The Relationship between the Value Effect and Industry Affiliation

John C. Banko
Finance Department
Northern Illinois University
DeKalb, IL 60115-2854
(815) 753-6391
jbanko@niu.edu

C. Mitchell Conover
Department of Finance
The E. Claiborne Robins School of Business
University of Richmond
Richmond, VA 23173
(804) 287-1921
mconover@richmond.edu

Gerald R. Jensen
Finance Department
Northern Illinois University
DeKalb, IL 60115-2854
(815) 753-6399
gjensen@niu.edu

November 2004

The Relationship between the Value Effect and Industry Affiliation

Abstract

Using data for twenty-one industries over a thirty-three year period, we examine industry affiliation and the relationship between stock returns and book-to-market-equity (the value effect). Our findings indicate that the value effect is a widespread phenomenon, as a significant value premium is shown to exist in fifteen of twenty-one industries. We identify a value effect at both the industry and firm level; however, the firm level effect is shown to be the stronger of the two. We also show that the industry and firm level effect are complementary, thus, the value effect is strongest in value industries and weakest in growth industries. Finally, we find results consistent with the contention that the value premium is a result of investors requiring higher returns from firms in relatively distressed conditions. Specifically, value firms are shown to have higher returns but also substantially higher earnings uncertainty, higher leverage, and higher risk of financial distress.

The Relationship between the Value Effect and Industry Affiliation

Asset pricing studies provide overwhelming evidence that variation in cross-sectional stock returns is significantly related to firm book-to-market-equity (BE/ME, the ratio of the book value of equity to the market value of equity).[1] Furthermore, these studies confirm that even after controlling for differences in beta and size, BE/ME still plays a significant role in explaining stock returns. This observation is commonly identified as the value effect or value anomaly. While the existence of the value effect is certain, there is considerable debate regarding the underlying explanation for the effect.

Researchers have proposed two alternative explanations for the value effect. One explanation is that the effect is due to an association between BE/ME and the risk of financial distress [Fama and French (1992, 1993, 1995) and Chen and Zhang (1998)]. According to this explanation, the value effect exists because BE/ME indicates a firm's degree of financial distress risk. In particular, firms with high BE/ME (value firms) are shown to have earnings problems and relatively high levels of financial leverage. Therefore, the risk-based explanation for the value effect contends that the premium attached to value firms is a rational result of the higher financial distress risk inherent in value firms.

A second explanation contends that the effect is due to irrational pricing as investors become overly optimistic or pessimistic about the prospects of firms exhibiting certain "growth- or value-related" characteristics [Lakonishok, Shleifer, and Vishny (1994) and Daniel and Titman (1997)]. Further, Shleifer and Vishny (1997) and Ali, Hwang, and Trombley (2003) argue that impediments such as risk and transactions costs prevent arbitrageurs from exploiting the systematic mispricing of investors. Griffin and Lemmon (2002) and Dichev (1998) find evidence suggesting that the mispricing associated with BE/ME exists even after controlling for

differences in bankruptcy risk. Specifically, the authors conclude that investors systematically

overprice growth firms that have high bankruptcy risk. The investors are subsequently

disappointed when the firms' fortunes do not improve.

In this research, we evaluate the relationship between BE/ME, industry affiliation, and

measures of financial distress risk. Given the important role that industry affiliation plays in

security analysis, we are particularly interested in determining the influence that industry

affiliation has on the value effect. The purpose of the analysis is to examine the relationship

between the value effect, firm risk and industry affiliation to provide a better understanding of

the value effect and possible explanations for its existence. Specifically, the goal is to determine

whether the value effect is consistent with the view that certain firm risk characteristics are being

priced by investors, and further, whether industry affiliation appears to influence the value effect.

The analysis, however, is not designed to determine whether the pricing patterns associated with

BE/ME are rational. For example, a relationship may exist between financial-distress proxies

and the value effect because investors are mispricing financial-distress risk.

The first objective of this paper is to evaluate the strength of the value effect at the firm

level relative to the effect at the industry level. Moskowitz and Grinblatt (1999) find evidence

indicating that much of the momentum anomaly is due to the industry component of stock

returns.[2] In a similar vein to Moskowitz and Grinblatt, we examine whether industry affiliation

plays a role in asset prices conditional on BE/ME. Moskowitz and Grinblatt argue that a

potential explanation for the observed relationship between momentum in returns and industry

affiliation lies in the behavioral research of Daniel and Titman (1997), Barberis, Shleifer, and

Vishny (1998), and Hong and Stein (1999). Specifically, Moskowitz and Grinblatt contend that

investor biases may be attached to industries rather than specific firms. Investors may become

overly confident or pessimistic about the prospects of an industry based on the arrival of new information, which may create conditional patterns in industry returns.

Industry-related problems are commonly identified as a contributing factor in a firm's financial demise [Hotchkiss (1995)]. Several studies, for example Clinch and Sinclair (1987) and Slovin, Sushka, and Bendeck (1991), identify industry-wide price reactions to firm specific announcements, supporting the view that industry affiliation may be associated with the value effect. Kothari, Shanken, and Sloan (1995) find a significant relationship between industry BE/ME and industry stock returns. The authors, however, consider only inter-industry BE/ME variation in explaining stock returns and do not examine the relationship between intra-industry variation in BE/ME and stock returns. They also do not consider the size of the value effect across or within specific industries.

The second objective of this paper then is to determine the prevalence and prominence of the value effect across various industries. Daniel, Hirshleifer, and Subrahmanyam (2001) present a model whereby the value effect should be stronger for those stocks with a higher proportion of intangible assets, due to the fact that these firms are harder to value. Chan, Lakonishok, and Sougiannis (2001) present evidence consistent with this model. Chan et. al. report research and development expenditures for various science and technology industries, ranging from 58% of earnings in the electrical equipment industry to 207% in the computer programming industry.[3] The authors note that the expensing of R&D and the accumulation of intangible R&D assets can result in widely different valuations using price-multiples. Failure to properly value R&D expenditures results in misvaluations, which are stronger in those industries where the intensity of R&D spending is higher.

Fama and French (1997) and Cohen and Polk (1998) examine the variation in BE/ME factor risk loadings across industries. The cross-industry variation in the factor loadings identified in these studies implies that industry affiliation represents a prominent part of the return premium associated with high BE/ME firms. In particular, Fama and French show that the factor risk loadings on the BE/ME factor vary substantially across industries, which motivates an evaluation of the value effect across industries. The authors also show that the sensitivity of industry returns to the BE/ME factor exhibits substantial variation through time. Much of the variation in the factor risk loadings may be attributed to changes in the relative BE/ME of the industry itself. Examining *factor loadings* on BE/ME assumes that the value effect is a result of rational investor pricing. Rather than examining the BE/ME *factor loadings* across industries, we examine industry affiliation and the relationship between stock returns and BE/ME.

Determining the role that industry affiliation plays in the value effect is essential before the value effect can be adequately incorporated into asset pricing models. For example, the effect may be limited to a relatively few prominent industries, in which case industry affiliation should play a pivotal role in pricing models. In contrast, if the value effect is essentially a firm level phenomenon, industry affiliation should have a limited role in asset pricing models.

An industry analysis of the value effect is also motivated by Chen and Zhang (1998), as they show that the prominence of the value effect varies by country. More specifically, the authors find that the value effect is much less pronounced in their sample of high-growth countries relative to the effect in more mature markets. The authors argue that this finding is consistent with the view that there is less dispersion in the risk of firms in markets that are experiencing relatively rapid growth. Thus, in growth markets, high BE/ME firms are less likely

4

to be financially distressed. Chan and Chen (1991) report a related finding as they show that small Nasdaq firms are much less prone to be distressed than small NYSE firms. Whereas Chen and Zhang examine the variation in the value premium across countries, we perform a similar investigation of the premium across industries.

