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Journal of Accounting Research
Vol. 38 No. 1 Spring 2000
Printed in U.S.A.

Comparing the Accuracy and Explainability of Dividend, Free Cash Flow, and Abnormal Earnings Equity Value Estimates

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1. *Introduction*

This study provides empirical evidence on the reliability of intrinsic value estimates derived from three theoretically equivalent valuation models: the discounted dividend (*DIV*) model, the discounted free cash flow (*FCF*) model, and the discounted abnormal earnings (*AE*) model. We use *Value Line* (*VL*) annual forecasts of the elements in these models to calculate value estimates for a sample of publicly traded firms followed by *Value Line* during 1989–93.[1] We contrast the reliability of value

*Duke University; †University of Wisconsin; ‡London Business School. This research was supported by the Institute of Professional Accounting and the Graduate School of Business at the University of Chicago, by the Bank Research Institute, Sweden, and Jan Wallanders och Tom Hedelius Stiftelse for Samhallsvetenskaplig Forskning, Stockholm, Sweden. We appreciate the comments and suggestions of workshop participants at the 1998 EAA meetings, Berkeley, Harvard, London Business School, London School of Economics, NYU, Ohio State, Portland State, Rochester, Stockholm School of Economics, Tilburg, and Wisconsin, and from Peter Easton, Frank Gigler, Paul Healy, Thomas Hemmer, Joakim Levin, Mark Mitchell, Krishna Palepu, Stephen Penman, Richard Ruback, Linda Vincent, Terry Warfield, and Jerry Zimmerman.

[1] We collect third-quarter annual forecast data over a five-year forecast horizon for all December year-end firms followed by *VL* in each of the years 1989–93. After excluding firms with missing data, the final sample contains between 554 and 607 firms per year (2,907 observations in the pooled sample).

estimates in terms of their accuracy (defined as the absolute price scaled difference between the value estimate and the current security price) and in terms of their explainability (defined as the ability of value estimates to explain cross-sectional variation in current security prices).

In theory, the models yield identical estimates of intrinsic values; in practice, they will differ if the forecasted attributes, growth rates, or discount rates are inconsistent.[2] Although by documenting significant differences across *DIV*, *FCF*, and *AE* value estimates our results speak to the consistency question, our objective is to present a pragmatic exercise comparing the reliability of these value estimates, recognizing that the forecasts underlying them may be inconsistent. That is, we try to replicate the typical situation facing an investor using a valuation model to calculate an estimate of the intrinsic value of a firm. Under this view, the empirical work addresses which series of forecasts investors seem to use to value equity securities.

The results show that *AE* value estimates perform significantly better than *DIV* or *FCF* value estimates. The median absolute prediction error for the *AE* model is about three-quarters that of the *FCF* model (30% versus 41%) and less than one-half that of the *DIV* model (30% versus 69%). Further, *AE* value estimates explain 71% of the variation in current prices compared to 51% (35%) for *DIV* (*FCF*) value estimates. We conclude that *AE* value estimates dominate value estimates based on free cash flows or dividends.

Further analyses explore two explanations for the superiority of *AE* value estimates. *AE* value estimates may be superior to *DIV* and *FCF* value estimates when distortions in book values resulting from accounting procedures and accounting choices are less severe than forecast errors and measurement errors in discount rates and growth rates. This effect is potentially large for our sample, as indicated by the high proportion of *AE* value estimates represented by book value of equity (72% on average) and the high proportion of *FCF* and *DIV* value estimates represented by terminal values (82% and 65%, on average, versus 21% for *AE* value estimates).[3] Value estimates may also differ when the precision and the predictability of the fundamental attributes themselves differ.[4] Ceteris paribus, more precise and more predictable attributes should result in more reliable value estimates. Tests of these conjectures suggest that the greater reliability of *AE* value estimates is driven by the ability of

[2] For example, inconsistencies arise if the attributes violate clean surplus, if discount rates violate the assumptions of no arbitrage, unlimited borrowing, and lending at the rate of return, or if growth rates are not constant (i.e., the firm is not in steady state).

[3] We focus on the terminal value calculation because it is likely the noisiest component of the value estimate, reflecting errors in forecasting the attribute itself, the growth rate, and the discount factor.

[4] We define precision as the absolute difference between the predicted value of an attribute and its realization, scaled by share price. We define predictability as the ease with which market participants can forecast the attribute, and we measure this construct as the standard deviation of historical year-to-year percentage changes in the attribute.

book value to explain a large portion of intrinsic value and, perhaps, by the greater precision and predictability of *AE* forecasts. Moreover, neither accounting discretion nor accounting conservatism has a significant impact on the reliability of *AE* value estimates, suggesting that the superiority of the *AE* measure is robust to differences in firms' accounting practices and policies.

To our knowledge, this is the first study to provide large-sample evidence on the relative performance of these models using *individual* security value estimates based on *forecast* data. As discussed in section 2, Penman and Sougiannis [1998] (henceforth PS) provide empirical evaluations of these models for a large sample of firms, for *portfolio* value estimates based on *realized* attributes. The forecast versus realization distinction is important because realizations contain unpredictable components which may confound comparisons of the valuations models (which are based on expectations).[5] PS use a portfolio design to average out the unpredictable components of the valuation errors, whereas the use of forecasts avoids this problem entirely and permits a focus on individual securities' valuation errors. Another important difference between the two studies concerns the performance metrics: bias in PS and accuracy and explainability in our study. PS focus on bias (we believe) because their portfolio approach is better suited to describing the relation between value estimates and observed prices for the market as a whole. Specifically, under a mean bias criterion, positive and negative prediction errors offset within and across portfolios to yield estimates of the net amount that portfolio value estimates deviate from observed prices. In our individual security setting, we have no reason to believe that individual shareholders care about net prediction errors or care more (or less) about over- versus undervaluations of the same amount. Thus, we believe accuracy rather than bias better reflects the loss function of an investor valuing a given security. Explainability is also an open question in an individual security setting but is not well motivated in a portfolio setting where the random assignment of securities to portfolios and the aggregation of value estimates and observed prices within the portfolio significantly reduce the variation in these variables.

Our final analysis links the two studies by examining whether, for our sample, their design yields the same results as our approach. We draw the same conclusion as PS concerning bias in portfolio prediction errors based on realizations: *AE* value estimates have smaller (in absolute terms)

[5] Realizations and forecasts also differ because realizations generally adhere to clean surplus, but forecasted attributes may not. Over two-thirds of the sample forecasts adhere to clean surplus in years 0, 1, and 3 but not in years 2, 4, and 5 because of the assumptions used to construct a series of five-year forecasts (described in section 3). We do not believe the differences across value estimates documented in this study are driven by violations of clean surplus both because the violations of clean surplus are modest relative to the documented absolute prediction errors and because we find similar patterns when we repeat our analyses using a one-year forecast horizon and include only those securities' forecasts which adhere to clean surplus.

bias than *FCF* or *DIV* value estimates. However, when forecasts rather than realizations are used to calculate value estimates, this ordering depends on the assumed growth rate: for $g = 0\%$ we find the same ranking, but for $g = 4\%$ we find that *FCF* value estimates have the smallest (absolute) bias, followed by *AE* and *DIV* value estimates.[6] In terms of accuracy, we find that *AE* value estimates generally outperform *FCF* and *DIV* value estimates regardless of whether forecasts or realizations are used. Absolute prediction errors are, however, significantly (at the .00 level) smaller when forecasts rather than realizations are used to calculate value estimates. The forecast versus realization distinction is also important for comparing *DIV* and *FCF* value estimates. While we find that *FCF* value estimates based on realizations are more biased than *DIV* value estimates based on realizations (consistent with *PS*), we also find that *FCF* value estimates based on forecasts dominate *DIV* value estimates based on forecasts in terms of both bias and accuracy.

Section 2 describes the three valuation models and reviews the results of prior studies' investigations of estimates derived from these models. Section 3 describes the sample and data and presents the formulations of the *DIV*, *FCF*, and *AE* models we estimate. The empirical tests and results are reported in section 4, and section 5 reports the results of applying PS's design to our sample firms. Section 6 summarizes the results and concludes.

2. *Valuation Methods*

2.1 MODELS

The three equity valuation techniques considered in this paper build on the notion that the market value of a share is the discounted value of the expected future payoffs generated by the share. Although the three models differ with respect to the payoff attribute considered, it can be shown that (under certain conditions) the models yield theoretically equivalent measures of intrinsic value.

The *discounted dividend* model, attributed to Williams [1938], equates the value of a firm's equity with the sum of the discounted expected dividend payments to shareholders over the life of the firm, with the terminal value equal to the liquidating dividend:

$$V_F^{DIV} = \sum_{t=1}^{T} \frac{DIV_t}{(1 + r_E)^t} \tag{1}$$

where:

V_F^{DIV} = market value of equity at time F;
F = valuation date;

[6] For all other growth rates examined (2%, 6%, 8%, and 10%), we find that *AE* value estimates dominate *FCF* and *DIV* value estimates in terms of accuracy and smallest absolute bias.

