Journal of Accounting Research
Vol. 40 No. 1 March 2002
Printed in U.S.A.

Equity Valuation Using Multiples

JING LIU,* DORON NISSIM,† AND JACOB THOMAS‡

Received 2 January 2000; accepted 27 July 2001

ABSTRACT

We examine the valuation performance of a comprehensive list of value drivers and find that multiples derived from forward earnings explain stock prices remarkably well: pricing errors are within 15 percent of stock prices for about half our sample. In terms of relative performance, the following general rankings are observed consistently each year: forward earnings measures are followed by historical earnings measures, cash flow measures and book value of equity are tied for third, and sales performs the worst. Curiously, performance declines when we consider more complex measures of intrinsic value based on short-cut residual income models. Contrary to the popular view that different industries have different "best" multiples, these overall rankings are observed consistently for almost all industries examined. Since we require analysts' earnings and growth forecasts and positive values for all measures, our results may not be representative of the many firm-years excluded from our sample.

1. Introduction

In this study we examine the proximity to stock prices of valuations generated by multiplying a value driver (such as earnings) by the corresponding multiple, where the multiple is obtained from the ratio of stock price to that value driver for a group of comparable firms. While multiples are used extensively in practice, there is little published research in the academic literature documenting the absolute and relative performance of different

* University of California at Los Angeles; † Columbia University; ‡ Columbia University. We thank Richard Leftwich and an anonymous referee for their many useful suggestions. We also received helpful comments from David Aboody, Sanjay Bhagat, Ted Christensen, Glen Hansen, Jack Hughes, Jim Ohlson, Stephen Penman, Phil Shane, Michael Williams, and seminar participants at the AAA Annual Meeting at Philadelphia, University of Colorado, Columbia University, Copenhagen Business School, Ohio State University, and UCLA.

Copyright ©, University of Chicago on behalf of the Institute of Professional Accounting, 2002

multiples.[1] We seek to investigate the performance of a comprehensive list of multiples, and also examine a variety of related issues, such as the variation in performance across industries and over time and the performance improvement obtained by using alternative approaches to compute multiples.

Although the actual valuation process used by market participants is unobservable, we assume that stock prices can be replicated by comprehensive valuations that convert all available information into detailed projections of future flows. Given this efficient markets framework for traded stocks, what role do multiples play? Even in situations where market valuations are absent, either because the equity is privately-held or because the proposed publicly traded entity has not yet been created (e.g., mergers and spinoffs), is there a role for multiples vis-à-vis comprehensive valuations? While the multiple approach bypasses explicit projections and present value calculations, it relies on the same principles underlying the more comprehensive approach: value is an increasing function of future payoffs and a decreasing function of risk. Therefore, multiples are used often as a substitute for comprehensive valuations, because they communicate efficiently the essence of those valuations. Multiples are also used to complement comprehensive valuations, typically to calibrate those valuations and to obtain terminal values.[2]

In effect, our study documents the extent to which different value drivers serve as a summary statistic for the stream of expected payoffs, and comparable firms resemble the target firm along important value attributes, such as growth and risk. We first evaluate value drivers using the conventional ratio representation (i.e., price doubles when the value driver doubles). To identify the importance of incorporating the average effect of omitted variables, we extend the ratio representation to allow for an intercept in the price/value driver relation. To study the impact of selecting comparable firms from the same industry, we contrast our results obtained by using industry comparables (the middle category from the Sector/Industry/Group classification provided by IBES) with results obtained when all firms available each year are used as comparables. As in prior research, we evaluate performance by examining the distribution of pricing errors (actual price less predicted price, scaled by actual price).

The value drivers we consider include measures of historical cash flow, such as cash flow from operations and EBITDA (earnings before interest,

[1] Studies offering descriptive evidence include Boatsman and Baskin [1981], LeClair [1990], and Alford [1992]. Recently, a number of studies have examined the role of multiples for firm valuation in specific contexts, such as tax and bankruptcy court cases and initial public offerings (e.g., Beatty, Riffe, and Thompson [1999], Gilson, Hutchkiss, and Ruback [2000], Kim and Ritter [1999], and Tasker [1998]).

[2] Another very different role for multiples that has been examined in the literature is the identification of mispriced stocks. We do not investigate that role because we assume market efficiency. Two such market inefficiency studies are Basu [1977] and Stattman [1980], where portfolios derived from earnings and book value multiples are shown to earn abnormal returns.

taxes, depreciation, and amortization), and historical accrual-based measures, such as sales, earnings, and book value of equity. We also consider forward-looking measures derived from analysts' forecasts of EPS (earnings per share) and long-term growth in EPS, such as 2-year out consensus EPS forecasts and PEG (price-earnings-growth) ratios (e.g., Bradshaw [1999a; 1999b]). Since sales and EBITDA should properly be associated with enterprise value (debt plus equity), rather than equity alone, for those two value drivers we also consider multiples based on enterprise value (market value of equity plus book value of debt). Finally, we consider short-cut intrinsic value measures based on the residual income model that have been used recently in the academic literature (e.g., Frankel and Lee [1998], and Gebhardt, Lee, and Swaminathan [2001]).

The following is an overview of the relative performance of different value drivers: (1) forward earnings perform the best, and performance improves if the forecast horizon lengthens (1-year to 2-year to 3-year out EPS forecasts) and if earnings forecasted over different horizons are aggregated; (2) the intrinsic value measures, based on short-cut residual income models, perform considerably worse than forward earnings;[3] (3) among drivers derived from historical data, sales performs the worst, earnings performs better than book value; and IBES earnings (which excludes many one-time items) outperforms COMPUSTAT earnings; (4) cash flow measures, defined in various forms, perform poorly; and (5) using enterprise value, rather than equity value, for sales and EBITDA further reduces performance.

Turning from relative performance to absolute performance, forward earnings measures describe actual stock prices reasonably well for a majority of firms. For example, for 2-year out forecasted earnings, approximately half the firms have absolute pricing errors less than 16 percent. The dispersion of pricing errors increases substantially for multiples based on historical drivers, such as earnings and cash flows, and is especially large for sales multiples.

Some other important findings are as follows: (1) performance improves when multiples are computed using the harmonic mean, relative to the mean or median ratio of price to value driver for comparable firms, (2) performance declines substantially when all firms in the cross-section each year are used as comparable firms, (3) allowing for an intercept improves performance mainly for poorly-performing multiples, and (4) relative performance is relatively unchanged over time and across industries.

Our findings have a number of implications for valuation research. First, we confirm the validity of two precepts underlying the valuation role of accounting numbers: (1) accruals improve the valuation properties of cash flows, and (2) despite the importance of top-line revenues, its value

[3] Bradshaw [1999a and 1999b] observes results that are related to ours. He finds that valuations based on PEG ratios (this ratio of forward P/E to forecast growth in EPS is described later in section 3.1) explain more variation in analysts' target prices and recommendations than more complex intrinsic value models.

relevance is limited until it is matched with expenses. Second, we confirm that forward earnings contain considerably more value-relevant information than historical data, and they should be used as long as earnings forecasts are available. Third, contrary to general perception, different industries are not associated with different "best multiples." Finally, our investigation of the signal/noise tradeoff associated with the more complex intrinsic value drivers based on the residual income model suggests that even though these measures utilize more information than that contained in forward earnings and impose a structure derived from valuation theory on that information, measurement error associated with the additional variables required, especially terminal value estimates, negatively impacts performance.[4]

These findings are associated with certain caveats. Since we exclude firms not covered by IBES, typically firms with low and medium market capitalization, we are uncertain about the extent to which our results extend to those firms. Even firms with IBES data are not fully represented in our sample, since we exclude firm-years with negative values for any value driver. In particular, our results may not be descriptive of start-up firms reporting losses and high growth firms with negative operating cash flows.

2. *Prior Research*

While textbooks on valuation (e.g., Copeland, Koller, and Murrin [1994], Damodaran [1996], and Palepu, Healy, and Bernard [2000]) devote considerable space to discussing multiples, most published papers that study multiples examine a limited set of firm-years and consider only a subset of multiples, such as earnings and EBITDA. Also, comparisons across different studies are hindered by methodological differences.

Among commonly used value drivers, historical earnings and cash flows have received most of the attention. Boatsman and Baskin [1981] compare the valuation accuracy of P/E multiples based on two sets of comparable firms from the same industry. They find that valuation errors are smaller when comparable firms are chosen based on similar historical earnings growth, relative to when they are chosen randomly. Alford [1992] investigates the effects of choosing comparables based on industry, size (risk), and earnings growth on the precision of valuation using P/E multiples. He finds that pricing errors decline when the industry definition used to select comparable firms is narrowed from a broad, single digit SIC code to classifications based on two and three digits, but there is no additional improvement when the four-digit classification is considered. He also finds that controlling for size and earnings growth, over and above industry controls, does not reduce valuation errors.

---

[4] Given our efficient markets framework, we do not investigate here whether the relatively poor performance of the intrinsic value measures is due to an inefficient market that values stocks using multiples of forward earnings. We find evidence inconsistent with that explanation in a separate paper (Liu, Nissim, and Thomas [2001]).

Kaplan and Ruback [1995] examine the valuation properties of the discounted cash flow (DCF) approach for highly leveraged transactions. While they conclude that DCF valuations approximate transacted values reasonably well, they find that simple EBITDA multiples result in similar valuation accuracy. Beatty, Riffe, and Thompson [1999] examine different linear combinations of value drivers derived from earnings, book value, dividends, and total assets. They derive and document the benefits of using the harmonic mean, and introduce the price-scaled regressions we use. They find the best performance is achieved by using (1) weights derived from harmonic mean book and earnings multiples and (2) coefficients from price-scaled regressions on earnings and book value.

In a recent study, Baker and Ruback [1999] examine econometric problems associated with different ways of computing industry multiples, and compare the relative performance of multiples based on EBITDA, EBIT (or earnings before interest and taxes), and sales. They provide theoretical and empirical evidence that absolute valuation errors are proportional to value. They also show that industry multiples estimated using the harmonic mean are close to minimum-variance estimates based on Monte Carlo simulations. Using the minimum-variance estimator as a benchmark, they find that the harmonic mean dominates alternative simple estimators such as the simple mean, median, and value-weighted mean. Finally, they use the harmonic mean estimator to calculate multiples based on EBITDA, EBIT, and sales, and find that industry-adjusted EBITDA performs better than EBIT and sales.

Instead of focusing only on historical accounting numbers, Kim and Ritter [1999], in their investigation of how initial public offering prices are set using multiples, add forecasted earnings to a conventional list of value drivers, which includes book value, earnings, cash flows, and sales. Consistent with our results, they find that forward P/E multiples (based on forecasted earnings) dominate all other multiples in valuation accuracy, and that the EPS forecast for next year dominates the current year EPS forecast.

Using large data sets could diminish the performance of multiples, since the researcher selects comparable firms in a mechanical way. In contrast, market participants may select comparable firms more carefully and take into account situation-specific factors not considered by researchers. Tasker [1998] examines across-industry patterns in the selection of comparable firms by investment bankers and analysts in acquisition transactions. She finds the systematic use of industry-specific multiples, which is consistent with different multiples being more appropriate in different industries.[5]

[5] Since it is not clear whether the objective of investment bankers/analysts is to achieve the most accurate valuation in terms of smallest dispersion in pricing errors, our results may not be directly comparable with those in Tasker [1998].

3. Methodology

3.1 VALUE DRIVERS

We group the value drivers based on whether they refer to cash flows or accruals, whether they relate to stocks or flows, and whether they are based on historical or forward-looking information.[6] We provide a brief description here for some variables that readers may not be familiar with (details for all variables are provided in Appendix A) and then describe the links drawn in the prior literature between different value drivers and equity value. (1) Accrual flows: sales, actual earnings from COMPUSTAT (CACT) and actual earnings from IBES (IACT). (2) Accrual stocks: book value of equity (BV). (3) Cash flows: cash flow from operations (CFO), free cash flow to debt and equity holders (FCF), maintenance cash flow (MCF), equal to free cash flows for the case when capital expenditures equal depreciation expense, and earnings before interest, taxes, depreciation and amortization (EBITDA). (4) Forward looking information: consensus (mean) one year and two year out earnings forecasts (EPS1, and EPS2), and two forecasted earnings-growth combinations (EG1 = EPS2*(1 + g) and EG2 = EPS2*g), which are derived from EPS2 and *g* (the mean long-term EPS growth forecast provided by analysts). (5) Intrinsic value measures (P1*, P2*, and P3*): These measures are based on the residual income (or abnormal earnings) valuation approach, where equity value equals the book value today plus the present value of future abnormal earnings. Abnormal earnings for years +1 to +5, projected from explicit or implied earnings forecasts for those years, are the same for the first two measures. We assume that after year +5, abnormal earnings remain constant for P1* and equal zero for P2*. For P3*, we assume the level of profitability (measured by ROE) trends linearly from the level implied by earnings forecasted for year +3 to the industry median by year +12, and abnormal earnings remains constant thereafter. (6) Sum of forward earnings (ES1 and ES2): These measures aggregate the separate forward earnings forecasts. ES1 is the sum of the EPS forecasts for years +1 to +5, and ES2 is the sum of the present value of those forecasts.[7] As explained later, these two measures are designed to provide evidence on the poor performance of the intrinsic value measures.

