. Standard errors are robust to heteroskedasticity.

	Intercept (alpha)	t- stat	Annualized Return	Mean Monthly Raw Return	t- stat	
Panel A: Equal Weighted						
6 Months	0.0074	2.04**	8.94%	0.0152	1.59	
12 Months	0.0066	2.06**	7.92%	0.0206	2.14	**
Panel B: Value Weighted						
6 Months	-0.0007	-0.25	-0.83%	0.0031	0.45	
12 Months	0.0012	0.49	1.44%	0.0099	1.57	

*** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Similar to the BHAR analysis, we examine the abnormal returns of the calendar time portfolios by size quintiles. Equal-weighted results are shown in Table 32. Consistent with our BHAR results, the smallest quintiles in both the 125-day period, shown in panel A, and the 250-day period, shown in panel B, have the largest alpha. And again consistent with the BHAR

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[19] The raw returns are the mean returns of the portfolios minus the risk free rate, but not adjusted for risk using

results, there is not a monotonic relation among the different size quintiles. However, contrary to our BHAR results, we do not find a negative alpha in the largest quintile. Since the abnormal return for the smallest quintile is greater than for the largest quintile in both time periods, we construct an arbitrage portfolio by going long in the smallest quintile and shorting the largest quintile[20]. This yields annual returns of 8.52% and 6.2% for the 125- day and 250- day studies, respectively, but neither of these returns is statistically significant. The mean monthly raw returns are positive and significant for both arbitrage portfolios, but once we adjust for risk, the alphas are not significantly different from zero.

Table 33 shows the results for the same analysis using the value-weighted portfolios. The 125- day results, shown in panel A, do not exhibit any discernible pattern and there is only one quintile that has even weakly significant results. The 250-day study, shown in panel B, has similar results. There is no discernible pattern and none of the quintiles have results with statistical significance. In both cases the smallest quintile has a larger alpha than the largest quintile, but the smallest quintile does not have the largest. Nevertheless, we form arbitrage portfolios by going long in the smallest quintile and shorting the largest quintile[21]. The results, shown in Table 33, are neither economically nor statistically significant. Thus, overall, the equal-weighted calendar time results are consistent with the CAR and BHAR results; we find positive and significant abnormal returns.

MKT, SMB, HML, and UMD.

[20] In the 125-day period, the smallest quintile and largest quintile do not have the same number of observations. There are two months in the largest quintile portfolio where there were no firms with impairments. Therefore, in estimating the regression for the difference portfolio, the two months with no data were removed from the smallest quintile. Thus, the alpha for the arbitrage portfolio is not equivalent to the difference between the alpha for the smallest quintile and the alpha for the largest quintile.

[21] Again there are different numbers of observations between the smallest and largest portfolios. Thus, the alphas for the arbitrage portfolio will not be equivalent to the difference between the alpha for the smallest quintile portfolio and the alpha for the largest quintile portfolio.

Table 32: Equal Weighted Calendar Time Regression Estimations by Size Quintile

The calendar time portfolios are split by size quintile based on the quintile splits of NYSE listed firms exclusive of utilities and financial firms. Calendar time portfolios are constructed consisting of 6 months (12 months) of returns. The mean return is calculated for each month. The risk free rate is subtracted from the monthly mean return and regressed on the factors MKT, SMB, HML, and UMD. The intercept (alpha) and its t-statistic are presented in the first two columns. The annualized return is the alpha times 12. The mean monthly raw return is the mean of the monthly returns minus the risk free rate. Panel A shows the results using equal-weighted portfolios. In the 125-day period, the smallest quintile and largest quintile do not have the same number of observations. There are two months in the largest quintile portfolio where there were no firms with impairments. Therefore, in estimating the regression for the difference portfolio, the two months with no data were removed from the smallest quintile. Thus, the alpha for the arbitrage portfolio is not equivalent to the difference between the alpha for the smallest quintile and the alpha for the largest quintile Panel B has the same analysis using value-weighted portfolios. Standard errors are robust to heteroskedasticity.

	Intercept (alpha)	t- stat	Annualized Return	Mean Monthly Raw Return	t- stat
Panel A: 6 Month Equal Weighted by size quintile					
Smallest -1	0.0103	1.90*	12.39%	0.0188	1.73*
2	0.0014	0.25	1.64%	0.0102	0.92
3	0.0089	1.96*	10.67%	0.0154	1.70*
4	0.0025	0.32	3.00%	0.0094	0.94
Largest -5	0.0027	0.86	3.18%	0.0074	1.10
1-5	0.0071	1.30	8.52%	0.0130	1.82*

	Intercept (alpha)	t- stat	Annualized Return	Mean Monthly Raw Return	t- stat
Panel B: 12 Month Equal Weighted by size quintile					
Smallest -1	0.0085	1.80*	10.25%	0.0237	2.19**
2	0.0014	0.34	1.73%	0.0177	1.57
3	0.0065	1.66*	7.75%	0.0202	2.13**
4	0.0069	1.43	8.29%	0.0179	1.98**
Largest -5	0.0034	1.25	4.06%	0.0117	1.86*
1-5	0.0052	1.00	6.20%	0.0120	1.78*

*** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Table 33: Value Weighted Calendar Time Regression Estimations By Size Quintile

The calendar time portfolios are split by size quintile based on the quintile splits of NYSE listed firms exclusive of utilities and financial firms. Calendar time portfolios are constructed consisting of 6 months (12 months) of returns. The mean return is calculated for each month. The risk free rate is subtracted from the monthly mean return and regressed on the factors MKT, SMB, HML, and UMD. The intercept (alpha) and its t-statistic are presented in the first two columns. The annualized return is the alpha times 12. The mean monthly raw return is the mean of the monthly returns minus the risk free rate. Panel A shows the results using equal-weighted portfolios In the 125-day period, the smallest quintile and largest quintile do not have the same number of observations. There are two months in the largest quintile portfolio where there were no firms with impairments. Therefore, in estimating the regression for the difference portfolio, the two months with no data were removed from the smallest quintile. Thus, the alpha for the arbitrage portfolio is not equivalent to the difference between the alpha for the smallest quintile and the alpha for the largest quintile. Panel B has the same analysis using value-weighted portfolios. Standard errors are robust to heteroskedasticity.

