

Peer Pressure

Industry group impacts on stock valuation precision and contrarian strategy performance.

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Stock valuation and portfolio construction are two core activities for active equity investment managers, although investment textbooks traditionally treat the two functions practically as separate functions. 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 according to discounted cash flow models and in *relative* terms according to various multiples that show the company's standing among comparable firms.

More recently, portfolio construction schemes based on sorting stocks according to 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 investment managers use to 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 that favor 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 generated by identifying cheap stocks, as price/book

value is one of a set of multiples practitioners use to determine the relative valuations of individual companies. For example, investment bankers routinely include an assessment of company value in terms of multiples as part of their due diligence for mergers and acquisitions proposals and initial public offering-related background.

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. One practical and quite important difference between practitioner use of the ratio for individual company valuation and academics' use for portfolio construction concerns the universe of stocks considered.

When they test the effectiveness of contrarian portfolio strategies, academic researchers 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). When they assess the relative value of any specific individual company, practitioners, however, 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

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 on company valuation and hedge fund trading practice, we explore here the implications of invoking industry effects in 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 by itself 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 how quickly individual firm value ratios correct themselves back toward the peer group median. Surprisingly, we find no studies of the dynamics of individual firm characteristic value ratios in the literature.

Our analysis of the dynamics of the three valuation ratios indicates substantial inertia in relative value rankings. In other words, mean reversion for deviations of an individual firm's ratio from its industry median is quite slow. Nevertheless, because of substantial initial relative value differences, the 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 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 a more generic contrarian strategy in Sharpe ratio terms.

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] apply 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 They examine 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).

As the Lie and Lie [2002] study is based on a one-year snapshot of data (fiscal 1998), it does not report 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 determining 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 very few authors attempt to identify and incorporate industry effects in their analysis. Within a voluminous literature, we know of only three articles that attempt 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 1970–1995 sample to examine within-industry value rankings of firms sorted 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 marketwide sortings. They find evidence from average contrarian strategy returns that industry sortings reveal a relative-value component beyond that in the aggregated analysis. Furthermore, industry-neutral long-short portfolios could perform better than industry-exposed marketwide hedge portfolios in Sharpe ratio terms if industry effects on return risk are important.

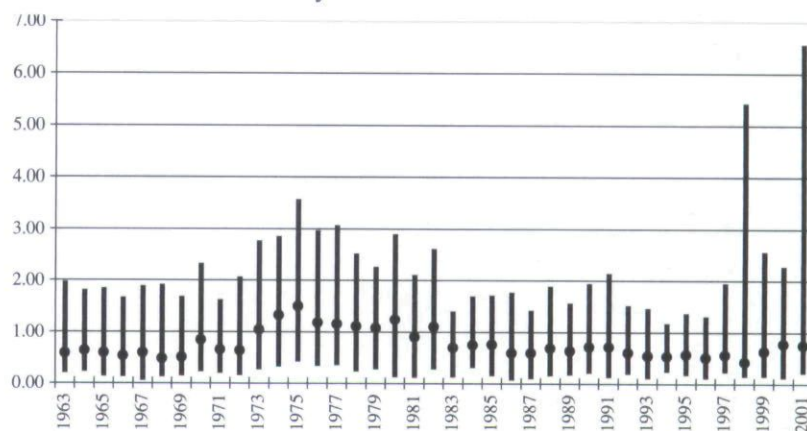
Cohen and Polk [1998] provide some evidence that industry-neutral long-short strategies do improve Sharpe ratios using data from a 1968–1991 sample period. Asness, Porter, and Stevens [2000] also compare marketwide sortings on book value and cash flow ratios to within-industry sortings based on the deviation 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 as particularly interesting with 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 the late 1990s.

Furthermore, we view predicting subsequent moves in individual firm stock value ratios on the basis of the

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.

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 toward the peer group median. None of these earlier studies provide 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 Security 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 through April of year $t + 1$. This alignment ensures that the accounting variables are known to the market in advance of return realizations (see Lakonishok, Shleifer, and Vishny [1994]).⁶

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 according to 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 1962–2002 period.⁷ Alford [1992] notes very little marginal valuation performance improvement in moving from three-digit to four-digit SIC code industry groupings, so we group firms on the basis of three-digit SIC codes if the resulting industry includes 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. In our work 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. Other authors acknowledge that the aggregate book-to-market ratio fluctuates over time (e.g., Kothari and Shanken [1997]), but Exhibit 1 reveals that there is also 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 valua-

tion 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 time.

