Using Mechanical Earnings and Residual Income Forecasts In Equity Valuation

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Revised: April 2001.

This research was supported by the Fuqua School of Business, Duke University, London Business School and the University of Wisconsin. We appreciate the comments and suggestions of anonymous reviewers, workshop participants at the 1999 American Accounting Association Annual Meeting, the 2000 Accounting and Finance in Tel Aviv Conference, 1999 Inquire UK / Europe Conference, Columbia University, Cornell University, Duke University, Hong Kong University of Science and Technology, Humboldt University, New York University, Northwestern University, University of Alberta, University of British Columbia, UCLA, University of Chicago, University of Southern California and the University of Wisconsin; and from Tom Dyckman, Carolyn Levine, Michael Moore, Katherine Schipper, Lenny Soffer, K.R. Subramanyam, Jacob Thomas, Terry Warfield and Beverly Walther. Analysts' earnings forecasts are from Zacks Investment Research.

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Abstract

We document the reliability of value estimates based on forecasts from *firm- and time- specific* mechanical models of residual income and of earnings over 1976-1997. Reliability refers to the signed and absolute deviation between value estimates and observed market prices, and to the ability of value estimates to explain variation in prices (or the ability of book-scaled value estimates to explain variation in market-to-book ratios). Estimating firm- and time- specific models of residual income (specifically autoregressive models of order 1) produces mechanical residual income value estimates that are superior to book value alone and to residual income value estimates based on forecasts from firm- and time-specific models of earnings. While value estimates based on analysts' forecasts are less biased than firm-specific residual income value estimates, the two estimates do not differ in terms of accuracy or explainability. These results extend prior research, which does not estimate firm-specific residual income models, and finds that mechanical residual income based value estimates do not improve on book value alone and perform significantly worse than analyst-based value estimates.

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I. *Introduction*

This study contrasts the reliability of value estimates based on firm-specific mechanical residual income forecasts with value estimates based on firm-specific mechanical earnings forecasts. In addition, for a sample of firms followed by analysts, we compare the reliability of firm-specific mechanical based value estimates with value estimates based on analysts' earnings forecasts. We measure reliability in several ways: bias (the signed value of the prediction error, equal to the price-scaled difference between the value estimate and observed price), accuracy (the absolute value of the prediction error), explainability of observed prices (as captured by the R^2 of the regression of observed price on the value estimate) and explainability of market-to-book ratios (as captured by the R^2 of the regression of the market-to-book ratio on the difference between the value estimate and the book value of equity, scaled by book value of equity).[1]

The first comparison – of the reliability of mechanical residual income value estimates versus mechanical earnings value estimates and values estimates based on book value of equity alone – extends prior empirical valuation studies which describe the properties of residual income value estimates based on realized earnings (Penman and Sougiannis [1998]) and on analysts' earnings forecasts (e.g., Francis, Olsson and Oswald [2000], Frankel and Lee [1998]). By documenting the performance of mechanical time-series model forecasts in a valuation context, we shed light on how well investors can estimate intrinsic values when there are no analysts' earnings forecasts and they [investors] must rely on some other source of forecasts.[2] Dechow, Hutton and Sloan [1999] provide some evidence on this issue,

[1] Which of these measures best captures reliability depends on investors' loss functions, e.g., if investors care equally about value estimates that are above or below observed price by a given amount, we expect accuracy to be preferred to bias as a measure of reliability. We do not rank the reliability metrics a priori, and our results suggest no ranking is needed as we generally observe consistent evidence across the metrics. In sensitivity tests reported in section IV, we confirm the assumption of market efficiency underlying the reliability metrics.

[2] Our inferences are confined to firms that have the necessary data (12 yearly observations in our analyses) to estimate the firm-specific mechanical models. Future research could investigate the reliability gains and losses from extending or reducing this data series.

documenting that residual income value estimates derived from a mechanical model that assumes constant across-firm and over-time persistence in residual income do not improve on book value alone.

Following prior research which finds, in other contexts,[3] significant improvements when firm-specific estimations are used, we examine the performance of value estimates based on firm- and time-specific estimations of residual income models (specifically, autoregressive of order 1), and separately, earnings based models (specifically autoregressive of order 2). We perform these estimations for a large sample of firms each year, 1976-1997 (on average, 1,314 firms per year). Further, because our within-firm research design holds both the firm and the valuation formula constant – varying only the estimation of the residual income attribute – comparisons of the value estimates derived from the forecasts of the residual income and earnings models reflect the relative ability of linear residual income and earnings models to characterize profitability streams. Given the economic rationale for mean reversion in residual income, but not earnings, we expect (and find) the linear residual income model will outperform the linear earnings model.

