Peer Pressure: Industry Group Impacts on Stock Valuation Precision and Contrarian Strategy Performance♣

Turan G. Bali, K. Ozgur Demirtas, Armen Hovakimian and John J. Merrick, Jr.[*]

June 2005

This draft: January 2006

♣ We would like to Frank Fabozzi (the editor) and an anonymous referee for their helpful comments and suggestions. We also benefited from discussions with Nusret Cakici, Haim Levy, Robert Schwartz, and Liuren Wu. Turan Bali gratefully acknowledges the financial support from the Eugene Lang Research Foundation of the Baruch College. K. Ozgur Demirtas gratefully acknowledges the financial support from the PSC-CUNY Research Foundation of the City University of New York.

[*] Turan G. Bali is Associate Professor of Finance at the Department of Finance, Zicklin School of Business, Baruch College, One Bernard Baruch Way, Box 10-225, New York, New York 10010, Phone: (646) 312-3506, Fax: (646) 312-3451, E-mail: Turan_Bali@baruch.cuny.edu; K. Ozgur Demirtas is Assistant Professor of Finance at the Department of Finance, Zicklin School of Business, Baruch College, One Bernard Baruch Way, Box 10-225, New York, New York 10010, Phone: (646) 312-3484, Fax: (646) 312-3451, E-mail: Ozgur_Demirtas@baruch.cuny.edu; Armen Hovakimian is Associate Professor of Finance at the Department of Finance, Zicklin School of Business, Baruch College, One Bernard Baruch Way, Box 10-225, New York, New York 10010, Phone: (646) 312-3490, Fax: (646) 312-3451, E-mail: Armen_Hovakimian@baruch.cuny.edu; John J. Merrick, Jr. is Richard S. Reynolds Associate Professor of Business at the Mason School of Business, College of William and Mary, P.O. Box 8795, Williamsburg, Virginia 23187, Phone: (757) 221-2721, Fax: (757) 221-2937, E-mail: John.Merrick@mason.wm.edu.

Peer Pressure: Industry Group Impacts on Stock Valuation Precision and Contrarian Strategy Performance

ABSTRACT

Investment bankers focus on narrow, industry-based peer groups for individual stock valuation. And some market-neutral equity hedge fund managers restrict their portfolios to be sector-neutral as well. Yet, academic research into contrarian strategy investment performance has typically invoked full universe valuation and ignored industry effects. Here, we find in favor of the bankers' and hedge fund managers' approach. Industry effects matter. Narrow industry-based peer groups improve stock valuation precision for three key valuation ratios. While our analysis of the *dynamics* of these ratios indicates substantial inertia in relative value rankings, we find that average returns to industry-based contrarian portfolio strategies are positive, statistically significant, and persistent. And over a sample that extends through the "new economy/old economy" and boom/bust period of the late 1990s, contrarian strategies were particularly profitable for NASDAQ-listed stocks. Most importantly, using our full sample of stocks, we show that an industry-neutral strategy is far superior to an industry-exposed, full universe strategy in Sharpe ratio terms over every horizon for each valuation ratio. Thus, contrarian strategy portfolio performance is significantly improved in risk-adjusted terms when implemented in its industry-neutral hedging form.

INTRODUCTION

Stock valuation and portfolio construction are two core activities for active equity investment managers. Yet, investment textbooks traditionally have treated these two functions as nearly separate topics. Portfolio construction is studied from the viewpoint of efficient diversification of risk given inputs for individual stock expected returns, return standard deviations and return correlations. Company stock valuation is analyzed in *absolute* terms through discounted cash flow models and in *relative* terms via the company's standing among comparable firms vis-à-vis key characteristic-based value multiples (e.g., Price/Earnings, Price/Book Value, etc.). However, more recently, portfolio construction schemes based upon sorting stocks via rankings on both firm size (market capitalization) and characteristic-based value ratios have moved solidly into the academic mainstream. Perhaps not so coincidentally, these size and characteristic ratio sortings mimic the general styles through which investment managers classify themselves: large-cap, mid-cap or small-cap as well as value, blended or growth.[1]

Indeed, the academic literature now gives particular emphasis to analyzing the long run positive excess returns to contrarian investment strategies favoring portfolios overweighted in high book-to-market (value) stocks as opposed to low book-to-market (growth) stocks (e.g., Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994)). Debate continues as to whether the observed positive excess return to high book-to-market stocks reflects an equilibrium fair return necessary to compensate for a special dimension of risk.[2] An alternative interpretation is that this excess return is garnered from identifying cheap stocks since Price/Book Value is one of a set of multiples used pervasively by practitioners to determine the relative valuations of individual companies. For example, investment bankers routinely include an assessment of company value via such multiples as part of their due diligence work for mergers and acquisitions proposals and initial public offering-related background material.

We leave for others the puzzle as to why stock valuation practitioners talk in terms of the "Price/Book" multiple and academic researchers prefer analyzing this ratio in its inverted "book-to-market" form. However, one practical and quite important difference between use of the ratio by practitioners for individual company valuation and by academics for portfolio construction concerns the universe of stocks considered. When testing the effectiveness of contrarian portfolio strategies, academic studies typically sort over a universe of *all* listed stocks or, at most, a few large subsets defined by market capitalization (i.e., high-cap, mid-cap and low-cap). In sharp contrast, to assess the relative value of any specific individual company, practitioners generally focus on a narrow group of firms drawn from the same industry. Industries are presumed to be distinct clusters of firms with their own particular centers of gravity for the key characteristic multiples. Indeed, identification of this peer group is deemed to be an important first step in the company valuation process.[3] Furthermore, some market-neutral hedge fund managers also restrict their long-short equity portfolios to be sector-neutral as well. This particular style can be interpreted as providing implicit evidence that industry effects are important for risk management.

Taking our cue from this industry peer group focus in company valuation and hedge fund trading practice, we explore here the implications of invoking industry effects on tests of the efficacy of contrarian investment strategies. On one level, we test whether the peer group perspective actually improves upon assessments of relative value. Is narrowly focused peer group analysis per se meaningful? This is an important question from the viewpoint of generating a consistent financial framework for both understanding stock valuation and factor-based portfolio risk management. We first examine the usefulness of median industry-group book-to-market, cash flow-to-market and earnings-to-market ratios in explaining the cross-section of observed individual stock values. In our sample, narrow industry-based peer groups do improve stock valuation precision for these three key valuation ratios.

