9-2006

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Recommended Citation

Banko, John C., C. Mitchell Conover, and Gerald R. Jensen. "The Relationship between the Value Effect and Industry Affiliation." *The Journal of Business* 79, no. 5 (September 2006): 2595-616. doi:10.1086/505245.

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The Relationship between the Value Effect and Industry Affiliation*

We examine industry affiliation and the relationship between stock returns and book-to-market equity (the value effect). The robustness of the value effect is supported as a significant value premium is shown to exist in 15 of 21 industries. Both industry- and firm-level value effects are identified; however, the firm-level effect is the more prominent of the two. Further, the value effect is shown to be strongest in value industries and weakest in growth industries. Finally, we show evidence consistent with the claim that the value premium is due to investors requiring higher returns from firms in distressed conditions.

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,

* We are grateful to Tom Arnold, Albert Madansky (the editor), Robert Miller, Jerry Stevens, an anonymous referee, and seminar participants at Texas Tech University, the University of Richmond, and the 2003 Southern Finance Association meeting for their helpful comments. This research is partially funded by a University of Richmond research grant. Contact the corresponding author, Gerald R. Jensen, at gjensen@niu.edu.

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

(*Journal of Business*, 2006, vol. 79, no. 5)

0021-9398/2006/7905-0011$10.00

1993, 1995; 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; 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. Dichev (1998) and Griffin and Lemmon (2002) 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 article 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's efforts, 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

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

biases may be attached to industries rather than to 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 interindustry BE/ME variation in explaining stock returns and do not examine the relationship between intraindustry 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 article, 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

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

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 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 article 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 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 firm and industry BE/MEs are 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 21 different industries.[4] Firms are ranked by BE/ME within each industry and formed into portfolios by quintiles; that is, the 20% of firms with the lowest BE/ME in an industry are placed in portfolio 1, 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 15 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 6 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 are available prior to the return interval, which runs from July of year t through

4. Consistent with Chan et al. (1995), we search the history of CUSIPs on CRSP to obtain matches with COMPUSTAT. See Chan et al. (1995) 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.

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 the end of June in 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 33 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 indicate 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 15 firms throughout the sample period. The petroleum industry has the lowest average representation with 24 firms per year, while the retail industry has the largest representation with 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 com-

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; 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 are more complete (see CRSP 2001).

7. Our approach differs from that of 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 Real Estate Investment Trusts (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 15-firm minimum.

TABLE 1 **Summary Statistics by Industry**

Industry	SIC	Mean Sample Size	BE/ME	BE/ME Standard Deviation	Market Capitalization (ME)	Beta
Communications	48	35	.41	.46	210.63	1.29
Services	70–87, 89	240	.48	.59	37.21	1.52
Chemicals	28	142	.49	.49	155.04	1.22
Publishing	27	55	.52	.45	116.30	1.23
Food	20	71	.57	.74	111.56	.95
Electrical equipment	36	196	.59	.55	34.10	1.58
Retail	50–52, 54–59	273	.61	.84	42.42	1.34
Mining	10	163	.62	.60	73.15	1.07
Miscellaneous manufacturing	24–25, 30–31, 38–39	258	.63	.67	37.75	1.40
Machinery	35	197	.67	.63	63.31	1.43
Paper	26	42	.71	.49	247.06	1.15
Department stores	53	28	.72	.78	305.41	1.31
Fabricated metals	34	89	.73	.74	54.13	1.26
Petroleum	29	24	.75	.47	1,182.16	.95
Transportation	41–47	52	.75	.66	64.08	1.29
Utilities	49	157	.76	.32	307.13	.54
Transport equipment	37	66	.78	.62	134.97	1.37
Financial	60–65	158	.84	.62	104.37	1.25
Construction	32	29	.85	.51	122.36	1.24
Apparel	22–23	74	.92	.76	35.06	1.34
Primary metals	33	52	.96	.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 15.

munications, 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 interindustry BE/MEs (identified in table 1) is statistically significant, we employ a standard ANOVA using industry dummy