	Intercept (alpha)	t- stat	Annualized Return	Mean Monthly Raw Return	t- stat
Panel A: 6 Month Value Weighted by size quintile					
Smallest -1	0.0041	0.88	4.97%	0.0133	1.26
2	0.0070	1.62	8.37%	0.0163	1.57
3	0.0096	1.96*	11.57%	0.0156	1.81*
4	0.0019	0.25	2.24%	0.0077	0.79
Largest -5	-0.0005	-0.15	-0.57%	0.0040	0.62
1-5	0.0047	0.94	5.62%	0.0111	1.58

	Intercept (alpha)	t- stat	Annualized Return	Mean Monthly Raw Return	t- stat
Panel B: 12 Month Value Weighted by size quintile					
Smallest -1	0.0042	1.06	4.99%	0.0200	1.89*
2	0.0033	0.99	3.97%	0.0193	1.85*
3	0.0063	1.61	7.56%	0.0191	2.17**
4	0.0075	1.42	8.97%	0.0173	1.99*
Largest -5	0.0012	0.44	1.47%	0.0088	1.47
1-5	0.0029	0.72	3.52%	0.0112	1.69*

*** Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Since all three studies show long-term evidence of positive abnormal returns, and the CAR study showed negative results both pre-event (see Figure 1) and during the two-day event window, we examine if there is also a change in risk. We use a Wald test on the calendar time regressions to determine if the coefficient estimates for each of the risk factors changes from pre-event to post-event. We estimate the same regressions on calendar time portfolios composed of the monthly returns prior to the write-off event as we did for the calendar time portfolios composed of monthly returns after the write-off event. We do this for each of our four portfolios: 6-month equal-weighted, 12-month equal-weighted, 6-month value-weighted and 12-month value-weighted.

The results, shown in Table 34, are the F-statistics from a Wald test on the differences in the coefficient estimates, pre-write-off to post write-off. In each case, none of the estimated coefficient values significantly change from before the write-off to after the write- off.

Table 34: Results of Wald Test on Estimated Factor Coefficients

The calendar time portfolios are formed for the 6 months (12 months) prior to the event and for the 6 months (12 months) post event. The mean return is calculated for the equally weighted portfolio and for the value-weighted portfolio for each month. The risk free rate is subtracted from the monthly mean return. A regression is estimated using the time series of mean monthly returns on factors MKT, SMB, HML, and UMD. Coefficient estimates were obtained for the factors, MKT, SMB, HML, and UMD for both pre-event portfolios and corresponding post-event portfolios. These coefficient estimates were compared to determine if there were changes in the coefficient estimates from pre-event to post-event. The F test statistic from a Wald test is provided. Panel A shows the results for equally weighted portfolios consisting of 6 months of returns. Panel B shows the results for equally weighted portfolios consisting of 12 months of returns. Panel C shows the results for value-weighted portfolios consisting of 6 months of returns. Panel D shows the results for value-weighted portfolios consisting of 12 months of returns.

Table 34- continued

	F test statistic	Probability >F
Panel A: 6 months equal weighted		
Market	0.17	0.6788
SMB	0.33	0.5636
HML	0.80	0.3725
UMD	0.51	0.4764

	F test statistic	Probability >F
Panel B: 12 months equal weighted		
Market	0.03	0.8572
SMB	2.42	0.1211
HML	1.28	0.2592
UMD	2.14	0.1453

	F test statistic	Probability >F
Panel C: 6 months value weighted		
Market	0	0.9651
SMB	0.07	0.7892
HML	0.26	0.6092
UMD	0.26	0.6119

	F test statistic	Probability>F
Panel D: 12 months value weighted		
Market	1.16	0.2824
SMB	1.35	0.2468
HML	0.03	0.8622
UMD	0.04	0.8504

2.4.4 Operating Performance

Having shown that there is positive stock price reaction for firms taking impairment write-offs, we next examine if the increase in stock price is justified by an increase in the firm's performance.

We examine the median net income scaled by sales, shown in table 35. The left hand side of the table shows the median value by year relative to the impairment year. The right hand side of the table shows the median change between years. The significance of the change is determined by a signed rank test and is denoted by stars. Three stars indicate that the change is significantly different from zero at the 1% level, two stars indicate significance at the 5% level, and one star indicates significance at the 10% level. In both the unadjusted and industry adjusted results we see an improvement in results from the year of the impairment to the subsequent year and from year zero to two years post impairment. These improvements are both economically and statistically significant. We see these significant improvements in the entire population and in every size quintile. There is a perfectly monotonic pattern across size quintiles where the smaller size firms have the greatest improvement and the larger firms have the smallest improvement.

However, when we examine the performance compared to a matched firm (industry and performance adjusted) we find that the performance erodes from the year of the impairment to the subsequent year and continues to erode in year two. This is true for the entire population and for each size quintile but the erosion in performance loses statistical significance in the size quintiles above the smallest firms with the exception of the fourth quintile.

We see the same patterns when we measure performance by scaling the net median income by assets instead of sales, shown in table 36. We add any goodwill impairment back into the total assets in order to ensure we are not seeing improved performance by simply reducing the value of the denominator in the impairment year. Again we see improved performance for both year one and year two post write-off for the unadjusted and industry adjusted measures. We see erosion in performance when using the industry and performance adjusted measure.