DIV_t = forecasted dividends for year t;
r_E = cost of equity capital; and
T = expected end of life of the firm (often $T \to \infty$).

(For ease of notation, firm subscripts and expectation operators are suppressed. All variables are to be interpreted as time F expectations for firm j.)

The *discounted free cash flow* model substitutes free cash flows for dividends, based on the assumption that free cash flows provide a better representation of value added over a short horizon. Free cash flows equal the cash available to the firm's providers of capital after all required investments. In this paper, we follow the *FCF* model specified by Copeland, Koller, and Murrin [1994]:[7]

$$V_F^{FCF} = \sum_{t=1}^{T} \frac{FCF}{(1 + r_{WACC})^t} + ECMS_F - D_F - PS_F \tag{2}$$

$$FCF_t = (SALES_t - OPEXP_t - DEPEXP_t)(1 - \tau) + DEPEXP_t - \Delta WC_t - CAPEXP_t \tag{2a}$$

$$r_{WACC} = w_D(1 - \tau) r_D + w_{PS} r_{PS} + w_E r_E \tag{2b}$$

where:
V_F^{FCF} = market value of equity at time F;
$SALES_t$ = sales revenues for year t;
$OPEXP_t$ = operating expenses for year t;
$DEPEXP_t$ = depreciation expense for year t;
ΔWC_t = change in working capital in year t;
$CAPEXP_t$ = capital expenditures in year t;
$ECMS_t$ = excess cash and marketable securities at time t;[8]
D_t = market value of debt at time t;
PS_t = market value of preferred stock at time t;
r_{WACC} = weighted average cost of capital;
r_D = cost of debt;
r_{PS} = cost of preferred stock;
w_D = proportion of debt in target capital structure;
w_{PS} = proportion of preferred stock in target capital structure;
w_E = proportion of equity in target capital structure; and
τ = corporate tax rate.

The *discounted abnormal earnings* model is based on valuation techniques introduced by Preinreich [1938] and Edwards and Bell [1961],

[7] The *FCF* measure specified in equation (2*a*) is similar to Copeland, Koller, and Murrin's [1994] specification except we omit the change in deferred taxes because *VL* does not forecast this item.

[8] Excess cash and marketable securities (*ECMS*) are the short-term cash and investments that the company holds over and above its target cash balances.

and further developed by Ohlson [1995]. The *AE* model assumes an accounting identity—the clean surplus relation (3*b*)—to express equity values as a function of book values and abnormal earnings:[9]

$$V_F^{AE} = B_F + \sum_{t=1}^{T} \frac{AE_t}{(1+r_E)^t} \tag{3}$$

$$AE_t = X_t - r_E B_{t-1} \tag{3a}$$

$$B_t = B_{t-1} + X_t - DIV_t \tag{3b}$$

where:

V_t^{AE} = market value of equity at time F;
AE_t = abnormal earnings in year t;
B_t = book value of equity at end of year t; and
X_t = earnings in year t.

2.2 PRIOR RESEARCH COMPARING ESTIMATES OF INTRINSIC VALUES

Several studies investigate the ability of one or more of these valuation methods to generate reasonable estimates of market values. Kaplan and Ruback [1995] provide evidence on the ability of discounted cash flow estimates to explain transaction values for a sample of 51 firms engaged in high leverage transactions.[10] Their results indicate that the median cash flow value estimate is within 10% of the market price, and that cash flow estimates significantly outperform estimates based on comparables or multiples approaches. Frankel and Lee [1995; 1996] find that the *AE* value estimates explain a significantly larger portion of the variation in security prices than value estimates based on earnings, book values, or a combination of the two.

In addition to these horse races (which pit theoretically based value estimates against one or more atheoretically based, but perhaps best practice, value estimates), there are at least two studies which contrast the elements of, or the value estimates from, the *DIV*, *FCF*, and/or *AE* models. Bernard [1995] compares the ability of forecasted dividends and forecasted abnormal earnings to explain variation in current security prices. Specifically, he regresses current stock price on current year, one-year-ahead, and the average of the three- to five-year-ahead forecasted dividends and contrasts the explanatory power of this model with the explanatory power of the regression of current stock price on current book value and current year, one-year-ahead and the average of three- to five-year-ahead abnormal earnings forecasts. He finds that dividends explain 29% of the variation in stock prices, compared to 68% for the combination of current book value and abnormal earnings forecasts. Penman and Sougiannis [1998] also compare dividend, cash flow, and abnormal

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[9] Clean surplus requires that any change in book value must flow through earnings. The exception is dividends, which are defined net of capital contributions.

[10] Transaction value equals the sum of the market value of common stock and preferred stock, book value of debt not repaid as part of the transaction, repayment value of debt for debt repaid, and transaction fees; less cash balances and marketable securities.

earnings-based value estimates using infinite life assumptions. Using realizations of the payoff attributes as proxies for expected values at the valuation date, they estimate intrinsic values for horizons of $T = 1$ to $T = 10$ years, accounting for the value of the firm after time T using a terminal value calculation. Regardless of the length of the horizon, PS find that *AE* value estimates have significantly smaller (in absolute terms) mean signed prediction errors than do *FCF* value estimates, with *DIV* value estimates falling in between.

Our study extends previous investigations by comparing individual securities' *DIV*, *FCF*, and *AE* value estimates calculated using ex ante data for a large sample of publicly traded firms. In addition to evaluating value estimates in terms of their accuracy (absolute deviation between the value estimate and market price at the valuation date, scaled by the latter), we contrast their ability to explain cross-sectional variation in current market prices. Both metrics assume that forecasts reflect all available information and that valuation date securities prices are efficient with respect to these forecasts. Under the accuracy metric, value estimates with the smallest absolute forecast errors are the most reliable. The explainability tests—which compare value estimates in terms of their ability to explain cross-sectional variation in current market prices—control for systematic over- or underestimation by the valuation models.[11]

3. Data and Model Specification

Our analyses require data on historical book values (from *Compustat*), market prices (from *CRSP*), and proxies for the market's expectations of the fundamental attributes (from *VL*). *VL* data are preferred to other analyst forecast sources (such as *I/B/E/S* or *Zacks*) because *VL* reports contain a broader set of variables forecast over longer horizons than the typical data provided by sell-side analysts. In particular, *VL* reports dividend, earnings, book value, revenue, operating margin, capital expenditure, working capital, and income tax rate forecasts for the current year ($t = 0$), the following year ($t = 1$), and "3–5 years ahead."[12] Because the valuation models require projected attributes for *each* period in the forecast horizon, we assume that three- to five-year forecasts apply to all years in that interval (results are not sensitive to this assumption). Also, because *VL* does not report two-year-ahead forecasts, we set year 2 forecasts equal to the average of the one-year-ahead and the three-year-ahead forecast. We use data from third-quarter *VL* reports because this is the first time data are reported for the complete five-year forecast

[11] In the *OLS* regression, bias is captured both by the inclusion of an intercept and by allowing the coefficient relating the value estimate to current market price to deviate from a theoretical value of one (bias which is correlated with the value estimate itself). Rank regressions implicitly control for bias by using the ranks of the variables rather than the values of the variables.

[12] In contrast, *I/B/E/S* and *Zacks* contain, at most, analysts' current-year and one-year-ahead earnings forecasts (annual and quarterly) and an earnings growth rate.

horizon; these reports have calendar dates ranging from F = July 1 to September 30 (incrementing weekly) for each sample year, 1989–93. Finally, we restrict our analysis to December year-end firms to simplify calculations.

VL publishes reports on about 1,700 firms every 13 weeks; 800–900 of these firms have December year-ends. Because *VL* does not forecast all of the inputs to the three valuation models for all firms (e.g., they do not forecast capital expenditures for retail firms), the sample is reduced to those firms with a complete set of forecasts. This requirement excludes about 250–300 firms each year, leaving a pooled sample of 3,085 firm-year observations (a firm appears at most once each year). Missing *Compustat* and *CRSP* data reduce the sample to 2,907 firm-year observations, ranging from 554 to 607 firms annually. The sample firms are large, with a mean market capitalization of \$2.6 billion and a mean beta of 0.97. Most of the sample firms are listed on either the *NYSE* or the *AMEX* (82%), with the remainder trading on the *NASDAQ*.