TABLE 2 ANOVA Results Examining Variation in Industry BE/MEs

Variable	BE/ME	*t*-Statistic
Intercept	−.3179	−5.65**
Dummy variables:		
Communications	−.4837	−5.96**
Services	−.3981	−4.90**
Chemical	−.4472	−5.51**
Publishing	−.2620	−3.23**
Food	−.1031	−1.27
Electrical equipment	−.2439	−3.00**
Retail	.0790	−.97
Mining	−.2756	−3.40**
Miscellaneous manufacturing	−.1349	−1.66
Machinery	−.1385	−1.71
Paper	Base industry	Base industry
Department stores	−.0125	−.15
Fabricated metals	−.0274	−.34
Petroleum	.0397	.49
Transportation	−.0136	−.17
Utilities	.0800	.99
Transport equipment	.0801	.99
Financial	.1347	1.66
Construction	.1813	2.23**
Apparel	.3131	3.86**
Primary metals	.2564	3.16**
R^2 and *F*-statistic of regression	.0734	14.71**

NOTE.—Coefficients and *t*-statistics are reported for the following OLS regression using annual data over the portfolio formation periods 1968–2000: $\mathrm{BE/ME}_{pt} = \alpha_0 + \sum_{p=1}^{20} B_p \mathrm{IndustryDummy}_{pt} + \varepsilon_{pt}$. $\mathrm{BE/ME}_{pt}$ is the natural log of book-to-market for portfolio *p*. See note for table 1 for the calculation of BE/ME. $\mathrm{IndustryDummy}_{pt}$ 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 × 21 industries × 33 years).

** Significantly different from zero at the 1% level (two-tailed test).

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*-squared indicates that a significant amount of the variation in the BE/MEs (7%) is explained by the industry. This evidence indicates that BE/ME has sufficient interindustry 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 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

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

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	.0111	.0068			
	(8.49)**	(13.62)**			
2	.0128		.0061		
	(9.63)**		(5.87)**		
3	.0117	.0056	.0018		
	(8.73)**	(11.15)**	(1.81)		
4	.0021	.0065	.0018	.0008	.0082
	(.98)	(12.63)**	(1.75)	(3.25)**	(3.66)**

NOTE.—Coefficients (t-statistics) are presented from the following Parks GLS regressions using monthly pooled cross-sectional time-series data: $R_{pt} = \alpha_0 + B_1(\text{BE/ME}_{pt}) + B_2(\text{IndBE/ME}_{pt}) + B_3 ME_{pt} + B_4\beta_p + \varepsilon_{pt}$. 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 logs 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 6 months prior to the return measurement interval, and the market equity is measured at calendar year end of $t-1$. 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 21 different industries, which are defined in table 1. The portfolios are reformed annually. There are 41,580 observations in each regression (21 industries × 5 portfolios × 33 years × 12 months). Data are from the portfolio formation periods 1968–2000.

** Significantly different from zero at the 1% level (two-tailed test).

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 are 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 21 industry quintiles over 33 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 sep-

11. Following previous empirical work, the regressions are estimated using the natural logs 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 this article are available from the authors on request.

arately. 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. Finally, 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 et al. (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.'s and suggest that intraindustry variation in BE/ME is more important in explaining portfolio returns relative to interindustry variation in BE/ME. This finding suggests that most of the value effect can be attributed to differences in firm BE/MEs 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 Standard and Poor's (S&P) industry data. Specifically, it appears that most of the value anomaly is due to intraindustry 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]

13. While the coefficient on industry BE/ME is only marginally significant in models 3 and 4, it is significant at the 1% level when the sort order is reversed. This and other table 3 robustness checks are discussed in more detail later in this article. 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 = 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. Although the relationship between size and stock returns is not the focus of the portfolio formation methodology in our study, we investigated this re-

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, that is, 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 cross-sectional, time-series GLS regressions (Parks approach) within each of the 21 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, 15 of the 21 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 uni-

lationship further and found 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, 16 of the industries show a significant value effect under this less strict criteria.