Since net income includes nonrecurring items of cost, we next examine the firm performance using operating income before depreciation. Using operating income before depreciation provides a measure that examines the performance based on ordinary operating costs (COGS and SG&A) and eliminates any improvements due to changes in the amount of nonrecurring costs. If the acquisition created improvement in the firm's day to day business, we should see it reflected in improved operating income.

Table 37 shows median operating income scaled by sales. Similar to the previous measure, performance improves from year zero to year one and from year zero to year two for the unadjusted measure however the increase in performance is much smaller. The industry and performance adjusted results show that performance erodes in the two years subsequent to the impairment write-off. This pattern exists for each of the size quintiles as well, but the statistical significance is lost in many of the quintiles. We do not see the monotonic pattern of gains across the size quintiles using this measure.

The industry adjusted measure shows a minor improvement from year zero to year two but no improvement from year zero to year one. The industry and performance adjusted measure shows that performance declined from year zero to year one and from year zero to year two.

Using operating income scaled by assets, shown in Table 38, produces similar results. Years one and two post impairment show modest performance improvements for the unadjusted and industry adjusted categories. Using the industry and performance adjusted measure; we see erosion in the performance in the years subsequent to the write-off. Overall, any improvements in performance post write-off are much smaller using operating income versus using net income.

Table 35: Median Net Income Scaled by Sales

This is the median annual net income scaled by sales. This data is from 2002-2011 and excludes financial firms and utilities. The data is shown for the year of the goodwill impairment, one year prior, and one and two years subsequent to the event. Unadjusted is the data for all firms with a good will impairment write-off. Industry adjusted shows the difference between the median for all firms with impairments and the median value for all other firms in that industry. Industry and performance adjusted is the difference between the impaired firm and a matched firm using the same criteria for matching that was used in the BHAR analysis. The date is shown for all firms, and then shown by size quintile, with quintile 1 being the smallest and quintile 5 being the largest. The left side of the panel shows that actual data. The right-hand side shows the median change between years. The significance is from a singed rank test with *** indicating significance at the 1% level, ** indicating significance at the 5% level, and * indicating significance at the 10% level.

		Fiscal Year Relative to Impairment Year				Changes									
		-1	**0**	**+1**	**+2**	**-1 to 0**		**-1 to +1**		**-1 to +2**		**0 to +1**		**0 to +2**	
All Firms with Impairments															
Observations	1381														
Unadjusted		0.016	-0.045	0.009	0.020	-0.044	***	-0.003	***	0.004	***	0.037	***	0.047	***
Industry Adjusted		-0.002	-0.059	-0.012	-0.005	-0.041	***	-0.008	***	-0.003		0.034	***	0.041	***
Industry/performance adjusted		-0.079	-0.069	-0.072	-0.076	0.003	***	0.001		-0.003		-0.003	***	-0.007	***
Size Quintile 1															
Observations	626														
Unadjusted		-0.002	-0.119	-0.023	-0.005	-0.078	***	-0.011	***	-0.001		0.064	***	0.087	***
Industry Adjusted		-0.021	-0.128	-0.043	-0.033	-0.075	***	-0.013	***	-0.006		0.063	***	0.074	***
Industry/performance adjusted		-0.110	-0.087	-0.093	-0.109	0.007	***	0.005		-0.005	*	-0.004	***	-0.010	***

Table 35 – continued

		Fiscal Year Relative to Impairment Year				Changes									
		-1	**0**	**+1**	**+2**	**-1 to 0**		**-1 to +1**		**-1 to +2**		**0 to +1**		**0 to +2**	
Size Quintile 2															
Observations	268														
Unadjusted		0.025	-0.034	0.014	0.021	-0.060	***	-0.008	*	0.000		0.040	***	0.053	***
Industry Adjusted		0.008	-0.046	-0.005	-0.002	-0.058	***	-0.009	**	-0.005		0.036	***	0.042	***
Industry/performance adjusted		-0.087	-0.086	-0.084	-0.070	0.008	***	0.007	**	0.008	**	-0.001		-0.005	
Size Quintile 3															
Observations	180														
Unadjusted		0.037	-0.005	0.028	0.042	-0.024	***	-0.001		0.007	*	0.032	***	0.037	***
Industry Adjusted		0.019	-0.021	0.003	0.017	-0.028	***	-0.006	*	-0.001		0.026	***	0.025	***
Industry/performance adjusted		-0.059	-0.072	-0.058	-0.060	0.002		-0.002		-0.003		-0.004		-0.004	
Size Quintile 4															
Observations	147														
Unadjusted		0.026	-0.003	0.030	0.042	-0.012	***	0.002		0.011	***	0.019	***	0.030	***
Industry Adjusted		0.005	-0.018	0.004	0.012	-0.012	***	-0.002		0.004	**	0.022	***	0.019	***
Industry/performance adjusted		-0.052	-0.045	-0.054	-0.057	0.002		-0.002		-0.009	*	-0.002		-0.007	***
Size Quintile 5															
Observations	160														
Unadjusted		0.047	0.044	0.053	0.067	0.001		0.003		0.007	***	0.009	***	0.012	***
Industry Adjusted		0.028	0.025	0.037	0.035	-0.005	***	-0.003		-0.001		0.003	***	0.009	***
Industry/performance adjusted		-0.044	-0.046	-0.048	-0.041	-0.002		-0.004	**	-0.005	**	-0.004	***	-0.003	

Table 36: Median Net Income Scaled by Total Assets

This is the median annual net income scaled by total assets. Goodwill is added back into the assets for any year with a goodwill impairment write-off. This data is from 2002-2011 and excludes financial firms and utilities. The data is shown for the year of the goodwill impairment, one year prior, and one and two years subsequent to the event. Unadjusted is the data for all firms with a good will impairment write-off. Industry adjusted shows the difference between the median for all firms with impairments and the median value for all other firms in that industry. Industry and performance adjusted is the difference between the impaired firm and a matched firm using the same criteria for matching that was used in the BHAR analysis. The date is shown for all firms, and then shown by size quintile, with quintile 1 being the smallest and quintile 5 being the largest. The left side of the panel shows that actual data. The right-hand side shows the median change between years. The significance is from a singed rank test with *** indicating significance at the 1% level, ** indicating significance at the 5% level, and * indicating significance at the 10% level.