For each valuation model, we discount the forecasted fundamental attributes to date F. We adjust both for the horizon of the forecast (e.g., three years for a three-year-ahead forecast) and for a part-year factor, f (f equals the number of days between F and December 31, divided by 365), to bring the current-year estimate back to the forecast date. We estimate discount rates using the following industry cost of equity model:[13]

$$r_E = r_f + \beta[E(r_m) - r_f] \tag{4}$$

where:

r_E = industry-specific discount rate;

r_f = intermediate-term Treasury bond yield minus the historical premium on Treasury bonds over Treasury bills (Ibbotson and Sinquefield [1993]);

β = estimate of the systematic risk for the industry to which firm j belongs. Industry betas are calculated by averaging the firm-specific betas of all sample firms in each two-digit *SIC* code. Firm-specific betas are calculated using daily returns over fiscal year $t - 1$;

$E(r_m) - r_f$ = market risk premium = 6%.[14]

For a given firm and valuation date, we assume r_E(r_{WACC} for the *FCF* model) is constant across the forecast horizon. The average cost of equity for the pooled sample is about 13%. The r_{WACC} calculation requires estimates of r_D, r_{PS}, capital structure (w_D, w_{PS}, and w_E), and *ECMS*. The cost of debt is measured as the ratio of the *VL* reported interest on long-term

[13] Fama and French [1997] argue that industry costs of equity are more precise than firm-specific costs of equity. Results using firm-specific discount rates yield similar inferences and are not reported.

[14] Six percent is advocated by Stewart [1991] and is similar to the 5–6% geometric mean risk premium recommended by Copeland, Koller, and Murrin [1994]. We obtain qualitatively similar results using the arithmetic average market risk premium.

debt to the book value of long-term debt; the cost of preferred stock is proxied by the *VL* reported preferred dividends divided by the book value of preferred stock.[15] We set the pretax upper bound on the cost of debt and the cost of preferred stock equal to the industry cost of equity, and we set the pretax lower bound equal to the risk-free rate (results are not sensitive to these boundary conditions). Following Copeland, Koller, and Murrin [1994, pp. 241–42] we develop long-term target capital weights for the r_{WACC} formula rather than use the weights implied by the capital structure at the valuation date.[16] For the pooled sample, the mean cost of debt is 9.3%, the mean cost of preferred stock is 10.3%, and the mean weighted average cost of capital is 11.8%. Based on Copeland, Koller, and Murrin's [1994, p. 161] suggestion that short-term cash and investments above 0.5–2% of sales revenues are not necessary to support operations, we define *ECMS* as cash and marketable securities in excess of 2% of revenues.

We compute two terminal values for each valuation model, TV^{FUND}, where *FUND* = *DIV, FCF*, or *AE*. Both terminal values discount into perpetuity the stream of forecasted fundamentals after $T = 5$; the first specification assumes these fundamentals do not grow; the second assumes they grow at 4%.[17] If the forecasted $T = 5$ fundamental is negative, we set the terminal value to zero based on the assumption that the firm will not survive if it continues to generate negative cash flows or negative abnormal earnings (dividends cannot be less than zero). (The results are not sensitive to this assumption.) Because we draw similar inferences from the results based on the no growth and the 4% growth assumptions, we discuss only the latter but report both sets of results in the tables.[18]

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[15] *VL* reports book values of long-term debt and preferred stock as of the end of quarter 1. The results are not affected if we use *Compustat* data on book values of debt and preferred stock at the end of quarter 2. In theory, we should use the market values of debt and preferred stock, but these data are not available.

[16] Specifically, we use *Value Line*'s long-term (three- to five-year-ahead) predictions to infer the long-term capital structure. We use the long-term price–earnings ratio multiplied by the long-term earnings prediction to calculate the implied market value of equity five years hence. For debt, we use *VL*'s long-term prediction of the book value of debt. For preferred stock, we assume that it remains unchanged from the valuation date. The equity weight in the *WACC* formula, w_E, is then given by w_E = implied equity value/(implied equity value + forecasted debt + current book value of preferred stock). The debt and preferred stock weights are calculated similarly.

[17] The growth rate is often assumed to equal the rate of inflation. Consistent with Kaplan and Ruback [1995] and Penman and Sougiannis [1998], we use a 4% growth rate. We draw similar conclusions using growth rates of 2%, 6%, 8%, and 10%.

[18] We also examine a terminal value equal to *VL*'s long-term price projection (equal to the *VL* three- to five-year-ahead price–earnings ratio multiplied by the three- to five-year-ahead earnings forecast). All models perform extremely well using the inferred price terminal value, with absolute (signed) prediction errors of 16–24% (5–14%) and adjusted R^2s of .77 to .91. Although the magnitudes of the differences are smaller, we find that *AE* value estimates dominate *FCF* value estimates and perform at least as well as *DIV* value estimates. Because long-term price forecasts are not available for most firms, we focus on the more common scenario where terminal values must be calculated.

Discounted dividend model specification:

$$V_F^{DIV} = (1 + r_E)^{-f}.5DIV_0 + \sum_{t=1}^{5} (1 + r_E)^{-(t+f)} DIV_t + (1 + r_E)^{-(5+f)} TV^{DIV}. \quad (5)$$

For the pooled sample, the average forecasted dividends for the second half of the current year and the next five years are, on average, \$0.36, \$0.76, \$0.91, \$1.05, \$1.05, and \$1.05. The mean terminal value estimates for the pooled sample are \$8.24 and \$12.68 for the no growth and 4% growth specifications, respectively.[19]

Discounted free cash flow specification:

$$V_F^{FCF} = (1 + r_{WACC})^{-f}.5FCF_0 + \sum_{t=1}^{5} (1 + r_{WACC})^{-(t+f)} FCF_t + (1 + r_{WACC})^{-(5+f)} TV^{FCF} + ECMS_0 - D_0 - PS_0. \quad (6)$$

The mean estimates of free cash flows for the remaining half of the current year and the next five years for the pooled sample are \$0.57, \$1.56, \$0.99, \$1.80, \$3.98, and \$3.98.[20] The average terminal values for the pooled sample are \$34.59 (no growth) and \$55.86 (4% growth).

Discounted abnormal earnings model specification:[21]

$$V_F^{AE} = B_{Q2} + (1 + r_E)^{-f}.5(X_0 - r_E \times B_{Q2}) + \sum_{t=1}^{5} (1 + r_E)^{-(t+f)} [X_t - r_E \times B_{t-1}] + (1 + r_E)^{-(5+f)} TV^{AE}. \quad (7)$$

For the pooled sample, the average forecasted abnormal earnings for the remainder of the current year and the next five years are \$-0.05, \$0.33, \$0.87, \$1.14, \$0.66, and \$0.66.[22] The terminal value estimates for

[19] For the 564 (of 2,907) observations where the firm pays no dividends, the value estimates equal zero. We retain these observations in the analysis, unless noted otherwise. Results excluding these 564 observations are similar to the full sample and are not reported.

[20] The *FCF* estimate for year 3 is different from years 4 and 5. For $t = 3$ the change in working capital is based on the estimate of working capital in $t = 2$. For $t = 4$ and $t = 5$, the change in working capital is zero because working capital forecasts are equal across $t = 3$, $t = 4$, and $t = 5$ (recall that we assume that *VL* three- to five-year forecasts apply to *each* year in that interval). This causes the *FCF* forecasts for years 4 and 5 to exceed the *FCF* forecast for year 3.

[21] We measure book value of equity at the end of *Q2*, year 0, B_{Q2}. We obtain similar results using book value at the end of year −1.

[22] The abnormal earnings estimate for year 3 is a function of the estimated book value at the end of year 2. Hence, the estimate of abnormal earnings for year 3 differs from the estimate of abnormal earnings for years 4 and 5 (which is a function of the constant book value estimate for years 3–5).

TABLE 1
Pooled Sample Prediction Errors[a]

Panel A: Signed Prediction Errors (Bias)[b]

	Mean	Mean % Difference	α-Level Difference = 0	Median	Median % Difference	α-Level Difference = 0
Current Share Price	31.27	n/a	n/a	25.12	n/a	n/a
Value Estimate						
DIV (g = 0%)	7.84	−75.5%	0.00	5.78	−75.8%	0.00
FCF (g = 0%)	18.40	−31.5%	0.00	13.79	−42.7%	0.00
AE (g = 0%)	22.04	−20.0%	0.00	17.91	−28.2%	0.00
DIV (g = 4%)	10.21	−68.0%	0.00	7.44	−68.7%	0.00
FCF (g = 4%)	30.02	18.2%	0.00	22.93	−8.8%	0.07
AE (g = 4%)	24.16	−12.7%	0.00	19.37	−22.9%	0.00

Panel B: Absolute Prediction Errors (Accuracy)[c]

Value Estimate	Median	versus *FCF*	versus *AE*	Central Tendency
DIV (g = 0%)	75.8%	0.00	0.00	0.9%
FCF (g = 0%)	48.5%		0.00	13.2%
AE (g = 0%)	33.1%			20.2%
DIV (g = 4%)	69.1%	0.00	0.00	1.7%
FCF (g = 4%)	41.0%		0.00	18.4%
AE (g = 4%)	30.3%			22.5%

[a]The sample securities are for December year-end firms with the following information available for any year t = 1989–93: third-quarter *Value Line* forecasts of all fundamental values; *Compustat* data on the book value of common equity for year $t-1$; and *CRSP* security prices. $P_{j,F}$ = observed share price of security j on the *Value Line* forecast date; V_j^{FUND} = security j's estimate of intrinsic value based on *FUND* = dividends (*DIV*), free cash flows (*FCF*), or abnormal earnings (*AE*). We calculate terminal values based on a no growth assumption and a 4% growth assumption.