Value drivers based on accruals, which distinguish accounting numbers from their cash flow counterparts, have been used extensively in multiple valuations. Book value and earnings, which are often assumed to represent "fundamentals," have been linked formally to firm value (e.g., Ohlson [1995] and Feltham and Ohlson [1995]). Although the use of sales as a value driver has less theoretical basis, relative to earnings and cash flows,

---

[6] Some value drivers are not easily classified. For example, Sales, which we categorize as an accrual flow, could contain fewer accruals than EBITDA, which we categorize as a cash flow measure.

[7] We thank Jim Ohlson for suggesting ES1.

we consider it because of its wide use in certain emerging industries where earnings and cash flow are perceived to be uninformative.

At an intuitive level, accounting earnings could be more value-relevant than reported cash flows because some cash flows do not reflect value creation (e.g., asset purchases/sales), and accruals allow managers to reflect their judgment about future prospects. The COMPUSTAT EPS measure we consider is reported primary EPS excluding extraordinary items and discontinued operation and the IBES EPS measure is derived from reported EPS by deleting some one-time items, such as write-offs and restructuring charges. To the extent that the IBES measure is a better proxy for "permanent" or "core" earnings expected to persist in the future, it should exhibit superior performance.

The use of cash flow multiples in practice appears to be motivated by the implicit assumption that reported cash flow is the best available proxy for the future cash flows that underlie stock prices, and by the feeling that they are less susceptible to manipulation by management. The four cash flow measures we consider remove the impact of accruals to different extents. EBITDA adjusts pre-tax earnings to debt and equity holders for the effects of depreciation and amortization only. CFO deducts interest and taxes from EBITDA and also deducts the net investment in working capital. FCF deducts from CFO net investments in all long-term assets, whereas MCF only deducts from CFO an investment equal to the depreciation expense for that year.

The potential for analysts' EPS forecasts to reflect value-relevant data not captured by historical earnings has long been recognized in the literature. For example, Liu and Thomas [2000] find that revisions in analysts' earnings forecasts along with changes in interest rates explain a substantially larger portion of contemporaneous stock returns than do earnings surprises based on reported earnings. Consensus estimates are often available for forecasted earnings for the current year (EPS1) and the following year (EPS2). Consensus estimates are also frequently available for the long-term growth forecast (g) for earnings over the next business cycle (commonly interpreted to represent the next 5 years). The measure EG1 ($=$EPS2$^*(1+g)$), which is an estimate of three-year out earnings, should reflect value better than EPS2, if three-year out earnings reflect long-term profitability better than two-year out earnings.

While the second earnings-growth measure EG2 ($=$EPS2*g) also combines the information contained in EPS2 and g, it imposes a different structure. Recently, analysts have justified valuations using the following rule of thumb: forward P/E ratios (current price divided by EPS2) should equal g. If, for example, EPS is expected to grow at 30 percent over the next business cycle, forward P/E should equal 30. Stated differently, the ratio of forward P/E to g (referred to as the PEG ratio) should equal 1. For certain sectors, such as technology, analysts have suggested that even higher PEG ratios are appropriate. Using EG2 as a value driver is equivalent to using a PEG ratio obtained from the PEG ratios of comparable firms.

Several recent studies provide evidence that the intrinsic values derived using the residual income model explain stock prices (e.g., Abarbanell and Bernard [2000], Claus and Thomas [2000]) and returns (e.g., Liu and Thomas [2000], Liu [1999]). The three generic patterns we use to project abnormal earnings past a horizon date have been considered in Frankel and Lee [1998] (P1*), Palepu, Healy, and Bernard [2000] (P2*), and Gebhardt, Lee, and Swaminathan [2001] (P3*). Although these generic approaches do not allow for firm-specific growth patterns for abnormal earnings past a terminal date, they offer a convenient alternative to comprehensive valuations as long as observed long-term growth patterns tend to converge to the generic patterns assumed by these measures.

While the two final earnings sum measures we consider (ES1 and ES2) have not been discussed in the literature, we examine them to understand better the poor performance observed for the intrinsic value measures. ES1 simply sums the earnings forecasted for years +1 to +5, and ES2 attempts to control heuristically for the timing and risk of the different earnings numbers by discounting those forecasted earnings before summing them. If both ES1 and ES2 perform poorly, relative to simple forward earnings multiple (e.g., EPS2) the earnings projected for years +3 to +5 probably contain considerable error. If ES1 performs well, but ES2 does not, estimation errors in the firm-specific discount rates used to discount flows at different horizons are responsible for the poor performance of the intrinsic value measures. If both ES1 and ES2 perform well, the poor performance of intrinsic value measures is probably because the assumed terminal values in each case diverge substantially from the market's estimates of terminal values.

We also consider the impact of using enterprise value (TP), rather than equity value, for sales and EBITDA multiples, since both value drivers reflect an investment base that includes debt and equity. We measure TP as the market value of equity plus the book value of debt. To obtain predicted share prices, we estimate the relation between TP and the value driver for comparable firms, generate predicted TP for target firms, and then subtract the book value of their debt.

3.2 TRADITIONAL MULTIPLE VALUATION

In the first stage of our analysis, we follow the traditional ratio representation and require that the price of firm i (from the comparable group) in year t (p_{it}) is directly proportional to the value driver:

$$p_{it} = \beta_t x_{it} + \varepsilon_{it} \tag{1}$$

where x_{it} is the value driver for firm i in year t, β_t is the multiple on the value driver and ε_t is the pricing error. To improve efficiency, we divide equation (1) by price:

$$1 = \beta_t \frac{x_{it}}{p_{it}} + \frac{\varepsilon_{it}}{p_{it}}. \tag{2}$$

Baker and Ruback [1999] and Beatty, Riffe, and Thompson [1999] demonstrate that estimating the slope using equation (2) rather than equation (1) is likely to produce more precise estimates because the valuation error (the residual in equation (1)) is approximately proportional to price.

When estimating β_t, we elected to impose the restriction that expected pricing errors (E[ε/p]) be zero, even though an unrestricted estimate for β_t from equation (2) offers a lower value of mean squared pricing error. (Throughout the paper, the term "pricing error" refers to proportional pricing error, or the pricing error scaled by share price.) Empirically, we find that our approach generates lower pricing errors for most firms, relative to an unrestricted estimate, but it generates substantially higher errors in the tails of the distribution.[8] By restricting ourselves to unbiased pricing errors, we are in effect assigning lower weight to extreme pricing errors, relative to the unrestricted approach. We are also maintaining consistency with the tradition in econometrics that strongly prefers unbiasedness over reduced dispersion.

β_t is the only parameter to be estimated in equation (2), and it is determined by the restriction we impose that pricing errors be zero on average, i.e., $E[\frac{\varepsilon_{it}}{p_{it}}] = 0$. Rearranging terms in equation (2) and applying the expected value operator, we obtain the harmonic mean of p_{it}/x_{it} as an estimate for β_t:

$$E\left[\frac{\varepsilon_{it}}{p_{it}}\right] = 1 - E\left[\frac{\beta x_{it}}{p_{it}}\right] = 0 \Rightarrow \beta_t = \frac{1}{E\left[\frac{x_{it}}{p_{it}}\right]} \tag{3}$$

We multiply this harmonic mean estimate for β_t by the target firm's value driver to obtain a prediction for the target firm's equity value, and calculate the pricing error as follows:[9]

$$\frac{\varepsilon_{it}}{p_{it}} = \frac{p_{it} - \hat{\beta}_t x_{it}}{p_{it}}. \tag{4}$$

To evaluate the performance of multiples, we examine measures of dispersion, such as the interquartile range, for the pooled distribution of ε_{it}/p_{it}.

[8] We estimated equation (2) for comparable firms from the cross-section without imposing the unbiasedness restriction. (When using comparable firms from the same industry, the estimated multiples for this unrestricted case generated substantial pricing errors.) We find that the pricing error distributions for all multiples are shifted to the right substantially, relative to the distributions for the restricted case reported in the paper (our distributions tend to peak around zero pricing error). This shift to the right indicates that the multiples and predicted valuations for the unrestricted case are on average lower than ours. We find that the bias created by this shift causes greater pricing errors for the bulk of the firms not in the tails of the distribution, relative to our restricted case.

[9] While some studies measure pricing error as predicted value minus price (e.g., Alford [1992]) we measure pricing error as price minus predicted value.

3.3 INTERCEPT ADJUSTED MULTIPLES

For the second stage of our analysis, we relax the direct proportionality requirement and allow for an intercept:

$$p_{it} = \alpha_t + \beta_t x_{it} + \varepsilon_{it}. \tag{5}$$

Many factors, besides the value driver under investigation, affect price, and the average effect of such omitted factors is unlikely to be zero.[10] Since the intercept in equation (5) captures the average effect of omitted factors, allowing for an intercept should improve the precision of out of sample predictions.

As with the simple multiple approach, we divide equation (5) by price to improve estimation efficiency:

$$1 = \alpha_t \frac{1}{p_{it}} + \beta_t \frac{x_{it}}{p_{it}} + \frac{\varepsilon_{it}}{p_{it}}, \tag{6}$$

Estimating equation (6) with no restrictions minimizes the square of pricing errors, but the expected value of those errors is nonzero.[11] For the reasons mentioned in section 3.2, we again impose the restriction that pricing errors be unbiased.[12] That is, we seek to estimate the parameters α_t and β_t that minimize the variance of ε_{it}/p_{it}, subject to the restriction that the expected value of ε_{it}/p_{it} is zero:

$$\begin{aligned}\min_{\alpha,\beta} \operatorname{var}(\varepsilon_{it}/p_{it}) &= \operatorname{var}[(p_{it} - \alpha_t - \beta_t \cdot x_{it})/p_{it}] \\ &= \operatorname{var}\left[1 - \left(\alpha_t \frac{1}{p_{it}} + \beta_t \frac{x_{it}}{p_{it}}\right)\right] \end{aligned} \tag{7a}$$

$$s.t. \quad \mathrm{E}\left[\frac{\varepsilon_{it}}{p_{it}}\right] = 0. \tag{7b}$$

It can be shown that the estimates for α_t and β_t that satisfy (7a) and (7b) are as follows

$$\beta_t = \frac{E\left[\frac{x_t}{p_t}\right]\operatorname{var}\left(\frac{1}{p_t}\right) - \operatorname{cov}\left(\frac{1}{p_t}, \frac{x_t}{p_t}\right)E\left[\frac{1}{p_t}\right]}{E\left[\frac{1}{p_t}\right]^2\operatorname{var}\left(\frac{x_t}{p_t}\right) + E\left[\frac{x_t}{p_t}\right]^2\operatorname{var}\left(\frac{1}{p_t}\right) - 2E\left[\frac{1}{p_t}\right]E\left[\frac{x_t}{p_t}\right]\operatorname{cov}\left(\frac{1}{p_t}, \frac{x_t}{p_t}\right)} \tag{8}$$

$$\alpha_t = \frac{1 - \beta_t E\left[\frac{x_t}{p_t}\right]}{E\left[\frac{1}{p_t}\right]} \tag{9}$$

[10] If the relation between price and the value driver is non-linear, the omitted factors include higher powers of the value driver.

[11] In general, this bias could be removed by allowing for an intercept. That avenue is not available, however, when the dependent variable is a constant (=1), since the intercept captures all the variation in the dependent variable, thereby making the independent variables redundant.

[12] As with equation (2), pricing errors from the unrestricted approach for equation (6) are higher for most firms (in the middle of the distribution) but there are fewer firms in the tails of the distribution. (See footnote 8.)

where the different $E_t[.]$, var(.), and cov(.) represent the means, variances, and covariances of those expressions for the population, and are estimated using the corresponding sample moments for the comparable group. We compute prediction errors, defined by equation (10), and examine their distribution to determine performance.

$$\frac{\varepsilon_{it}}{p_{it}} = \frac{p_{it} - \hat{\alpha}_t - \hat{\beta}_t x_{it}}{p_{it}}. \tag{10}$$

4. *Sample and Data*

To construct our sample, we merge data from three sources: accounting numbers from COMPUSTAT; price, analyst forecasts, and actual earnings per share from IBES; and stock returns from CRSP. As of April of each year (labeled year t + 1), we select firm-years that satisfy the following criteria: (1) COMPUSTAT data items 4, 5, 12, 13, 25, 27, 58, and 60 are non-missing for the previous fiscal year (year t); (2) at least 30 monthly returns (not necessarily contiguous) are available on CRSP from the prior 60 month period; (3) price, actual EPS, forecasted EPS for years t + 1 and t + 2, and the long term growth forecast are available in the IBES summary file; and (4) all price to value-driver ratios for the simple multiples (excluding the three P* and two ES measures) lie within the 1st and 99th percentiles of the pooled distribution. The resulting sample, which includes 26,613 observations between 1982 and 1999, is used for the descriptive statistics reported in table 1.