		Fiscal Year Relative to Impairment Year				Changes									
		-1	**0**	**+1**	**+2**	**-1 to 0**		**-1 to +1**		**-1 to +2**		**0 to +1**		**0 to +2**	
All Firms with Impairments															
Observations	1774														
Unadjusted		0.019	-0.051	0.009	0.024	-0.052	***	-0.005	***	0.008	***	0.039	***	0.055	***
Industry Adjusted		0.000	-0.064	-0.010	0.001	-0.050	***	-0.011	***	-0.002		0.033	***	0.046	***
Industry/performance adjusted		-0.089	-0.077	-0.078	-0.088	0.007	***	0.008	***	0.003	*	-0.003		-0.006	***
Size Quintile 1															
Observations	809														
Unadjusted		-0.005	-0.140	-0.028	-0.007	-0.097	***	-0.014	***	0.005		0.069	***	0.093	***
Industry Adjusted		-0.024	-0.142	-0.044	-0.032	-0.094	***	-0.020	***	-0.011	**	0.060	***	0.087	***
Industry/performance adjusted		-0.129	-0.101	-0.113	-0.129	0.018	***	0.016	***	0.004		-0.003		-0.010	***

Table 36 - continued

		Fiscal Year Relative to Impairment Year				Changes									
		-1	**0**	**+1**	**+2**	**-1 to 0**		**-1 to +1**		**-1 to +2**		**0 to +1**		**0 to +2**	
Size Quintile 2															
Observations	332														
Unadjusted		0.028	-0.032	0.018	0.024	-0.053	***	-0.009	***	-0.003		0.044	***	0.059	***
Industry Adjusted		0.011	-0.044	-0.003	0.000	-0.050	***	-0.013	***	-0.008	*	0.032	***	0.040	***
Industry/performance adjusted		-0.099	-0.080	-0.082	-0.092	0.007	***	0.015	***	0.014	***	0.002		-0.004	
Size Quintile 3															
Observations	230														
Unadjusted		0.037	-0.011	0.033	0.047	-0.047	***	-0.003		0.009	***	0.038	***	0.051	***
Industry Adjusted		0.023	-0.025	0.012	0.019	-0.047	***	-0.009	**	-0.003		0.036	***	0.041	***
Industry/performance adjusted		-0.071	-0.078	-0.067	-0.063	0.000		0.003		0.004		-0.003		0.002	
Size Quintile 4															
Observations	196														
Unadjusted		0.025	-0.002	0.032	0.041	-0.018	***	0.006		0.010	***	0.020	***	0.035	***
Industry Adjusted		0.012	-0.009	0.014	0.018	-0.018	***	0.003		0.006	***	0.022	***	0.025	***
Industry/performance adjusted		-0.061	-0.062	-0.059	-0.064	0.001		0.001		-0.003		-0.002		-0.006	**
Size Quintile 5															
Observations	207														
Unadjusted		0.050	0.044	0.053	0.061	0.001		0.009	**	0.013	***	0.010	***	0.015	***
Industry Adjusted		0.030	0.024	0.027	0.034	-0.008	***	-0.002		0.0005	*	0.004	***	0.011	***
Industry/performance adjusted		-0.03345	-0.036	-0.037	-0.038	-0.002		-0.007	**	-0.006	**	-0.005	***	-0.007	**

Table 37: Median Operating Income Scaled by Total Sales

This is the median annual operating income before depreciation (OIBDP) scaled by total sales.. OIBDP is defined as revenue less cost of goods sold and SG&A. This data is from 2002-2011 and excludes financial firms and utilities. The data is shown for the year of the goodwill impairment, one year prior, and one and two years subsequent to the event. Unadjusted is the data for all firms with a good will impairment write-off. Industry adjusted shows the difference between the median for all firms with impairments and the median value for all other firms in that industry. Industry and performance adjusted is the difference between the impaired firm and a matched firm using the same criteria for matching that was used in the BHAR analysis. The date is shown for all firms, and then shown by size quintile, with quintile 1 being the smallest and quintile 5 being the largest. The left side of the panel shows that actual data. The right-hand side shows the median change between years. The significance is from a singed rank test with *** indicating significance at the 1% level, ** indicating significance at the 5% level, and * indicating significance at the 10% level.