[b]Panel A reports mean and median signed prediction errors, equal to $(V_j^{FUND} - P_{j,F})/P_{j,F}$. We also report the significance level associated with the t-statistics (sign rank statistic) of whether the mean (median) prediction error equals zero.

[c]Panel B shows the median absolute prediction error, $|V_j^{FUND} - P_{j,F}|/P_{j,F}$, and the measure of central tendency (the percentage of observations with value estimates within 15% of observed security price). The third and fourth columns report the significance levels for Wilcoxon tests comparing the pooled sample median absolute prediction errors for the noted row–column combination.

the pooled sample are, on average, \$6.87 (no growth) and \$10.74 (4% growth).

4. *Empirical Work*

Panel A of table 1 reports mean and median security prices at the valuation date and value estimates for the pooled sample.[23] For all analyses we set negative value estimates to zero, affecting 16 *AE*, 80 *FCF*, and no *DIV* value estimates. We obtain similar results if we do not set these estimates to zero. For comparison with Penman and Sougiannis's results, panel A shows information on signed prediction errors, $(V^{FUND} - P)/P$.

[23] Results for individual years, and using prices five days after the valuation date (to ensure investors have fully impounded the information in *VL* analysts' forecasts made at time F), are similar and are not reported.

Summary statistics show that all of the models tend to underestimate security prices, with mean (median) signed prediction errors of −68% (−69%) for V^{DIV}, 18% (−9%) for V^{FCF}, and −13% (−23%) for V^{AE}. The frequency and magnitude of the underestimation is most severe for *DIV* value estimates which are less than price 99% of the time (not reported in table 1). Tests of the accuracy of the value estimates, reported in panel B, show median absolute prediction errors along with a measure of the central tendency of the value estimate distribution. Following Kaplan and Ruback [1995] we define central tendency as the percentage of observations where the value estimate is within 15% of the observed security price. The median accuracy of V^{AE} of 30% is significantly (at the .00 level) smaller than the median accuracy of V^{FCF} (41%) and of V^{DIV} (69%). *AE* value estimates also show more central tendency than *FCF* estimates (.22 versus .18); both of these models significantly outperform *DIV* estimates, where fewer than 2% of the observations are within 15% of observed price.

We also examine the ability of the value estimates to explain cross-sectional variation in securities prices. Panel A of table 2 reports R^2s for the *OLS* and rank univariate regressions of market price at time F on each value estimate,[24] and panel B reports the multivariate regressions of price on V^{DIV}, V^{FCF}, and V^{AE} (the full model). The explained variability of the rank univariate regressions is high for all three valuation models (between 77% and 90%); however, the *OLS* results show greater variation in R^2s—between 35% and 71%—with *FCF* value estimates performing substantially worse than *AE* or *DIV* value estimates. In particular, V^{FCF} explains about one-half (two-thirds) of the variation in price explained by V^{AE}(V^{DIV}).[25] Results in panel B calibrate the incremental importance of each value estimate by decomposing the explanatory power of the full model into the portion explained by each value estimate controlling for the other two.[26] For example, the incremental ex-

[24] *OLS* regressions include an intercept; rank regressions do not. We report *OLS* results after deleting observations with studentized residuals in excess of two; this rule eliminates between 44 and 105 observations for each model. Results based on the full sample are similar to those reported with one exception: when all observations are retained, the explanatory power of *DIV* estimates is 22% (versus 51% when outliers are deleted).

[25] If the value estimates are unbiased predictors of market security prices, then the intercept (λ_0) should equal zero and the coefficient relating value estimate to price (λ_1) should be one. In all cases, we reject the joint hypothesis that $\lambda_0 = 0$ and $\lambda_1 = 1$. Because these rejections may arise from heteroscedasticity (for the *DIV* and *FCF* estimates—but not the *AE* estimates—White [1980] tests reject the hypothesis that the variance of the disturbance term is constant across observations), we repeat all analyses after transforming the variables to eliminate the heteroscedasticity. The transformed results (not reported) show small changes in the parameter estimates; in all cases the results are qualitatively similar to the untransformed results reported in the tables.

[26] For $g = 4\%$, we are unable to reject the joint hypothesis that the intercept equals zero and the sum of the slope coefficients equals one. For $g = 0\%$, we reject at the .08 level.

TABLE 2

Results of Pooled Sample Regressions of Contemporaneous Stock Prices on Intrinsic Value Estimates[a]

Panel A: Univariate Regressions of Price on Value Estimate[b]

	Growth Rate = 0%			Growth Rate = 4%		
	DIV	*FCF*	*AE*	*DIV*	*FCF*	*AE*
OLS Coefficient	1.75	0.76	1.23	1.30	0.46	1.09
OLS R^2	0.54	0.40	0.73	0.51	0.35	0.71
Rank R^2	0.84	0.77	0.90	0.84	0.77	0.90

Panel B: Multivariate Regressions of Price on Value Estimates[c]

	Growth Rate = 0%			Growth Rate = 4%		
	DIV	*FCF*	*AE*	*DIV*	*FCF*	*AE*
OLS Coefficient	0.16	0.10	1.04	0.04	−0.02	1.06
t-Statistic *OLS* Coefficient = 0	2.04	4.93	22.18	0.53	−1.14	22.20
t-Statistic Rank Coefficient = 0	10.99	9.67	34.00	11.19	3.95	33.87
Model *OLS* R^2	0.73			0.71		
Model Rank R^2	0.91			0.91		
Incremental *OLS* R^2	0.01	0.00	0.12	0.00	0.00	0.14
Incremental Rank R^2	0.00	0.00	0.04	0.00	0.00	0.04

[a]See n. a to table 1 for the sample description and the calculations of value estimates.

[b]Panel A reports results of estimating the following regression: $P_{j,F} = \lambda_0 + \lambda_1 V_j^{FUND} + \varepsilon_j$, where $P_{j,F}$ = observed share price of security j on the *Value Line* forecast date; V_j^{FUND} = value estimate for security j for *FUND* = dividends (*DIV*), free cash flows (*FCF*), or abnormal earnings (*AE*).

[c]Panel B shows results of estimating the following regression: $P_{j,F} = \mu_0 + \mu_1 V_j^{DIV} + \mu_2 V_j^{FCF} + \mu_3 V_j^{AE} + \varepsilon_j$. The last two rows in panel B show the incremental adjusted R^2 provided by the noted value estimate, beyond that provided by the other two value estimates. For the *OLS* regression, we report White [1980] adjusted *t*-statistics. The incremental adjusted R^2 is the difference between the adjusted R^2 for the *OLS* (rank) regression containing all three value estimates and the adjusted R^2 for the *OLS* (rank) regression which excludes the value estimate in the noted column.

planatory power of V^{DIV} equals the adjusted R^2 from the full model minus the adjusted R^2 from the regression of price on V^{FCF} and V^{AE}. Controlling for V^{FCF} and V^{DIV}, V^{AE} adds 14% explanatory power for the *OLS* regressions and 4% for the rank regressions. In contrast, neither V^{FCF} nor V^{DIV} adds much (0–1% incremental adjusted R^2) to explaining variation in security prices.