For the results reported after table 1, we impose three additional requirements: (1) share price on the day IBES publishes summary forecasts in April is greater than or equal to \$2; (2) all multiples are positive; and (3) each industry-year combination has at least five observations. The first condition avoids large pricing errors in the second stage analysis (where an intercept is allowed) due to firms with low share prices. The second condition avoids negative predicted prices, and the third condition ensures that the comparable group is not unreasonably small. Regarding the second condition, we discovered that many firm-years were eliminated because of negative values for two cash flow measures: free cash flow and maintenance cash flow. More important, preliminary analysis indicated that both measures exhibited larger pricing errors than the other measures. As a result, we felt that these two measures were unsuitable for large sample multiples analyses and dropped them from the remainder of our study. The final sample has 19,879 firm-years.

Our sample represents a small fraction of the NYSE + AMAX + NASDAQ population that it is drawn from: the fraction included varies between 11 percent earlier in the sample period to 18 percent later in our sample period. The fraction of market value of the population represented, however, is considerably larger because the firms deleted for lack of analyst data are on average much smaller than our sample firms. Also, firm-years excluded because they have negative value drivers are potentially different from our

TABLE 1

Distribution of Ratio of Value Driver to Price

Summary descriptions of the variables are as follows (all amounts are on per share basis): P is stock price; BV is book value of equity; MCF is maintenance cash flow (equivalent to free cash flow when depreciation expense equals capital expenditure); FCF is free cash flow to debt and equity holders; CFO is cash flow from operations; EBITDA is earnings before interest, taxes, depreciation and amortization; CACT is COMPUSTAT earnings before extraordinary items; IACT is IBES actual earnings; EPS1 and EPS2 are one year out and two year out EPS forecasts; EG1 = EPS2*(1 + g), EG2 = EPS2*g, where g is the growth forecast; and TP is enterprise value (market value of equity + book value of debt).

$$P1_t^* = BV_t + \sum_{s=1}^{5}\left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right) + \frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+4})}{k_t(1+k_t)^s},$$

$$P2_t^* = BV_t + \sum_{s=1}^{5}\left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right)$$

$$P3_t^* = BV_t + \sum_{s=1}^{2}\left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right) + \sum_{s=3}^{11}\frac{[\mathrm{E}_t(ROE_{t+s}) - k_t]BV_{t+s-1}}{(1+k_l)^s}$$
$$+ \frac{[\mathrm{E}_t(ROE_{t+12}) - k_t]BV_{t+11}}{k_t(1+k_t)^{11}},$$

where $\mathrm{E}_t(ROE_{t+s})$ for s = 4, 5, ..., 12 is forecasted using a linear interpolation to the industry median ROE. The industry median ROE is calculated as a moving median of the past ten years' ROE of all firms in the industry. To eliminate outliers, industry median ROEs are Winsorized at the risk free rate and 20%.

$$ES1_t = \sum_{s=1}^{5}\mathrm{E}_t(EPS_{t+s}), \text{ and } ES2_t = \sum_{s=1}^{5}\left(\frac{\mathrm{E}_t(EPS_{t+s})}{(1+k_t)^s}\right).$$

Sample firms are collected in April each year between 1982 and 1999, and we require non-missing values for a set of core financial variables from COMPUSTAT, 30 non-missing monthly returns from the prior 60 months from CRSP, and non-missing share price, 1 and 2-year out EPS forecasts and long-term growth forecasts from IBES. The sample is trimmed at 1% and 99% for each value driver using the pooled distribution, resulting in a sample of 26,613 firm-years.

	Mean	Median	SD	1%	5%	10%	25%	75%	90%	95%	99%
BV/P	0.549	0.489	0.336	0.050	0.131	0.184	0.308	0.717	0.985	1.180	1.620
MCF/P	0.035	0.035	0.183	−0.566	−0.171	−0.076	−0.002	0.074	0.145	0.238	0.626
FCF/P	−0.025	0.002	0.252	−1.008	−0.379	−0.218	−0.069	0.050	0.131	0.234	0.648
CFO/P	0.093	0.079	0.190	−0.516	−0.100	−0.019	0.034	0.146	0.239	0.328	0.693
CACT/P	0.050	0.056	0.073	−0.249	−0.043	0.005	0.033	0.080	0.108	0.130	0.178
IACT/P	0.057	0.059	0.060	−0.184	−0.013	0.018	0.040	0.082	0.109	0.130	0.175
Ebitda/P	0.173	0.148	0.128	−0.051	0.032	0.055	0.095	0.224	0.320	0.397	0.617
Sales/P	1.419	0.988	1.416	0.098	0.215	0.313	0.552	1.773	2.991	4.080	7.112
EPS1/P	0.073	0.070	0.037	−0.026	0.024	0.036	0.052	0.092	0.117	0.137	0.178
EPS2/P	0.091	0.085	0.036	0.027	0.043	0.052	0.067	0.108	0.138	0.160	0.205
EG1/P	0.105	0.097	0.040	0.034	0.052	0.062	0.077	0.124	0.159	0.183	0.235
EG2/P	0.013	0.011	0.007	0.002	0.004	0.005	0.008	0.016	0.021	0.026	0.036
P1*/P	0.708	0.658	0.296	0.222	0.318	0.383	0.500	0.863	1.086	1.264	1.660
P2*/P	0.587	0.553	0.241	0.186	0.258	0.308	0.407	0.732	0.910	1.029	1.304
P3*/P	0.652	0.577	0.366	0.125	0.203	0.266	0.393	0.834	1.120	1.330	1.918
ES1/P	0.525	0.489	0.202	0.164	0.259	0.310	0.389	0.624	0.794	0.912	1.168
ES2/P	0.350	0.334	0.125	0.111	0.173	0.209	0.265	0.417	0.517	0.588	0.723
Ebitda/TP	0.113	0.110	0.060	−0.031	0.026	0.044	0.075	0.147	0.187	0.215	0.276
Sales/TP	0.939	0.708	0.788	0.086	0.169	0.234	0.396	1.234	1.925	2.495	3.981

sample, because they are more likely to be young firms and/or technology firms. For these reasons, our results may not be descriptive of the general population.

We adjust all per share numbers for stock splits and stock dividends using IBES adjustment factors. If IBES indicates that the consensus forecast for that firm-year is on a fully diluted basis, we use IBES dilution factors to convert those numbers to a primary basis. We use a discount rate (k_t) equal to the risk-free rate plus beta times the equity risk premium. The risk-free rate is the 10-year Treasury bond yield on April 1 of year $t+1$ and we assume the equity premium is 5 percent. We estimate betas using monthly stock returns and value-weighted CRSP returns over the 60 month period ending in March of year $t+1$. Since individual firm betas are measured with considerable error, we set firm beta equal to the median beta of all firms in the same beta decile.

For a subgroup of firm-years (less than 5 percent), we were able to obtain mean IBES forecasts for all years in the five-year horizon. For all other firms, with less than complete forecasts available between years 3 and 5, we generate forecasts by applying the mean long-term growth forecast (g) to the mean forecast for the prior year in the horizon; i.e., $eps_{t+s} = eps_{t+s-1}{}^{*}(1+g)$.

We obtain book values for future years by assuming the "ex-ante clean surplus relation" (ending book value in each future period equals beginning book value plus forecasted earnings less forecasted dividends). Since analyst forecasts of future dividends are not available on IBES, we assume that the current dividend payout ratio will be maintained in the future. We measure the current dividend payout as the ratio of the indicated annual cash dividends to the earnings forecast for year $t+1$ (both obtained from the IBES summary file).[13] To minimize biases that could be induced by extreme dividend payout ratios (caused by forecast $t+1$ earnings that are close to zero), we Winsorize payout ratios to lie between 10% and 50%. The results are relatively insensitive to assumed payout ratios, since altering the payout has only a small effect on future book values and an even smaller effect on computed future abnormal earnings.

5. *Results*

We report results separately for two sets of comparable firms with data available that year: all firms from the same industry and all firms in the cross-section. In either case, our analysis is always conducted out of sample; i.e., the target firm is removed from the group of comparable firms. Since the traditional approach involves the no-intercept relation and the selection of comparable firms from the same industry, much of our discussion focuses

[13] Indicated annual dividends are four times the most recent quarter's declared dividends. We use EPS1 as the deflator because it varies less than current year's earnings and is less likely to be close to zero or negative.

on that combination, and most of our ancillary investigations relate only to this combination.

To conduct the analysis using comparable firms from the same industry, we considered alternative industry classifications. Because of the evidence that SIC codes frequently misclassify firms (Kim and Ritter [1999]), we use the industry classification provided by IBES, which is indicated to be based loosely on SIC codes, but is also subject to detailed adjustments.[14] The IBES industry classification has three levels (in increasing fineness): sector, industry, and group. We use the intermediate (industry) classification level because visual examination of firms included in the same sector suggested it was too broad a classification to allow the selection of homogeneous firms, and tabulation of the number of firms in different groups suggested it was too narrow to allow the inclusion of sufficient comparable firms (given the loss of observations due to our data requirements).

Because of the volume of results generated, we report only some representative results and describe briefly some interesting extensions. In particular, we do not report on tests of statistical significance we conducted to compare differences in performance across value drivers. Our statistical significance tests focus on the interquartile range as the primary measure of dispersion that is relevant to us, and we conduct a bootstrap-type analysis for each pair of value drivers for all sets of results reported in tables 2 and 3. We generate "samples" of 19,879 firm-years by drawing observations randomly from our sample, with replacement. For each trial we compute the inter-quartile range for each multiple, and then compute the difference between all pairs of inter-quartile ranges. This process is repeated 100 times and a distribution is obtained for each pairwise difference. (Increasing the number of trials beyond 100 has little impact on the t-statistics generated.) We compute a t-statistic by dividing the mean by the standard deviation for each of these distributions. Those t-statistics (available from the authors) indicate that almost every pairwise difference for the different interquartile ranges reported in our tables is statistically significant (t-statistic greater than 2). In essence, readers can safely assume that if differences in performance across value drivers are economically significant, they are also statistically significant.

In section 5.4, we provide a summary of our results on variation in performance of different value drivers across different industries and years in our sample. Appendix B contains more details of the across-industry variation in performance.

5.1 DESCRIPTIVE STATISTICS

Table 1 reports the pooled distribution of different value drivers, scaled by price. While most distributions contain very few negative values, the

[14] The IBES classification resembles the industry groupings suggested by Morgan Stanley.

TABLE 2

Distribution of Pricing Errors for Simple Multiples

Value and value drivers are assumed to be proportional: $p_{it} = \beta_t x_{it} + \varepsilon_{it}$. Multiples are estimated using harmonic means: $\beta_t = 1/E_t(\frac{x_{it}}{p_{it}})$ in panels A&B, and medians are used in panel C. Pricing error is $\frac{\varepsilon_{it}}{p_{it}} = \frac{p_{it} - \beta x_{it}}{p_{it}}$ Summary descriptions of the variables are as follows (all amounts are on per share basis): P is stock price; BV is book value of equity; CFO is cash flow from operations; EBITDA is earnings before interest, taxes, depreciation and amortization; CACT is COMPUSTAT earnings before extraordinary items; IACT is IBES actual earnings; EPS1, EPS2 are one year out and two year out EPS forecasts; EG1 = EPS2*(1 + g), EG2 = EPS2*g, where g is growth forecast. TP is enterprise value (market value of equity plus book value of debt). When TP multiples are used, predicted equity value is calculated by subtracting the book value of debt.

$$P1_t^* = BV_t + \sum_{s=1}^{5} \left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s} \right) + \frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+4})}{k_t(1+k_t)^s},$$

$$P2_t^* = BV_t + \sum_{s=1}^{5} \left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s} \right)$$

$$P3_t^* = BV_t + \sum_{s=1}^{2} \left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s} \right) + \sum_{s=3}^{11} \frac{[\mathrm{E}_t(ROE_{t+s}) - k_t]BV_{t+s-1}}{(1+k_l)^s}$$

$$+ \frac{[\mathrm{E}_t(ROE_{t+12}) - k_t]BV_{t+11}}{k_t(1+k_1)^{11}},$$

where $\mathrm{E}_t(ROE_{t+s})$ for s = 4, 5, ..., 12 is forecasted using a linear interpolation to the industry median ROE. The industry median ROE is calculated as a moving median of the past ten years' ROE of all firms in the industry. To eliminate outliers, industry median ROEs are Winsorized at the risk free rate and 20%.

$$ES1_t = \sum_{s=1}^{5} \mathrm{E}_t(EPS_{t+s}), \text{ and } ES2_t = \sum_{s=1}^{5} \left(\frac{\mathrm{E}_t(EPS_{t+s})}{(1+k_t)^s} \right).$$

Sample firms are collected in April each year between 1982 and 1999, and we require non-missing values for a set of core financial variables from COMPUSTAT, 30 non-missing monthly returns from the prior 60 months from CRSP, and non-missing share price, 1- and 2-year out EPS forecasts and long-term growth forecasts from IBES. The sample is trimmed at 1% and 99% for each value driver. We then require a minimum $2 share price, that all value drivers be positive, and that each industry-year combination have at least five observations. The final sample contains 19,879 firm-years.