	Fiscal Year Relative to Impairment Year					Changes									
		-1	**0**	**+1**	**+2**	**-1 to 0**		**-1 to +1**		**-1 to +2**		**0 to +1**		**0 to +2**	
All Firms with Impairments															
Observations	1381														
Unadjusted		0.096	0.076	0.082	0.092	-0.010	***	-0.006	***	-0.002		0.003	***	0.006	***
Industry Adjusted		0.004	-0.010	-0.011	-0.006	-0.011	***	-0.011	***	-0.009	***	-0.001		0.001	***
Industry/performance adjusted		-0.032	-0.027	-0.029	-0.035	0.004	***	0.002	**	-0.001		-0.002	**	-0.006	***
Size Quintile 1															
Observations	626														
Unadjusted		0.066	0.046	0.049	0.056	-0.016	***	-0.014	***	-0.005	**	0.002		0.009	***
Industry Adjusted		-0.018	-0.039	-0.037	-0.034	-0.017	***	-0.015	***	-0.015	***	-0.002		0.003	**
Industry/performance adjusted		-0.025	-0.016	-0.024	-0.025	0.006	***	0.004		-0.001		-0.002	*	-0.007	***

Table 37 - continued

	Fiscal Year Relative to Impairment Year					Changes									
		-1	**0**	**+1**	**+2**	**-1 to 0**		**-1 to +1**		**-1 to +2**		**0 to +1**		**0 to +2**	
Size Quintile 2															
Observations	268														
Unadjusted		0.112	0.091	0.101	0.113	-0.012	***	-0.008	***	-0.004		0.003	**	0.005	***
Industry Adjusted		0.019	0.005	0.002	0.010	-0.010	***	-0.011	***	-0.008	***	0.000		0.001	
Industry/performance adjusted		-0.029	-0.018	-0.019	-0.023	0.011	***	0.008	***	0.006	**	0.002		-0.001	
Size Quintile 3															
Observations	180														
Unadjusted		0.108	0.107	0.106	0.116	-0.006	***	-0.001		0.001		0.003	**	0.008	***
Industry Adjusted		0.022	0.015	0.011	0.025	-0.007	***	-0.009	***	-0.006		0.001		0.001	
Industry/performance adjusted		-0.040	-0.038	-0.033	-0.034	0.002		-0.002		-0.003		0.000		-0.005	
Size Quintile 4															
Observations	147														
Unadjusted		0.125	0.114	0.118	0.121	-0.006	***	0.001		0.005	**	0.004	***	0.007	***
Industry Adjusted		0.026	0.016	0.016	0.022	-0.009	***	-0.005		0.002		0.007	***	0.005	***
Industry/performance adjusted		-0.039	-0.036	-0.038	-0.050	-0.001		-0.003	**	-0.009	***	-0.002	***	-0.007	***
Size Quintile 5															
Observations	160														
Unadjusted		0.136	0.135	0.133	0.135	-0.001		-0.002		-0.002		0.001		-0.004	
Industry Adjusted		0.040	0.038	0.028	0.029	-0.004	***	-0.012	***	-0.014	***	-0.004	***	-0.008	***
Industry/performance adjusted		-0.054	-0.043	-0.058	-0.058	0.001		-0.001		-0.001		-0.005	***	-0.004	**

Performance based on operating income show much smaller gains than performance based on net income. This evidence is consistent with our hypothesis that managers pull forward potential write-offs in order to take one “big bath’ as opposed to spreading out a number of smaller write-offs across subsequent years.

2.4.5 Big Bath

We further test our “big bath’ hypothesis by examining the special items of costs (SPI) charges for the two years prior to the impairment year, the impairment year, and the two years after the impairment year for all firms with goodwill impairment charges. Special items of cost include the majority of unusual or nonrecurring charges a company incurs. SPI may include: applicable prior year adjustments (excluding recurring tax adjustments, any nonrecurring items that are significant, results from discontinued operations, natural disaster losses, interest on tax settlements, inventory write-downs, nonrecurring profit or loss from the sale of an asset or investment, gains or losses from the repurchase of debentures, research and development that is purchased, moving expenses, reserves for litigation expenses, restructuring costs, severance pay, construction allowances, transfers from previous reserves, write-downs (or write-offs) of intangibles or receivables, write-offs of capitalized software, and year 2000 (Y2K) costs, in addition to the goodwill impairment charges. This is shown across all firms with impairments and by size quintile in Table 39. On the left hand side of the table are the median SPI charges in millions of dollars by year, from two years prior to the impairment year to two years post the impairment event. We analyze all firms, then we analyze firms by size quintile, with quintile one being the smallest firm size and quintile five being the largest firm size. We add the goodwill impairment charges back into SPI totals for year zero so that we are comparing SPI charges exclusive of the goodwill, with SPI charges in subsequent years.

The right hand side of the table shows the median difference between years listed. SPI is represented as a negative number since it is a cost. The median difference between years is negative if the amount of SPI increases and it is positive if the amount of SPI decreases. A signed rank test is used to determine if the amount of the change is significantly different from zero. The stars represent the significance of the change, with three stars representing significance at the 1% level, two stars indicating significance at the 5% level, and one star indicating significance at the 10% level.

Overall we see that there is an economically and statistically significant reduction in the magnitude of the SPI charges in both the first year and the second year subsequent to the goodwill impairment year. SPI charges, exclusive of the goodwill impairment charge are greatest in the year of the goodwill impairment charge. This is consistent with our big bath hypothesis. Managers may elect to take every charge they can foresee in the year of the goodwill impairment charge so that the firm experiences only one negative event. Then the subsequent years have less SPI and therefore improved overall firm performance which is consistent with the positive abnormal returns after a goodwill impairment.

The SPI reductions in the years subsequent to the goodwill impairment write-off are economically and statistically significant for the smallest size quintile. The largest size quintile does not exhibit an SPI reduction in the year following the goodwill impairment charge. Size quintiles two through four show reductions in the SPI in the year following the impairment, but it is not always a significant change. The second year after the impairment does show significant SPI reductions for these size quintiles. This is consistent with our results showing that the largest size quintile has a negative stock price reaction to impairment write-offs.