Next, we analyze the predictive power of an individual firm's initial peer group valuation ranking for subsequent moves in its own ratios. In particular, we estimate the speed of the convergence process by which individual firm value ratios correct themselves back toward the peer group median. Surprisingly, no such studies of the dynamics of individual firm characteristic value ratios appear in the literature. Our analysis of the dynamics of the three valuation ratios indicates substantial inertia in relative value rankings. In other words, the implicit speed of mean reversion for deviations of an individual firm's ratio from its industry median is quite slow. Nevertheless, because the initial relative value differences are substantial, we find that average returns to contrarian portfolio strategies are positive and statistically significant. And over our sample period, contrarian strategies were particularly profitable for NASDAQ-listed stocks. Moreover, in line with the estimated slow speed of mean-reversion in value ratios, excess returns persist beyond the one year horizon.

Finally, we specifically highlight industry effects on portfolio design and returns to contrarian strategies. By construction, our featured quasi-arbitrage hedge portfolio formed by purchasing the cheapest stock and selling the richest stock in each industry has no net exposure to industry effects (i.e., it is both market-neutral and industry-neutral). This industry-neutral strategy outperforms that from the more generic contrarian strategy on the basis of Sharpe ratios. Clearly, industry effects have a material impact on portfolio return risk. Contrarian strategy portfolio performance is significantly improved in risk-adjusted terms when implemented in its industry-neutral hedging form.

LITERATURE REVIEW

Lie and Lie (2002) have recently applied the multiples-based firm valuation model in a peer group setting where industry peers are determined by the Bureau of Labor Statistics' Standard Industrial Classification (SIC) groupings.[4] Their study examines the explanatory power of both asset-based multiples (e.g., using book value as the characteristic) and flow multiples (e.g., using earnings or earnings forecasts as the characteristic) in company valuations (both total enterprise value and equity value alone). Since the study is based upon a one-year snapshot of data (fiscal 1998), it does not report on any explicit tests on subsequent returns (or changes in multiples over time) as might be suggested by a richness/cheapness interpretation. Our interest lies in following up on an individual firm's initial value classification for its predictive power for future value ratios and stock returns.

Contrarian strategies continue to attract strong academic and practitioner research interest.[5] Yet, precious few papers attempt to identify and incorporate industry effects in their analysis. Within a voluminous literature, we know of only three studies that have attempted to integrate industry effects into contrarian strategy analysis: Dremen and Lufkin (1997), Cohen and Polk (1998), and Asness, Porter, and Stevens (2000). Dremen and Lufkin (1997) use data from a 1970 to 1995 sample to examine within-industry value rankings of firms sorting on book value, earnings and cash flow ratios. They analyze returns to contrarian strategies using these relative value rankings and compare them to returns from corresponding rankings based on aggregated, market-wide sortings. Dremen and Lufkin (1997) find evidence from average contrarian strategy returns that industry sortings reveal a relative value component beyond that contained in the aggregated analysis. Furthermore, industry-neutral long-short portfolios could perform better than industry-exposed market-wide hedge portfolios in Sharpe ratio terms if industry effects on return risk are important. Indeed, Cohen and Polk (1998) provide some evidence that industry-neutral long-short strategies do improve Sharpe ratios using data from a 1968 to 1991 sample period. Asness, Porter and Stevens (2000) also compare market-wide sortings on book value and cash flow ratios to “within-industry” sortings based on the deviation of individual firm ratio from the industry mean. In their 1963-1998 sample, Asness, Porter and Stevens find that these alternative sorting strategies generate comparable returns, but that within-industry based returns have lower standard deviation.

Note that Cohen and Polk’s sample ends in 1991, Dremen and Lufkin’s sample ends in 1995, and Asness, Porter and Stevens’s sample ends in 1998. Thus, these studies do not address the very interesting boom and bust cycle of the late 1990s and early 2000s. We view this period to be particularly interesting in regard to the potential importance of industry effects given the popular focus in the financial press on “new economy” versus “old economy” firms. Our Exhibit 1 hints that cross-sectional dispersion in valuations among industries increased in late 1990s. Furthermore, as previously explained, we view predicting subsequent moves in individual firm stock value ratios on the basis of the initial valuation ranking as an important pre-condition for invoking any exploitable relative value interpretations. Thus, we investigate the speed and extent of the convergence process by which individual firm stock value ratios correct themselves back toward the peer group median. None of these earlier studies provided any evidence on mean reversion in the ratios.

DATA AND PEER GROUP CONSTRUCTION

We obtain monthly returns, prices and adjustment factors from the Center for Research in Securities Prices (CRSP) monthly file. Financial statement data come from the COMPUSTAT annual files. We match the COMPUSTAT variables for all fiscal year-ends in calendar year t-1 with the returns from May of year t to April of year t+1.[6] This alignment ensures that the accounting variables are known to the market in advance of return realizations (see Lakonishok, Shleifer and Vishny, 1994). We use a firm's market equity at the end of April of year t to compute its book-to-market (BM), cash flow-to-market (CM), and earnings-to-market (EM) ratios. Book value is defined as the book value of common equity plus the balance sheet deferred taxes. Earnings are defined as income before extraordinary items plus deferred taxes from the income statement. Cash flow is defined as earnings plus depreciation and amortization. At the end of each April, we sort stocks into portfolios based on the ranked values of BM, CM and EM. For each stock, we compute the one-year-ahead return from May of year t to April of year t+1, and then also compute returns for the three subsequent years. Thus, for each portfolio, we are able to calculate the equal-weighted annual portfolio returns for one, two, three and four years after portfolio formation.

We examine industry peer groups using the SIC industry definition scheme. Our data set includes all NYSE, AMEX and NASDAQ stocks for the 1962 to 2002 period.[7] Alford (1992) found very little marginal valuation performance improvement in moving from three-digit to four-digit SIC code industry groupings. Therefore, we group firms on the basis of three-digit SIC codes if the resulting industry contains at least five firms. The five-firm minimum allows us to populate value quintiles for each industry. We drop any industries that do not meet the five-firm minimum. The results using this industry grouping scheme can be benchmarked versus an alternative that combines all firms in one broad group.

As Kim and Ritter (1999) emphasize, investment bankers use valuation via median peer group characteristic multiples for a prospective IPO. In that application, individual firm multiples are seen to differ because of random firm-specific factors. There is no presumption that a firm’s stock is mispriced just because its currently observed multiple is higher or lower than the industry’s median multiple. Here, the industry’s median multiple estimates the current multiple for a “typical” firm in that industry. Implicitly, this approach assumes that median industry multiples differ significantly across industries. Exhibit 1 plots annual data for the cross-sectional maximum, median, and minimum industry peer group median book-to-market ratios in our sample. The previous academic literature acknowledges that the aggregate book-to-market ratio fluctuates over time (e.g., Kothari and Shanken (1997)). But our Exhibit 1 reveals that there also exists a wide degree of *dispersion* among the median book-to-market multiples across industry groups within any given year. Formal tests for all three valuation ratios strongly reject the hypothesis that the median multiple's value in a given year is equal for all industries.[8] Thus, the typical investment banker's emphasis on narrow, industry-matched peer group definitions for multiples-based valuation analysis seems quite useful. Median multiple levels – the key levels around which firms in the same industry are perceived to cluster – differ significantly across industry peer groups at any given point in time.