In summary, the results in tables 1 and 2 indicate that *AE* value estimates dominate *DIV* and *FCF* value estimates in terms of accuracy and explainability. One explanation for this superiority is that differences in reliability stem from the *AE* model containing both a stock component (B_F) and a flow component (AE_t), whereas the *DIV* and *FCF* models are pure flow-based models. *AE* value estimates will dominate *DIV* and *FCF* value estimates when biases in book values resulting from accounting procedures (such as expensing *R&D*) or accounting choices (such as a firm's accrual practices) are less severe than errors in forecasting attributes and errors in estimating discount rates and growth rates. As an indication of the potential severity of this issue, we note that book value of equity represents 72% of the sample mean V^{AE}, and that the terminal value represents 21%, 65%, and 82% of the mean V^{AE}, V^{DIV}, and V^{FCF}, respectively. Thus, biases in measuring book values may substantially affect *AE* value estimates (but have no effect on *DIV* or *FCF* value estimates),

TABLE 3

Results of Pooled Sample Regressions of Contemporaneous Stock Prices on the Components of Value Estimates[a]

Panel A: *DIV* Model[b]

	Growth Rate = 0%			Growth Rate = 4%		
		PV	*DTV*		*PV*	*DTV*
OLS Coefficient		6.47	−2.04		5.64	−0.87
t-Statistic: *OLS* Coefficient = 1		15.41	−10.66		21.91	−18.45
t-Statistic: Rank Coefficient = 0		9.52	−0.34		12.86	−0.80
Model *OLS* R^2	0.57			0.57		
Model Rank R^2	0.84			0.84		
Incremental *OLS* R^2		0.05	0.00		0.10	0.01
Incremental Rank R^2		0.00	0.00		0.01	0.00

Panel B: *FCF* Model[c]

	Growth Rate = 0%			Growth Rate = 4%		
	NFA	*PV*	*DTV*	*NFA*	*PV*	*DTV*
OLS Coefficient	0.26	0.36	0.71	0.19	0.84	0.21
t-Statistic: *OLS* Coefficient = 1	−21.30	−6.48	−4.87	−22.97	−1.59	−20.73
t-Statistic: Rank Coefficient = 0	26.94	10.00	15.61	27.03	13.31	12.98
Model *OLS* R^2	0.35			0.32		
Model Rank R^2	0.82			0.82		
Incremental *OLS* R^2	0.04	0.01	0.05	0.04	0.05	0.03
Incremental Rank R^2	0.04	0.01	0.12	0.05	0.01	0.12

Panel C: *AE* Model[d]

	Growth Rate = 0%			Growth Rate = 4%		
	B	*PV*	*DTV*	*B*	*PV*	*DTV*
OLS Coefficient	1.24	2.99	−0.48	1.24	3.05	−0.31
t-Statistic: *OLS* Coefficient = 1	12.36	19.96	−15.82	12.51	22.73	−28.03
t-Statistic: Rank Coefficient = 0	66.84	22.64	−4.95	67.03	23.75	−5.52
Model *OLS* R^2	0.74			0.74		
Model Rank R^2	0.91			0.91		
Incremental *OLS* R^2	0.45	0.11	0.00	0.45	0.14	0.00
Incremental Rank R^2	0.15	0.02	0.00	0.15	0.02	0.00

[a]See n. a to table 1 for a description of the sample and the calculations of value estimates and terminal values.

[b]Panel A reports coefficient estimates and White-adjusted *t*-statistics for the following regression: $P_{j,F} = \omega_0 + \omega_1 PV_{j,F}^{DIV} + \omega_2 DTV_{j,F}^{DIV} + \varepsilon_{j,t}$, where $P_{j,F}$ = observed share price of security j on the *Value Line* forecast date; $PV_{j,F}^{DIV}$ = the present value of the five-year stream of forecasted dividends; $DTV_{j,F}^{DIV}$ = discounted (to time F) value of the terminal value for the noted specification.

[c]Panel B reports coefficient estimates and White-adjusted *t*-statistics for the following regression: $P_{j,F} = \omega_0 + \omega_1 NFA_{j,F}^{FCF} + \omega_2 PV_{j,F}^{FCF} + \omega_3 DTV_{j,F}^{FCF} + \varepsilon_{j,t}$, where $P_{j,F}$ = observed share price of security j on the *Value Line* forecast date; $NFA_{j,F}$ = net financial assets at the valuation date (excess cash and marketable securities − debt − preferred stock); $PV_{j,F}^{FCF}$ = the present value of the five-year stream of forecasted free cash flows; $DTV_{j,F}^{DIV}$ = discounted (to time F) value of the terminal value for the noted specification.

[d]Panel C reports coefficient estimates and White-adjusted *t*-statistics for the following regression: $P_{j,F} = \omega_0 + \omega_1 B_{j,F} + \omega_2 PV_{j,F}^{AE} + \omega_3 DTV_{j,F}^{AE} + \varepsilon_{j,t}$, where $P_{j,F}$ = observed share price of security j on the *Value Line* forecast date; $B_{j,F}$ = book value of equity at the valuation date; $PV_{j,F}^{AE}$ = the present value of the five-year stream of forecasted dividends; $DTV_{j,F}^{AE}$ = discounted (to time F) value of the terminal value for the noted specification.

while errors in forecasting flows and estimating discount rates and growth rates are likely to have a bigger effect on V^{DIV} and V^{FCF} than on V^{AE}.

Table 3 provides indirect evidence on the stock versus flow distinction by examining the incremental explanatory power of the components of each value estimate:[27]

$$P_{j,F} = \omega_0 + \omega_1 PV_j^{DIV} + \omega_2 DTV_{j,F}^{DIV} + \varepsilon_j, \tag{8}$$

$$P_{j,F} = \omega_0 + \omega_1 NFA_j + \omega_2 PV_j^{FCF} + \omega_3 DTV_{j,F}^{FCF} + \varepsilon_j, \tag{9}$$

$$P_{j,F} = \omega_0 + \omega_1 B_j + \omega_2 PV_j^{AE} + \omega_3 DTV_{j,F}^{AE} + \varepsilon_j \tag{10}$$

where:

PV_j^{FUND} = the present value of the five-year stream of the forecasted attribute;

$DTV_{j,F}^{FUND}$ = the discounted (to time F) value of the terminal value; and

NFA_j = net financial assets at time $F = ECMS - D - PS$.

For each regression, we report White-adjusted t-statistics of whether the estimate differs from its theoretical value of one, the adjusted R^2 for each equation and model, and the additional explanatory power added by each component of the model holding constant the other component(s). Turning first to the coefficient estimates, we note that for all three models, we strongly reject the null hypothesis that the coefficient relating DTV^{FUND} to price equals one, suggesting that none of the terminal values is well specified. For the *AE* model, the results also reject the hypothesis that the coefficient relating price to book value is one, although in all cases ω_1 is significantly positive. Comparing *OLS* [rank] results across the three panels, we note that the incremental explanatory power provided by PV^{DIV} of 10% [1%] and by PV^{FCF} of 5% [1%] is substantially less than the 45% [15%] explanatory power provided by book value alone in the *AE* model. Book value also adds more than either PV^{AE}—14% [2%] or DTV^{AE}—0% [1%]. Overall, these results suggest that, despite conservatism in its measurement, book value of equity explains a significant portion of the variation in observed prices.

Our second analysis of the stock versus flow explanation focuses on situations where we might expect accounting practices to result in book values that are biased estimates of market value. On the one hand, we expect that when the current book value of equity does a good job of recording the intrinsic value of the firm, *AE* value estimates are more

[27] The terminal value component equals the present value, at the valuation date, of the estimated terminal value five years hence. To be consistent with the *FCF* model specified by equation (2), we include net financial assets (*NFA*), equal to excess cash and marketable securities minus debt minus preferred stock, as a component in the *FCF* model.

reliable—than *FCF* or *DIV* value estimates—because more of intrinsic value is included in the forecast horizon (and therefore less in the terminal value calculation). On the other hand, even if book values exclude value-relevant assets, the *AE* model's articulation of the balance sheet and the income statement will link lower book values today with larger abnormal earnings in future periods. For example, if the net *R&D* payoff component of earnings is stable through time (as we expect in equilibrium), then the sum of current book value of equity and the discounted stream of abnormal earnings will result in the same estimate of intrinsic value if *R&D* investments were capitalized at their net present values (Bernard [1995, n. 9] makes a similar point with respect to accounting distortions which result in overstatements of book values).

We test whether the *AE* model performs differently for firms with high *R&D* spending than for firms with low or no *R&D* spending. We identify a sample of *High R&D* firms by first ranking the sample firms based on the ratio of *Compustat R&D* spending in year $t-1$ to total assets at the beginning of year $t-1$. About 48% (1,390 firm-year observations) of the sample disclose no, or immaterial amounts of, *R&D* expenditures (the *Low R&D* sample); the top 25% of firms (the *High R&D* sample) have mean annual *R&D* spending of 7.2% of total assets. Table 4, panel A reports the results of accuracy comparisons; table 5, panel A shows the results of the explainability tests. These findings show no evidence that, for the *High R&D* sample, *AE* value estimates are less reliable than *DIV* or *FCF* estimates; in fact, they are significantly *more* accurate and explain *more* of the variation in security prices. Within-model, across-partition comparisons of accuracy (far right column of table 4) show no difference in the accuracy of *AE* value estimates for *High* versus *Low R&D* firms. Differences in R^2s between the *High* and *Low R&D* samples (panel A, table 5) indicate that the *AE* model performs better, not worse, for *High R&D* firms.[28]

We also partition the sample based on the ability of firms to affect the flow component of the *AE* model. Unlike free cash flows and dividends, management can influence the timing of abnormal earnings by exercising more or less discretion in their accrual practices. Whether such discretion leads to *AE* value estimates being more or less reliable measures of market prices depends on whether management uses accounting discretion to clarify or obfuscate value-relevant information. Because we have no a priori reason for believing that one effect dominates the other in explaining the accrual behavior of the sample firms, we do not

[28] Our results concerning the accuracy of *AE* value estimates for *High* versus *Low R&D* firms may be sensitive to our sample of large, relatively stable firms. For their broader sample, Sougiannis and Yaekura [1997] find that absolute prediction errors for *AE* value estimates increase with the amount of *R&D* spending, and Barth, Kasznik, and McNichols [forthcoming] report a significant negative relation between *R&D* spending and signed prediction errors (they define the prediction error as price minus value estimate, scaled by price).