Chen and Zhang (1998) argue that the value premium is a result of rational investor pricing that is based on differences in firm risk. The authors suggest that the value premium is associated with the relative growth prospects of the market in which a firm operates. They claim that the value premium should be smaller for value firms operating in markets with strong growth prospects because the chance of such firms experiencing financial distress is diminished when compared to the prospects of value firms operating in markets with limited growth prospects.

The third objective of this paper is to determine if the value-related return patterns are consistent with risk-based pricing decisions by investors. Specifically, using the framework of Chen and Zhang, we examine whether the value effect is associated with measures of financial distress risk. If the Chen and Zhang argument is applicable to U.S. industries, we expect to see a greater value premium in those industries with greater distress, due to heightened investor concern over these firms' survival. Although the presence of higher risk in value industries and value stocks is consistent with a risk-based explanation for the value effect, it does not rule out a mispricing explanation. In a review of asset pricing in a behavioral framework, Hirshleifer (2001) notes that the presence of risk-based return patterns is not sufficient evidence of rational pricing. Indeed, a behaviorist would argue that investors may recognize risk, but that they also misprice risk (e.g. overreaction to bad news). Thus, though an observation of higher risk in value stocks is a necessary condition for rational risk-based pricing, it is not a sufficient

5

condition to prove that rational pricing explains the value effect. If we find that value stocks and industries do not have higher risk than their growth counterparts, however, a rational, risk-based pricing explanation is certainly suspect.

Our intention is to rigorously evaluate the relationship between industry affiliation, risk measures, and the value effect. This research provides several contributions to the existing literature. First, we examine the relationship between portfolio returns and both industry and firm BE/ME. This allows us to differentiate the relationship between industry BE/ME and equity returns from that of firm BE/ME and returns. Second, we examine the prevalence of the value effect within various industries. If BE/ME is an effective proxy variable, a value effect should exist within a majority of our industries. Third, we employ a generalized least squares (GLS) methodology that assumes a more general error structure (relative to the traditional approach) that allows for serial correlation in returns and accounts for interdependence in stock performance at a point in time. Fourth, we examine the temporal consistency of industry BE/MEs to determine whether industries can be consistently classified into value or growth categories. Fifth, we follow Chen and Zhang (1998) in examining whether the BE/ME is related to risk characteristics. Specifically, we investigate the Chen and Zhang risk characteristics to determine whether they vary systematically across industries and portfolios that are formed on the basis of BE/ME rank. Finally, we examine the relationship between risk characteristics and the returns attributed to BE/ME to determine whether the value effect is consistent with a risk-based pricing explanation.

I. Sample and Methodology

Using Center for Research in Security Prices (CRSP) and COMPUSTAT data, we form

five equal-weighted portfolios within each of twenty-one different industries.[4] Firms are ranked

by BE/ME within each industry and formed into portfolios by quintiles i.e. the 20% of firms with

the highest BE/ME in an industry are placed in portfolio one, and so forth.[5] Portfolios are

reformed on an annual basis. Sorting firms into portfolios follows the long established practice

of forming portfolios to analyze time series returns for a large cross section of firms [e.g. Black,

Jensen, and Scholes (1972) and Fama and French (1992)]. By focusing on the explanatory

power of a single variable (BE/ME), however, we alleviate the potential statistical problems

created by such an approach. In particular, Berk (2000) shows that such an approach biases

against finding significant coefficients for other variables included in the model. In order to

establish robust statistics, we require industries to maintain a representation of at least fifteen

firms throughout the sample period.

We follow Fama and French (1992) in deriving BE/ME. Specifically, BE is measured at

fiscal year end in calendar year (t-1), which is at least six months prior to the return measurement

interval. The market equity used in calculating BE/ME is measured at calendar year-end (t-1).

This process represents a conservative approach to ensure that the accounting data is available

prior to the return interval, which runs from July of year t through June of year t+1. Portfolio

returns are derived as monthly equal-weighted returns for the firms in the portfolio.[6]

To isolate the returns uniquely associated with BE/ME, we also control for differences in

market capitalization and beta. Again, we follow Fama and French (1992) in calculating market

capitalization (ME) and beta. Specifically, ME is calculated as price per share times number of

shares outstanding at June of year t. We utilize full-period portfolio betas, which are calculated

using the value-weighted CRSP index and the Dimson (1979) approach to control for

nonsynchronous trading.

Following Moskowitz and Grinblatt (1999), we use two-digit Standard Industrial

Classification (SIC) codes to identify industries.[7] To allow for changes in a firm's SIC code over

time, the SIC codes are collected from CRSP.[8] The sample period includes thirty-three portfolio

formation years of data from 1968 through 2000.[9]

II. Firm and Industry Value Premiums

Table 1 reports summary statistics for the sample separated by industry grouping and

sorted by book-to-market (BE/ME) ratios. The sample size data indicates that, on average, each

industry is represented by a relatively large number of firms. As indicated previously, our

sample design required each included industry to have a minimum representation of fifteen firms

throughout the sample period. The petroleum industry has the lowest average representation of

24 firms per year, while the retail industry has the largest representation of 273 firms.

The book-to-market ratios for the industries indicate a fairly high level of variation across

industries, which is a necessary, but not a sufficient, condition to find a significant industry-

related value effect. The BE/ME ratios suggest that primary metals, apparel, and construction

are the most value-oriented industries, whereas the industries with the highest growth valuations

are communications, services, and chemicals. These classifications are consistent with

expectations as the industries classified as value are in general more mature, capital intensive

industries relative to those industries classified as growth. The standard deviations for the book-

to-market ratios reveal that retail, department stores, and apparel exhibit the highest within-

industry variation, while the BE/MEs for communications, publishing, and utilities show more within-industry consistency.

The market capitalizations and betas suggest that considerable variation exists in both of these characteristics across our sample of industries. In addition, these two firm characteristics have been shown to explain cross-sectional variation in stock returns in previous research. Therefore, failure to control for these characteristics may result in a spurious relationship between industry affiliation and the value effect. Finally, in viewing the numbers in Table 1, it is important to note that the values are averaged both cross-sectionally and temporally. Thus, the market capitalization variable (ME), which has increased considerably over time, is appreciably lower than current levels.

To ensure that the variation in inter-industry BE/ME's (identified in Table 1) is statistically significant, we employ a standard ANOVA using industry dummy variables.[10] In the dummy variable regression, the paper industry is the omitted industry because it is the midpoint industry based on BE/ME ranks (see Table 1). The F-statistic reported at the bottom of Table 2 confirms that overall, there are statistically significant differences across industry BE/ME ratios. In addition, the t-statistics provide statistical evidence that many of the industries have BE/MEs that are significantly different from average. The R-square indicates that a significant amount of the variation in BE/ME's (7%) is explained by the industry. This evidence indicates that BE/ME has sufficient inter-industry variation to allow the industry BE/ME to play a prominent role in the value effect.

In the regression analysis, we use the Generalized Least Squares (GLS) approach of Parks (1967) in a pooled cross-sectional, time-series setting to control for time-series and cross-sectional correlations and heteroskedasticity in the model residuals. Specifically, the model

assumes a first-order autoregressive error structure with contemporaneous correlation among cross sections. Relative to the traditional approach [e.g. Fama and MacBeth (1973)], the error structure assumed under the Parks method is more consistent with the variance/covariance structure of the data set. The traditional approaches do not consider the serial correlation in the individual disturbance terms nor do they account for the interdependence in stock performance at a point in time.