	Mean	Median	SD	75%-25%	90%-10%	95%-5%
Panel A: Multiples based on harmonic means of firms from the same industry						
BV/P	−0.016	0.066	0.560	0.602	1.266	1.710
CFO/P	−0.042	0.150	0.989	0.777	1.652	2.355
CACT/P	−0.012	0.012	0.490	0.518	1.119	1.549
IACT/P	−0.009	0.023	0.421	0.442	0.941	1.317
Ebitda/P	−0.017	0.066	0.573	0.553	1.163	1.631
Sales/P	−0.032	0.163	0.859	0.738	1.645	2.357
EPS1/P	−0.005	0.015	0.321	0.348	0.744	1.037
EPS2/P	−0.004	0.021	0.290	0.317	0.677	0.935
EG1/P	−0.004	0.027	0.290	0.313	0.671	0.936
EG2/P	−0.009	0.071	0.435	0.424	0.907	1.280
P1*/P	−0.006	0.037	0.351	0.377	0.807	1.118
P2*/P	−0.006	0.033	0.352	0.410	0.835	1.124
P3*/P	−0.009	0.055	0.443	0.469	0.983	1.377
ES1/P	−0.004	0.026	0.285	0.307	0.661	0.915

T A B L E 2—*continued*

	Mean	Median	SD	75%-25%	90%-10%	95%-5%
ES2/P	−0.004	0.023	0.283	0.311	0.664	0.919
Ebitda/TP	−0.013	0.024	0.645	0.619	1.266	1.753
Sales/TP	−0.057	0.156	1.067	0.901	1.919	2.763
Panel B: Multiples based on harmonic means of firms from the entire cross-section						
BV/P	0.000	0.080	0.565	0.744	1.343	1.732
CFO/P	−0.001	0.261	1.086	0.812	1.682	2.460
CACT/P	0.000	0.045	0.512	0.625	1.228	1.627
IACT/P	0.000	0.048	0.453	0.551	1.077	1.431
Ebitda/P	0.000	0.127	0.613	0.692	1.343	1.778
Sales/P	−0.001	0.265	0.943	0.801	1.766	2.531
EPS1/P	0.000	0.028	0.361	0.452	0.880	1.166
EPS2/P	0.000	0.030	0.320	0.388	0.781	1.038
EG1/P	0.000	0.041	0.317	0.368	0.754	1.024
EG2/P	0.000	0.077	0.500	0.526	1.168	1.608
P1*/P	0.000	0.053	0.378	0.479	0.923	1.211
P2*/P	0.000	0.052	0.396	0.549	0.986	1.250
P3*/P	0.000	0.098	0.511	0.652	1.257	1.587
ES1/P	0.000	0.040	0.312	0.362	0.740	1.008
ES2/P	0.000	0.030	0.312	0.379	0.760	1.011
Ebitda/TP	−0.008	0.029	0.734	0.704	1.415	1.939
Sales/TP	0.026	0.284	1.337	1.097	2.374	3.648
Panel C: Multiples based on median of comparable firms from the same industry						
BV/P	−0.110	0.000	0.638	0.649	1.407	1.962
CFO/P	−0.263	0.000	1.235	0.903	2.020	2.944
CACT/P	−0.041	0.000	0.527	0.513	1.164	1.640
IACT/P	−0.046	0.000	0.457	0.450	0.985	1.394
Ebitda/P	−0.111	0.000	0.676	0.581	1.283	1.814
Sales/P	−0.287	0.001	1.157	0.887	2.062	3.020
EPS1/P	−0.028	−0.001	0.351	0.350	0.761	1.074
EPS2/P	−0.033	0.000	0.314	0.320	0.696	0.980
EG1/P	−0.039	0.000	0.318	0.318	0.702	0.982
EG2/P	−0.099	−0.003	0.490	0.444	0.988	1.419
P1*/P	0.014	0.029	0.441	0.425	0.982	1.604
P2*/P	−0.051	0.000	0.378	0.421	0.882	1.205
P3*/P	−0.087	0.000	0.497	0.499	1.070	1.522
ES1/P	−0.039	0.000	0.312	0.312	0.691	0.967
ES2/P	−0.035	0.000	0.306	0.319	0.691	0.961
Ebitda/TP	−0.054	0.000	0.678	0.629	1.321	1.842
Sales/TP	−0.290	0.000	1.312	1.038	2.279	3.361

incidence of negative values is higher for cash flow measures. In particular, free cash flow and maintenance cash flow are often negative (approximately 30% and 20% of the sample, respectively). Moreover, the mean of FCF/P is negative, and the mean of MCF/P is close to zero, despite the deletion of observations with extreme values (top and bottom 1%). Including these two value drivers would result in a drastic reduction in sample size. Since we discovered that they perform considerably worse than other value

TABLE 3

Distribution of Pricing Errors for Intercept Adjusted Multiples

Value and value drivers are assumed to be linear: $p_{it} = \alpha_t + \beta_t x_{it} + \varepsilon_{it}$. Multiple is estimated excluding the firm under valuation, by solving the following constrained minimization problem:

$$\min_{\alpha,\beta} \operatorname{var}(\varepsilon_{it}/p_{it}) = \operatorname{var}[(p_{it} - \alpha_t - \beta_t \cdot x_{it})/p_{it}]];\ s.t.\ \mathrm{E}\left(\frac{\varepsilon_{it}}{p_{it}}\right) = 0.$$

Pricing error is $\frac{\varepsilon_{it}}{p_{it}} = \frac{p_{it}-\alpha_t-\beta_t x_{it}}{p_{it}}$ Summary descriptions of the variables are as follows (all amounts are on per share basis): P is stock price; BV is book value of equity; CFO is cash flow from operations; EBITDA is earnings before interest, taxes, depreciation and amortization; CACT is COMPUSTAT earnings before extraordinary items; IACT is IBES actual earnings; EPS1, EPS2 are one year out and two year out EPS forecasts; EG1 = EPS2*(1 + g), EG2 = EPS2*g, where g is growth forecast. TP is enterprise value (market value of equity plus book value of debt). When TP multiples are used, predicted equity value is calculated by subtracting the book value of debt.

$$P1_t^* = BV_t + \sum_{s=1}^{5}\left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right) + \frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+4})}{k_t(1+k_t)^s},$$

$$P2_t^* = BV_t + \sum_{s=1}^{5}\left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right)$$

$$P3_t^* = BV_t + \sum_{s=1}^{2}\left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right) + \sum_{s=3}^{11}\frac{[\mathrm{E}_t(ROE_{t+s}) - k_t]BV_{t+s-1}}{(1+k_l)^s}$$
$$+ \frac{[\mathrm{E}_t(ROE_{t+12}) - k_t]BV_{t-11}}{k_t(1+k_1)^{11}},$$

where $\mathrm{E}_t(ROE_{t+s})$ for s = 4, 5, ..., 12 is forecasted using a linear interpolation to the industry median ROE. The industry median ROE is calculated as a moving median of the past ten years' ROE of all firms in the industry. To eliminate outliers, industry median ROEs are Winsorized at the risk free rate and 20%.

$$ES1_t = \sum_{s=1}^{5}\mathrm{E}_t(EPS_{t+s}), \text{and } ES2_t = \sum_{s=1}^{5}\left(\frac{E_t(EPS_{t+s})}{(1+k_t)^s}\right).$$

Sample firms are collected in April each year between 1982 and 1999, and we require non-missing values for a set of core financial variables from COMPUSTAT, 30 non-missing monthly returns from the prior 60 months from CRSP, and non-missing share price, 1- and 2-year out EPS forecasts and long-term growth forecasts from IBES. The sample is trimmed at 1% and 99% for each value driver. We then require a minimum $2 share price, that all value drivers be positive, and that each industry-year combination have at least five observations. The final sample contains 19,879 firm-years.

	Mean	Median	SD	75%-25%	90%-10%	95%-5%
Panel A: Comparable firms from the same industry						
BV/P	−0.027	0.058	0.538	0.538	1.153	1.599
CFO/P	−0.037	0.091	0.621	0.577	1.237	1.765
CACT/P	−0.018	0.027	0.439	0.433	0.953	1.352
IACT/P	−0.015	0.029	0.387	0.390	0.843	1.179
Ebitda/P	−0.025	0.052	0.488	0.482	1.041	1.459
Sales/P	−0.039	0.101	0.646	0.614	1.312	1.841
EPS1/P	−0.010	0.018	0.310	0.323	0.704	0.982
EPS2/P	−0.008	0.019	0.290	0.305	0.656	0.917
EG1/P	−0.007	0.023	0.291	0.306	0.654	0.912
EG2/P	−0.012	0.055	0.400	0.402	0.855	1.195

TABLE 3—*continued*

	Mean	Median	SD	75%-25%	90%-10%	95%-5%
P1*/P	−0.013	0.034	0.348	0.365	0.775	1.078
P2*/P	−0.014	0.028	0.360	0.392	0.819	1.120
P3*/P	−0.020	0.045	0.428	0.433	0.919	1.276
ES1/P	−0.007	0.022	0.285	0.301	0.648	0.888
ES2/P	−0.007	0.021	0.283	0.302	0.649	0.891
Ebitda/TP	−0.008	0.025	0.626	0.538	1.121	1.576
Sales/TP	−0.038	0.094	0.838	0.730	1.532	2.154
Panel B: Comparable firms from the entire cross-section						
BV/P	0.008	0.084	0.518	0.610	1.171	1.581
CFO/P	0.013	0.175	0.654	0.582	1.279	1.833
CACT/P	−0.002	0.053	0.447	0.513	1.006	1.385
IACT/P	−0.005	0.050	0.405	0.475	0.923	1.252
Ebitda/P	0.012	0.111	0.517	0.560	1.090	1.513
Sales/P	0.038	0.206	0.646	0.595	1.293	1.849
EPS1/P	−0.009	0.025	0.339	0.415	0.811	1.092
EPS2/P	−0.007	0.023	0.315	0.376	0.759	1.024
EG1/P	−0.003	0.040	0.314	0.361	0.743	1.016
EG2/P	0.031	0.120	0.459	0.495	1.060	1.459
P1*/P	−0.007	0.049	0.359	0.445	0.855	1.141
P2*/P	−0.007	0.042	0.385	0.517	0.934	1.200
P3*/P	−0.010	0.078	0.455	0.556	1.047	1.380
ES1/P	−0.002	0.040	0.308	0.355	0.732	0.993
ES2/P	−0.006	0.028	0.307	0.366	0.739	0.994
Ebitda/TP	0.044	0.059	0.686	0.587	1.207	1.710
Sales/TP	0.143	0.246	1.010	0.835	1.860	2.805

drivers, we decided to remove them from the set of value drivers considered hereafter.

Examination of correlations for different pairs of value drivers, scaled by price, indicates that most value drivers are positively correlated, which suggests that they share considerable common information. (These results, which are available from the authors, show that Pearson correlations are very similar to Spearman correlations.) The correlations among different forward earnings and earnings-growth measures are especially high, generally around 90%. Interestingly, the correlations between the different forward earnings measures and the three intrinsic value measures (P1*, P2*, and P3*) are much lower (only about 50 percent).

5.2 NO-INTERCEPT RELATION BETWEEN PRICE AND VALUE DRIVERS

The results of the first stage analysis, based on the ratio representation (no intercept), are reported in table 2. Our primary results are those reported in panel A, where comparable firms are selected from the same industry. The results reported in panel B are based on comparable firms including all firms in the cross-section. We report the following statistics that describe the distribution of the pricing errors: two measures of central tendency (mean and median) and four measures of dispersion (the standard deviation and three non-parametric dispersion measures: interquartile range, 90th percentile less 10th percentile, and 95th percentile less 5th percentile). We separate our results into four categories: historical value drivers, forward earnings measures, intrinsic value and earnings sum measures, and multiples based on enterprise value.

To offer a visual picture of the relative and absolute performance of different categories of multiples, we provide in figure 1, Panel A, the histograms for pricing errors for the following selected multiples: EPS2, P1*, IACT, EBITDA, BV, and Sales. The histograms report the percentage of the sample that lies within ranges of pricing error that are of width equal to 10% of price (e.g. −0.1 to 0, 0 to 0.1, and so on). To reduce clutter, we draw a smooth line through the middle of the top of each histogram column, rather than provide the histograms for each of the multiples. We consider a multiple superior if it has a more peaked distribution. The differences in performance across the different value drivers are clearly visible in figure 1.