The results show that firm-specific AR1 models of residual income produce value estimates which are less biased, at least as accurate, and explain at least as much, if not significantly more, of the variation in observed prices and market-to-book ratios than value estimates based on forecasts from firm-specific AR2 models of earnings. In contrast to Dechow et al. and Myers [1999], we find that the firm-specific residual income value estimates generally outperform value estimates based on book value of equity alone.[4] These results are especially relevant for settings where other forecast sources (such as analysts' forecasts) are not available. For example, proposed goodwill impairment tests being considered by the Financial Accounting Standards Board [FASB] will require that managers compare the fair values

[3] For example, Teets and Walsley [1996] find that the use of pooled, rather than firm-specific, time series estimations leads to downward biased earnings response coefficients in short event windows.
[4] Myers estimates firm-specific AR1 models of residual income for one year, 1996.

and book values of business segments. One plausible approach to measuring segment fair value is to use a residual income value estimate with segment-specific residual income forecasts as inputs.[5]

The improvement in the reliability of residual income value estimates provided by firm-specific estimations of the residual income persistence parameter motivates our second comparison, of the reliability of the mechanical residual income estimates with analyst based value estimates. This analysis extends prior research which contrasts these two value estimates, but does not use firm-specific estimations to generate residual income forecasts (Dechow et al. and Frankel and Lee). While we expect analyst based value estimates to be more reliable than firm-specific mechanical residual income value estimates, we predict the decrement in valuation reliability is smaller than documented in prior studies (which do not use firm- and time-specific estimations). Careful documentation of this decrement is important because it provides a direct measure of how much analysts' superior access to, or processing of, information translates into market value. Further, by performing these comparisons *each* quarter using analysts' updated earnings forecasts, we contribute to prior research on the sources of the analyst's advantage (e.g., Brown et al. [1987a] and Brown, Richardson and Schwager [1987]). Specifically, by examining within year changes in analyst-based value estimates relative to mechanical based value estimates, we provide a market-based assessment of the portion of the decrement in reliability attributable to analysts' timing advantage.

Tests of the second comparison are performed on the subset of observations for which quarterly data on analysts' current year and 1-year out earnings forecasts are available; these restrictions yield an average of 837 firms per year over 1981-1997. The results show that while analyst-based value estimates are significantly less biased than value estimates based on mechanical forecasts of residual income, they have similar accuracy and explained variability. These results are similar by quarter, suggesting no meaningful valuation differences attributable to an analyst timing advantage (as we measure it).

[5] Such an approach was explicitly proposed to the FASB on May 31, 2000 by a team from Morgan Stanley Dean Witter. The PowerPoint presentation explaining this proposal is available at the FASB web site.

The rest of the paper is organized as follows. The next section details the within-firm comparison of value estimates based on mechanical residual income forecasts with value estimates based on mechanical earnings forecasts. Section III reports the within-firm comparisons of value estimates based on analyst forecasts versus value estimates based on mechanical residual income forecasts. Section IV reports evidence on the assumption of market efficiency underlying the reliability metrics. Section V summarizes and concludes.

II. Large Sample Properties of Mechanical-Based Forecasts and Value Estimates

This section presents evidence on the reliability of value estimates based on mechanical residual income forecasts and mechanical earnings forecasts. We predict that value estimates based on forecasts from residual income models will outperform value estimates that rely on forecasts from earnings models because the former incorporate information about earnings, book values and cost of equity, while the latter exclude all but earnings information. In addition, economic reasoning suggests residual income is mean-reverting, while there is no such intuition for earnings.[6] We include results for the mechanical earnings-based models both to link our analysis with prior valuation studies and to document the incremental reliability afforded by modeling residual income directly.

Section II.1 details the residual income and earnings time-series models we estimate, and describes the calculation of value estimates using forecasts from these models. Section II.2 reports summary information on the sample firms and provides descriptive information about the cross-sectional distribution of the parameter estimates of both mechanical models. Section II.3 compares the reliability of value estimates based on residual income forecasts with the reliability of value estimates based on earnings forecasts. Section II.4 considers extensions and section II.V summarizes the results.

[6] For example, Fama and French [2000] investigate mean reversion in profitability (measured as return on assets) and in earnings. They find evidence consistent with mean reversion in profitability, and conclude that it [mean reversion in profitability] explains much of the predictable variation in earnings.