As indicated previously, the regressions are estimated with portfolio data that is formed based on BE/ME ranks.[11] The purpose of the regression analysis is to examine the relationship between industry affiliation and the value effect. To avoid the identification of a spurious relationship, we control for other prominent variables that have been shown to have a significant relationship with returns (ME and beta). Our methodology for forming portfolios is designed to capture the cross-sectional variation in BE/ME. Forming portfolios based on BE/ME ranks, however, reduces the cross-sectional variation in market capitalization (ME) and beta, and thus diminishes the observed explanatory power of these two variables [see Berk (2000)]. Therefore, beta and ME are included in the regressions simply to control for any remaining influence that they may have.

Table 3 reports the results of the regression analysis on the complete data set of the twenty-one industry quintiles over thirty-three years of data. We regress monthly quintile returns against both quintile BE/ME and industry BE/ME to determine if the value effect is firm specific, industry specific, or present at both industry and firm levels.[12] The first two models indicate that portfolio BE/ME and industry BE/ME are both significant in explaining equity returns when considered separately. Interestingly, the coefficients on the two variables are remarkably similar. When the two are included simultaneously (model 3), industry BE/ME

becomes insignificant at the 5% level, however, the coefficient is significant at the 10% level.[13] Further, in the full model, portfolio BE/ME is significant and industry BE/ME is marginally significant even after controlling for differences in portfolio ME and beta. Lastly, the coefficient on portfolio BE/ME is approximately the same size in all the regressions, which provides strong support for the robustness of the portfolio BE/ME variable. The coefficient on industry BE/ME decreases substantially, yet remains marginally significant, once other factors are included in the model. These results suggest that the value effect is related to both firm and industry characteristics, and furthermore, the effects at each level are positive. Thus, value firms in value industries exhibit superior performance relative to other classifications of firms, such as value firms in growth industries. Chen and Zhang's (1998) findings are consistent with ours as they report that the value effect is more prominent in well-established markets relative to the effect identified in growth countries.

The findings in Table 3 are consistent with the results of Kothari, Shanken and Sloan (1995) in that industry BE/ME ratios (defined using SIC codes) show a significant relationship with security returns. Our results, however, extend Kothari et. al. and suggest that intra-industry variation in BE/ME is more important in explaining portfolio returns relative to inter-industry variation in BE/ME. This finding suggests that most of the value effect can be attributed to differences in firm BE/ME's, rather than differences in BE/ME ratios across industries. This result may also help to explain the inability of Kothari et al. to find a significant BE/ME effect when they used S&P industry data. Specifically, it appears that most of the value anomaly is due to intra-industry variation in BE/ME ratios; therefore, the use of industry data diminishes the prominence of the value effect. Furthermore, the broader the industry classification, the smaller the coefficient on industry BE/ME is likely to be.

As indicated previously, the coefficients on ME and beta indicate little about the significance of these firm characteristics since our methodology reduced the variation in these two measures. The fact that the two are statistically significant indicates, however, that our methodology did not *eliminate* the variation in the two measures. Further, the significance of these two variables implies that it was appropriate to control for their variation to avoid the identification of a spurious relationship.[14]

To validate our interpretation of the results in Table 3, we perform several robustness checks.[15] First, we sort firms into 21 groups based on annual BE/ME ratios (without regard to industry), and then into five quintiles. The same regressions as in Table 3 are then repeated. The results (not reported) for model 1 and model 2 are qualitatively similar to the findings reported in Table 3. However, in model 3, the magnitude of the coefficient on industry BE/ME falls from 0.0018 (significant at the 10% level) to 0.0008 (statistically insignificant). A similar result is observed in model 4. This suggests that the original results for portfolio versus industry BE/ME are not due to finer cuts in the BE/ME ratio across the two-step sort process. Next, we sort firms into five BE/ME quintiles, and then within each quintile, into the 21 industry portfolios i.e. we reverse the sort order relative to the original sort. Again, the regressions from Table 3 are repeated. These results (not reported) are also qualitatively similar to those in Table 3. Further, as with the original results, the coefficient on industry BE/ME remains lower than the firm-level BE/ME coefficient, although closer in magnitude. The results from the reversed sort, however, indicate that both the portfolio and industry BE/ME coefficients are significant at the 1% level.

III. Consistency of the Value Premium Across Industries

We next examine the prevalence of the value effect across our sample of industries. If BE/ME effectively proxies for financial distress risk, or serves as a consistent indicator of investor irrational pricing, we should expect the value effect to prevail across our entire sample of industries.

Table 4 presents the time-series, cross-sectional GLS regressions (Parks approach) within each of the twenty-one different industries. A separate regression is estimated for each industry and in each regression the portfolio/quintile return is included as the dependent variable and portfolio/quintile BE/ME, ME, and beta are included as explanatory variables. The results from these regressions establish the prevalence of the value effect across the various industries. Specifically, fifteen of the twenty-one industries have a significant BE/ME coefficient and none of the industries have a significant growth effect (i.e. a significant negative coefficient on BE/ME).[16] This provides evidence supporting the prominence of the value effect; however, the fact that six industries (communications, chemicals, publishing, paper, department stores, and construction) have insignificant coefficients indicates that the value effect is not universal.[17] Furthermore, there is considerable variation in the size of the BE/ME coefficient, ranging from a high of 0.01426 for the apparel industry to a low of –0.00017 for the department stores industry.

The wide dispersion in the BE/ME coefficient across industries suggests that industry affiliation should be a consideration when using asset-pricing models that include BE/ME. While the dispersion in the BE/ME coefficients appears large, to confirm the differences in coefficients are statistical significant, we perform a paired comparison of the coefficients across industries. In particular, a t-statistic for the difference between two industries is calculated utilizing a pooled variance between the two coefficients. We categorize the BE/ME coefficients

into three groups 1) relatively low BE/ME coefficients, 2) relatively high BE/ME coefficients and the final group contains the remaining coefficients. The high-coefficient group includes the apparel, electrical equipment, fabricated metals, food, miscellaneous manufacturing, transportation, and utilities industries and are identified with an "H" next to the industry name. Although the coefficients for these five industries cannot be distinguished from each other, they are statistically larger (at the 5% level) than the low-coefficient industries that include the chemicals, construction, department stores, paper, petroleum, primary metals, publishing, and services industries (identified with an "L"). Likewise, the low-coefficient industries cannot be distinguished from each other, but are significantly lower than the high coefficient group of industries. The remaining six industries cannot be distinguished from either group. These results indicate that the importance of BE/ME in explaining returns differs across industries, and thus, failure to consider industry affiliation could result in systematic mispricing of securities across industries.

While there has been relatively little research linking industry affiliation and the value effect, Daniel, Hirshleifer, and Subrahmanyam (2001) and Chan, Lakonishok, and Sougiannis (2001) suggest that the value effect should be stronger for those stocks with a relatively high commitment to R&D activities because such firms are harder to value. The relatively large coefficient on BE/ME for the electrical equipment industry would tend to support this contention as R&D expenditures are generally substantial for firms in this industry (see Chan et. al.). In contrast, the very large coefficient on BE/ME for the apparel industry is counter to this claim since the apparel industry generally devotes relatively few resources to R&D. Furthermore, the relatively strong value effect identified for the utilities industry runs counter to the view that firms that are difficult to value (e.g. those whose value is comprised largely of intangibles) are

more susceptible to mispricing and should therefore have a relatively prominent value effect. Clearly, this view would suggest that utilities, which are relatively easy to value, should have a relatively small BE/ME coefficient, rather than the large coefficient we observe.