USING CHARACTERISTIC MULTIPLES TO VALUE STOCKS

Assume that the *i*th stock $S_i, 1 \le i \le N,$ belongs to the *j*th industry $I_j, 1 \le j \le M$. We value S_i on the basis of three alternative peer group characteristic-based ratios: book-to-market, cash flow-to-market and earnings-to-market. For each of these three ratios, which we denote by $\rho_i^k, 1 \le k \le 3,$ we compute the median ratio in each industry group $\rho_{med}^{jk}, 1 \le j \le M, 1 \le k \le 3,$ i.e., $\rho_{med}^{jk} = \text{median}\{\rho_i^k \mid S_i \in I_j\}$. We assume that ρ_{med}^{jk} is the fair value of the characteristic for all stocks in industry *j*, and define the fair price of S_i using the *k*th characteristic to be

$$P_{ik}^* = \frac{C_i^k}{\rho_{med}^{jk}} \tag{1}$$

Next, for each characteristic, we define the *i*th stock's pricing residual, e_i^k, as the percentage difference between the market price and the fair price:

$$e_i^k = \frac{P_i - P_{ik}^*}{P_{ik}^*} \tag{2}$$

Exhibit 2 summarizes the distributions of the *absolute value* of percentage stock pricing errors, $|e_i^k|$, as derived from three alternative industry peer group median ratios. Lie and Lie (2002) began their analysis by *presuming* that forming industry peer groups increased valuation precision. For comparative purposes, we also examine the corresponding distribution of the absolute value of percentage stock pricing errors derived using a *single* median ratio based on the full universe of stocks. In each case, the industry-based median ratio approach significantly reduces stock pricing error relative to the aggregated, single median ratio approach. When pricing individual stocks via the book-to-market ratio, the median absolute percentage stock price error using the single aggregate median ratio is 42%. The corresponding value when pricing using the industry-specific median ratios falls to 35%. When invoking the model based upon the cash flow-to-market ratio, the median absolute percentage stock price error using the single aggregate median ratio is 40%. The corresponding value when pricing using the industry-specific median ratios falls to 32%. Finally, when using the earnings-to-market ratio model, the median absolute percentage stock price error using the single aggregate median ratio is 38%. The corresponding value when pricing using the industry-specific median ratios falls to 32%. In all cases, the test statistic strongly rejects the hypothesis that the median absolute percentage errors from the two methods are equal.[9] Furthermore, the use of the industry-based peer groups dramatically increases the fraction of firms with valuation errors within absolute percentage pricing errors within 15% (e.g., for the book-to-market ratio, from under one-fifth to over one-quarter).

As part of the due diligence pricing analysis preceding an IPO, the current median multiple for an industry peer group is commonly used as a forecast of the fair multiple for the soon-to-be-listed firm. This presumes that individual firm multiples are randomly scattered around their appropriate peer group median. However, scant attention is paid to alternative hypotheses concerning the *dynamics* of any existing firm's observed valuation errors over time. In particular, should positive ($e_i^k > 0$) or negative ($e_i^k < 0$) pricing errors derived from a group median multiple-based analysis be viewed as a fixed firm-specific effect? Or are such deviations signals of a stock's current relative richness or cheapness? Exhibit 3 provides some insight into the potential usefulness of currently observed pricing errors in relative value strategies. This exhibit presents estimates of transition probabilities designed to describe a given stock's subsequent one-period-ahead value quintile rank (as indexed by the columns) as a function of its current rank (as indexed by the rows). Estimates are presented for each of the three alternative value ratios. Panel A of Exhibit 3 presents quintile transition probabilities using the book-to-market ratio; Panels B and C present the corresponding results for the cash flow-to-market and earnings-to-market ratios, respectively.

For example, Panel A of Exhibit 3 shows that 71% of stocks in the highest book-to-market ("cheapest") quintile and 68% of stocks in the lowest book-to-market ("richest") quintile remain in these same quintiles after one year. In other words, relative stock valuations within a peer group appear sticky at the one-year horizon. Thus, currently observed differences in individual firm book-to-market ratios appear to reflect firm-specific factors that tend to persist. Nevertheless, when future re-rankings *do* occur, the previous year's valuation does seem to provide some useful clues. Specifically, consider the fourth highest book-to-market ("second cheapest") quintile. From Exhibit 3, 45% of stocks currently ranked in this quintile will remain in this same value quintile after one year passes. But of the 55% that do switch quintiles, 35% will appreciate (move toward the median) while only 20% will depreciate (move away from the median).

Panels B and C of Exhibit 3 present the corresponding transition probability magnitudes for the cash flow-to-market (Panel B) and earnings-to-market (Panel C) ratios. The results still reveal substantial inertia with respect to re-rankings among value quintiles. However, these flow-based multiples reveal a greater tendency to properly re-rank within one-year's time. For example, the fourth highest earnings-to-market ratio has a 33% chance of remaining in this same quintile after one year's time. However, of the 67% that do switch quintiles, 47% will appreciate (move toward the median) while only 20% will depreciate (move away from the median).

These transition probabilities provide some hints as to the high degree of persistence in key characteristic-based valuation measures. But the persistence/mean reversion question can be addressed much more directly. Does the current deviation of an individual firm's multiple from its industry peer group median multiple usefully predict a subsequent move in the firm's multiple back toward the peer group median? To address this question, we explicitly model the dynamics of a presumed convergence process.

Specifically, we posit a partial adjustment regression for the observed individual firm multiple $\rho_{i,t}$ of the form (suppressing the superscripts and subscripts that identify the particular characteristic and the industry):

$$(\rho_{i,t+1} - \rho_{i,t}) = a + b(\rho_{med,t} - \rho_{i,t}) + u_{i,t+1} \tag{3}$$

where $\rho_{med,t}$ is the median peer group ratio observed at time *t*. Under equation (3), the individual ratio adjusts toward a predetermined target equal to the previous period's median group ratio. We test whether the adjustment coefficient *b* is positive and significantly different from both zero and positive unity. A coefficient of 1.0 can be interpreted as implying "full reversion" back to the peer group median within the period. We also examine a second equation relating the current difference between the peer group median and the individual firm ratios to the previous period's difference:

$$(\rho_{i,t+1} - \rho_{med,t+1}) = c + d(\rho_{i,t} - \rho_{med,t}) + u_{i,t+1} \tag{4}$$

Under equation (4), the slope coefficient *d* describes the persistence in firm relative valuation in a form that incorporates date *t*+1 innovations in the median peer group multiple.