In general, the valuation errors we report are skewed to the left, indicated by medians that are greater than means.[15] While the skewness is less noticeable for multiples based on forward earnings, it is quite prominent for multiples based on sales and cash flows. Since predicted values are bounded from below at zero, while they are not bounded above, the right side of the pricing error distribution cannot exceed +1, whereas the left side is unbounded. One way to make the error distribution more symmetrical is to take the log of the ratio of predicted price to observed price (Kaplan and Ruback [1995]). Although we find that the distributions are indeed more symmetric for the log pricing error metric, we report the results using the pricing error metric because it is easier to interpret absolute performance using that metric. We did, however, recalculate the dispersion metrics reported here using the log pricing error metric to confirm that all our inferences regarding relative performance remain unchanged.

Examination of the standard deviation and the three non-parametric dispersion measures in panel A suggests the following ranking of multiples. Forecasted earnings, as a group, exhibit the lowest dispersion of pricing errors. This result is intuitively appealing because earnings forecasts should reflect future profitability better than historical measures. Consistent with this reasoning, performance increases with forecast horizon. The dispersion measures for two-year out forward earnings (EPS2) are lower than those for one-year out earnings (EPS1), and they are lower still for three-year out forward earnings (EG1). The multiple derived from PEG ratios (EG2) does not perform as well, however, suggesting that the specific relation between

[15] Means are close to zero because we require pricing errors to be unbiased, on average. Of course, the observed means would deviate slightly from zero by chance, since the valuations are done out of sample.

forward earnings and growth implied by the PEG ratio is not supported for our sample of firm-years.

Multiples generated from the three intrinsic value measures (P1*, P2*, and P3*) also do not perform as well as the simple forward earnings multiples. This result is consistent with measurement error in the estimated discount rates, forecasted forward abnormal earnings, or assumed terminal values for these three measures. The larger pricing errors associated with P2* relative to P1* suggests that the terminal value assumption of zero abnormal earnings past year +5 (for P2*) is less appropriate than the assumption of zero growth in abnormal earnings past year +5 (for P1*). The very high pricing errors associated with P3* suggest that the more complex structure of profitability trends imposed for this measure and/or the assumption that abnormal earnings remain constant past year +12 at the level determined by current industry profitability are inappropriate.

The sharp improvement in performance observed for ES1 and ES2 supports the view that the poor performance of the intrinsic value measures is caused by the generic terminal value assumptions. Recall that ES1 simply aggregates the same five years' earnings forecasts that are used for P1* and P2*, and ES2 discounts those forecasts using firm-specific discount rates (k_t) before summing them. The fact that the performance of ES2 is only slightly worse than that of ES1 suggests that the estimated values of k_t in the denominators of the intrinsic value terms (used to discount future abnormal earnings) are unlikely to be responsible for the poor performance of those measures. The improvement in performance observed for ES1 over the one-, two-, and three-year earnings forecasts suggests that despite the high correlation observed among these forecasts for different horizons, they contain independent value relevant information.

Comparing book value and earnings, the two popular accounting value drivers, we find that earnings measures clearly outperform book value. Pricing errors for book value (BV) exhibit greater dispersion than those for COMPUSTAT earnings (CACT). The performance of historical earnings is further enhanced by the removal of one-time transitory components. Consistent with the results in Liu and Thomas [2000], pricing errors for IBES earnings (IACT) exhibit lower dispersion than those for CACT. The sales multiple performs quite poorly, suggesting that sales do not reflect profitability until expenses have been considered.

Contrary to the belief voiced by some that cash flow measures are better than accrual measures at representing future cash flows, our results show that cash flows perform significantly worse than accounting earnings. Between the two cash flow measures, CFO fares considerably worse than EBITDA; in fact it is consistently the worst performer in all our analyses.

The last two rows in panel A of table 2 relate to valuations for sales and EBITDA multiples based on enterprise value. Even though enterprise value is more appropriate for these two value drivers, the performance for both multiples is even worse than that reported for the same multiples based on equity value. For example, the interquartile range of pricing errors for sales increases from 0.738 to 0.901 when the base is changed from equity value (P) to enterprise value (TP). We find this result surprising and are unable to provide any rationale for why such a result might be observed. (Similar results are reported in Alford [1992].)

A frequent reason for using sales as a value driver is because earnings and cash flows are negative. Since we restrict our sample to firms with positive earnings and cash flows, our sample is less likely to contain firms for which the sales multiple is more likely to be used in practice. In particular, our sample is unlikely to contain emerging technology firms such as Internet stocks. While some early research, such as Hand [1999] and Trueman, Wong, and Zhang [2000], suggests that traditional value drivers are inappropriate for such stocks, Hand [2000] finds that economic fundamentals, especially forward earnings forecasts, explain valuations for such firms.

To provide some evidence on the impact of deleting firms with negative values for earnings and cash flow measures, we examine the pricing errors for sales and forward earnings multiples for a larger sample of 44,563 firm-years with positive values for sales, EPS1, and EPS2. Although this sample is obtained by applying the same conditions used to generate our primary sample it is more than twice as large because we do not require positive values for all the other value drivers. We find that even though the relative performance differences reported in table 2, panel A, are observed again in this larger sample, the dispersion of pricing errors increases for all three multiples. For example, the interquartile ranges for sales, EPS1, and EPS2 increase to 0.805, 0.448, and 0.396, respectively, from 0.738, 0.348, and 0.317 in table 2, panel A. These results emphasize our earlier caution that the results reported for our main sample may not be descriptive of other samples.

In addition to ranking the relative performance of different multiples, the results in table 2, panel A, and the histograms in figure 1 can also be used to infer absolute performance. Our main finding is that industry multiples based on simple forward EPS forecasts provide reasonably accurate valuations for a large fraction of firms. Consider, for example, the percentages of the sample covered by the two intervals on either side of zero for EPS2 in figure 1. The sum of those four percentages (13 percent between −0.2 and −0.1, 18 percent between −0.1 and 0, 16.5 percent between 0 and 0.1, and 12 percent between 0.1 and 0.2) suggests that multiples based on industry harmonic means for EPS2 generate valuations within 20 percent of observed prices for almost 60 percent of firm years. Alternatively, halving the interquartile range of 0.348 for EPS2 in panel A suggests that absolute pricing errors below 17.4 percent are observed for approximately

50 percent of the sample.[16] The lower interquartile ranges for other value drivers, such as 0.313 for EG1 and 0.307 for ES1, indicate the potential for further improvement with other value drivers derived from forward earnings.

The pricing error distributions in panel B of table 2, when the comparable group includes all firms in the cross-section, are systematically more dispersed for all multiples, relative to those reported in panel A. The superior performance observed when the comparable group is selected from the same industry, is consistent with the joint hypothesis that (1) increased homogeneity in the value-relevant factors omitted from the multiples results in better valuation, and (2) the IBES industry classification identifies relatively homogeneous groups of firms.[17] Overall, we find that the frequency of small (medium) pricing errors increases (decreases), when comparable firms are selected from the same industry. (The frequency of large valuation error remains relatively unchanged.)

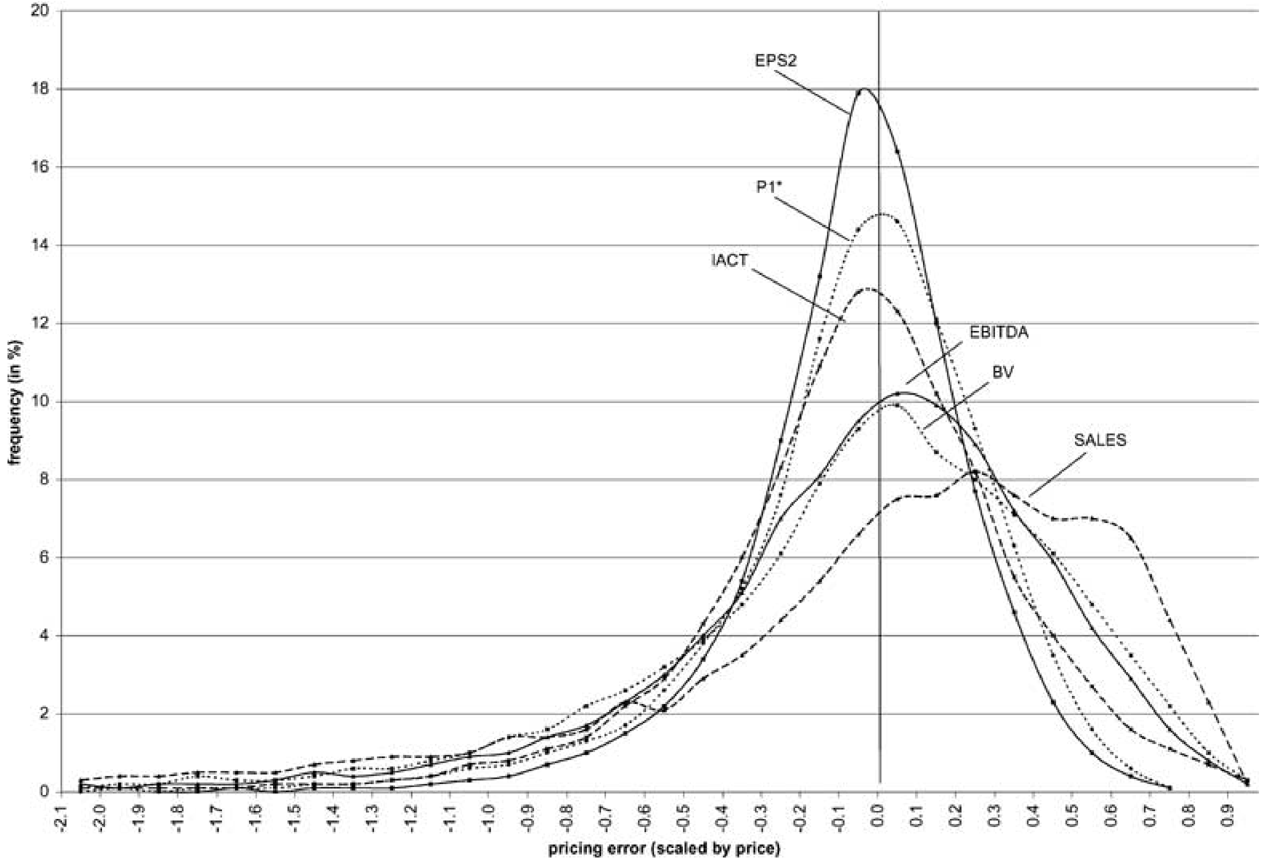
The multiples used in calculating the pricing errors in panels A and B are estimated using the harmonic mean. To allow comparison with results in previous studies (e.g., Alford [1992]), we repeat the panel A analysis using the median instead of the harmonic mean. Those results are reported in panel C. Consistent with the evidence in Baker and Ruback [1999] and Beatty, Riffe, and Thompson [1999], we find that the absolute

[16] This statement assumes the distribution is symmetric around zero. Since that assumption is only approximately true, and only for better-performing multiples (e.g. forward earnings), this description is intended primarily for illustrative purposes.

[17] Even if these conditions are satisfied, it is not clear that there should be an improvement. Moving from the cross-section to each industry results in a substantial decrease in sample size, and consequently the estimation is less precise. This fact is also reflected in the increase in the deviation of the sample mean of the valuation errors from zero.

FIG. 1.—Distribution of Pricing Errors Using Simple Industry Multiples. Value for firm i in year t (p_{it}) and value drivers (x_{it}) are assumed to be proportional: $p_{it} = \beta_i x_{it} + \varepsilon_{it}$. The multiple, β_t, is estimated using the industry harmonic mean: $\beta_t = 1/\mathrm{E}(\frac{x_{it}}{p_{it}})$, and pricing errors are computed as $\frac{\varepsilon_{it}}{p_{it}} = \frac{p_{it} - \hat{\beta}_t x_{it}}{p_{it}}$. The variables are defined as follows (all amounts are on a per share basis): P is stock price; BV is book value of equity; EBITDA is earnings before interest, taxes, depreciation and amortization; IACT is IBES actual earnings; EPS2 is two year out earnings forecast and g is growth forecast, and $P1_t^* = BV_t + \sum_{s=1}^{5} (\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}) + \frac{E_t(EPS_{t+s} - k_t BV_{t+4})}{k_t(1+k_t)^s}$. All multiples are calculated using the harmonic means for comparable firms within each industry (based on IBES industry classification), and the firm being valued is excluded when computing industry multiples. Sample firms are collected in April each year between 1982 and 1999, and we require non-missing values for a set of core financial variables from COMPUSTAT, 30 non-missing monthly returns from the prior 60 months from CRSP, and non-missing share price, 1- and 2-year out EPS forecasts and long-term growth forecasts from IBES. The sample is trimmed at 1% and 99% for each value driver. We then require a minimum $2 share price, that all value drivers be positive, and that each industry-year combination have at least five observations. The final sample contains 19,879 firm-years.