We also calculated the correlation between the industry BE/ME coefficients and industry BE/ME ratios and found a correlation of only 0.14 (p-value of 0.5360). The relatively low correlation indicates that the prominence of the value effect within an industry is not driven by the level of BE/ME existing in the industry. Further support for this contention is gained by additional analysis of the six industries with insignificant BE/ME coefficients. Specifically, the construction industry is a value industry, the communications, chemicals, and publishing industries are growth industries, and the remaining two industries (paper and department stores) cannot be clearly classified as either value or growth industries (see Table 2). Therefore, the lack of a significant value effect cannot be clearly attributed to an industry's average level of BE/ME.

The findings in Table 4 may understate the role that industry affiliation plays in the value anomaly because industry BE/ME ratios change over time, i.e. industries shift between value and growth over time. Table 5 provides a general view of the temporal consistency of the industry BE/ME ratios. The median, minimum, and maximum values are derived from annual BE/ME ranks for each of the twenty-one industries. The top annual rank (most growth oriented industry) is "1", while the lowest rank (most value oriented industry) is "21". It is apparent from the minimum and maximum values that many of the industries have moved dramatically along the value/growth spectrum during the thirty-three years. For example, the biggest range in ranks is nineteen and occurs for the mining, department stores, and petroleum industries. This extreme range in ranks indicates that during the thirty-three year period these three industries had strong value characteristics for at least one year, yet exhibited strong growth characteristics during

another year. In contrast, the apparel industry has the lowest range in annual ranks from 15 to 21, which indicates the industry has consistently been a value industry throughout the thirty-three years. The chemical industry has the second lowest range in annual ranks from 1 to 8, denoting that it has been fairly consistently categorized as a growth industry. In general, the results in Table 4 indicate that the growth prospects of an industry, as indicated by the industry's relative BE/ME, change considerably over time. Therefore, it is appropriate to consider the fluctuations in industry prospects that occur over time and periodically reclassify industries.

IV. Risk and the Value Effect

We next reexamine the intra-industry value effect while considering the temporal variation in industry BE/ME ranking. Given the temporal inconsistency of value/growth industry classifications in Table 5, we differentiate industries using their relative BE/ME ratio for each year. The twenty-one industries are ranked based on their annual BE/ME ratios (1 through 21) and separated into five categories (quintiles).[18] The industries are reclassified annually into quintiles based on industry BE/ME. Within each industry quintile, the firms are separated into quintiles based on firm BE/ME. Table 6 shows the twenty-five portfolios created with the two step sort process (first on industry BE/ME and then on firm BE/ME).

We follow Chen and Zhang (1998) in evaluating the risk characteristics of the alternative value/growth portfolios. Specifically, for each of the twenty-five portfolios, we use the three measures defined by Chen and Zhang to identify risks related to the level of financial distress, earnings uncertainty, and financial leverage. Financial distress is measured by the percentage of dividend paying firms with a dividend decrease of 25% or more, earnings uncertainty is measured by the standard deviation of the earnings yield, and financial leverage is measured by

16

the book value of debt divided by the market value of equity. We also provide statistics on the return on assets (ROA), where the ROA is operating income divided by total assets. Detailed descriptions of the three variables and their means for the twenty-five portfolios are reported in Table 6. If the value premium reflects compensation required for the higher risk associated with value companies as argued by Fama and French, the three risk measures should be higher for value portfolios relative to growth portfolios.

The values reported in Table 6 indicate that value portfolios have lower return on assets (ROAs) relative to growth portfolios, as one would expect. There is a monotonic decrease in ROA from the growth to value portfolio within each of the industry classifications, and further, there is a decreasing pattern in ROA for each portfolio across industry classification. The differences in ROA across the most extreme industry and firm classification (growth versus value) are especially pronounced. This indicates that our BE/ME classification of industries and portfolios serves to differentiate the portfolios by earnings performance.

Looking first at the risk measures across industry classification, the three risk measures indicate that risk is positively related to industry BE/ME. Specifically, there is a generally consistent increase in the risk measures as one moves from the growth industry classification (low industry BE/MEs) to the value industry classification (high industry BE/MEs). Thus, value industries exhibit higher risk levels than growth industries, which supports the view that the significant coefficient on the industry BE/ME variable identified in Table 3 reflects a premium that investors require as compensation for higher risk. The higher leverage of the value firms is probably a contributing factor to the higher incidence of financial distress.

Focusing next on the risk measures *within* industry classification, the consistent increase in risk measures from the growth to value category indicates that value firms within both value

and growth industries are riskier than growth firms in the same industry classification. Once again, these findings support the proposition that, relative to growth firms, value firms have higher required returns because they have higher risk. This result is consistent with the positive relation between BE/ME and distress risk identified by He and Ng (1994). Furthermore, this finding supports Chen and Zhang's (1998) claim that value firms tend to be relatively financially distressed, and thus, the premium attached to value firms is consistent with investors pricing this higher risk.

Finally, the degree of dispersion in the risk measures is generally higher in value industries relative to growth industries. For example, in value industries, the financial distress measure for value firms is approximately five times higher than it is for growth firms (17.31% vs. 3.68%), the same difference in growth industries is less than three times (8.40% vs. 3.14%). Comparable relationships exist for the earnings uncertainty measure as the differences are 14.56% vs. 3.33% and 7.27% vs. 2.05%. These findings support Chen and Zhang's (1998) argument that a growth market helps to alleviate the performance problems of marginal quality firms i.e. lesser quality firms in an established market are more likely to experience performance problems than their counterparts in a growth market. The financial distress measure for value firms in value industries is over 17%, which suggests this category contains a high proportion of firms suffering from past misfortunes and facing an uncertain future (fallen angels). The 8.4% financial distress measure for value firms in growth industries suggests that fallen angels comprise a smaller proportion of this category. This view is further supported by the observation that growth firms in value industries experience nearly the same incidence of financial distress as growth firms in growth industries (3.68% vs. 3.14%). Thus, it appears that the firms with the

18

best growth prospects have a low probability of becoming financially distressed whether they are in industries with relative strong or weak growth potential.

To further examine the relationship between the risk characteristics and the value effect, we calculate a measure of the relative return that is attributed to a portfolio's BE/ME. The measure is reported in Table 6 as "alpha" and is derived as the intercept in the regression of portfolio returns against the three known factors from Fama and French (1996), excluding the HML (high book-to-market less low book-to-market) factor.[19] Since alpha contains the portion of portfolio returns not explained by the market and size factor, it can be viewed as a measure of the return attributed to the BE/ME characteristic of the portfolio.

The consistent increase in alpha within each of the industry classifications, once again confirms the prevalence of the value effect. Within each industry classification, value firms provide much higher alphas than growth firms. Further, the alphas for the value firms are very consistent across the five industry classifications, ranging from a low of 1.23% to a high of 1.47%, with growth industries falling in the middle of the range at 1.35%. This evidence suggests that investors assign relatively cheap prices to value firms regardless of their industry affiliation. Thus, it appears that investors are consistent in their rather negative evaluation of value firms whether industry prospects are viewed favorably or unfavorably. The consistency in the alphas for value firms is somewhat surprising in light of the rather large differences in risk measures for value firms in growth versus value industries. In particular, if the value effect were driven purely by firm risk characteristics, the value firms in value industries should have considerably higher alphas relative to their counterparts in growth industries.

In contrast, the alphas for the growth firms show much more dispersion across the industry classifications, ranging from a low of 0.34% for growth industries to a high of 0.86%

for value industries. This finding indicates that the growth prospects of the industry impact investor pricing of growth companies. Specifically, investors assign lower prices to growth firms in value industries relative to their counterparts in growth industries. The pricing patterns for the growth companies align rather closely with the risk characteristics as growth companies in value industries exhibit higher risk relative to growth firms in growth industries.