USING CHARACTERISTIC MULTIPLES TO VALUE STOCKS

Assume that the i -th stock S_i , $1 \leq i \leq N$, belongs to the j -th industry I_j , $1 \leq j \leq M$. 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 ratio, which we denote by ρ_i^k , $1 \leq k \leq 3$, we compute the median ratio in each industry group, ρ_{med}^{jk} , $1 \leq j \leq M$, $1 \leq k \leq 3$, i.e., $\rho_{med}^{jk} = \text{median} \{ \rho_i^k | S_i \in I_j \}$. 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

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

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:

$$e_i^k = \frac{P_i - P_{ik}^*}{P_{ik}^*} \quad (2)$$

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.

EXHIBIT 2

Distribution of Absolute Percentage Stock Pricing Error for Three Valuation Ratios

Ratio Used	Model Form	Median Value	Percentage of Stocks with $ e_i^k < 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%

Lie and Lie [2002] began their analysis by *presuming* that forming industry peer groups improves 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 compared to the aggregated, single median ratio approach. 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 using the industry-specific median ratios falls to 35%. Using the model based upon the cash flow-to-market ratio, the median absolute percentage stock price error by the single aggregate median ratio is 40%. The corresponding value using the industry-specific median ratios falls to 32%. Finally, using the earnings-to-market ratio model, the median absolute percentage stock price error by the single aggregate median ratio is 38% compared to 32%. In all cases, the test statistic strongly rejects the hypothesis that the median absolute percentage errors in the two methods are equal.⁹

Furthermore, use of the industry-based peer groups dramatically increases the fraction of firms with valuation errors within absolute percentage pricing errors of 15% (e.g., for the book-to-market ratio, from under one-fifth to over one-quarter).

In 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. Yet scant attention is paid to alternative hypotheses concerning the *dynamics* of any 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. We estimate transition probabilities designed to describe a given stock's subsequent one-period-ahead value quintile rank (in the columns) as a function of its current rank (in the rows). Estimates are presented for each value ratio.

Panel A of Exhibit 3, for example, 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.

When future re-rankings *do* occur, however, 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 and earnings-to-market ratios. The results still reveal substantial inertia with respect to re-rankings among value quintiles, but 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. 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 a high degree of persistence in key characteristic-based valuation measures. But we can address the persistence/mean reversion question 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):

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

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

EXHIBIT 3

One-Year-Ahead Quintile Transition Probabilities

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

			Low B/M					Re-ranking frequencies	
			1	2	3	4	5	Correct Signal	Incorrect Signal
Current Relative Value Quintile	Low B/M	1	0.71	0.19	0.06	0.03	0.01	0.29	NA
		2	0.23	0.44	0.22	0.08	0.02	0.33	0.23
	High B/M	3	0.07	0.24	0.40	0.23	0.06	NA	NA
		4	0.02	0.08	0.24	0.45	0.20	0.35	0.20
		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					Re-ranking frequencies	
			1	2	3	4	5	Correct Signal	Incorrect Signal
Current Relative Value Quintile	Low C/M	1	0.60	0.21	0.11	0.05	0.02	0.40	NA
		2	0.25	0.36	0.23	0.12	0.04	0.39	0.25
	High C/M	3	0.12	0.23	0.33	0.24	0.08	NA	NA
		4	0.06	0.12	0.23	0.39	0.20	0.41	0.20
		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					Re-ranking frequencies	
			1	2	3	4	5	Correct Signal	Incorrect Signal
Current Relative Value Quintile	Low E/M	1	0.49	0.23	0.13	0.09	0.06	0.51	NA
		2	0.24	0.31	0.24	0.14	0.07	0.45	0.24
	High E/M	3	0.15	0.22	0.29	0.23	0.11	NA	NA
		4	0.11	0.13	0.22	0.33	0.20	0.47	0.20
		5	0.09	0.08	0.12	0.22	0.49	0.51	NA

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 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:

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

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 ratio. The results reveal a consistently low 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

EXHIBIT 4

Mean Reversion In Valuation Ratios

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

t-statistics in parentheses.