Table 38: Median Operating Income Scaled by Total Assets

This is the median annual operating income before depreciation (OIBDP) scaled by total sales.. OIBDP is defined as revenue less cost of goods sold and SG&A. Goodwill is added back to the total assets for all firms having goodwill impairments in the year being analyzed. This data is from 2002-2011 and excludes financial firms and utilities. The data is shown for the year of the goodwill impairment, one year prior, and one and two years subsequent to the event. Unadjusted is the data for all firms with a good will impairment write-off. Industry adjusted shows the difference between the median for all firms with impairments and the median value for all other firms in that industry. Industry and performance adjusted is the difference between the impaired firm and a matched firm using the same criteria for matching that was used in the BHAR analysis. The date is shown for all firms, and then shown by size quintile, with quintile 1 being the smallest and quintile 5 being the largest. The left side of the panel shows that actual data. The right-hand side shows the median change between years. The significance is from a singed rank test with *** indicating significance at the 1% level, ** indicating significance at the 5% level, and * indicating significance at the 10% level.

		Fiscal Year Relative to Impairment Year				Changes									
		-1	**0**	**+1**	**+2**	**-1 to 0**		**-1 to +1**		**-1 to +2**		**0 to +1**		**0 to +2**	
All Firms with Impairments															
Observations	1774														
Unadjusted		0.094	0.076	0.090	0.103	-0.011	***	-0.001	***	0.007	***	0.008	***	0.018	***
Industry Adjusted		0.006	-0.010	0.000	0.006	-0.012	***	-0.006	***	-0.001		0.006	***	0.014	***
Industry/performance adjusted		-0.036	-0.024	-0.023	-0.033	0.006	***	0.007	***	0.002	**	-0.002		-0.005	***
Size Quintile 1															
Observations	809														
Unadjusted		0.068	0.048	0.059	0.079	-0.019	***	-0.006	***	0.007		0.010	***	0.029	***
Industry Adjusted		-0.020	-0.043	-0.036	-0.022	-0.020	***	-0.010	***	0.000		0.007	**	0.021	***
Industry/performance adjusted		-0.041	-0.018	-0.024	-0.040	0.012	***	0.010	***	-0.001		-0.001		-0.008	***

Table 38 – continued

		Fiscal Year Relative to Impairment Year				Changes									
		-1	**0**	**+1**	**+2**	**-1 to 0**		**-1 to +1**		**-1 to +2**		**0 to +1**		**0 to +2**	
Size Quintile 2															
Observations	332														
Unadjusted		0.108	0.087	0.099	0.107	-0.010	***	-0.002	**	-0.002		0.009	***	0.017	***
Industry Adjusted		0.018	0.001	0.007	0.009	-0.010	***	-0.006	***	-0.003		0.007	**	0.009	***
Industry/performance adjusted		-0.033	-0.021	-0.015	-0.023	0.010	***	0.014	***	0.009	***	-0.001		-0.002	
Size Quintile 3															
Observations	230														
Unadjusted		0.110	0.104	0.110	0.121	-0.008	***	0.001		0.008	**	0.005	**	0.014	***
Industry Adjusted		0.027	0.018	0.020	0.030	-0.007	***	-0.005	*	0.002		0.000		0.009	***
Industry/performance adjusted		-0.028	-0.028	-0.018	-0.022	-0.001		0.003		0.002		0.000		0.002	
Size Quintile 4															
Observations	196														
Unadjusted		0.108	0.100	0.115	0.124	-0.007	**	0.004		0.009	***	0.010	***	0.020	***
Industry Adjusted		0.024	0.011	0.024	0.034	-0.011	***	0.001		0.004	*	0.010	***	0.014	***
Industry/performance adjusted		-0.046	-0.040	-0.033	-0.036	0.001		0.003		0.002		-0.003		-0.004	
Size Quintile 5															
Observations	207														
Unadjusted		0.134	0.128	0.134	0.138	0.000		0.002		0.008		0.005		0.007	*
Industry Adjusted		0.047	0.044	0.034	0.040	-0.002		-0.002		-0.007		0.002		0.004	
Industry/performance adjusted		-0.0267	-0.019	-0.0305	-0.031	0.001		-0.004		0.000		-0.005	**	-0.009	**

Table 39: Special Items of Cost

This table shows the median annual amount of special items of cost (SPI) charges the firms with goodwill impairments took in the two years prior to the year of the event, the year of the goodwill impairment event, and the two subsequent years. The Impairment charge is added back into the number. The table shows the values for all firms, and then the values sorted by firm's size quintile, with quintile 1 being the smallest and quintile 5 being the largest. The left-hand side shows the actual value in millions of dollars. The right hand side shows the median difference between the years identified. The significance is from a signed rank test with *** indicating significance at the 1% level, ** indicating significance at the 5% level, and * indicating significance at the 10% level. This data is for the timeframe 2002-2011 and excludes financial firms and utilities.

	Fiscal Year Relative to Impairment Year					Year-on-year changes in SPI			
	-2	**-1**	**0**	**+1**	**+2**	**-2 to -1**	**-1 to 0**	**0 to +1**	**+1 to +2**
All Firms with Impairments	-2.2	-5.660	-7.400	-5.200	-3.498	-0.350 ***	0.000	0.597 ***	0.342 ***
Size Quintile 1 (smallest)	-0.5	-1.391	-2.523	-1.175	-0.850	0.000	-0.001	0.481 ***	0.151 ***
Size Quintile 2	-2.02	-9.450	-9.864	-8.241	-7.348	-1.340 ***	-0.780	0.700	0.231 **
Size Quintile 3	-9.827	-10.225	-14.558	-10.113	-10.000	-0.520 *	0.000	2.600 **	1.531 *
Size Quintile 4	-23	-44.134	-57.061	-44.125	-27.300	-7.017 ***	5.000 **	3.440	6.544 ***
Size Quintile 5 (largest)	-42.87	-95.416	-57.450	-66.700	-50.000	-19.600 ***	20.492 ***	-3.115	9.767 *

We also analyze SPI scaled by sales and find the same patterns and draw the same conclusions as when we examine absolute SPI data. Therefore, these results are not included.