Overall, an analysis of the alphas reveals strong patterns in the alphas within each of the industry classifications. In contrast, the only obvious pattern in alphas across industry classification is that growth firms (firm classifications Growth and 2) in value industries (industry classification 4 and Value) have large alphas relative to their counterparts in the other industry classifications. This finding suggests that investor perceptions of the industry tend to influence their pricing decisions regarding growth firms, but have little influence on their pricing decisions for value firms. In particular, the alphas are consistent with the view that negative perceptions of an industry depress prices for growth firms versus the prices assigned if the perceptions of an industry are positive. In contrast, investor perceptions of value firms appear to be relatively negative regardless of the perception of the industry.

The patterns in the alphas appear to correspond with the within industry patterns for the three risk measures; however, a more robust analysis is required to confirm the statistical significance of this relationship. If the value effect is consistent with investor pricing of firm risk, then alpha should be significantly related to the risk measures. Table 7 reports the correlation of the risk characteristics with one another and with alpha. As expected, each of the three risk measures is highly correlated with each other. The earnings uncertainty and financial distress measures have a correlation of almost 94%, while leverage and financial distress are somewhat lower at 77%. The correlation between alpha and the three risk measures is also very

20

high, with correlation coefficients ranging from about 61% for both leverage and financial distress to 72% for earnings uncertainty. All are significant at the 5% level or better.

The cross-industry analysis of the value effect produces results that are consistent with Chen and Zhang's (1998) cross-country analysis and support their claim that value stocks are cheap because they tend to be firms in distress, with high financial leverage, and substantial earnings uncertainty. Therefore, the higher returns earned on value stocks are consistent with contention that investors assign lower prices to value stocks because of the higher risk associated with these firms.

V. Summary and Conclusions

We examine the role that industry affiliation plays in the value effect. Our findings indicate that even after controlling for other relevant factors, both inter- and intra-industry variation in BE/ME (book-to-market equity) are relevant in explaining stock returns. Our evidence, however, indicates that intra-industry variation in BE/ME is by far the more important characteristic of the two. This finding suggests that studies that use industry data will tend to understate the significance of the value effect, since much of the effect is attributed to firm level differences in BE/ME.

We find strong support for the prevalence of the value effect, as the effect is shown to exist in an overwhelming majority of SIC defined industries (fifteen of twenty-one). In addition, none of the industries report a significant growth effect, i.e. a significant negative coefficient on BE/ME. Our evidence on the value effect within industries does not support the view that the most prominent value effect occurs in those industries that are the most difficult to value (e.g. industries comprised of a high proportion of intangible assets). For example, we find the largest

coefficient on BE/ME for the apparel industry, and further, a very prominent value effect is shown to exist in the utilities industry.

By separating industries into value/growth classifications and calculating portfolio alphas, we show that the value effect exists consistently across all classifications. Thus, markets systematically provide higher rewards for holding value firms versus growth firms. Further, the returns attributed to value firms are very consistent regardless of whether the industry is classified as a value or growth industry. Specifically, investors attach relatively cheap prices to value firms whether the price multiple for the industry is high or low. In contrast, prices for growth firms in value industries are relatively cheap compared to the prices for growth firms in growth industries. Thus, it appears that industry affiliation has a more pronounced influence on the value effect for growth firms than for value firms.

Examining the risk characteristics, we show that firm risk is higher for value firms relative to growth firms; and further, value firms in value industries exhibit the highest risk, while growth firms in growth industries exhibit the lowest risk. The findings are consistent with Fama and French (1992, 1993, and 1995) and Chen and Zhang's (1998) contention that the value effect is created by investor pricing of firm risk. In particular, we show a strong and significant association exists between the returns attributed to BE/ME and risk measures. While our results support the view that the value effect is consistent with investor pricing of firm risk measures, we cannot state conclusively whether the effect is the result of rational pricing. Hirshleifer (2001) argues that the identification of risk-related return patterns is not sufficient evidence of rational pricing. Behaviorists would argue that investors recognize risk but also misprice it.

References

Alford, A. W., Jones, J. J., and Zmijewski, M. E. 1994. Extensions and Violations of the Statutory SEC Form 10-K Filing Requirements, *Journal of Accounting and Economics* 17, (January): 229-254.

Ali, A., Hwang, L., and Trombley, M. A. 2003. Arbitrage risk and the book-to-market anomaly. *Journal of Financial Economics* 17, (August): 355-373.

Barberis, N., Shleifer, A., and Vishny, R. 1998. A model of investor sentiment, *Journal of Finance* 49, (September): 307-343.

Berk, J. B. 2000. Sorting out sorts, *Journal of Finance* 55, (February): 407-427.

Black, F., Jensen, M. C., and Scholes, M. 1972. The capital asset pricing model: Some empirical tests, in Michael C. Jensen, Ed., *Studies in the Theory of Capital Markets* (Praeger, New York, NY).

Bradley, M., Jarrell, G. A., and Kim, H. E. 1984. On the existence of an optimal capital structure: Theory and evidence, *Journal of Finance* 39, (July): 857-878.

Center for Research in Security Prices, 2001, *CRSP Delisting Returns* (Center for Research in Security Prices, Chicago, Ill.).

Chan, L. K. C., and Chen, N. 1991. Structural and return characteristics of small and large firms, *Journal of Finance* 46, (September): 1467-84.

Chan, L. K. C., Jegadeesh, N., and Lakonishok, J. 1995. Evaluating the performance of value versus glamour stocks: The impact of selection bias, *Journal of Financial Economics* 38, (July): 269-296.

Chan, L. K. C., Lakonishok, J., and Sougiannis, T. 2001. The stock market valuation of research and development expenditures, *Journal of Finance* 56, (December): 2431-2458.

Chen, N., and Zhang, F. 1998. Risk and return of value stocks, *Journal of Business* 71, (October): 501-535.

Clinch, G., and Sinclair, N. 1987. Intra-industry information releases: A recursive systems approach, *Journal of Accounting and Economics* 9, (April): 89-106.

Cohen, R. B., and Polk, C. K. 1998. The impact of industry factors in asset-pricing tests, University of Chicago Working paper.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. 2001. Overconfidence, Arbitrage, and Equilibrium Asset Pricing, *Journal of Finance* 53, (June): 921-965.

Daniel, K., and Titman, S. 1997. Evidence on the characteristics of cross sectional variation in stock returns, *Journal of Finance* 52, (March): 1-33.

Davis, J., 1994. The cross-section of realized returns: The pre-COMPUSTAT evidence, *Journal of Finance* 49, (December): 1579-1593.

Dichev, I. D. 1998. Is the risk of bankruptcy a systematic risk? *Journal of Finance* 53, (June): 1131-1147.

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 7, (June): 197-226.

Fama, E. F., and French, K. R. 1992. The cross-section of expected stock returns, *Journal of Finance* 47, (June): 427-465.

Fama, E. F., and French, K. R. 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, (February): 3-56.

Fama, E. F., and French, K. R. 1995. Size and book-to-market factors in earnings and returns, *Journal of Finance* 50, (March): 131-155.

Fama, E. F., and French, K. R. 1996. Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, (March): 55-84.

Fama, E. F., and French, K. R. 1997. Industry costs of equity, *Journal of Financial Economics* 43, (February): 153-193.

Fama, E.F., and MacBeth, J.D. 1973. Risk, return, and equilibrium: empirical tests, *Journal of Political Economy* 81, (May-June): 607-636.

Griffin, J. M., and Lemmon, M. L. 2002. Book-to-market equity, distress risk, and stock returns, *Journal of Finance* 57, (October): 2317-2336.