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

Industry	Intercept	BE/ME	ME	Beta
Communications	.03208	.00618	−.00280	.00420
	(1.48)	(1.79)	(−1.81)	(.27)
Services[L]	.00209	.00579	.00004	.01008
	(.07)	(2.29)*	(.02)	(.48)
Chemicals[L]	.04370	.00311	.00043	−.02471
	(.56)	(.89)	(.33)	(−.39)
Publishing[L]	.02730	.00370	−.00058	−.00812
	(.83)	(1.51)	(−.38)	(−.33)
Food[H]	.02550	.00825	.00139	−.01819
	(1.16)	(2.97)**	(.94)	(−.87)
Electrical equipment[H]	−.01361	.01077	.00251	.01339
	(−.38)	(3.15)**	(1.57)	(.62)
Retail	−.03383	.00812	.00186	.02923
	(−1.11)	(3.13)**	(1.11)	(1.24)
Mining	.05142	.00782	.00032	−.03473
	(1.15)	(3.82)**	(.21)	(−.87)
Miscellaneous manufacturing[H]	−.06661	.01129	.00073	.05809
	(−1.16)	(2.53)**	(.46)	(1.42)
Machinery	.00748	.00611	−.00048	.00574
	(.27)	(1.97)*	(−.28)	(.32)
Paper[L]	.01347	.00430	−.00083	.00490
	(.58)	(1.61)	(−.58)	(.30)
Department stores[L]	−.01433	−.00017	−.00134	.02702
	(−.34)	(−.06)	(−.92)	(.79)
Fabricated metals[H]	−.03755	.01372	.00201	.03687
	(−1.68)	(4.89)**	(1.34)	(2.10)*
Petroleum[L]	−.01806	.00426	.00204	.01806
	(−1.64)	(2.01)*	(2.37)**	(2.35)**
Transportation[H]	−.03548	.00869	.00096	.03451
	(−1.27)	(2.79)**	(.56)	(1.60)
Utilities[H]	.00471	.00833	.00079	.00698
	(.69)	(4.25)**	(.74)	(1.62)
Transport equipment	.00270	.00816	.00011	.00797
	(.11)	(2.81)**	(.07)	(.55)
Financial	.01209	.00618	.00023	.00034
	(.88)	(3.84)**	(.18)	(.04)
Construction[L]	.02261	.00245	−.00003	−.00867
	(.92)	(.65)	(−.02)	(−.52)
Apparel[H]	−.05779	.01426	.00308	.04160
	(−1.80)	(2.91)**	(1.21)	(1.96)*
Primary metals[L]	−.00915	.00501	−.00076	.01854
	(−.57)	(2.19)*	(−.47)	(1.73)

NOTE.—Coefficients (t-statistics are in parentheses) are presented from the following Parks GLS regressions using monthly pooled cross-sectional time-series data: $R_{pt} = \alpha_0 + B_1\text{BE/ME}_{pt} + B_2\text{ME}_{pt} + B_3\text{Beta}_p + \varepsilon_{pt}$. 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 6 months prior to the return measurement interval and the market equity is measured at calendar year-end of $t-1$. 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 21 different industries, which are defined in table 1. The portfolios are reformed annually. Separate regressions are performed in each of the 21 industries. There are 1980 observations in each regression (5 portfolios × 33 years × 12 months). Data are from the portfolio formation periods 1968–2000. Superscript L identifies an industry group with a low coefficient on BE/ME. These coefficients are statistically indistinguishable from one another, but they are statistically smaller (at the 5% level or better) than the industry group with a high coefficient. Superscript H identifies an industry group with a high coefficient on BE/ME. These coefficients are statistically indistinguishable from one another, but they are statistically larger (at the 5% level or better) than the industry group with a low coefficient.

* Significantly different from zero at the 5% level (two-tailed test).