Panel A: Pooled distribution of pricing errors: The chart below is derived from a histogram with columns of width = 0.1 (or 10% of price). For example, for EPS2, the fraction of the sample with pricing error between 0 and −0.1 is about 18%



Panel B: Performance across industries: For each of 81 industries, value drivers are ranked based on the interquartile range for pricing errors (scaled by share price). Lower ranks imply lower pricing errors (better performance). The table and figure below report the # of industries for each value driver/rank combination. For example, Sales was never ranked first or second, was ranked third for 2 industries, and so on

	rank					
	1	**2**	**3**	**4**	**5**	**6**
SALES	0	0	2	5	14	60
BV	1	3	5	17	41	14
EBITDA	1	1	10	44	21	4
IACT	0	12	53	11	3	2
P1*	13	54	9	2	2	1
EPS2	66	11	2	2	0	0

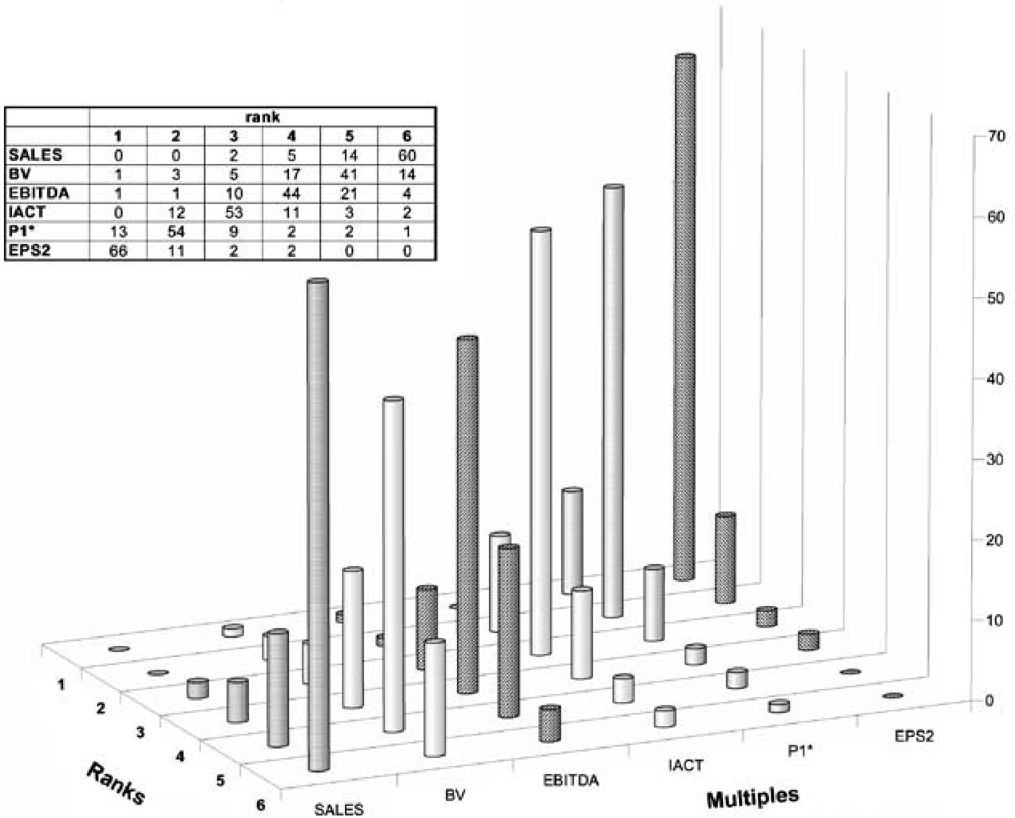


FIG. 1.—*continued*

Panel C: Performance across years: Plotted below are the annual interquartile ranges for the distribution of pricing errors (scaled by share price) for each value driver

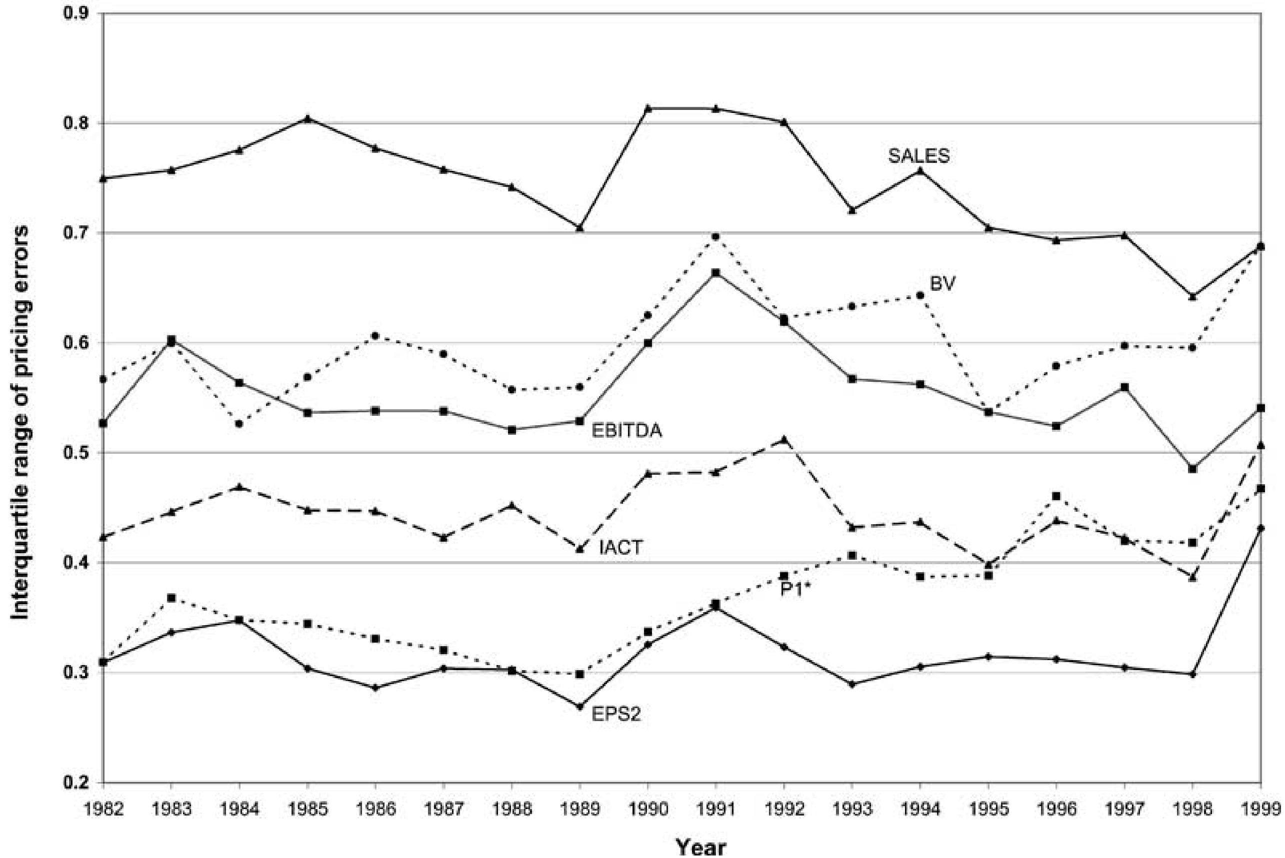


FIG. 1.—*continued*

performance of median multiples is worse than that for harmonic mean multiples. To be sure, the mean pricing error is no longer close to zero, whereas the median pricing error is now close to zero. Note that the improvement observed for harmonic means, relative to median multiples, is inversely related to the absolute performance of that multiple, and the improvement for forward earnings multiples is quite small. Importantly, the relative performance of the different multiples remains unchanged.

We also examined the impact of using the industry mean of price-to-value driver ratios as the multiple, rather than the harmonic mean (results available from authors). We find that the pricing error distributions for different value drivers exhibit much greater dispersion, and mean values that are substantially negative. Similar to the results reported for medians, the decline in performance is greater for multiples that perform poorly in table 2, panel A.

While it is inappropriate to include the target firm in the group of comparable firms, we investigated the bias caused by doing so. The bias (in terms of the impact on the distribution of pricing errors for multiples computed in sample versus out of sample) is negligible when the group of comparable firms includes all firms in the cross-section (corresponding to panel B results), since the addition of one firm has almost no effect on the multiple. When firms are selected from the same industry, however, there is a decrease in the dispersion of pricing errors when we use in-sample harmonic means (e.g. the interquartile range for EPS2 declines from 0.317 in table 2, panel A, to 0.301). The decline in dispersion is even larger for in-sample median multiples (e.g., interquartile range for EPS2 declines from 0.320 in table 2, panel C, to 0.290).

We considered two other extensions to the multiple approach (results available upon request). First, we combined two or more value drivers (e.g., Cheng and McNamara [1996]). Our results, based on a regression approach that is related to the intercept adjusted multiple approach discussed in section 3.3 (e.g., Beatty, Riffe, and Thompson [1999]) indicate only small improvements in performance over that obtained for forward earnings. Second, we investigated conditional earnings and book value multiples. That is, rather than using the harmonic mean P/E and P/B values of comparable firms, we use a P/E (P/B) that is appropriate given the forecast earnings growth (forecast book profitability) for that firm. We first estimate the relation between forward P/E ratios and forecast earnings growth (P/B ratios and forecast return on common equity) for each industry-year, and then read off from that relation the P/E (P/B) corresponding to the earnings growth forecast (forecast ROCE) for the firm being valued. Despite the intuitive appeal of conditioning the multiple on relevant information, little or no improvement in performance was observed over the unconditional P/E and P/B multiples.

5.3 INTERCEPT ALLOWED IN PRICE-VALUE DRIVER RELATION

In this subsection, we report results based on the second stage analysis, where we allow for an intercept in the relation between price and value drivers. Again, the analysis is conducted separately for comparable firms from the same industry (table 3, panel A) and for comparable firms from the entire cross-section (panel B).

As predicted, relaxing the no-intercept restriction improves the performance of all multiples. The best performance is achieved when we allow for an intercept and select comparable firms from the same industry (table 3, panel A). Comparison of these results with those in table 2, panel B, provides the joint improvement created by limiting comparable firms to be from the same industry and allowing for an intercept. Generally, the improvement generated by selecting comparable firms from the same industry (panel B to panel A in each table) is relatively uniform across value drivers. In contrast, the improvement generated by allowing an intercept (table 2 to table 3 for each panel) is inversely related to that value driver's performance in table 2. Value drivers that perform poorly in table 2 improve more than those that do well in that table. Contrast, for example, the improvement observed for Sales (interquartile range of 0.738 in table 2, panel A, to 0.614 in table 3, panel A) with the improvement observed for EG1 (interquartile range of 0.313 in table 2, panel A, to 0.306 in table 3, panel A). Although the improvement in absolute performance of the value drivers is not uniform, the rank order of different value drivers remains unchanged from table 2 to table 3.

5.4 VARIATION IN PERFORMANCE ACROSS INDUSTRIES AND YEARS

Given our focus on understanding the underlying information content of the different multiples, our results so far relate to pooled data. We consider next variation in the performance of different value drivers across years and industries to determine if the overall results are observed consistently in different years and industries. Arguments have been made before for different value drivers to perform better in certain industries than in others. For example, Tasker [1998] reports that investment bankers and analysts appear to use different preferred multiples in different industries. Although we recognize that our search is unlikely to offer conclusive results, since we do not pick comparable firms with the same skill and attention as is done in other contexts, we offer some preliminary findings.

Since investment professionals use simple multiples (no intercept) and select comparable firms from the same industry, we conduct the analysis only for that combination (corresponding to table 2, panel A). We pool the valuation results for each industry across years, and rank multiples based on the interquartile range of pricing errors within each industry. The results for the 81 industries we analyze are reported in Appendix B. The rankings range between 1 (best) and 17 (worst). We also report summary statistics of the rankings at the bottom of the table. The rankings reported in our pooled results are observed with remarkable consistency across all industries.

To illustrate graphically the essence of these rankings, we focus only on the six representative value drivers considered in figure 1, panel A, compute rankings again for each industry, and tabulate the number of times each value driver was ranked first, second, and so on in an industry. The results of that tabulation are reported in figure 1, panel B, and the consistency of the rankings across industries is clearly evident. EPS2 is ranked first in 66 of 81 industries, ranked second in 11 industries and ranked third and fourth in two industries each. It is never ranked fifth or sixth. The modal rank for P1* is second, is third for IACT, is fourth for EBITDA, is fifth for BV, and sixth for Sales. These modal ranks are observed in more than half the 81 industries in each case. Removing P1* from the analysis only strengthens further the performance of EPS2 (it is ranked first 77 times out of 81).

This pattern of superior relative performance for forward earnings multiples, which is consistent with the results in Kim and Ritter [1999], suggests that the information contained in forward looking value drivers captures a considerable fraction of value, and this feature is common to all industries. The absence of a significant number of industries where EBITDA performs better than other value drivers is inconsistent with the conventional wisdom that this cash flow measure is particularly useful in low growth industries or industries with considerable amortization of goodwill. The absence of superior performance for Sales in any industry (it is never ranked first or second in figure 1, panel B) is also inconsistent with Sales multiples being useful in certain industries.