2.5 Conclusion

This paper examines the impact of goodwill impairment write-offs on stock returns after the changes to the accounting rules that reclassified goodwill from a wasting asset to a perpetual asset. Prior to this rule change, studies found a negative stock price reaction to goodwill write-offs both in the short term and in the long term.

Our analysis confirms the previous findings of a short-term negative price reaction. Even with the rule changes and the subsequent increase in frequency of impairment write-offs, investors continue to perceive the goodwill write-off as negative news in the short term. We also find that the size of the write-off is related to the magnitude of the negative abnormal return in the two-day window around the write-off announcement. We do not find a relation between btm or firm size on the magnitude of the abnormal return during the two-day window.

The primary findings, however, are contradictory to previous studies. We find that in the long-term stock prices react positively to a goodwill impairment write-off after the rule changes and that this positive abnormal return exists for as much as 250 days post the write-off announcement. This positive abnormal return is greater than the negative abnormal return around the two-day event window and the negative abnormal return pre-event combined. These positive abnormal returns post write-off are not due to post-earnings announcement drift. Additionally, we find a strong correlation between the magnitude of the abnormal return and btm values, suggesting that firms with higher btm ratios (value firms) have more positive abnormal returns after a goodwill impairment write-off. We do not find a relation between the size of the impairment write-off and the magnitude of the abnormal return post-event.

The impact of firm size on the magnitude of the abnormal returns post write-off is not as straightforward as the btm results. The CAR analysis indicates a significant inverse relation between firm size and the magnitude of the abnormal returns post write-off. Our BHAR analysis indicates that smaller firms have more positive abnormal returns than larger firms, but that it is not a monotonic relation. The significance is weaker with this more powerful BHAR test as opposed to the CAR analysis. We find that in the BHAR analysis, for both the 125-day and 250-day studies, the largest quintile of firms have negative and significant results post write-off which is consistent with findings from studies pre-rule change. Our equal-weighted calendar time regression analysis is consistent with the BHAR analysis; the smallest firms exhibit the largest positive abnormal returns, and the largest firms exhibit the smallest abnormal returns, but there is not a monotonic relation between the firm size and the magnitude of the abnormal returns. However, contrary to the BHAR study, we do not find negative and significant abnormal returns using the calendar time approach. The value-weighted calendar time regression analysis shows no discernible pattern between firm size and the magnitude of the abnormal returns.

An analysis of the risk factors shows no significant changes in the coefficient estimates for the risk factors, MKT, SMB, HML, and UMD from before the impairment write-off to after the impairment write-off.

Overall, these results suggest that investors have changed their perceptions about goodwill impairment write-offs after the implementation of the new rules. They now perceive an impairment write-off of the goodwill from a previous acquisition as a positive event.

Prior to the rule change, goodwill impairment write-offs were infrequent events that signaled ambiguous information. Since the rule changes, goodwill impairments are more systematic since the goodwill must be assessed annually for impairment. Our evidence suggests that firms use this requirement that they write off some or all of the goodwill to write off additional non-goodwill items at the same time. In other words the requirement for the goodwill impairment write-off may be a catalyst for the firm to take a "big bath". The forced goodwill impairment determines that the firm will have negative news. Since the amount of the impairment does not appear as relevant to investors as the event itself, the firm takes all potentially negative news and incorporates it into the goodwill impairment announcement or as in many cases the earnings announcement that contains the write-off announcement. Investors may perceive this "big bath" as indicative that the subsequent performance of the firm will be positive since all foreseeable nonrecurring costs have already been absorbed.

There is a negative correlation between the size of the firm and the relative size of the goodwill impairment write-off. Our evidence shows that small firms have larger relative impairment write-offs. Thus, they may experience a more negative short term reaction, leading to larger abnormal returns in the long term.

Further research on this topic could be to examine the difference between the goodwill impairment amount required to be written off by a fair-value assessment and the actual write-off that the firms take. In addition, the amount of exposure a firm's goodwill write-off receives may also impact investors' perceptions of the write-off. Since smaller firms often have less analyst coverage this could help explain the relation of size to abnormal returns. Thus it would be interesting to track the amount of analyst coverage for the firms with write-offs. It would also be interesting to examine how many firms that are required to take a goodwill impairment write-off do not survive.

REFERENCES

Ahmed, Anwer S., and Lale Guler. 2007. Evidence on the Effects of SFAS 142 on the Reliability of Goodwill Write-offs. Working Paper, Texas A&M University.

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

Altman, E., 1993. Corporate Financial Distress and Bankruptcy. John Wiley & Sons, New York.

Bartov, E., F. W. Lindahl and W. E. Ricks. 1998. Stock Price Behavior Around Announcements of Write-Offs. *Review of Accounting Studies* 3: 327-346.

Bens, Daniel A., and Wendy Heltzer, 2005, The Information Content and Timeliness of Fair Value Accounting: An Examination of Goodwill Write-offs Before, During and After Implementation of SFAS 142. Working Paper, University of Chicago.

Bens, Daniel A.; Heltzer, Wendy; Segal, Benjamin. 2011. The Information Content of Goodwill Impairments and SFAS 142. *Journal of Accounting, Auditing & Finance*, Jul2011, Vol. 26 Issue 3, p 527-555.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist ,1996, The Financial Accelerator and Flight to Quality. *The Review of Economics and Statistics* 78, 1-15.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In Search of Distress Risk, *Journal of Finance* 63, 2899-2939.

Chan, K.C., and Nai-Fu Chen, 1991, Structural and Return Characteristics of Small and Large Firms, *Journal of Finance* 46, 1467 – 1484.