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 in 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 this figure is statistically significant, the degree of mean reversion applicable for contrarian investment strategies appears low.

DO 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. 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 the results to results 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 formed with the cheapest and the richest stocks in the full universe. 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.¹¹

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 (the industry-neutral and full-universe) for each valuation ratio. 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

EXHIBIT 5

All NYSE/Amex/Nasdaq Stocks: 1962-2001

Valuation Ratio	Hedging Approach	Investment Horizon			
		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)
	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)
	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)
	Full Universe	0.0242 (0.87)	0.0851 (3.49)	0.0632 (2.52)	0.0422 (1.23)

t-statistics (scaled Sharpe ratios) in parentheses.

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 high (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 are in reasonable agreement with those in 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 considered only 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 multiyear horizons.

Columns 2, 3, and 4 of Exhibit 5 present results for annual returns of the industry-neutral and full-universe strategies over additional years after portfolio formation. 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 on the valuation ratio used and the 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.

We have so far examined individual stocks and defined industry peer groups based upon all available firms in our sample. But Kim and Ritter [1999] note that identification of the appropriate peer group is the crucial first step in the company valuation process. Furthermore, one of our motivations for investigating the potential importance of industry effects is 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.

Compared to NYSE-listed companies, companies listed on Nasdaq are typically younger and smaller, 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 valuation ratio.

The most striking result in 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 in Exhibit 5). At the same horizon, the corresponding figure is 17.5% using the cash flow-to-market ratio for valuation.

The 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 lower than that of the aggregated approach (3.35). Interestingly enough, at the one-year horizon for that same ratio, we cannot reject the hypothesis that the average net return is zero under the aggregated approach.

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 the 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. 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.¹³

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 this analysis of one-year-ahead returns for the two net return series (i.e., the industry-neutral and full universe) using our full comple-

EXHIBIT 6

Nasdaq Stocks Only: 1974-2001

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

t-statistics (scaled Sharpe ratios) in parentheses.

EXHIBIT 7

Decile Portfolios: All NYSE/Amex/Nasdaq Stocks: 1962-2001

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

t-statistics (scaled Sharpe ratios) in parentheses.

ment 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. (The plotted data are for the book-to-market contrarian strategy and encompass our full sample of all NYSE/Amex/Nasdaq stocks.)¹⁴

By 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 higher than that of the full-universe strategy in 32 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