Our evidence on the consistency of these rankings across different years is reported in figure 1, panel C. We focus only on the six representative value drivers and report the interquartile range of pricing errors each year for the six value drivers. The absolute and relative levels of those interquartile ranges appear fairly consistent over time. One noticeable deviation from that overall description is that although the performance of P1* is similar to that of EPS2 during the 1980s, it declines during the 1990s (interquartile range for EPS2 increases from about 0.35 in 1991 to 0.46 by 1999). Notwithstanding this deviation, these results suggest that our overall results are robust and observed consistently throughout the 18-year sample period.

6. *Conclusions*

In this study we examine the valuation properties of a comprehensive list of value drivers. Although our primary focus is on the traditional approach, which assumes direct proportionality between price and value driver and selects comparable firms from the same industry, we also consider a less restrictive approach that allows for an intercept and examine the effect of expanding the group of comparable firms to include all firms in the cross-section.

We find that multiples based on forward earnings explain stock prices reasonably well for a majority of our sample. In terms of relative performance, our results show historical earnings measures are ranked second after forward earnings measures, cash flow measures and book value are tied for third, and sales performs the worst. This ranking is robust to the use of different statistical methods and, more importantly, similar results are obtained across different industries and sample years. We find that the common practice of selecting firms from the same industry improves performance for all value drivers. Although we find that the improvement in performance obtained by allowing for an intercept in the price/value driver relation is quite large for value drivers that perform poorly, it is minimal for value drivers that perform well (such as forward earnings). We speculate that multiples are used primarily because they are simple to comprehend and communicate and the additional complexity associated with including an intercept may exceed the benefits of improved fit.

Our results regarding the information in different value drivers are consistent with intuition. For example, forward-looking earnings forecasts reflect value better than historical accounting information, accounting accruals add value-relevant information to cash flows, and profitability can be better measured when revenue is matched with expenses. Some results in this paper are surprising, however. For example, multiples based on the residual income model, which explicitly forecasts terminal value and adjusts for risk, perform worse than simple multiples based on earnings forecasts. And adjusting for leverage does not improve the valuation properties of EBITDA and Sales. We investigate these results further and feel that these results indicate the trade-off that exists between signal and noise when more complex but theoretically correct structures are imposed. As a caveat, we recognize that our study is designed to provide an overview of aggregate patterns, and thus may have missed more subtle relationships that are apparent only in small sample studies.

APPENDIX A

This appendix describes how the variables are constructed. The #s in parentheses refer to data items from COMPUSTAT. Number of shares and per share data from COMPUSTAT are adjusted for subsequent splits and stock dividends to allow comparability with IBES per share data.

P:	Share price from IBES, as of April each year.
TP:	Enterprise value per share = book value of debt, deflated by shares outstanding (#25), plus share price (P), where book value of debt = long term debt (#9) + debt in current liabilities (#34) + preferred stock (#130) − preferred treasury stock (#227) + preferred dividends in arrears (#242).
BV:	Per share book value of equity = book equity (#60) deflated by shares outstanding (#25).
SALES:	Per share sales = sales (#12) deflated by shares outstanding (#25).
CACT:	COMPUSTAT actual earnings per share = EPS excluding extraordinary items (#58).
IACT:	IBES actual earnings per share (per share earnings adjusted for one-time items).
EBITDA:	Per share earnings before interest, taxes, depreciation and amortization = EBITDA (#13), deflated by shares outstanding (#25).
CFO:	Per share cash flow from operations = EBITDA minus the total of interest expense (#15), tax expense (#16) and the net change in working capital, deflated by shares outstanding (#25), where net change in working capital is change in current assets (#4) minus change in cash and cash equivalents (#1) minus change in current liabilities (#5) plus change in debt included in current liabilities (#34). Data items 15, 16, 1 or 34 are set to zero if missing.
FCF:	Per share free cash flow = CFO minus net investment, where net investment is capital expenditures (#128) plus acquisitions (#129) plus increase in investment (#113) minus sale of PP&E (#107) minus sale of investment (#109), deflated by shares outstanding (#25). Data items 128, 129, 113, 107 or 109 are set to zero if missing.
MCF:	Per share maintenance cash flow = CFO minus depreciation expense (#125), deflated by shares outstanding (#25).
EPS1:	mean IBES one year out earnings per share forecast
EPS2:	mean IBES two year out earnings per share forecast
EG1:	IBES three year out earnings per share forecast, measured as EPS2*(1 + g), where g is mean IBES long term growth forecast
EG2:	EPS2*g, where g is mean IBES long term EPS growth forecast

The three P* measures are defined as follows:

$$P1_t^* = BV_t + \sum_{s=1}^{5}\left(\frac{E_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right) + \frac{E_t(EPS_{t+s} - k_t BV_{t+4})}{k_t(1+k_t)^s}$$

$$P2_t^* = BV_t + \sum_{s=1}^{5} \left(\frac{E_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s} \right)$$

$$P3_t^* = BV_t + \sum_{s=1}^{2} \left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s} \right)$$

$$+ \sum_{s=3}^{11} \frac{[\mathrm{E}_t(ROE_{t+5}) - k_t]BV_{t+s-1})}{(1+k_t)^s} + \frac{[\mathrm{E}_t(ROE_{t+12}) - k_t]BV_{t+11}}{K_t(1+k_t)^{11}}$$

The variables used in the P* calculations are obtained as follows: The discount rate (k_t) is calculated as the risk-free rate plus beta times the equity risk premium. We use the 10-year Treasury bond yield on April 1 of year t + 1 as the risk-free rate and assume a constant 5% equity risk premium. We measure beta as the median beta of all firms in the same beta decile in year t. We estimate betas using monthly stock returns and value-weighted CRSP returns for the five years ending in March of year t + 1 (we require a minimum of 30 non-missing monthly returns in those 5 years).

For a subgroup of firm-years (less than 5 percent), we were able to obtain mean IBES forecasts for all years in the five-year horizon. For all other firms, with less than complete forecasts available between years 3 and 5, we generated forecasts by applying the mean long-term growth forecast (g) to the mean forecast for the prior year in the horizon; i.e., $EPS_{t+s} = EPS_{t+s-1}{}^*(1+g)$.

The book values for future years, corresponding to the earnings forecasts, are determined by assuming the "ex-ante clean surplus" relation (ending book value in each future period equals beginning book value plus forecasted earnings less forecasted dividends). Since analyst forecasts of future dividends are not available on IBES, we assume that the current dividend payout ratio will be maintained in the future. We measure the current dividend payout as the ratio of the indicated annual cash dividends to the earnings forecast for year t + 1 (both obtained from the IBES summary file). To minimize biases that could be induced by extreme dividend payout ratios (caused by forecast t + 1 earnings that are close to zero), we Winsorize payout ratios at 10% and 50%.

In the calculation of $P3_t^*$, we forecast $\mathrm{E}_t(ROE_{t+5})$ for s = 4, 5, . . . , 12 using a linear interpolation to the industry median ROE. The industry median ROE is calculated as a moving median of the past ten years' ROE of all firms in the industry. To eliminate outliers, industry median ROEs are Winsorized at the risk free rate and 20%.

The earnings forecasts for years +1 to +5 are summed to obtain the two earnings sum measures.

$$ES1_t = \sum_{s=1}^{5} \mathrm{E}_t(EPS_{t+s}) \quad \text{and} \quad ES2_t = \sum_{s=1}^{5} \left(\frac{\mathrm{E}_t(EPS_{t+s})}{(1+k_t)^s} \right)$$

APPENDIX B

INDUSTRY RANKINGS OF MULTIPLES

Pricing errors (scaled by share price) are computed for each firm-year using harmonic means of firms in each industry. Multiples are ranked for each industry according to the inter-quartile range of pricing errors. Lower ranks indicate better performance. Industry classification is from the IBES sector/industry group classification code. Years covered are 1981 through 1999. Sample size is 19,879. Summary descriptions of the variables are as follows (all amounts are on per share basis): P is stock price; BV is book value of equity; CFO is cash flow from operations; EBITDA is earnings before interest, taxes, depreciation and amortization; CACT is COMPUSTAT earnings before extraordinary items; IACT is IBES actual earnings; EPS1, EPS2 are one year out and two year out earnings forecasts; EG1 = EPS2*(1 + g), EG2 = EPS2*g, where g is growth forecast. TP is enterprise value (market value of equity plus book value of debt). When TP multiples are used, predicted equity value is calculated by subtracting the book value of debt.

$$P1_t^* = BV_t + \sum_{s=1}^{5}\left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right) + \frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+4})}{k_t(1+k_t)^s},$$

$$P2_t^* = BV_t + \sum_{s=1}^{5}\left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right)$$

$$P3_t^* = BV_t + \sum_{s=1}^{2}\left(\frac{\mathrm{E}_t(EPS_{t+s} - k_t BV_{t+s-1})}{(1+k_t)^s}\right) + \sum_{s=3}^{11}\frac{[\mathrm{E}_t(ROE_{t+s}) - k_t]BV_{t+s-1}}{(1+k_t)^s}$$
$$+ \frac{[\mathrm{E}_t(ROE_{t+12}) - k_t]BV_{t+11}}{k_t(1+k_t)^{11}},$$

where $\mathrm{E}_t(ROE_{t+s})$ for s = 4, 5, ..., 12 is forecasted using a linear interpolation to the industry median ROE. The industry median ROE is calculated as a moving median of the past ten years' ROE of all firms in the industry. To eliminate outliers, industry median ROEs are Winsorized at the risk free rate and 20%.

$$ES1_t = \sum_{s=1}^{5}\mathrm{E}_t(EPS_{t+s}), \quad \text{and} \quad ES2_t = \sum_{s=1}^{5}\left(\frac{\mathrm{E}_t(EPS_{t+s})}{(1+k_t)^s}\right).$$

Years covered are 1982 through 1999. Sample size is 19,879.

Sector	Industry	BV	CFO	CACT	IACT	Ebitda	Sales	EPS1	EPS2	EG1	EG2	P1*	P2*	P3*	ES1	ES2	Ebitda/ TP	Sales/ TP
Basic Ind.	Building & Related	17	15	10	11	12	16	8	6	7	2	1	9	3	5	4	13	14
Basic Ind.	Chemicals	14	16	11	8	13	15	5	4	3	7	6	9	10	1	2	12	17
Basic Ind.	Containers	14	17	15	10	11	16	6	3	2	7	5	9	8	4	1	12	13
Basic Ind.	EAFE Metals-Nonfer	8	17	16	15	6	7	13	4	1	11	12	3	9	2	5	10	14
Basic Ind.	Forest Products	13	14	15	11	10	16	8	2	4	9	6	5	7	3	1	12	17
Basic Ind.	Metal Fab & Dist	14	15	9	10	13	16	4	5	3	2	8	7	12	1	6	11	17
Basic Ind.	Multi-Ind Basic	11	16	10	9	12	14	3	1	4	15	7	6	8	5	2	13	17
Basic Ind.	Nonfer Base Met	13	15	11	12	10	16	7	1	8	6	9	5	2	3	4	14	17
Basic Ind.	Paper	13	16	11	10	12	15	7	6	2	9	3	8	5	4	1	14	17
Basic Ind.	Precious Metals	13	12	14	8	10	16	11	6	4	15	2	7	1	5	3	9	17
Basic Ind.	Steel	5	16	14	11	12	15	8	2	3	10	7	1	9	6	4	13	17
Basic Ind.	Textiles	14	17	10	9	13	15	5	2	4	8	6	7	11	1	3	12	16
Cap. Goods	Aerospace	14	15	11	9	13	16	6	1	3	5	7	10	8	2	4	12	17
Cap. Goods	Auto OEMS	10	17	11	12	13	14	6	1	2	8	7	5	9	3	4	15	16
Cap. Goods	Bldg Materials	14	16	11	10	13	15	5	2	3	7	6	9	8	1	4	12	17
Cap. Goods	Defense	12	17	11	10	13	15	6	3	5	8	4	7	9	1	2	14	16
Cap. Goods	Electrical	14	16	11	10	12	15	3	7	5	9	1	6	8	2	4	13	17
Cap. Goods	Machinery	12	16	13	9	11	15	5	3	1	8	6	7	10	2	4	14	17
Cap. Goods	Multi-Ind Cap Good	17	16	8	9	10	12	2	3	4	1	7	14	13	5	6	11	15
Cap. Goods	Office Products	16	14	9	7	13	15	3	1	2	8	6	12	11	4	5	10	17
Cap. Goods	Undesig Capital	15	14	11	13	8	16	5	1	2	12	6	10	9	4	3	7	17