Grundy, B. D., and Martin, J. S. 2001. Understanding the nature of the risks and the source of the rewards to momentum investing, *The Review of Financial Studies* 14, (Spring): 29-78.

He, J., and Ng, L. K. 1994. Economic forces, fundamental variables, and equity returns, *Journal of Business* 67, (October): 599-609.

Hirshleifer, D. 2001. Investor psychology and asset pricing, *Journal of Finance* 56, (August): 1533-1597.

Hong, H., and Stein, J. C. 1999. A unified theory of underreaction, momentum trading, and overreaction in assets markets, *Journal of Finance* 54, (December): 2143-2184.

Hotchkiss, E. S. 1995. Postbankruptcy performance and management turnover, *Journal of Finance* 50, (March): 3-21.

Kothari, S.P., Shanken, J., and Sloan, R. G. 1995. Another look at the cross-section of expected stock returns, *Journal of Finance* 50, (March): 185-224.

Lakonishok, J., Shleifer, A., and Vishny, R. 1994. Contrarian investment, extrapolation, and risk, *Journal of Finance* 49, (December): 1541-1578.

Moskowitz, T. J., and Grinblatt, M. 1999. Do industries explain momentum? *Journal of Finance* 54, (August): 1249-1290.

Parks, R. W. 1967. Efficient estimation of a system of regression equations when disturbances are both serially and contemporaneously correlated, *Journal of the American Statistical Association* 62, (June): 500-509.

Rosenberg, B., Reid, K., and Lanstein, R. 1985. Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, (Spring): 9-17.

Shumway, T. 1997. The delisting bias in CRSP data, *Journal of Finance* 52, (March): 327-340.

Shumway, T., and Warther, V. A. 1999. The delisting bias in CRSP's NASDAQ data and its implications for the size effect, *Journal of Finance* 54, (December): 2361-2379.

Shleifer, A., and Vishny, R. 1997. The limits to arbitrage, *Journal of Finance* 52, (March): 35-55.

Slovin, M. B., Sushka, M. E., and Bendeck, Y. M. 1991. The intra-industry effects of going-private transactions, *Journal of Finance* 46, (September): 1537-1550.

[1] See for example, Rosenberg, Reid, and Lanstein (1985), Davis (1994), He and Ng (1994), Chan, Jegadeesh, and Lakonishok (1995), and Fama and French (1992, 1993, 1995 and 1996).

[2] More recently, Grundy and Martin (2001) present evidence to the contrary.

[3] Chan et. al. (2001) define their sample of selected industries using a variation of two and three digit SIC codes.

[4] Consistent with Chan, Jagadeesh, and Lakonishok (1995), we search the history of CUSIPs on CRSP to obtain matches with COMPUSTAT. See Chan, Jagadeesh, and Lakonishok for a discussion of the differing methods of handling CUSIP changes used by CRSP and COMPUSTAT.

[5] Following Fama and French (1992), we drop firms with negative book value.

[6] We calculate the last monthly return for delisted companies using the delisting return provided by CRSP. Recent controversy has focused on the lack of delisting returns on the CRSP database for firms delisted for negative reasons [see Shumway (1997) and Shumway and Warther (1999)]. Shumway examines the findings of Fama and French (1992), however, and finds that the book-to-market effect is not biased by CRSP's treatment of the delisting return. Additionally, in 1999, CRSP substantially revised their database so that the delisting return data is more complete [see CRSP (2001)].

[7] Our approach differs from Moskowitz and Grinblatt with respect to a few industries. First, we add the following three industries, Printing and Publishing (SIC 27), Communications (SIC 48), and Services (SIC 70-87, 89). Second, by adding the three industries identified above, we eliminate an "other" industry classification. Third, due to their unique nature, we eliminate REITs and other financial holding companies. Finally, we add Lumber, Furniture, Rubber, and Leather (SICs 24, 25, 30 and 31) to the miscellaneous manufacturing category because of the limited firm representation in each of these SICs.

[8] CRSP reports changes in a firm's SIC code, whereas, COMPUSTAT reports only the firm's most recent code.

[9] The sample period starts in 1968 in order to allow for a sufficient number of industries that satisfy the fifteen firm minimum.

[10] This approach has been employed in previous studies to test for industry patterns in debt ratios [for example, see Bradley, Jarrell and Kim (1984)].

[11] Following previous empirical work, the regressions are estimated using the natural log of BE/ME and ME.

[12] The regressions in Tables 3 and 4 utilize equal-weighted returns; however, value-weighted returns were also examined. The findings using value-weighted returns were not materially different from those reported. These results and any other results that are mentioned, but not included in the paper, are available from the authors on request.

[13] While the coefficient on industry BE/ME is only marginally significant in models 3 and 4 when used as the first order sort variable, it is significant at the 1% level when the sort order is reversed and it used as the second order sort variable. This and other Table 3 robustness checks are discussed in more detail later in the paper. Further, the reduction in significance for the BE/ME coefficients in models 3 and 4 is not entirely unexpected due to the rather high correlation between portfolio BE/ME ratios and industry BE/ME ratios. For the entire sample, the correlation between these two ratios is 0.55 (p-value of 0.0001), which creates potential multicollinearity problems with the coefficients.

[14] The positive relationship we find between size and return is in contrast to the negative relationship found in previous studies. Though the relationship between size and stock returns is not the focus of the portfolio formation

methodology in our study, we investigate this relationship further and find that the sign of the size coefficient is time specific. If we examine a sample period with return measurement ending in 1990 as in Fama and French (1992), we find a negative coefficient on the size variable. Using the full sample in our study, we find a positive coefficient.

[15] We thank an anonymous referee for suggesting these checks.

[16] The coefficient on BE/ME for the communications industry is significant at the 10% level of significance. Thus, sixteen of the industries show a significant value effect under this less strict criteria.

[17] The insignificance of the coefficients cannot be attributed to a lack of intra-industry variation in BE/ME ratios within these six industries. The BE/ME standard deviation measures reported in Table 1 show a relatively high variation exists within each of these six industries. Further, ANOVA results with quintile dummies indicate a highly significant level of variation in BE/ME exists in each of the 21 industries. For the sake of brevity, these ANOVA results are not reported in the analysis.

[18] The SAS® rank procedure is used to assign industries to quintiles. By default, it assigns five industries to the middle (3rd) quintile. Although the rank procedure used by SAS® was not expected to significantly influence the results, we re-ran the rank procedure forcing the 5th industry into other quintiles. The results were not materially different from those reported in Table 6.

[19] In addition to the equal-weighted portfolio returns, the alphas were also derived using value-weighted portfolio returns. The results are not materially different from those reported in Table 6.

Table 1   Summary Statistics by Industry

Industry	SIC	Mean Sample Size	BE/ME	BE/ME Std. Dev.	Market Capitalization (ME)	Beta
Communications	48	35	0.41	0.46	210.63	1.29
Services	70-87,89	240	0.48	0.59	37.21	1.52
Chemicals	28	142	0.49	0.49	155.04	1.22
Publishing	27	55	0.52	0.45	116.30	1.23
Food	20	71	0.57	0.74	111.56	0.95
Electrical Equipment	36	196	0.59	0.55	34.10	1.58
Retail	50-52, 54-59	273	0.61	0.84	42.42	1.34
Mining	10	163	0.62	0.60	73.15	1.07
Miscellaneous Manufacturing	24,25,30, 31,38,39	258	0.63	0.67	37.75	1.40
Machinery	35	197	0.67	0.63	63.31	1.43
Paper	26	42	0.71	0.49	247.06	1.15
Department Stores	53	28	0.72	0.78	305.41	1.31
Fabricated Metals	34	89	0.73	0.74	54.13	1.26
Petroleum	29	24	0.75	0.47	1182.16	0.95
Transportation	41-47	52	0.75	0.66	64.08	1.29
Utilities	49	157	0.76	0.32	307.13	0.54
Transport Equipment	37	66	0.78	0.62	134.97	1.37
Financial	60-65	158	0.84	0.62	104.37	1.25
Construction	32	29	0.85	0.51	122.36	1.24
Apparel	22-23	74	0.92	0.76	35.06	1.34
Primary Metals	33	52	0.96	0.69	83.69	1.22

Note. -*BE/ME* is book-to-market equity, where book equity is measured at fiscal year end in calendar year ($t-1$) and market equity is measured at calendar year-end ($t-1$). *ME* is market capitalization (in millions of dollars) measured at June-end of year t. *Beta* is the full period beta calculated relative to the value-weighted index of NYSE, AMEX and Nasdaq stocks. Following Alford, Jones, and Zmijewski (1994) the values for sample size, *BE/ME*, *BE/ME* standard deviation, and market cap (*ME*) utilize annual medians. The required minimum number of firms in any industry was fifteen.