TABLE 4

Comparison of the Accuracy of Value Estimates Across and Within Sample Partitions[a]

Panel A: *R&D* (as Percentage of Total Assets)

	High *R&D* Sample[b]			Low *R&D* Sample[b]			
Value Estimate	Median	versus *FCF*	versus *AE*	Median	versus *FCF*	versus *AE*	High versus Low Difference
DIV (g = 0%)	77.5%	0.00	0.00	78.2%	0.00	0.00	0.01
FCF (g = 0%)	46.1%		0.00	49.2%		0.00	0.00
AE (g = 0%)	35.0%			33.9%			0.35
DIV (g = 4%)	71.8%	0.00	0.00	71.9%	0.00	0.00	0.01
FCF (g = 4%)	33.7%		0.00	45.7%		0.00	0.00
AE (g = 4%)	30.9%			32.0%			0.36

Panel B: Accruals (as Percentage of Total Assets)

	High Accrual Sample[c]			Low Accrual Sample[c]			
Value Estimate	Median	versus *FCF*	versus *AE*	Median	versus *FCF*	versus *AE*	High versus Low Difference
DIV (g = 0%)	78.7%	0.00	0.00	77.0%	0.00	0.00	0.09
FCF (g = 0%)	48.6%		0.00	46.8%		0.00	0.40
AE (g = 0%)	32.9%			34.9%			0.19
DIV (g = 4%)	72.7%	0.00	0.00	71.4%	0.00	0.00	0.34
FCF (g = 4%)	41.9%		0.00	38.3%		0.00	0.17
AE (g = 4%)	29.8%			32.0%			0.38

Panel C: Precision of Attribute

	High Precision Sample[d]			Low Precision Sample[d]			
Value Estimate	Median	versus *FCF*	versus *AE*	Median	versus *FCF*	versus *AE*	High versus Low Difference
DIV (g = 0%)	100.0%	0.00	0.00	67.0%	0.00	0.00	0.00
FCF (g = 0%)	50.5%		0.00	49.3%		0.00	0.67
AE (g = 0%)	43.8%			23.8%			0.00
DIV (g = 4%)	100.0%	0.00	0.00	58.5%	0.00	0.00	0.00
FCF (g = 4%)	34.8%		0.36	61.2%		0.00	0.00
AE (g = 4%)	39.3%			24.4%			0.00

Panel D: Predictability of Attribute

	High Predictability Sample[e]			Low Predictability Sample[e]			
Value Estimate	Median	versus *FCF*	versus *AE*	Median	versus *FCF*	versus *AE*	High versus Low Difference
DIV (g = 0%)	71.2%	0.00	0.00	77.1%	0.00	0.00	0.00
FCF (g = 0%)	48.0%		0.00	48.7%		0.00	0.28
AE (g = 0%)	37.4%			31.0%			0.00
DIV (g = 4%)	63.7%	0.00	0.00	72.0%	0.00	0.00	0.00
FCF (g = 4%)	42.0%		0.00	39.0%		0.00	0.40
AE (g = 4%)	32.4%			29.4%			0.08

[a]See n. a to table 1 for a description of the sample and the calculations of value estimates and terminal values. In the columns labeled "versus *FCF*(*AE*)" we report significance levels comparing the median absolute prediction errors of the noted variables. The column labeled "High versus Low Difference" shows the significance level for the Wilcoxon test for whether the accuracy of the noted High sample differs from the accuracy of the Low sample.

[b]The High *R&D* sample consists of the firms in the top quartile of *R&D* expenses as a percentage of total assets, measured in year $t-1$; the Low *R&D* sample contains all firms with no disclosed research and development expenses in year $t-1$.

[c]The High (Low) Accrual sample consists of the top (bottom) quartile of firms ranked on the absolute value of total accruals as a percentage of total assets, measured in year $t-1$.

[d]Precision equals the absolute value of the difference between the forecast attribute and its realization, scaled by forecast attribute. The Low (High) Precision sample for each *FCF*(*AE*) attribute consists of the top (bottom) quartile of firms ranked on the average precision of the current-year, one-year-ahead, and three-year-ahead forecasts of that attribute.

[e]Predictability equals the standard deviation of percentage yearly changes in the historical realized values of the attribute valued by each model. The Low (High) Predictability sample for each *FCF*(*AE*) attribute consists of the top (bottom) quartile of firms ranked on the predictability of that attribute.

TABLE 5

Comparisons of the Explainability of Value Estimates Across and Within Sample Partitions[a]

Panel A: *R&D* (as Percentage of Total Assets)

	High *R&D* Sample						Low *R&D* Sample					
	Growth Rate = 0%			Growth Rate = 4%			Growth rate = 0%			Growth Rate = 4%		
	DIV	*FCF*	*AE*	*DIV*	*FCF*	*AE*	*DIV*	*FCF*	*AE*	*DIV*	*FCF*	*AE*
OLS Coefficient	2.13	1.02	1.26	1.69	0.64	1.15	1.34	0.59	1.34	0.90	0.34	1.06
OLS R^2	0.75	0.58	0.79	0.74	0.51	0.81	0.32	0.29	0.71	0.28	0.22	0.62
Rank R^2	0.87	0.87	0.94	0.87	0.86	0.94	0.81	0.72	0.88	0.81	0.71	0.88

Panel B: Accruals (as Percentage of Total Assets)

	High Accrual Sample						Low Accrual Sample					
	Growth Rate = 0%			Growth Rate = 4%			Growth Rate = 0%			Growth Rate = 4%		
	DIV	*FCF*	*AE*	*DIV*	*FCF*	*AE*	*DIV*	*FCF*	*AE*	*DIV*	*FCF*	*AE*
OLS Coefficient	1.89	0.81	1.26	1.44	0.52	1.13	1.47	0.82	1.21	0.98	0.52	1.04
OLS R^2	0.56	0.40	0.75	0.54	0.34	0.72	0.40	0.41	0.66	0.35	0.35	0.63
Rank R^2	0.84	0.77	0.91	0.84	0.76	0.90	0.82	0.81	0.89	0.82	0.79	0.89

Panel C: Precision of Attribute

	High Precision Sample						Low Precision Sample					
	Growth Rate = 0%			Growth Rate = 4%			Growth Rate = 0%			Growth Rate = 4%		
	DIV	*FCF*	*AE*	*DIV*	*FCF*	*AE*	*DIV*	*FCF*	*AE*	*DIV*	*FCF*	*AE*
OLS Coefficient	1.82	1.09	1.36	1.34	0.54	1.14	2.11	0.46	0.92	1.55	0.25	0.78
OLS R^2	0.32	0.58	0.72	0.30	0.79	0.66	0.70	0.39	0.80	0.66	0.32	0.78
Rank R^2	0.80	0.79	0.91	0.80	0.78	0.90	0.92	0.74	0.93	0.92	0.75	0.93

Panel D: Predictability of Attribute

	High Predictability Sample						Low Predictability Sample					
	Growth Rate = 0%			Growth Rate = 4%			Growth Rate = 0%			Growth Rate = 4%		
	DIV	*FCF*	*AE*	*DIV*	*FCF*	*AE*	*DIV*	*FCF*	*AE*	*DIV*	*FCF*	*AE*
OLS Coefficient	1.69	0.60	1.43	1.27	0.33	1.21	0.90	1.21	1.15	0.54	0.49	1.04
OLS R^2	0.60	0.42	0.71	0.58	0.34	0.68	0.31	0.77	0.72	0.26	0.31	0.71
Rank R^2	0.86	0.77	0.91	0.86	0.78	0.91	0.82	0.77	0.92	0.82	0.76	0.91

[a]See n. a to table 1 for a description of the sample and the calculations of value estimates and terminal values. We report regression results of observed price on the value estimates for each sample partition. See table 4 for a description of the sample partitions.

predict whether *AE* value estimates perform better or worse for firms with high accounting discretion. We partition firms based on the level of accounting discretion available to firms, as proxied by the ratio of the absolute value of the ratio of total accruals to total assets (Healy [1985]).[29] Securities in the top (bottom) quartile of the ranked distribution are assigned to the *High* (*Low*) *Accruals* sample. The mean (median) ratio of accruals to assets for the *High Accruals* sample is 14% (12%); for the *Low Accruals* sample the mean and the median value is 1.5%. Table 4, panel B summarizes the accuracy of the value estimates for the accruals

[29] Total accruals equal change in current assets (*Compustat* item #4) − change in current liabilities (#5) − change in cash (#1) + change in short-term debt (#34) − depreciation (#16).

subsamples; table 5, panel B shows similar comparisons for the explainability measure. Within the *High Accruals* sample, both measures show that V^{AE} is superior to V^{DIV} and V^{FCF}. Comparisons of *AE* estimates between the *High* and *Low Accrual* samples show no evidence that *AE* estimates perform worse for the *High Accrual* sample than for the *Low Accrual* sample.