APPENDIX B—*continued*

Sector	Industry	BV	CFO	CACT	IACT	Ebitda	Sales	EPS1	EPS2	EG1	EG2	P1*	P2*	P3*	ES1	ES2	Ebitda/ TP	Sales/ TP
Consumer Dur.	Auto Part Mfg	14	17	11	7	12	15	4	1	3	8	9	6	10	2	5	13	16
Consumer Dur.	Automotive Mfg	3	8	15	14	16	7	13	11	12	6	4	1	2	10	9	17	5
Consumer Dur.	Home Bldg	13	17	11	10	12	15	5	1	3	6	7	8	9	2	4	14	16
Consumer Dur.	Home Furnish	14	17	12	8	11	15	5	3	4	10	6	7	13	2	1	9	16
Consumer Dur.	Leisure Prods	14	15	7	4	11	16	1	2	3	6	9	10	13	5	8	12	17
Consumer Dur.	Rec Vehicles	14	16	10	7	13	17	1	3	5	6	8	9	12	2	4	11	15
Consumer Dur.	Rubber	16	17	13	9	10	15	7	5	4	8	3	11	6	2	1	12	14
Consumer Dur.	Tools & Hardware	12	15	3	4	16	17	7	2	5	13	10	9	11	6	1	8	14
Cons. Non-Dur.	Beverages	15	14	10	8	12	16	7	5	2	6	4	11	9	1	3	13	17
Cons. Non-Dur.	Clothing	14	16	12	10	9	15	4	1	5	6	7	8	13	3	2	11	17
Cons. Non-Dur.	Consumer Containers	13	15	12	10	9	16	2	4	5	11	6	7	8	3	1	14	17
Cons. Non-Dur.	Cosmetics	17	14	8	6	13	15	5	3	2	11	7	12	9	1	4	10	16
Cons. Non-Dur.	Food Processors	15	14	9	8	13	16	1	3	5	6	7	12	11	2	4	10	17
Cons. Non-Dur.	Home Prods	14	15	12	8	13	16	6	5	1	3	7	9	10	2	4	11	17
Cons. Non-Dur.	Leisure Time	16	17	14	12	10	13	5	4	3	9	8	6	11	1	2	7	15
Cons. Non-Dur.	Leisure Times	12	14	11	9	15	16	7	4	1	8	6	5	10	2	3	13	17
Cons. Non-Dur.	Paint & Rel Mats	13	16	10	8	12	15	6	4	5	2	7	11	9	3	1	14	17
Cons. Non-Dur.	Tobacco	16	15	13	7	11	14	6	1	3	8	5	10	9	4	2	12	17
Cons. Services	Communications	15	14	13	8	12	16	7	3	5	4	6	10	9	1	2	11	17
Cons. Services	Ind Svcs	13	16	10	6	14	15	4	7	3	8	1	9	11	5	2	12	17
Cons. Services	Retail—Foods	14	15	10	8	12	16	5	4	2	7	6	9	11	1	3	13	17
Cons. Services	Retail—Goods	14	16	10	9	12	15	6	4	2	3	7	8	11	1	5	13	17
Cons. Services	Undesig Conr Svc	12	16	10	8	14	15	4	3	2	7	6	9	11	1	5	13	17

APPENDIX B—*continued*

Sector	Industry	BV	CFO	CACT	IACT	Ebitda	Sales	EPS1	EPS2	EG1	EG2	P1*	P2*	P3*	ES1	ES2	Ebitda/ TP	Sales/ TP
Energy	Canadian Energy	14	16	10	8	11	15	5	1	6	13	7	9	2	3	4	12	17
Energy	Coal	12	16	7	10	14	17	6	5	2	8	4	11	9	3	1	13	15
Energy	EAFE Energy Srcs	2	13	16	15	1	12	11	8	4	9	10	6	14	3	5	7	17
Energy	Gas	7	14	8	12	10	16	3	4	6	15	11	1	9	5	2	13	17
Energy	Oil	9	13	15	12	11	16	8	5	2	10	6	1	7	3	4	14	17
Finance	Banking	11	16	9	6	12	13	5	3	4	8	10	7	14	2	1	17	15
Finance	Finan & Loan	8	17	7	4	11	10	6	1	2	13	12	9	14	3	5	15	16
Finance	Finan Svcs	17	16	12	6	13	11	9	5	3	8	1	7	10	4	2	14	15
Finance	Insurance	15	16	12	8	10	14	5	2	3	7	6	11	9	4	1	13	17
Finance	Investments	14	15	11	9	12	17	6	2	5	10	4	8	7	3	1	13	16
Finance	S & L	11	15	12	7	9	14	1	4	2	10	8	5	13	3	6	17	16
Finance	Undesignated Finance	10	14	6	7	12	16	15	11	9	2	1	4	3	8	5	13	17
Health Care	Biotech	14	17	13	11	9	15	10	1	4	2	7	8	3	6	5	16	12
Health Care	Drugs	15	17	13	10	11	14	5	4	2	9	7	6	8	1	3	12	16
Health Care	Hosp Supplies	14	17	11	9	12	15	7	6	2	4	5	8	10	1	3	13	16
Health Care	Hospitals	14	15	12	10	13	16	6	1	5	9	4	8	7	2	3	11	17
Health Care	Med Supplies	15	17	10	9	13	14	5	4	2	6	7	8	12	1	3	11	16
Health Care	Svc to Med Prof	14	15	12	9	11	16	7	5	4	1	8	6	13	2	3	10	17
Misc. Undesig.	Unclassified	12	13	11	10	14	16	5	3	4	7	6	9	8	2	1	15	17
Public Utilities	Electrical Util	11	14	10	9	12	15	5	2	4	13	6	7	8	3	1	16	17
Public Utilities	Gas Util	8	16	11	9	10	15	5	1	2°	14	7°	6°	12	3°	4°	13	17
Public Utilities	Phone Util	15	16	13	8	12	11	5	4	2°	10	7°	6°	9°	1°	3°	17	14
Public Utilities	Water Util	9	12	8	4	5	13	1	3°	2°	15	11	10	14	6°	7°	16	17

APPENDIX B—*continued*

Sector	Industry	BV	CFO	CACT	IACT	Ebitda	Sales	EPS1	EPS2	EG1	EG2	P1*	P2*	P3*	ES1	ES2	Ebitda/ TP	Sales/ TP
Technology	Computers	14	17	11	10	12	15	6	4	2	5	7	8	9	1	3	13	16
Technology	Electronics Sys/Dev	14	15	10	8	11	16	6	4	3	5	7	9	12	1	2	13	17
Technology	Electronics	13	15	14	11	12	16	6	3	4	7	5	8	9	2	1	10	17
Technology	Office/Comm Equip	13	17	15	9	14	12	5	3	1	7	6	8	10	2	4	11	16
Technology	Other Computers	15	14	11	9	13	16	4	6	3	5	7	8	10	1	2	12	17
Technology	Photo-Optic Equip	14	17	11	10	15	13	5	4	2	7	6	8	9	3	1	16	12
Technology	Semicond/Comp	14	15	12	9	11	16	6	4	3	8	7	5	13	1	2	10	17
Technology	Software EDP	17	15	14	8	12	13	5	4	1	6	9	7	10	3	2	11	16
Technology	Undesignated Tech	12	14	7	9	15	16	1	3	4	10	8	6	11	2	5	13	17
Technology	Undesignated Technology	15	17	12	11	10	13	7	2	6	14	8	5	9	3	4	1	16
Transportation	Airlines	11	15	13	10	12	16	8	7	5	1	6	3	9	2	4	14	17
Transportation	Maritime	9	16	13	8	12	17	7	4	2	11	3	1	14	6	5	10	15
Transportation	Railroads	12	13	11	7	15	16	5	2	4	8	6	9	10	3	1	14	17
Transportation	Trucking	12	14	8	10	16	15	4	3	5	9	7	6	11	1	2	13	17
	Mean Rank	12.9	15.3	11.1	9.0	11.7	14.8	5.7	3.5	3.5	7.5	6.4	7.5	9.4	2.8	3.2	12.3	16.1
	Median Rank	14	16	11	9	12	15	5	3	3	8	7	8	9	2	3	13	17
	Standard Deviation of Rank	2.90	1.53	2.37	2.18	2.30	1.90	2.61	2.08	1.87	3.44	2.35	2.68	2.95	1.79	1.76	2.55	1.72

REFERENCES

ABARBANELL, J., AND V. L. BERNARD. "Is the U.S. Stock Market Myopic?" *Journal of Accounting Research* (Autumn, 2000): 221–42.

ALFORD, A. "The Effect of the Set of Comparable Firms on the Accuracy of the Price-earnings Valuation Method." *Journal of Accounting Research* 30 (1992): 94–108.

BAKER, M., AND R. RUBACK. "Estimating Industry Multiples." Working paper, Harvard University, Cambridge, MA, 1999.

BASU, S. "Investment Performance of Common Stocks in Relation to Their Price-earnings Ratios: A Test of the Efficient Markets Hypothesis." *Journal of Finance* (1977): 663–82.

BEATTY, R. P.; S. M. RIFFE; AND R. THOMPSON. "The Method of Comparables and Tax Court Valuations of Private Firms: An Empirical Investigation." *Accounting Horizons* 13 (1999): 177–99.

BOATSMAN, J., AND E. BASKIN. "Asset Valuation with Incomplete Markets." *The Accounting Review* 56 (1981): 38–53.

BRADSHAW, M. T. "How Do Analysts Use Their Earning Forecasts in Generating Stock Recommendations?" Working paper, University of Michigan, Ann Arbor, MI, 1999a.

BRADSHAW, M. T. "Analysts Reports, Target Prices, and Stock Recommendations." Working paper, University of Michigan, Ann Arbor, MI, 1999b.

CHENG, C. S. A., AND R. MCNAMARA. "The Valuation Accuracy of the Price-Earnings and Price-Book Benchmark Valuation Methods." Working paper, University of Houston, Houston, TX, 1996.

CLAUS, J. J., AND J. K. THOMAS. "Equity Premia as Low as Three Percent? Empirical Evidence from Analysts' Earnings Forecasts for Domestic and International Stock Markets." Working paper, Columbia University, New York, NY, 2000.

COPELAND, T.; T. KOLLER; AND J. MURRIN. *Valuation.* New York: Wiley, 1994.

DAMODARAN, A. *Damodaran on Valuation.* New York: Wiley, 1996.

FELTHAM, G., AND J. A. OHLSON. "Valuation and Clean Surplus Accounting for Operating and Financial Activities." *Contemporary Accounting Research* (Spring 1995): 689–731.

FRANKEL, R., AND C. M. C. LEE. "Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns." *Journal of Accounting and Economics* 25 (1998): 283–319.

GEBHARDT, W. R.; C. M. C. LEE; AND B. SWAMINATHAN. "Toward an Implied Cost-of-Capital." *Journal of Accounting Research* 39 (June 2001): 135–176.

GILSON, S. C.; E. S. HOTCHKISS; AND R. S. RUBACK. "Valuation of Bankrupt Firms." *Review of Financial Studies* 13 (2000): 43–74.

HAND, J. R. M. "Profits, Losses, and the Stock of Internet Firms." Working paper, University of North Carolina, Chapel Hill, NC, 1999.

HAND, J. R. M. "The Role of Economic Fundamentals, Web Traffic, and Supply and Demand in the Pricing of US Internet Stocks." Working paper, University of North Carolina, Chapel Hill, NC, 2000.

KAPLAN, S. N., AND R. S. RUBACK. "The Valuation of Cash Flow Forecasts: An Empirical Analysis." *The Journal of Finance* 50 (1995): 1059–93.

KIM, M., AND J. RITTER. "Valuing IPOs." *Journal of Financial Economics* 53 (1999): 409–37.

LECLAIR, M. S. "Valuing the Closely-held Corporation: The Validity and Performance of Established Valuation Procedures." *Accounting Horizons* 4 (September, 1990) 31–42.

LIU, J. 1999. "Post-earnings-announcement Drift and Analyst Forecasts." Working paper, UCLA, Los Angeles, CA, 1999.

LIU, J., AND J. THOMAS. "Stock Returns and Accounting Earnings." *Journal of Accounting Research* 38 (Spring 2000): 71–101.

LIU, J.; D. NISSIM; AND J. THOMAS. "Valuations Based on Multiples and Future Stock Returns." Working paper, Columbia University, New York, NY, 2001.

OHLSON, J. "Earnings, Book Values, and Dividends in Equity Valuation." *Contemporary Accounting Research* (Spring 1995): 661–87.

PALEPU, K.; P. HEALY; AND V. BERNARD. "Business Analysis and Valuation." 2nd Edition. Cincinnati, Ohio: South-Western College Publishing, 2000.

PENMAN, S. H. "Financial Statement Analysis and Security Valuation." Irwin: McGraw-Hill, 2001.

STATTMAN, D. "Book Value and Stock Returns." *The Chicago MBA: A Journal of Selected Papers*, Chicago: University of Chicago, 1980, pp. 25–45.

TASKER, S. C. "Industry Preferred Multiples in Acquisition Valuation." Working paper, Cornell University, Ithaca, NY, 1998.

TRUEMAN, B.; M. H. F. WONG; AND X. ZHANG. "The Eyeballs Have It: Searching for the Value in Internet Stocks." *Journal of Accounting Research* 38 (2000): 137–62.