Exhibit 4 presents the regression estimates for equations (3) and (4) for each of the three ratios studied. The results reveal consistently low magnitudes for the key reversion parameter *b* in equation (3), ranging from just 0.03 (for the book-to-market ratio) to 0.09 (for the earnings-to-market ratio). Conversely, the three estimates for *d*, the persistence parameter in equation (4) applied to relative value differences through time, range between 0.97 (for the book-to-market ratio) and 0.91 (for the earnings-to-market ratio). The estimates from both equations tell a consistent story: currently observed stock price cheapness or richness based on peer group ratio analysis tends to persist over a one-year horizon. Again, for the key book-to-market ratio emphasized by the academic literature, a trader should expect that only 3% of any current mispricing in a particular stock will be eliminated within a year's time. While statistically significant, the degree of mean reversion applicable for contrarian investment strategies appears small.

TEST WHETHER RANKINGS PRODUCE EXCESS RETURNS IN HEDGE PORTFOLIOS

Ultimately, the usefulness of industry peer groups for contrarian investment strategies must be proven directly through analyzing returns. Here, we test for the marginal contribution of industry-based peer group valuation analysis in terms of the risk-adjusted returns to contrarian strategies. Specifically, we analyze annual returns on two equal-weighted portfolios created by drawing one stock from each three-digit SIC code industry.[10] We form the first portfolio with the "cheapest" stocks in each industry. We form the second portfolio with the "richest" stocks in each industry. We create a net return series by subtracting the return on the portfolio of rich stocks from the return on the portfolio of cheap stocks. We test the hypothesis that the average net return between these two portfolios equals zero. This net return series can be interpreted as the return on a quasi-arbitrage strategy that purchases the portfolio of the cheapest stocks in each industry and sells the portfolio of the richest stocks in each industry. In effect, this net return series is the return on a portfolio of "pair" trades. By construction, this hedge portfolio has no net exposure to industry effects.

We compare these results to those for the more generic contrarian strategy. The generic contrarian strategy is constructed without regard to industry exposures based on relative value rankings across the full universe of firms. For this full universe strategy, we again analyze annual returns on two equal-weighted portfolios. We form the first portfolio with the "cheapest" stocks in the full universe. We form the second portfolio with the "richest" stocks in the full universe.[11] We create a second net return series by subtracting the return on the portfolio of full universe rich stocks from the return on the portfolio of full universe cheap stocks. Again, this net return series can be interpreted as the return on a quasi-arbitrage strategy that purchases the portfolio of the cheapest stocks in the universe and sells the portfolio of the richest stocks in the universe. Note that this hedge portfolio may have a substantial net exposure to any given industry.

The first column of Exhibit 5 reports the results of our analysis of one-year-ahead returns for the two net return series (i.e., the industry-neutral and full universe) for each of the three valuation ratios (i.e., book-to-market, cash flow-to-market and earnings-to-market). For this one-year-ahead horizon, the results derived from the book-to-market valuation ratio are quite striking. First, in each case, the average net return to each strategy is positive and significantly different from zero. Thus, while the estimates of the implicit speed of mean reversion reported in Exhibit 4 are very slow, the initial value spreads between the cheapest and richest stocks are wide enough to generate consistently profitable opportunities. Furthermore, the average net returns from the industry-neutral and full universe strategies are essentially identical. Each strategy earns an average net return of 6.8% per year. But the reported t-statistic for the industry-neutral version is almost twice as large (4.04 versus 2.27) since the standard error from the industry-neutral strategy is just over half of that from the full universe strategy. Thus, in Sharpe ratio terms, the industry-neutral strategy is far superior to the full universe strategy.[12]

The results for one-year-ahead returns based on the cash flow-to-market and earnings-to-market valuation ratios (further down in column one) are in reasonable agreement with those from the book-to-market ratio analysis. Using the cash flow-to-market ratio, the average net return from the industry-neutral (7.2%) version is positive but lower than that for the full universe version (8.7%). Using the earnings-to-market ratio, the average net return from the industry-neutral version (4.2%) is significantly positive and *higher* than that for the full universe strategy (2.4%). Interestingly, using the earnings-to-market ratio, the average net return for the full universe strategy does not differ significantly from zero. But in every case studied, the industry-neutral strategy is far superior to the full universe strategy in Sharpe ratio terms. Industry effects have a material impact on portfolio return risk.

So far, we have only considered one-year-ahead investment horizons. But recall that the implicit mean reversion speeds for the key valuation ratios presented in Exhibit 4 were extremely slow. Thus, there is some scope for additional interesting results over multi-year horizons. Columns 2, 3 and 4 of Exhibit 5 present results for annual returns of the industry-neutral and full universe strategies over the second, third and fourth years after portfolio formation, respectively. The results reveal that the excess returns to contrarian strategies persist. Indeed, the estimates imply that annualized returns to contrarian strategies are even higher in the second and third years (e.g., the second year return to the industry-neutral book-to-market strategy averaged 9.8% per year versus only 6.8% for the first year). Furthermore, the average return on the industry-neutral version of the contrarian strategy is sometimes higher and sometimes lower than that for the full universe version depending upon the valuation ratio used and particular forward period considered.

Nevertheless, the industry-neutral strategy is superior to the full universe strategy in Sharpe ratio terms over every horizon for each valuation ratio.

Up until this point, we have examined individual stocks and defined industry peer groups based upon all available firms in our sample. But Kim and Ritter (1999) have emphasized that identification of the appropriate peer group is crucial first step in the company valuation process. Furthermore, one of our motivations for investigating the potential importance of industry effects was the popular focus in the financial press during the 1990s on distinguishing between “new economy” and “old economy” stocks. We seek to address (at least partially) both concerns via some additional work examining individual stock valuation and contrarian strategy performance solely among the subset of NASDAQ stocks. Relative to NYSE-listed companies, companies listed on NASDAQ are typically younger, smaller in size, and have stronger “new economy” associations. Thus, limiting our scope to NASDAQ-only firms in industry peer group definition, median value ratio computation, and stock relative value classifications may result in a more appropriate set of comparable firms for hedge portfolio construction.