** Significantly different from zero at the 1% level (two-tailed test).

versal.[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 statistically 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 (3) the remaining coefficients. The high-coefficient group includes the apparel, electrical equipment, fabricated metals, food, miscellaneous manufacturing, transportation, and utilities industries, and these are identified with an H next to the industry name. Although the coefficients for these seven industries cannot be distinguished from each other, they are statistically larger (at the 5% level) than the low-coefficient industries, which include the chemicals, construction, department stores, paper, petroleum, primary metals, publishing, and services industries (these are identified with an L). Likewise, the low-coefficient industries cannot be distinguished from each other, but they 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, Chan et al. (2001) and Daniel et al. (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. 2001). 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 composed largely of intangibles) are more susceptible to mispricing and should therefore have a relatively prominent value

17. The insignificance of the coefficients cannot be attributed to a lack of intraindustry variation in BE/ME ratios within these six industries. The BE/ME standard deviation measures reported in table 1 show that a relatively high variation exists within each of these six industries. Further, ANOVA results with quintile dummies indicate that 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.

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
Miscellaneous 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 (1–21) in each of the 33 years in the sample period based on industry BE/ME. See the note of table 1 for calculation of BE/ME. Data are from the portfolio formation periods 1968–2000.

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 = 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, that is, 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 21 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 33 years. For example, the biggest range in ranks is 19, and that occurs for the mining, department stores, and petroleum industries. This extreme range in ranks indicates that, during the 33-year period, these three industries had strong value characteristics for at least 1 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 that the industry has consistently been a value industry throughout the 33 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 to periodically reclassify industries.

IV. Risk and the Value Effect

We next reexamine the intraindustry 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 21 industries are ranked based on their annual BE/ME ratios (1–21) 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 25 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 25 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 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 25 portfolios are reported in table 6. If the

18. The SAS rank procedure is used to assign industries to quintiles. By default, it assigns five of the 21 industries to the middle (third) quintile. Although the rank procedure used by SAS was not expected to significantly influence the results, we reran the rank procedure forcing the fifth industry into other quintiles. The results were not materially different from those reported in table 6.

TABLE 6 Risk and Return 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	.20	.36
Growth	2	8.32	2.34	2.99	.43	.71
Growth	3	6.86	3.10	4.05	.65	1.05
Growth	4	6.12	3.12	4.45	.90	1.24
Growth	Value	4.93	8.40	7.27	1.26	1.35
2	Growth	10.93	1.06	2.46	.33	.47
2	2	8.81	2.05	3.73	.76	.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	.41	.34
3	2	6.45	2.15	3.88	.93	.70
3	3	4.78	3.13	5.24	1.53	.90
3	4	3.02	6.23	6.53	2.45	.88
3	Value	1.38	12.15	12.00	4.01	1.23
4	Growth	6.01	2.43	3.04	1.19	.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	.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 21 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 are from the portfolio formation periods 1968–2000. 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, that is, 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. Alpha (α_0) is 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, $R_{pt} = \alpha_0 + B_1\text{MRP}_{pt} + B_2\text{SMB}_{pt} + \varepsilon_{pt}$. 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 were obtained from Kenneth French's Web site.

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 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 vs. 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% versus 3.33% and 7.27% versus 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, that is, that 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 that 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 make up 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 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 those of 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% to a high of 0.86%. This finding indicates that the growth prospects of the industry affect 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 that they 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.

19. In addition to the equal-weighted portfolio returns, alpha was also derived using value-weighted portfolio returns. The results are not materially different from those reported in table 6.

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 the note of table 6 for the description of earnings uncertainty, leverage, financial distress, and alpha.

* Significantly different from zero at the 5% level (two-tailed test).

** Significantly different from zero at the 1% level (two-tailed test).

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 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 the 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 intraindustry variation in BE/ME (book-to-market equity) are relevant in explaining stock returns. Our evidence, however, indicates that intraindustry 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 (15 of 21). In addition, none of the industries report a significant growth effect, that is, 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 made up 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 industry or a 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; 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, 1995) and Chen and Zhang's (1998) contention that the value effect is created by investor pricing of firm risk. In particular, we show that 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 that they also misprice it.

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