In summary, we find no evidence that *AE* estimates are less reliable for firms where book values poorly reflect intrinsic values (firms with high *R&D* spending) or for firms where there is scope for managing earnings (firms with high accruals). If anything, the within-sample and across-sample tests indicate that high *R&D* spending and high accounting discretion are associated with more reliable *AE* value estimates.[30]

A second potential explanation for differences in the reliability of V^{DIV}, V^{FCF}, and V^{AE} is that the precision and predictability of the fundamental attributes themselves differ. We measure precision as the absolute difference between the predicted value of an attribute and its realization, scaled by share price.[31] We also examine the bias in the fundamental attributes, measured as the signed difference between the predicted value and its realization, scaled by share price. We define predictability as the ease with which market participants can forecast the attribute, measured as the standard deviation of historical year-to-year percentage changes in the attribute.[32] Ceteris paribus, more precise and more predictable attributes should result in more accurate value estimates which explain a greater portion of the variation in observed prices.

We compute bias and precision statistics for each of the current year, one-year-ahead and three- to five-year-ahead forecasted attributes;[33] median values are reported in table 6, panel A. Bias measures indicate that

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[30] We also partition the sample securities by capital expenditure spending to investigate whether *FCF* value estimates outperform *AE* and *DIV* value estimates when forecasted capital expenditures are low. (We thank Peter Easton for suggesting this analysis.) Results (not reported) show no evidence that *FCF* value estimates are more accurate or explain more variation in prices than do *AE* value estimates for the *LOW* capital expenditure sample. Across-sample, within-model tests, however, show some evidence that *FCF* value estimates are more accurate for the *LOW* capital expenditure sample than for the *HIGH* capital expenditure sample.

[31] We find similar results if we scale by the absolute value of the predicted attribute.

[32] Results based on the coefficient of variation of yearly changes are similar and are not reported.

[33] We use the three-year-ahead realization to measure the bias in the three- to five-year-ahead forecast of each attribute. The realized dividend for year t equals the total amount of common stock dividends declared in year t (#121). The realized free cash flow per share in year t equals the net cash flow from operating activities (#308) minus capital expenditures (#128). The realized abnormal earnings for year t equal earnings per share after extraordinary items (#53) minus the estimated discount rate multiplied by the book value of common equity in year $t-1$ (#60). To ensure consistency across models, we scale all variables by the number of shares used to calculate primary earnings per share (#54), and we delete observations with missing data for dividends, free cash flow, or abnormal earnings.

TABLE 6

Comparison of Selected Properties of the Forecast Attributes [a]

Panel A: Bias and Precision[b]

	Bias			Precision		
		Wilcoxon Tests[b]			Wilcoxon Tests[b]	
	Median	versus *FCF*	versus *AE*	Median	versus *FCF*	versus *AE*
Current-Year						
DIV	0.00%	0.00	0.00	0.00%	0.00	0.00
FCF	0.85%		0.00	4.88%		0.00
AE	0.65%			1.32%		
One-Year-Ahead						
DIV	0.01%	0.00	0.00	0.09%	0.00	0.00
FCF	1.75%		0.00	5.93%		0.00
AE	2.22%			2.85%		
Three-Year-Ahead						
DIV	0.46%	0.00	0.00	0.57%	0.00	0.00
FCF	4.72%		0.00	7.76%		0.01
AE	4.54%			5.10%		

Panel B: Predictability[b]

		Wilcoxon Tests	
Attribute	Median	versus *FCF*	versus *AE*
DIV	0.22	0.00	0.00
FCF	7.72		0.00
AE	3.64		

[a]See n. a to table 1 for a description of the sample and the calculations of value estimates and terminal values.

[b]Bias (precision) equals the signed (absolute value of the) difference between the forecast attribute and its realization, scaled by the share price. Predictability equals the standard deviation of percentage yearly changes in the historical realized values of the attribute valued by each model. We report median bias, precision, and predictability measures as well as the significance levels for Wilcoxon tests comparing these statistics across models.

the median current-year *AE* (*FCF*) forecast overstates realized abnormal earnings by about 0.6% (0.8%) of security price, with current-year *DIV* forecasts showing no bias. For all attributes, forecast optimism increases with the forecast horizon: the median one-year-ahead *AE* (*FCF*) forecast overstates its realization by about 2.2% (1.8%) of price, compared to 4.5 (4.7%) for the three-year-ahead *AE* (*FCF*) forecasts. More importantly, we find that for all horizons, *AE* forecasts are significantly more accurate than *FCF* forecasts, with *AE* prediction errors ranging from roughly 25% of *FCF* prediction errors for current-year forecasts (1.3% versus 4.9%) to 65% for three-year-ahead forecasts (5.1% versus 7.8%). The finding that *DIV* forecasts are the most precisely forecasted attribute is to be expected given firms' reluctance to alter dividend policies.

For *each* fundamental attribute, we average the precision of current-year, one-year-ahead and three-year-ahead forecasts and identify those observations in the top quartile of average precision (i.e., those with the largest percentage differences between forecasts and realizations) as the *Low Precision* sample and those observations in the bottom quartile of average precision as the *High Precision* sample. Comparisons of the accuracy and explainability of the value estimates for precision subsamples are shown in panel C of tables 4 and 5. With the exception of the accuracy of V^{FCF} (4% growth rate), there is no evidence that more precise forecasts result in more reliable value estimates; if anything, we find the opposite. For the *DIV* model, this result is not unexpected, since for a large portion of the sample firms, V^{DIV} understates intrinsic values (as shown in table 1);[34] in these cases, the slight average optimism in *DIV* forecasts (documented in table 6) improves the accuracy of V^{DIV}. Similarly, the optimism in *AE* forecasts compensates for the underestimation by V^{AE} observed in table 1, resulting in more reliable *AE* value estimates for the *Low Precision* partition than for the *High Precision* partition.

We also partition the sample based on the standard deviation of the percentage changes in the attribute; for these calculations, we require a minimum of ten annual changes in realized dividends, free cash flows, and abnormal earnings. Table 6, panel B reports median values of the predictability measure for each model; we also report comparisons of predictability between each pair of models. Consistent with firms making few changes in dividend payments and policies, we find that dividends are highly predictable. Of more interest (we believe) is the finding that abnormal earnings are significantly (at the .00 level) more predictable than free cash flows. To assess the importance of predictability on the reliability of the value estimates, we rank *each* set of value estimates based on the magnitude of the relevant predictability measure and repeat our tests on the bottom quartile (*High Predictability* sample) and on the top quartile (*Low Predictability* sample). The results in panel D of tables 4 and 5 show no evidence that a more predictable *AE* or *FCF* series leads to significantly more reliable value estimates; however, we do observe this pattern for the *DIV* series.

Overall, the results in tables 4–6 provide mixed evidence on whether the precision and the predictability of the attribute valued by each model are important determinants of the reliability of the value estimates. Consistent with the *AE* model's relative superiority over the *FCF* model, we find that *AE* forecasts are generally more precise and more predictable than *FCF* forecasts. However, within-model tests show no consistent evidence that securities with the most precise or the most predictable forecasts have more reliable value estimates than do securities with the least precise or the least predictable forecasts.

5. *Comparison to Penman and Sougiannis [1998]*

Penman and Sougiannis [1998] compare the signed prediction errors of *DIV*, *FCF*, and *AE* value estimates calculated using realized values of

[34] This is certainly true for the 20% of firms in our sample which do not pay dividends. Even for dividend-paying firms, *DIV* estimates likely understate value because our terminal value calculations do not include a liquidating dividend.

these attributes.[35] Although both PS and we conclude that V^{AE} dominates V^{DIV} and V^{FCF}, the studies differ in several respects: PS's sample is larger and more diversified than our sample of (median and large) *VL* firms; PS's approach uses realizations and a portfolio averaging process, while our design examines analysts' forecasts for individual securities; PS evaluate bias, while we focus on accuracy and explainability. We link the two studies by examining, for our sample, the effects of using forecasts versus realizations, the portfolio methodology, and other performance metrics.

For each firm-year observation with available data, we collect realized values of *DIV, FCF,* and *AE* from the 1997 *Compustat* tape (which includes fiscal years through 1996). Because we have a five-year forecast horizon, we are limited to analyzing years 1989, 1990, and 1991. For each sample year, we randomly assign the sample securities to ten portfolios and calculate the average portfolio value of each attribute for each year of the horizon. We then discount (at the average discount rate) the mean values of the attributes to the average valuation date to arrive at a mean value estimate for each portfolio. We perform this analysis using both forecasts and realizations, so that we have both an ex ante and an ex post mean value estimate for each portfolio to compare to the mean portfolio price. We believe the calculation of the mean value estimates follows that of PS, except that we have fewer portfolios (30 versus 400) and fewer firms per portfolio (50–60 versus about 200).