Exhibit 6 presents the results of our NASDAQ-only contrarian quasi-arbitrage strategy of buying an equal-weighted portfolio of the cheapest stock in each industry while selling an equal-weighted portfolio of the richest stock in each industry. The sample begins in 1974 (our earliest data for NASDAQ stocks) and ends in 2001. Following the format of Exhibit 5, the entries in Exhibit 6 are differences in the average returns in the cheapest and richest portfolios for each of the three key valuation ratios. The most striking result from Exhibit 6 is that the average returns from these NASDAQ-only contrarian strategies are much higher than those based upon the broader full universe stock sample. For example, at the one-year horizon, the average return difference between industry-sorted high book-to-market and low book-to-market NASDAQ stock portfolios is 13.6% (versus 6.8% for this industry-sorted case using all stocks from Exhibit 5). At the same horizon, the corresponding number is 17.5% using the cash flow-to-market ratio for valuation. The other basic pattern found earlier tends to hold here as well: the industry-sorted peer groups outperform the aggregated approach. The second year return case for the earnings-to-market ratio is the sole example where the computed t-statistic for the industry-sorted approach (3.03) is less than that of the aggregated approach

(3.35). Interestingly enough, at the one-year horizon for that same ratio, the hypothesis that the average net return is zero under the aggregated approach cannot be rejected.

RESULTS FROM DECILE PORTFOLIOS

Our two key equal-weighted portfolios have been created by drawing the “cheapest” and “richest” stocks in each industry. We now examine the robustness of our basic results to broadening our stock selection algorithm. If the number of companies in a particular three-digit SIC code industry permits, we create new portfolios formed with all stocks in the top and bottom valuation deciles.[13] We create a corresponding net return series by subtracting the return on the portfolio of rich stocks from the return on the portfolio of cheap stocks. Again, by construction, this hedge portfolio has no net exposure to industry effects and we test the hypothesis that the average net return between these two portfolios equals zero. Again, we compare these results to those for the more generic contrarian strategy constructed without regard to industry exposures based on relative value rankings across the full universe of firms.

Exhibit 7 reports the results of our analysis of one-year-ahead returns for the two net return series (i.e., the industry-neutral and full universe) for each of the three valuation ratios (i.e., book-to-market, cash flow-to-market and earnings-to-market) using our full complement of all NYSE/AMEX/NASDAQ stocks. The basic results are quite similar to those found in Exhibit 5. But the added diversification gained from the extra stocks increases the t-statistics (scaled Sharpe ratios) across the board.

YEAR-BY-YEAR SCALED RETURNS

So far, we have used the scaled Sharpe ratio over the entire 1962-2001 period to evaluate the contrarian strategy performances of industry-neutral portfolios versus full-universe, industry-exposed portfolios. We can assess the value-added (in Sharpe ratio terms) of the industry-neutral portfolio approach versus the full-universe approach on a year-by-year basis. Exhibit 8 plots the ratio of each year’s return to its conditional standard deviation for both the industry-neutral and full-universe investment strategies.[14] (The plotted data are for the book-to-market contrarian strategy and encompass our full sample of all NYSE/AMEX/NASDAQ stocks.) Using this measure of performance, Exhibit 8 clearly shows that the industry-neutral strategy typically outperformed the full-universe strategy between 1962 and 2001. Indeed, the industry-neutral strategy's ratio was greater than that of the full-universe strategy in 32 out of 40 years. For example, this return-to-conditional standard deviation ratio was about five times as high as that from the full-universe strategy in 1984. Interestingly, the industry-neutral strategy appeared to be particularly useful in the boom and bust cycle of the late 1990s and early 2000s (i.e., substantially higher scaled gains combined with substantially lower scaled losses).

CONCLUSION

Investment bankers have long focused on narrow, industry-based peer groups for individual stock valuation analysis such as that done for pricing IPOs. Furthermore, some market-neutral equity hedge fund managers restrict their portfolios to be sector-neutral as well. However, academic research into contrarian strategy investment performance has typically invoked full universe valuation and ignored industry effects.

Here, we find in favor of the bankers' and hedge fund managers' approach. Industry effects matter. In our sample, narrow industry-based peer groups improve stock valuation precision for three key valuation ratios. But our analysis of the dynamics of the three valuation ratios indicates substantial inertia in relative value rankings. In other words, the implicit speed of mean reversion for deviations of an individual firm's ratio from its industry median is quite slow. Nevertheless, because the initial relative value differences are substantial, we find that average returns to contrarian portfolio strategies are positive and statistically significant. Contrarian strategies were particularly profitable for NASDAQ-listed stocks. Consistent with the slow speed of the mean reversion process for the key value ratios, excess returns persist beyond the one year horizon. Most importantly, using our full sample of stocks, we show that an industry-neutral strategy is far superior to an industry-exposed, full universe strategy in Sharpe Ratio terms over every horizon for each valuation ratio. Clearly, industry effects have a material impact on portfolio risk. Contrarian strategy portfolio performance is significantly improved in risk-adjusted terms when implemented in its industry-neutral hedging form. Hedging industry effects appears to have been particularly useful in the boom and bust cycle of the late 1990s and early 2000s.

References

Alford, Andrew W. “The Effect of the Set of Comparable Firms on the Accuracy of the Price-Earnings Valuation Method.” *Journal of Accounting Research*, 30 (1992), pp. 94-108.

Arshanapalli, Bala, T. Daniel Coggin, and John Doukas. “Multifactor Asset Pricing Analysis of International Value Investment Strategies.” *Journal of Portfolio Management*, 24 (1998), pp. 10-23.

Asness, Clifford S., R. Burt Porter, and Ross L. Stevens. “Predicting Stock Returns Using Industry-Relative Firm Characteristics.” Working Paper (2000).

Bourguignon, Francois, and Marielle de Jong. “Value Versus Growth.” *Journal of Portfolio Management*, 29 (2003), pp. 71-79.

Chan, Louis, K.C., Narasimhan Jegadeesh, and Josef Lakonishok. “Evaluating the Performance of Value versus Glamour Stocks: The Impact of Selection Bias.” *Journal of Financial Economics*, 38 (1995), pp. 269-296.

Cohen, Randolph B., and Christopher K. Polk. “The Impact of Industry Factors in Asset-Pricing Tests.” Working Paper, Harvard University, (1998).

Coggin, Daniel, Frank Fabozzi, and Robert Arnott. *The Handbook of Equity Style Managament.* New Hope, PA: Frank J. Fabozzi Associates, 1997.

Daniel, Kenneth, and Sheridan Titman. “Characteristics or Covariances?” *Journal of Portfolio Management*, 24 (1998), pp. 24-33.

Dreman, David N., and Eric A. Lufkin. “Do Contrarian Strategies Work within Industries?” *Journal of Investing*, 6 (1997), pp. 7-29.

Bollerslev, Tim. “Generalized Autoregressive Conditional Heteroscedasticity.” *Journal of Econometrics*, 31 (1986), pp. 307-327.

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

Fama, Eugene F., and Kenneth R. French. “Common Risk Factors in the Returns on Stock and Bonds.” *Journal of Financial Economics*, 33, (1993), pp. 3-56.