Chen, C., M. Kohlbeck and T. Warfield. 2008. Timeliness of Impairment Recognition: Evidence from the Initial Adoption of SFAS 142. *Advances in Accounting*, Vol. 24 Issue 1, p 72-81.

Churyk, Natalie Tatiana. 2005. Reporting Goodwill: Are the New Accounting Standards Consistent With Market Valuations? *Journal of Business Research,* October 2005, Volume 58, Issue 10, Pages 1353-1361.

Daniel, Kent and Sheridan Titman, 1997, Evidence on the Characteristics of Cross-Sectional Variation in Stock Returns, *Journal of Finance* 52, 1-33.

Dichev, Ilia D., 1998, Is the Risk of Bankruptcy a Systematic Risk? *Journal of Finance* 53, 1131-1147.

Eberthart, Allan C., William F. Maxwell, and Akhtar R. Siddique. 2004. An Examination of Long-Term Abnormal Stock Returns and Operating Performance Following R&D Increases. *The Journal of Finance.* 59: 623-650.

Fama, Eugene F., and Kenneth French, 2008. Dissecting Anomalies. *Journal of Finance* 63: 1653–1678.

Fama, Eugene F., and Kenneth R. French, 2006, The Value Premium and the CAPM, *Journal of Finance* 61, 2163 – 2185.

Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3- 56.

Fama, Eugene F., and Kenneth R. French, 1992, The Cross-Section of Expected Stock Returns, *Journal of Finance* 47, 427- 465.

Fama, Eugene F., and MacBeth, James D., 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy.* 81: 607–636.

Fama, Eugene F., and MacBeth, James D., 1973. Risk, return, and equilibrium: empirical tests. *Journal of Political Economy*. 81: 607–636.

Federal Reserve website: http://www.federalreserve.gov/releases/Z1/Current/data.htm

Financial Accounting Standards Board, 2001. Goodwill and other intangible assets. Financial Accounting Series. Statement of Financial Accounting Standards No. 142. June.

Financial Accounting Standards Board. 2007. Business Combinations. Financial Accounting Series. Statement of Financial Accounting Standards No. 141.

Frances, J., D. Hannah, and L. Vincent. 1996. Causes and Effects of Discretionary Asset Write – offs. *Journal of Accounting Research* (Supplement 1996) : 91-119.

Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Griffin, J. M., and M. L. Lemmon. 2002. Book-to-Market Equity, Distress Risk, and Stock Returns. *Journal of Finance* 57:2317–36.

Hayn, Carla, and Patricia J. Hughes. 2006. Leading Indicators of Goodwill Impairment. *Journal of Accounting, Auditing and Finance.* Summer 2006, Vol.21 Issue 3, p 223-265.

Hirschey, M., and V. Richardson. 2003. Investor Underreaction to Goodwill Write-Offs. *Financial Analysts Journal* November/December (2003): 75-84.

Jennings, Ross, John Robinson, Robert B. Thompson II and Linda Duvall. 1996. The Relation Between Accounting Goodwill Numbers and Equity Values. *Journal of Business Finance & Accounting*, Jun 96, Vol. 23 Issue 4, p513-533.

Kapadia, Nishad, 2011, Tracking Down Distress Risk. *Journal of Financial Economics* 102, 167-182.

Lee, Cheol. 2011. The Effect of SFAS 142 on the Ability of Goodwill to Predict Future Cash Flows. *Journal of Accounting and Public Policy*, Vol. 30, p.236-255.

Li K. and G. Meeks. 2006. The impairment of purchased goodwill: effects on market value. Working Paper, University of Cambridge.

Li, Zining, Pervin Shroff, and Ramgopal Venkataraman. 2011. Causes and Consequences of Goodwill Impairment Losses. *Review of Accounting Studies*, Dec 2011, Vol. 16 Issue 4, 745-778.

Lintner, John, 1965, The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets, *Review of Economics and Statistics* 47, 13 -37.

Lys, Thomas, Linda Vincent, and Nir Yehuda. 2011. The Nature and Implications of Acquisition Goodwill. Working paper, Northwestern University.

Morrissey, Michael J., Deloitte & Touche LLP . 2007. Accounting for Business Combinations, Goodwill, and Other Intangible Assets: A Roadmap to Applying Statements 141 and 142.

Newey, Whitney K. and Kenneth D. West. 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica,* May 1987, Vol. 55 No. 3, 703-708.

Norden, Lars and Martin Weber, 2009, The Co-movement of Credit Default Swap, Bond and Stock Markets: an Empirical Analysis, *European Financial Management* 15, 529-562.

Ohlson, J. 1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research* 18, 109–31.

Shalev, Ron. 2009. The Information Content of Business Combination Disclosure Level. *Accounting Review* 84 (1): 239-270.

Sharpe, William F., 1964, Capital Asset Prices: A Theory of Market Equilibrium, *Journal of Finance* 19, 425-442.

Sloan. R. 1996. Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71: 289-315.

U.S. Bureau of Economic Analysis website: http://www.bea.gov

Vassalou, Maria, 2003. News Related to Future GDP Growth as a Risk Factor in Equity Returns. *Journal of Financial Economics* 68, 47-73.

BIOGRAPHICAL SKETCH

Karen Sherrill previously held the position of Worldwide Service Director at Eastman Kodak Company, where she worked for over twenty years. As Eastman Kodak headed towards bankruptcy, Karen decided to make a career change and use the knowledge and experience gained in business to teach others. She obtained a Master's in Finance from Florida State University in 2011. She then entered the Ph.D. program in Finance at Florida State University and expects to graduate in the spring of 2015. She has accepted a job at Sam Houston State University and is excited to start her new career beginning in the fall semester of 2015.