Table 2   ANOVA Results Examining Variation in Industry BE/ME's

Variable	BE/ME	t-statistic
Intercept	-0.3179	-5.65[**]
Dummy Variables		
Communications	-0.4837	-5.96[**]
Services	-0.3981	-4.90[**]
Chemical	-0.4472	-5.51[**]
Printing & Publishing	-0.2620	-3.23[**]
Food	-0.1031	-1.27
Electrical Equipment	-0.2439	-3.00[**]
Retail	-0.0790	-0.97
Mining	-0.2756	-3.40[**]
Misc. Manufacturing	-0.1349	-1.66
Machinery	-0.1385	-1.71
Paper	Base Industry	Base Industry
Department Stores	-0.0125	-0.15
Fabricated Metals	-0.0274	-0.34
Petroleum	0.0397	0.49
Transportation	-0.0136	-0.17
Utilities	0.0800	0.99
Transport Equipment	0.0801	0.99
Financial	0.1347	1.66
Construction	0.1813	2.23[**]
Apparel	0.3131	3.86[**]
Primary Metals	0.2564	3.16[**]
R-Square and F-Statistic of regression	0.0734	14.71[**]

Note. - Coefficients and t-statistics are reported for the OLS regression using annual data over the portfolio formation periods 1968 through 2000: $BE/ME_{pt} = \alpha_0 + \sum_{p=1}^{20} B_p IndustryDummy_{pt} + \varepsilon_{pt}$.

BE/ME_{pt} is the natural log of book-to-market for portfolio p. See Table 1 note for the calculation of BE/ME. $IndustryDummy_{pt}$ is a 0/1 dummy variable that takes the value 1 if the portfolio falls within the industry or 0 if it does not. The paper industry is the omitted industry in the regression. The sample size is 3,465 observations (5 portfolios times 21 industries times 33 years).
[*] - Denotes significantly different from zero by two-tailed test at a 5% significance level.
[**] - Denotes significantly different from zero by two-tailed test at a 1% significance level.

Table 3   Regression Results of Monthly Portfolio Returns on Portfolio BE/ME, Industry BE/ME, and Control Variables

Model	Intercept	BE/ME	Industry BE/ME	ME	Beta
1	0.0111 $(8.49)^{**}$	0.0068 $(13.62)^{**}$			
2	0.0128 $(9.63)^{**}$		0.0061 $(5.87)^{**}$		
3	0.0117 $(8.73)^{**}$	0.0056 $(11.15)^{**}$	0.0018 (1.81)		
4	0.0021 (0.98)	0.0065 $(12.63)^{**}$	0.0018 (1.75)	0.0008 $(3.25)^{**}$	0.0082 $(3.66)^{**}$

Note. - Coefficients (t-statistics) are presented from the following Parks GLS regressions using monthly pooled cross section time series data: $R_{pt} = \alpha_0 + B_1 BE/ME_{pt} + B_2 IndBE/ME_{pt} + B_3 ME_{pt} + B_4 Beta_p + \varepsilon_{pt}$. R_{pt} is the equally weighted return on BE/ME portfolio p calculated from July of year t through June of year $t+1$. BE/ME_{pt} and $IndBE/ME_{pt}$ are the natural log of book-to-market for portfolio p and for the industry that includes portfolio p, respectively. For both measures, BE is measured at fiscal year end in calendar year $(t-1)$, which is at least six months prior to the return measurement interval and the market equity is measured at calendar year-end $(t-1)$. ME_{pt} is the natural log of the market capitalization of portfolio p at June-end of year t. $Beta_p$ is the full period beta for portfolio p calculated relative to the value-weighted index of NYSE, AMEX and Nasdaq stocks. Portfolios are formed as quintiles of BE/ME ranked firms within each of twenty-one different industries, which are defined in Table 1. The portfolios are reformed annually. There are 41,580 observations in each regression (21 industries times 5 portfolios times 33 years times 12 months). Data is from the portfolio formation periods 1968 through 2000.

[*] - Denotes significantly different from zero by two-tailed test at a 5% significance level.
[**] - Denotes significantly different from zero by two-tailed test at a 1% significance level.

Table 4   Regression Results of Monthly Portfolio Returns on Portfolio BE/ME and Control Variables by Industry

Industry	Intercept	BE/ME	ME	Beta
Communications	0.03208 (1.48)	0.00618 (1.79)	-0.00280 (-1.81)	0.00420 (0.27)
Services[L]	0.00209 (0.07)	0.00579 (2.29)[*]	0.00004 (0.02)	0.01008 (0.48)
Chemicals[L]	0.04370 (0.56)	0.00311 (0.89)	0.00043 (0.33)	-0.02471 (-0.39)
Publishing[L]	0.02730 (0.83)	0.00370 (1.51)	-0.00058 (-0.38)	-0.00812 (-0.33)
Food[H]	0.02550 (1.16)	0.00825 (2.97)[**]	0.00139 (0.94)	-0.01819 (-0.87)
Electrical Equipment[H]	-0.01361 (-0.38)	0.01077 (3.15)[**]	0.00251 (1.57)	0.01339 (0.62)
Retail	-0.03383 (-1.11)	0.00812 (3.13)[**]	0.00186 (1.11)	0.02923 (1.24)
Mining	0.05142 (1.15)	0.00782 (3.82)[**]	0.00032 (0.21)	-0.03473 (-0.87)
Miscellaneous Manufacturing[H]	-0.06661 (-1.16)	0.01129 (2.53)[**]	0.00073 (0.46)	0.05809 (1.42)
Machinery	0.00748 (0.27)	0.00611 (1.97)[*]	-0.00048 (-0.28)	0.00574 (0.32)
Paper[L]	0.01347 (0.58)	0.00430 (1.61)	-0.00083 (-0.58)	0.00490 (0.30)
Department Stores[L]	-0.01433 (-0.34)	-0.00017 (-0.06)	-0.00134 (-0.92)	0.02702 (0.79)
Fabricated Metals[H]	-0.03755 (-1.68)	0.01372 (4.89)[**]	0.00201 (1.34)	0.03687 (2.10)[*]
Petroleum[L]	-0.01806 (-1.64)	0.00426 (2.01)[*]	0.00204 (2.37)[**]	0.01806 (2.35)[**]
Transportation[H]	-0.03548 (-1.27)	0.00869 (2.79)[**]	0.00096 (0.56)	0.03451 (1.60)
Utilities[H]	0.00471 (0.69)	0.00833 (4.25)[**]	0.00079 (0.74)	0.00698 (1.62)
Transport Equipment	0.00270 (0.11)	0.00816 (2.81)[**]	0.00011 (0.07)	0.00797 (0.55)
Financial	0.01209 (0.88)	0.00618 (3.84)[**]	0.00023 (0.18)	0.00034 (0.04)
Construction[L]	0.02261 (0.92)	0.00245 (0.65)	-0.00003 (-0.02)	-0.00867 (-0.52)
Apparel[H]	-0.05779 (-1.80)	0.01426 (2.91)[**]	0.00308 (1.21)	0.04160 (1.96)[*]
Primary Metals[L]	-0.00915 (-0.57)	0.00501 (2.19)[*]	-0.00076 (-0.47)	0.01854 (1.73)