Kim, Moonchul, and Jay R. Ritter. “Valuing IPOs.” *Journal of Financial Economics*, 53 (1999), pp. 409-437.

Kothari, S.P. and Jay Shanken. “Book-to-Market, Dividend Yield, and Expected Market Returns: A Time-Series Analysis.” *Journal of Financial Economics*, 44 (1997), pp. 169-203.

La Porta, Rafael. “Expectations and the Cross-Section of Stock Returns.” *Journal of Finance*, 51 (1996), pp. 1715-1742.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny. “Contrarian Investment, Extrapolation, and Risk.” *Journal of Finance*, 49 (1994), pp. 1541-1578.

Lie, Erik, and Heidi J. Lie. "Multiples Used to Estimate Corporate Value." *Financial Analysts Journal*, 58 (2002), pp. 44-54.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein. "Persuasive Evidence of Market Inefficiency." *Journal of Portfolio Management*, 11 (1985), pp. 9-17.

Exhibit 1
Dispersion of median industry peer group book-to-market ratios by year
(each bar shows cross-sectional range of observed industry medians;
each marker shows median of industry group medians)

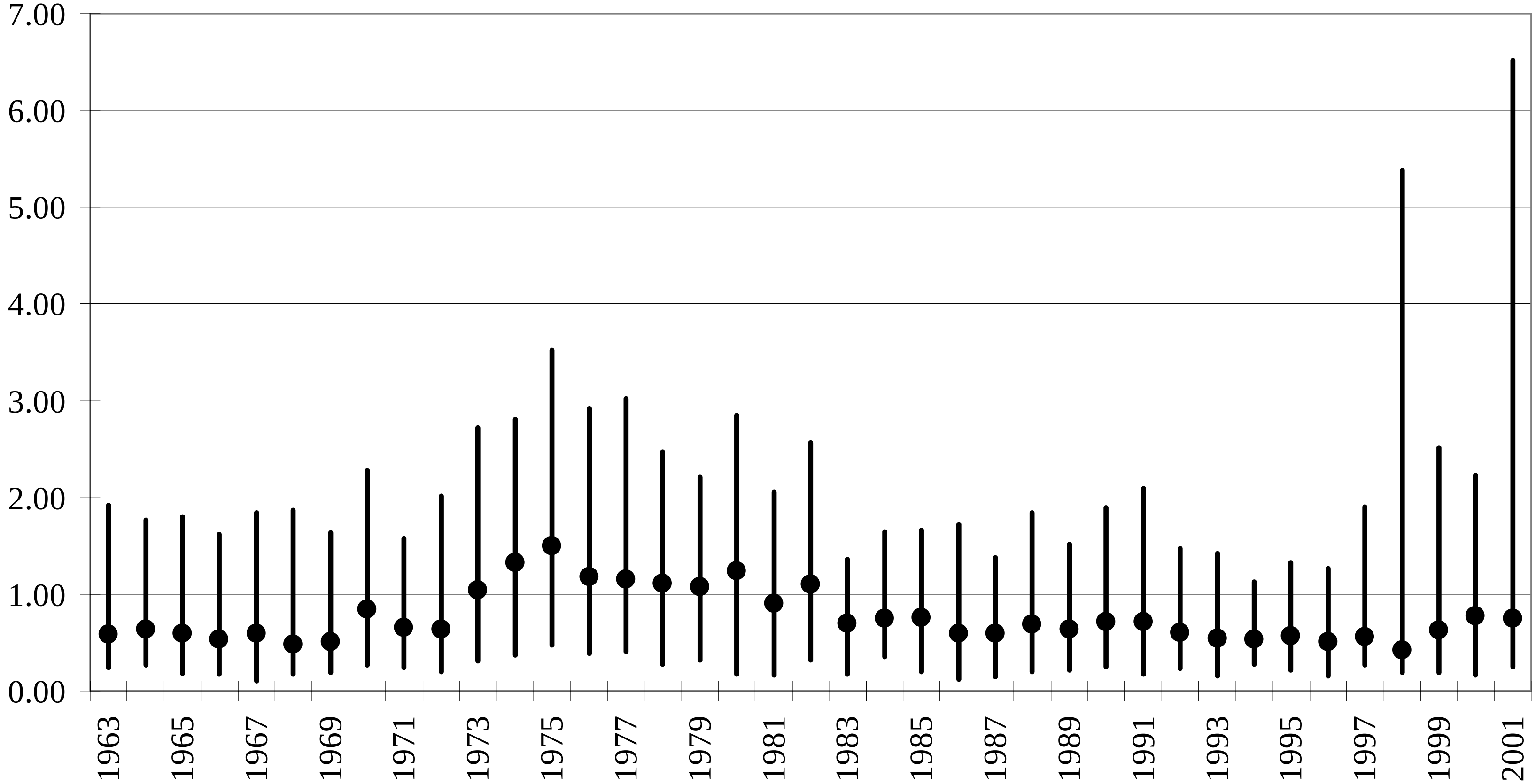


Exhibit 2

Distribution of absolute percentage stock pricing error for each of three valuation ratios under (1) an aggregate median multiple and (2) industry-based peer group median multiples. Absolute percentage pricing error for stock *i* is defined as

$$\left|e_i^k\right| = \left|\frac{P_i - P_{ik}^*}{P_{ik}^*}\right|$$

Ratio Used	Model Form	Median Value	Percentage of Stocks with $\lvert e_i^k \rvert < 0.15$
Book-to-market (B/M)	Aggregate median	0.42	18.2%
Book-to-market (B/M)	Industry-based medians	0.35	26.1%
Cash flow-to-market (C/M)	Aggregate median	0.40	19.8%
Cash flow-to-market (C/M)	Industry-based medians	0.32	28.5%
Earnings-to-market (E/M)	Aggregate median	0.38	21.1%
Earnings-to-market (E/M)	Industry-based medians	0.32	28.5%

Exhibit 3
Do valuation rankings revert towards the median? One-year-ahead Quintiles Transition Probabilities

Value rank based upon Book-to-Market Ratio (B/M)
One-year-ahead relative value quintile

			Low B/M 1	2	3	4	High B/M 5	Re-ranking frequencies Correct Signal	Incorrect Signal
	Low B/M	1	**0.71**	0.19	0.06	0.03	0.01	0.29	NA
Current		2	0.23	**0.44**	0.22	0.08	0.02	0.33	0.23
Relative		3	0.07	0.24	**0.40**	0.23	0.06	NA	NA
Value		4	0.02	0.08	0.24	**0.45**	0.20	0.35	0.20
Quintile	High B/M	5	0.01	0.02	0.07	0.23	**0.68**	0.32	NA

Value rank based upon Cash Flow-to-Market Ratio (C/M)
One-year-ahead relative value quintile