Panel A of table 7 shows the median value estimates and median bias for the 30 portfolios.[36] We report the median signed prediction error for portfolio value estimates based on realizations ("ex post" value estimates), for portfolio value estimates based on forecasts ("ex ante" value estimates), and for these same securities' value estimates calculated using forecasts and the individual security approach. A comparison of the ex post portfolio and ex ante portfolio results shows the effects of using realizations versus forecasts, holding constant the methodology; a comparison of ex ante portfolio value estimates with ex ante individual security value estimates highlights the effects of the portfolio methodology, controlling for the use of forecast data. Panel B shows similar comparisons for the accuracy metric.[37]

We draw the following conclusions from the results in table 7. First, ex post value estimates are considerably smaller than ex ante value estimates,

[35] For the specification closest to ours, PS report mean biases of –17% (V^{DIV}), –76% (V^{FCF}), and 6% (V^{AE}); these compare to our sample mean bias measures of –68% (V^{DIV}), 18% (V^{FCF}), and –13% (V^{AE}), reported in table 1.

[36] We report median statistics for consistency with tables 1 and 4. Results based on means are similar.

[37] We do not examine the explainability metric for the portfolio measures because the point of the portfolio averaging process—to reduce the variability in observed prices and in value estimates—runs counter to the point of the explainability tests—to assess the extent to which value estimates explain variation in observed prices.

TABLE 7

Sample Prediction Errors for Value Estimates Based on Realizations versus Forecasts and Portfolios versus Individual Securities[a]

Panel A: Signed Prediction Errors (Bias)[b]

	Portfolio Approach							Individual Security Approach		
	Realizations			Forecasts			Real versus Forecast[c]	Forecasts		
	Median	Median % Difference	α-Level Difference = 0	Median	Median % Difference	Difference = 0	α-Level Difference	Median	Median % Difference	α-Level Difference = 0
Share Price	31.55	n/a	n/a	31.55	n/a	n/a	n/a	31.55	n/a	n/a
Value Estimate										
DIV ($g = 0\%$)	5.13	−83.0%	0.00	8.53	−73.3%	0.00	0.00	6.53	−74.1%	0.00
FCF ($g = 0\%$)	0.00	−100.0%	0.00	17.24	−44.4%	0.00	0.00	15.01	−41.6%	0.00
AE ($g = 0\%$)	14.15	−55.0%	0.00	22.30	−30.4%	0.00	0.00	19.22	−26.3%	0.00
DIV ($g = 4\%$)	6.36	−78.8%	0.00	10.83	−66.0%	0.00	0.00	8.30	−66.8%	0.00
FCF ($g = 4\%$)	0.00	−100.0%	0.00	28.19	−10.2%	0.00	0.00	24.55	−8.0%	0.00
AE ($g = 4\%$)	14.15	−54.9%	0.00	23.70	−26.1%	0.00	0.00	20.68	−21.7%	0.00

Panel B: Absolute Prediction Errors (Accuracy)[b]

	Portfolio Approach							Individual Security Approach		
	Realizations			Forecasts			Real versus Forecast[c]	Forecasts		
Value Estimate	Median	versus *FCF*	versus *AE*	Median	versus *FCF*	versus *AE*	α-Level, Difference	Median	versus *FCF*	versus *AE*
DIV ($g = 0\%$)	83.0%	0.00	0.00	73.3%	0.00	0.00	0.00	74.1%	0.00	0.00
FCF ($g = 0\%$)	100.0%		0.00	44.4%		0.00	0.00	47.5%		0.00
AE ($g = 0\%$)	55.0%			30.4%			0.00	32.3%		
DIV ($g = 4\%$)	78.8%	0.00	0.00	66.0%	0.00	0.00	0.00	67.1%	0.00	0.00
FCF ($g = 4\%$)	100.0%		0.00	11.9%		0.00	0.00	40.7%		0.00
AE ($g = 4\%$)	54.9%			26.1%			0.00	29.4%		

[a]See n. a to table 1 for a description of the sample and the calculations of value estimates and terminal values. The portfolio approach randomly assigns securities to ten portfolios each year, 1989–91, and then calculates the mean value of each forecast attribute for each year of the horizon. We then discount (at the average discount rate) the mean values of the attributes to the average valuation date to arrive at a mean value estimate for each portfolio. We perform this analysis using both forecasts and realizations. The individual security approach is the same as that used in table 1 but is applied to the sample securities with realization data.

[b]Panel A (B) reports median signed (absolute) prediction errors, where the prediction errors equals $(V_j^{FUND} - P_{j,F})/P_{j,F}$. We also report the significance level associated with the sign rank statistic of whether the median value equals zero.

[c]We report the significance level of the test of the equality of the median bias (panel A) or median accuracy (panel B) for portfolio-based value estimates calculated using realizations versus forecasts.

regardless of whether the portfolio or individual security approach is used. This difference is particularly striking for *FCF* value estimates where the median V^{FCF} based on realizations is zero, reflecting the fact that most of the sample portfolios (20 of 30, not reported) had negative realized mean free cash flows. The smaller ex post value estimates are also consistent with the results in table 6 which show that, for our sample, realizations fell short of analysts' expectations by a wide margin. Second, comparisons of observed prices with both ex ante and ex post value estimates indicate that ex ante value estimates dominate ex post value estimates: for all models, ex ante values have significantly (at the .00 level) smaller bias and are more accurate than comparable ex post values. Third, using either smallest absolute bias or smallest absolute prediction error as the performance criterion, the realization-portfolio results show that *AE* value estimates dominate *DIV* and *FCF* value estimates. In contrast, the forecast-portfolio results depend on the growth rate: for $g = 0\%$, V^{AE} dominates V^{DIV} and V^{FCF} in terms of bias and accuracy, but for $g = 4\%$, V^{FCF} dominates.[38] This disparity between the bias and the accuracy results observed for *FCF* value estimates (for $g = 4\%$) highlights the effect that variation in the value estimates has on the performance metric. When the variability in value estimates is retained—as it is when individual securities rather than portfolios are valued—the results (far right columns of table 7) show that *AE* value estimates consistently dominate *FCF* and *DIV* estimates in terms of accuracy.

We draw the following inferences from these results. The conclusion that *AE* value estimates dominate *FCF* or *DIV* value estimates is fairly robust to the level of aggregation (portfolio versus individual securities), the type of data (realizations versus forecasts), and the performance metric (bias versus accuracy). We find, however, that the levels of bias and accuracy are significantly (at the .00 level) smaller when forecasts rather than realizations are used to calculate value estimates. The forecast versus realization distinction is also important for conclusions concerning *FCF* and *DIV* value estimates. Consistent with PS, we find that ex post *FCF* value estimates are more biased than ex post *DIV* value estimates; however, ex ante *FCF* value estimates dominate ex ante *DIV* value estimates in terms of both bias and accuracy.

6. *Summary and Conclusions*

This paper compares the reliability of value estimates from the discounted dividend model, the discounted free cash flow model, and the discounted abnormal earnings model. Using a sample of five-year forecasts for nearly 3,000 firm-year observations over 1989–93, we find that

[38] See n. 6 for results based on other growth rates.

the *AE* value estimates are more accurate and explain more of the variation in security prices than do *FCF* or *DIV* value estimates. Our explorations of the sources of the relative superiority of the *AE* model show that the greater reliability of *AE* value estimates is likely driven by the sufficiency of book value of equity as a measure of intrinsic value, and perhaps by the greater precision and predictability of abnormal earnings.

Our analysis of whether accounting discretion enhances or detracts from the performance of the *AE* model indicates no difference in the accuracy of *AE* estimates between firms exercising high versus low accounting discretion, although there is some evidence that *AE* value estimates explain more of the variation in current market prices for high discretion firms than for low discretion firms. We also find no evidence that *AE* value estimates are less reliable for firms with high versus low *R&D* expenditures. Together these findings indicate no empirical basis for concerns that accounting practices (such as immediate expensing of *R&D* or the flexibility afforded by accruals) result in inferior estimates of market equity value. Our results are more consistent with the argument that the articulation of clean surplus financial statements ensures that value estimates are unaffected by conservatism or accrual practices.

We conclude there is little to gain—and if anything something to lose—from selecting dividends or free cash flows over abnormal earnings as the fundamental attribute to be valued. Together with the fact that earnings are by far the most consistently forecasted attribute, our results suggest little basis for manipulating accounting data (for example, to general estimates of free cash flows) when earnings forecasts and book values are available.

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