Coefficients (t-statistics) are presented from the following Parks GLS regressions using monthly pooled cross section time series data: $R_{pt} = \alpha_0 + B_1 BE/ME_{pt} + B_2 ME_{pt} + B_3 Beta_p + \varepsilon_{pt}$. R_{pt} is the

equally weighted return on *BE/ME* portfolio *p* calculated from July of year *t* through June of year *t +1*. BE/ME_{pt} is the natural log of book-to-market for portfolio *p*. In deriving the variable, *BE* is measured at fiscal year end in calendar year $(t-1)$, which is at least six months prior to the return measurement interval and the market equity is measured at calendar year-end $(t-1)$. ME_{pt} is the natural log of the market capitalization of portfolio *p* at June-end of year *t*. $Beta_p$ is the full period beta for portfolio *p* calculated relative to the value-weighted index of NYSE, AMEX and Nasdaq stocks. Portfolios are formed as quintiles of BE/ME ranked firms within each of twenty-one different industries, which are defined in Table 1. The portfolios are reformed annually. Separate regressions are performed in each of the twenty-one industries. There are 1980 observations in each regression (5 portfolios times 33 years times 12 months). Data is from the portfolio formation periods 1968 through 2000.

[*] - Denotes significantly different from zero by two tailed test at a 5% significance level.
[**] - Denotes significantly different from zero by two-tailed test at a 1% significance level.

[L] Industry group with a low coefficient on BE/ME. These coefficients are statistically indistinguishable from one another, but are statistically smaller (at the 5% level or better) than the industry group with a high coefficient.

[H] Industry group with a high coefficient on BE/ME. These coefficients are statistically indistinguishable from one another, but are statistically larger (at the 5% level or better) than the industry group with a low coefficient.

Table 5   Temporal Consistency of Relative BE/ME by Industry

Industry	Median BE/ME Rank	Minimum BE/ME Rank	Maximum BE/ME Rank	Range in BE/ME Rank
Communications	2	1	11	10
Services	3	1	13	12
Chemicals	3	1	8	7
Publishing	5	2	18	16
Food	8	3	17	14
Electrical Equipment	5	2	17	15
Retail	10	5	16	11
Mining	7	1	20	19
Misc. Manufacturing	9	6	17	11
Machinery	9	5	19	14
Paper	13	6	20	14
Department Stores	12	1	20	19
Fabricated Metals	11	8	17	9
Petroleum	15	2	21	19
Transportation	14	1	19	18
Utilities	16	5	21	16
Transport Equipment	14	8	20	12
Financial	17	6	21	15
Construction	18	8	21	13
Apparel	20	15	21	6
Primary Metals	19	7	21	14

Note. - Ranks are calculated for each industry (1 through 21) in each of the thirty-three years in the sample period based on industry *BE/ME*. See Table 1 note for calculation of *BE/ME*. Data is from the portfolio formation periods 1968 through 2000.

Table 6   Risk and Growth Characteristics of Portfolios Ranked by BE/ME

| Classification | | | Risk Measures | | | |
Industry	Firm	ROA	Financial Distress	Earnings Uncertainty	Leverage	Alpha
Growth	Growth	12.98%	3.14%	2.05%	0.20	0.36%
Growth	2	8.32%	2.34%	2.99%	0.43	0.71%
Growth	3	6.86%	3.10%	4.05%	0.65	1.05%
Growth	4	6.12%	3.12%	4.45%	0.90	1.24%
Growth	Value	4.93%	8.40%	7.27%	1.26	1.35%
2	Growth	10.93%	1.06%	2.46%	0.33	0.47%
2	2	8.81%	2.05%	3.73%	0.76	0.79%
2	3	5.99%	3.01%	4.44%	1.15	1.01%
2	4	3.71%	4.62%	5.84%	1.79	1.07%
2	Value	2.05%	12.39%	8.97%	2.50	1.33%
3	Growth	9.37%	3.03%	2.97%	0.41	0.34%
3	2	6.45%	2.15%	3.88%	0.93	0.70%
3	3	4.78%	3.13%	5.24%	1.53	0.90%
3	4	3.02%	6.23%	6.53%	2.45	0.88%
3	Value	1.38%	12.15%	12.00%	4.01	1.23%
4	Growth	6.01%	2.43%	3.04%	1.19	0.70%
4	2	5.22%	2.69%	4.33%	1.93	1.05%
4	3	4.02%	3.45%	6.08%	3.00	1.24%
4	4	2.93%	4.76%	7.12%	4.08	1.39%
4	Value	2.04%	13.50%	14.69%	5.56	1.47%
Value	Growth	4.78%	3.68%	3.33%	2.13	0.86%
Value	2	4.14%	2.05%	4.43%	3.16	1.06%
Value	3	3.11%	3.19%	5.46%	3.87	1.09%
Value	4	2.67%	7.58%	6.03%	5.30	1.09%
Value	Value	1.30%	17.31%	14.56%	9.61	1.29%

Note. – Portfolio formation is as follows: The twenty-one industries (see Table 1) are classified into quintiles annually based on the rank of the industry *BE/ME* and then within each industry classification firms are classified into quintiles annually based on the rank of firm *BE/ME*. Data is from the portfolio formation periods 1968 through 2000. Return on assets (*ROA*) is income from operations in portfolio formation year *t* divided by total assets at fiscal year end in year *t –1*. *Earnings uncertainty* is the standard deviation of (earnings/price), where the earnings are from year t and price is the market value of equity at calendar year end *t –1*. *Leverage* is the financial leverage, defined as total book value of debt at fiscal year end in year *t –1* divided by market value of equity at calendar year end *t –1*. *Financial distress* is the percentage of dividend paying firms that cut their dividend in fiscal year *t –1* (relative to fiscal year *t –2*) by 25% or more, i.e. the number of firms that cut dividends by 25% or more divided by the total number of dividend paying firms in year *t –1*. *ROA* and the risk measures are reported as annual averages. *Alphas* (α_0) are calculated in the following manner.   Portfolio returns are regressed against known risk factors from Fama and French (1996), excluding the *HML* (high minus low) factor. That is, $R_{pt} = \alpha_0$

$+B_1MRP_{pt} + B_2SMB_{pt} + \varepsilon_{pt}.$ R_{pt} is the equally weighted return on *BE/ME* portfolio *p* calculated from July of year *t* through June of year *t +1*. *MRP* is the market risk premium and *SMB* is the small minus big series. *MRP* and *SMB* are obtained from Kenneth French's website.

Table 7　　　Correlation among Risk Characteristics and Alpha

	Alpha	Earnings Uncertainty	Leverage	Financial Distress
Alpha	100.0%			
Earnings Uncertainty	72.4%**	100.0%		
Leverage	61.2%*	82.1%**	100.0%	
Financial Distress	60.5%*	93.6%**	77.3%**	100.0%

Note. – See Table 6 note for the description of the *Earnings Uncertainty*, *Leverage*, *Financial Distress* and *Alpha* variables.

* - Denotes significantly different from zero by two-tailed test at a 5% significance level.
** - Denotes significantly different from zero by two-tailed test at a 1% significance level.