			Low C/M 1	2	3	4	High C/M 5	Re-ranking frequencies Correct Signal	Incorrect Signal
	Low C/M	1	**0.60**	0.21	0.11	0.05	0.02	0.40	NA
Current		2	0.25	**0.36**	0.23	0.12	0.04	0.39	0.25
Relative		3	0.12	0.23	**0.33**	0.24	0.08	NA	NA
Value		4	0.06	0.12	0.23	**0.39**	0.20	0.41	0.20
Quintile	High C/M	5	0.03	0.05	0.10	0.23	**0.60**	0.40	NA

Value rank based upon Earnings-to-Market Ratio (E/M)
One-year-ahead relative value quintile

			Low E/M 1	2	3	4	High E/M 5	Re-ranking frequencies Correct Signal	Incorrect Signal
	Low E/M	1	**0.49**	0.23	0.13	0.09	0.06	0.51	NA
Current		2	0.24	**0.31**	0.24	0.14	0.07	0.45	0.24
Relative		3	0.15	0.22	**0.29**	0.23	0.11	NA	NA
Value		4	0.11	0.13	0.22	**0.33**	0.20	0.47	0.20
Quintile	High E/M	5	0.09	0.08	0.12	0.22	**0.49**	0.51	NA

Exhibit 4
Mean reversion in valuation ratios
The parameter estimates, t-statistics (in parentheses), and R^2 values are reported for two regressions

Dependent Variable	Change in individual stock ratio ($\rho_{i,t+1} - \rho_{i,t}$)			Individual stock ratio minus Median ($\rho_{i,t+1} - \rho_{med,t+1}$)		
Regression	$(\rho_{i,t+1} - \rho_{i,t}) = a + b(\rho_{med,t} - \rho_{i,t}) + u_{i,t+1}$			$(\rho_{i,t+1} - \rho_{med,t+1}) = c + d(\rho_{i,t} - \rho_{med,t}) + u_{i,t+1}$		
Valuation Ratio	Intercept (*a*)	Slope (*b*)	R^2	Intercept (*c*)	Slope (*d*)	R^2
Book-to-market	0.066 (2.40)	0.029 (5.43)	0.007	0.037 (5.38)	0.969 (178.65)	0.898
Cash flow-to-market	0.011 (1.85)	0.047 (5.81)	0.016	0.008 (5.43)	0.951 (118.25)	0.877
Earnings-to-market	0.006 (1.52)	0.090 (9.09)	0.035	0.005 (5.80)	0.910 (93.89)	0.800

Exhibit 5

All NYSE/AMEX/NASDAQ stocks: 1962-2001

Average difference between annualized returns on equal-weighted valuation ratio-based portfolios

t-statistics (scaled Sharpe ratios) are reported in parentheses below average return difference entries

		Investment Horizon			
Valuation Ratio	**Hedging Approach**	**1-year**	**2-year**	**3-year**	**4-year**
Book-to-market	Industry-neutral	0.0680 (4.04)	0.0982 (5.88)	0.0939 (5.29)	0.0637 (3.54)
Book-to-market	Full Universe	0.0681 (2.27)	0.1156 (4.21)	0.0887 (2.88)	0.0540 (1.63)
Cash flow-to-market	Industry-neutral	0.0721 (3.35)	0.0974 (5.20)	0.0758 (4.77)	0.0695 (4.00)
Cash flow-to-market	Full Universe	0.0871 (2.32)	0.0982 (3.28)	0.0841 (2.60)	0.0453 (1.35)
Earnings-to-market	Industry-neutral	0.0416 (2.32)	0.0546 (3.94)	0.0477 (3.10)	0.0588 (3.35)
Earnings-to-market	Full Universe	0.0242 (0.87)	0.0851 (3.49)	0.0632 (2.52)	0.0422 (1.23)

Exhibit 6

NASDAQ stocks only: 1974-2001

Average difference between annualized returns on equal-weighted valuation ratio-based portfolios

t-statistics (scaled Sharpe ratios) are reported in parentheses below average return difference entries

		Investment Horizon			
Valuation Ratio	**Hedging Approach**	**1-year**	**2-year**	**3-year**	**4-year**
Book-to-market	Industry-neutral	0.1363 (4.88)	0.1248 (4.44)	0.1326 (4.99)	0.0603 (1.72)
Book-to-market	Full Universe	0.1317 (2.92)	0.1760 (3.46)	0.1148 (2.30)	0.0468 (0.72)
Cash flow-to-market	Industry-neutral	0.1752 (5.81)	0.1320 (4.08)	0.1359 (4.99)	0.0800 (2.10)
Cash flow-to-market	Full Universe	0.1150 (2.21)	0.1667 (3.09)	0.1363 (2.74)	0.0547 (0.81)
Earnings-to-market	Industry-neutral	0.1178 (5.99)	0.0973 (3.03)	0.0756 (2.38)	0.0529 (1.64)
Earnings-to-market	Full Universe	0.0803 (1.85)	0.1386 (3.35)	0.0880 (1.91)	0.0633 (1.27)