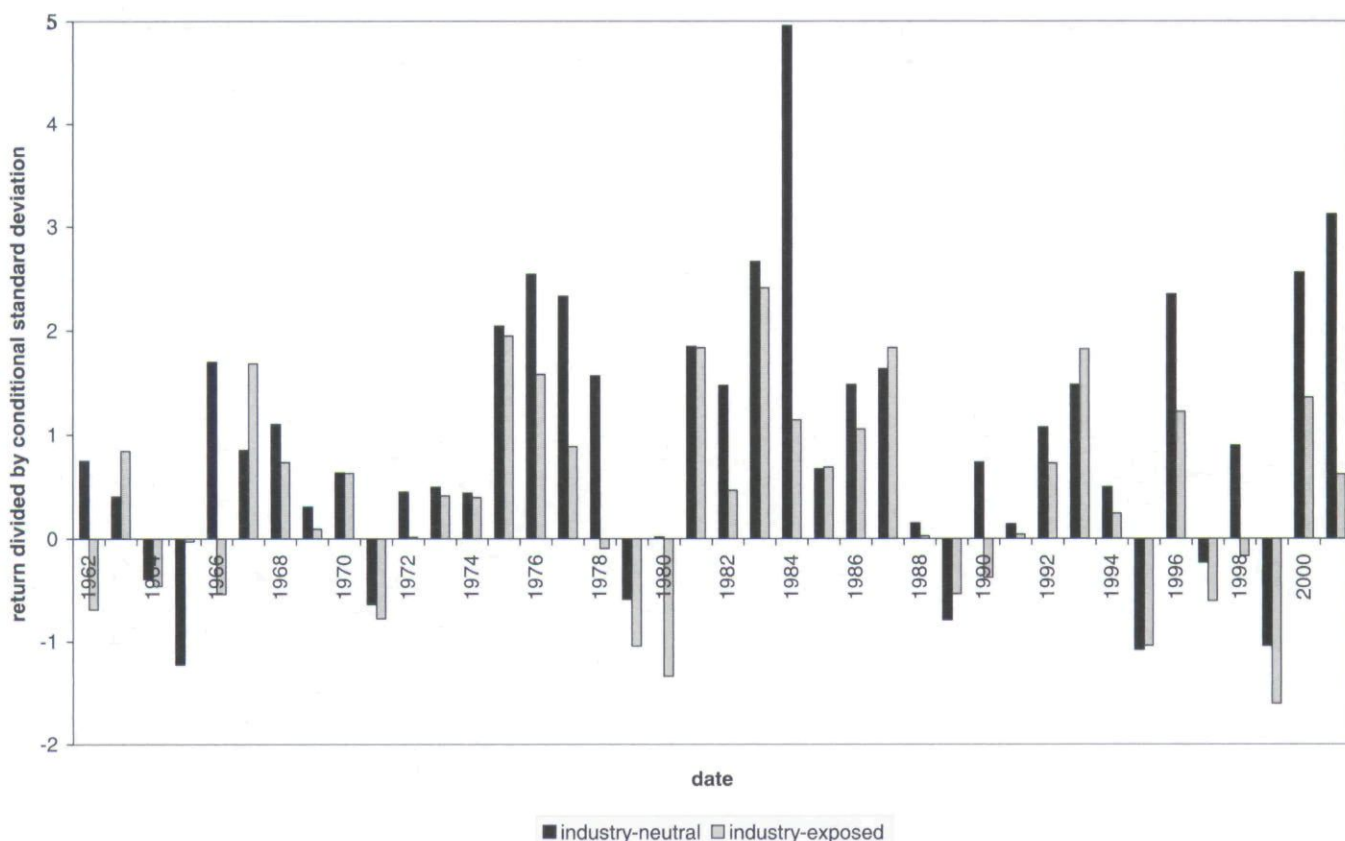
Investment bankers have long focused on narrow industry-based peer groups for individual stock valuation analysis such as in pricing IPOs. Some market-neutral equity hedge fund managers restrict portfolios to be sector-neutral as well. Academic research into contrarian strategy investment performance,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

Here, we find in favor of the bankers and the hedge fund managers. Industry effects matter. In our sample, narrow industry-based peer groups improve stock valuation precision for three key valuation ratios. At the same time, our analysis of the dynamics of the three valuation ratios indicates substantial inertia in relative-value rankings. In other words, 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

EXHIBIT 8

Year-by-Year Scaled Returns: Industry-Neutral versus Industry-Exposed



speed of the mean reversion process for the key value ratios, excess returns persist beyond the one-year horizon.

Most important, 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 appear to have been particularly useful in the boom and bust cycle of the late 1990s and early 2000s.

ENDNOTES

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support from the PSC-CUNY Research Foundation of the City University of New York.

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

²The interpretation of higher returns to contrarian strategies has been controversial. Two main explanations are based on 1) higher risk premiums due to distress risk (e.g., Fama and French [1992, 1993], and Bourguignon and de Jong [2003]), and 2) mispricing due to naive investor expectations of future growth (e.g., Lakonishok, Shleifer, and Vishny [1994] and La Porta [1996]). Furthermore, Arshanapalli, Coggin, and Doukas [1998] and Daniel and Titman [1998] do not find any evidence that value stocks are riskier than growth stocks.

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

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

⁵A partial list includes Rosenberg, Reid, and Lanstein [1984],

Fama and French [1992, 1993], Lakonishok, Shleifer, and Vishny [1994], Chan, Jegadeesh, and Lakonishok [1995], and La Porta [1996].

⁶Our data set includes 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 is 4,348 (1998), and the minimum number is 75 (1962).

⁷Although the original sample covers the period from 1962 through 2002, when we use one-year-ahead returns we lose one observation, so that our empirical analysis is based on the period from 1962 through 2001.

⁸We 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 through 2001.

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

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

¹¹The 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 includes the 60 cheapest stocks and the 60 richest stocks).

¹²The 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 $= \mu/\sigma = t/\sqrt{n}$.

¹³If 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, and so on. 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.)

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

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