Exhibit 7

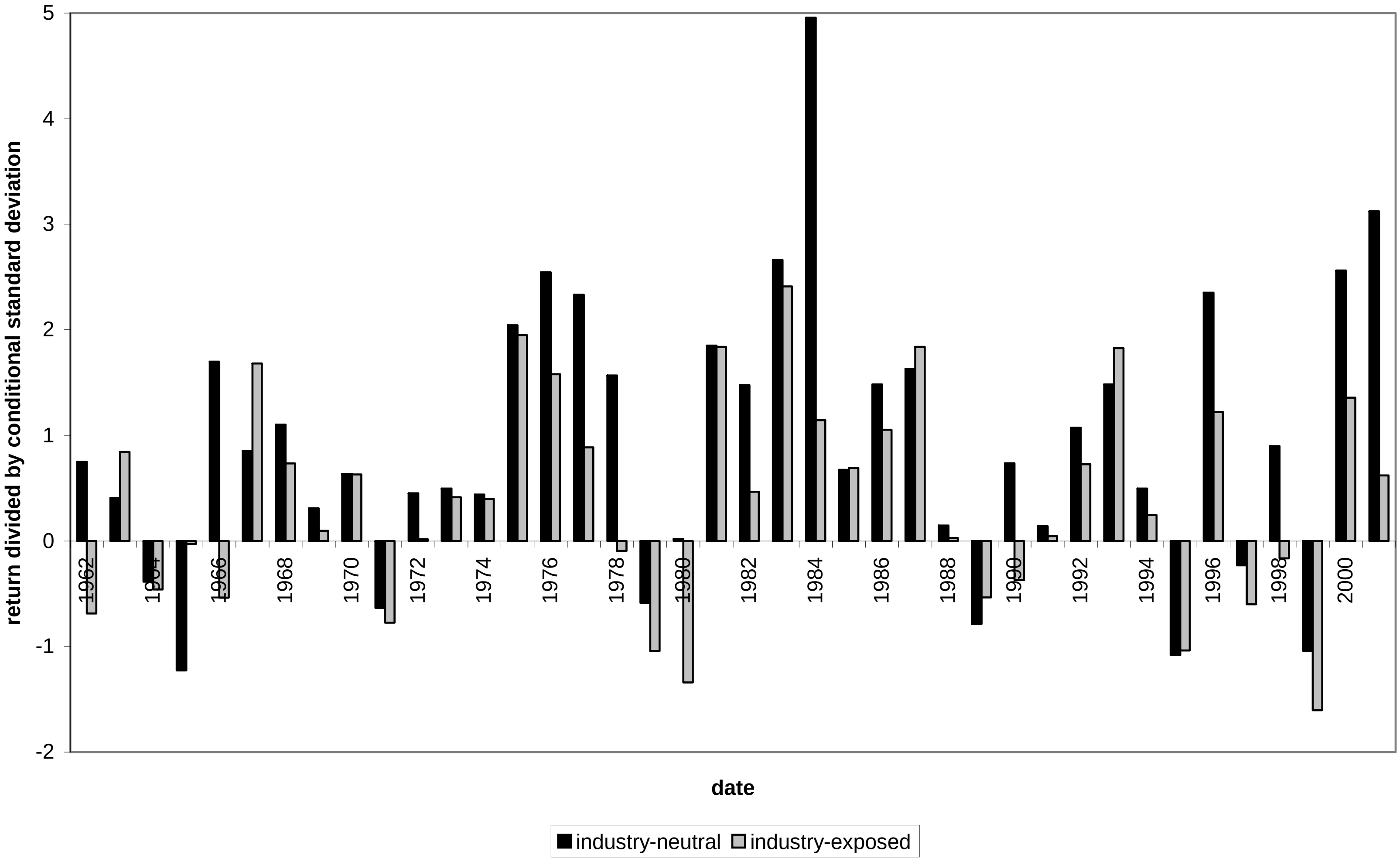
All NYSE/AMEX/NASDAQ stocks: 1962-2001

Average difference between annualized returns on equal-weighted valuation ratio-based portfolios

t-statistics (scaled Sharpe ratios) are reported in parentheses below average return difference entries

		Investment Horizon			
Valuation Ratio	**Hedging Approach**	**1-year**	**2-year**	**3-year**	**4-year**
Book-to-market	Industry-neutral	0.0691 (4.58)	0.0968 (6.24)	0.0864 (5.07)	0.0695 (4.37)
Book-to-market	Full Universe	0.0724 (2.57)	0.1083 (4.31)	0.0884 (3.23)	0.0626 (2.18)
Cash flow-to-market	Industry-neutral	0.0681 (3.94)	0.0979 (6.12)	0.0935 (5.90)	0.0721 (5.03)
Cash flow-to-market	Full Universe	0.0871 (2.91)	0.0970 (3.88)	0.0806 (2.98)	0.0551 (1.71)
Earnings-to-market	Industry-neutral	0.0360 (2.20)	0.0593 (4.52)	0.0483 (3.32)	0.0529 (3.81)
Earnings-to-market	Full Universe	0.0361 (1.45)	0.0749 (3.22)	0.0618 (2.87)	0.0465 (1.88)

Exhibit 8. Year-by-Year Scaled Returns: Industry-Neutral vs Industry-Exposed



ENDNOTES

[1] See Coggin, Fabozzi, and Arnott (1997) for a general definition of value versus growth stocks.

[2] The interpretation of higher returns to contrarian strategies has been very controversial. There are two main explanations that are based on higher risk premiums due to distress risk (e.g., Fama and French (1992, 1993), and Bourguignon and de Jong (2003)) and mispricing due to naive investor expectations of future growth (e.g., Lakonishok, Shleifer, and Vishny (1994) and La Porta (1996)). Furthermore, Daniel and Titman (1998) and Arshanapalli, Coggin and Doukas (1998) do not find any evidence that value stocks are riskier than growth stocks.

[3] Kim and Ritter (1999) discuss the importance of peer group composition and compare valuation results under alternative peer group definitions for a sample of IPOs.

[4] A decade earlier, Alford (1992) had examined price-earnings multiples under alternative peer grouping choices for a three-year sample and concluded that such SIC-based industry groupings captured much of the same information that other non-industry groupings matched on size or profitability contained.

[5] A partial list includes Rosenberg, Reid, and Lanstein (1984), Fama and French (1992, 1993), Lakonishok, Shleifer, and Vishny (1994), La Porta (1996), and Chan, Jegadeesh, and Lakonishok (1995).

[6] Our data set contains 92,266 stock observations over the 1962-2001 sample. On average, this implies 2,307 stocks per year. The maximum number of stocks in one year was 4,348 (1998) and the minimum number was 75 (1962).

[7] Although the original sample covers the period from 1962 to 2002, when we use one-year-ahead returns we lose one observation so that our empirical analyses are based on the period from 1962 to 2001.

[8] We test the equality of median book-to-market, cash flow-to-market, and earnings-to-market ratios across different industry groups using the Kruskal-Wallis test. The *p*-value of each test statistic is below 1% for all years from 1963 to 2001.

[9] The *p*-value of each Kruskal-Wallis test statistic is below 1% for all three multiples.

[10] In each year, the number of stocks in each portfolio depends on the number of industries defined for that year.

[11] The number of stocks in each year's "full universe" portfolio equals the number of industries defined for that year (e.g., if there were 60 industries, our "full universe" portfolio contains the 60 cheapest stocks and the 60 richest stocks, respectively).

[12] The t-statistics reported in Exhibit 5 are calculated as the ratio of mean returns (μ) to the time-series standard error of returns ($\sigma / \sqrt{n}$), where σ is the standard deviation of returns and n is the number of observations: $t = \mu / (\sigma / \sqrt{n})$. Hence, the t-statistic can be interpreted as a *scaled* Sharpe ratio since the *Sharpe ratio* = $\mu / \sigma = t / \sqrt{n}$.

[13] If there are more than 20 but fewer than 30 companies in an industry, we buy two stocks and sell two stocks. If there are more than 30, but fewer than 40 companies in an industry, we buy three stocks and sell three stocks, etc. The full-universe portfolios are formed using an identical overall number of stocks. (For industries with fewer than 20 stocks, we buy one stock and sell one stock.)

[14] We used the standard GARCH(1,1) approach of Bollerslev (1986) to estimate the conditional variance of portfolio returns for each year.