II.1. Methodology

Mechanical Residual Income Model: We begin our analysis of the properties of firms' residual income streams by inspecting the autocorrelation and partial autocorrelation plots and by performing Box-Jenkins tests on a random sample of Compustat firms with at least 12 yearly observations of earnings and book values of equity. Firm j's residual income is defined as $RI_{j,t} = X_{j,t} - r_j B_{j,t-1}$, where $X_{j,t}$ = firm j's reported EPS in year t, $B_{j,t-1}$ = firm j's book value of equity at the end of year t-1, and r_j = firm j's cost of equity (the estimation of r_j is described in section II.2). These analyses (not reported) indicate that residual income is described by an AR1 process, consistent with prior studies' conclusions (e.g., Dechow et al. [1999]).[7]

For each firm j and year t, we estimate the following mechanical model of residual income, RI-AR1:

$$RI_{j,t-1} = \omega_{j,0} + \omega_{j,1} RI_{j,t-2} + \varsigma_{j,t-1} \tag{1}$$

Equation (1) implies that RI $\rightarrow$ $\omega_0/(1-\omega_1)$ as $t \rightarrow \propto$. We use each firm's RI-AR1 parameter estimates for year t to generate residual income forecasts, $RI_{j,t}$, for years t=1,…,5. We input these forecasts into a finite horizon version of the residual income valuation model, where we assume steady state at the end of T=5 years at which time we estimate a terminal value:[8]

$$V(RI - AR1)_0 = B_0 + \sum_{t=1}^{5} \frac{RI_t}{(1+r)^t} + \frac{RI_5}{r(1+r)^5} \tag{2}$$

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[7] As an additional check on the appropriateness of the AR1 specification for residual income, we estimated the partial autocorrelations of the time-series of residual income for all firms with at least 10 years more data than the number of lags, and calculated the percentage of observations where the partial autocorrelation function was significant at the .10 level. (A result that the first partial autocorrelation (lag=1) is significant for firm j indicates that residual income follows an AR process of at least order 1; if the second partial autocorrelation is also significant, then residual income follows an AR process of at least order 2, etc.) These results showed that the majority (57%) of firms' residual income streams are described by an AR1 process, compared to 11% for AR2, 5% for AR3 and 4% for AR4.

[8] As detailed in section II.4, our results are not sensitive to using a finite horizon and calculating a terminal value versus using the consistent form of the mechanical-based value estimates which does not require terminal value assumptions.

In calculating value estimates using expression (2), we set negative terminal values (i.e., RI_5<0) equal to zero. We choose this alternative rather than assume that investors mechanically capitalize the terminal year residual income into perpetuity irrespective of its sign, because we have never seen this mechanical assumption implemented in practice. Another alternative would be to set residual income in year T to zero. This assumption derives from the argument that competition will drive positive economic rents towards zero (so no firm can expect to earn, in perpetuity, more than its opportunity cost of capital), while market discipline will drive out firms that earn negative economic rents (since investors will not allow a business to perpetually invest in negative net present value projects). While compelling, these arguments turn on economic profits, not accounting profits which are the basis for calculating residual income. This distinction is important, as accounting conservatism will lead to positive residual income in steady state (Penman [2000], Zhang [2000]); Zhang shows that setting these positive residual income values to zero will understate terminal values. With the exception of the bias results, our conclusions are not sensitive to the assumption we make about terminal values.[9]

Mechanical Earnings Model: Our choice of a time-series model of earnings is based on prior research, in particular Finger [1994], which generally supports an autoregressive model of order 2 for annual earnings, X-AR2:

$$X_{j,t-1} = \phi_{j,0} + \phi_{j,1} X_{j,t-2} + \phi_{j,2} X_{j,t-3} + \upsilon_{j,t-1} \tag{3}$$

Equation (3) implies that X $\rightarrow \phi_0 / (1 - \phi_1 - \phi_2)$ as $t \rightarrow \propto$. We use each firm's X-AR2 parameters to generate earnings forecasts, $X_{j,t}$, for years t=1,…,5. Using these forecasts, an assumed dividend payout ratio and the clean surplus relation, we forecast the firm's book value of equity. As with the calculation of V(RI-AR1), we assume steady state is reached at T=5, and we calculate a terminal value and a value estimate:

[9] Specifically, if we set terminal values equal to zero, we find that V(RI-AR1) continues to be at least as accurate and explain at least as much of the variability in observed prices as V(X-AR2) or V(B). Under this assumption, V(RI-AR1) continues to be less biased than V(X-AR2) but is more biased than V(B).

$$V(X-AR2)_0 = B_0 + \sum_{t=1}^{5} \frac{(X_t - rB_{t-1})}{(1+r)^t} + \frac{(X_5 - rB_4)}{r(1+r)^5} \tag{4}$$

where $B_{j,h} = B_{j,h-1} + X_{j,h} - DIV_{j,h}$

$DIV_{j,h}$ = the ratio of firm j's common stock dividends in year t-1 to net income in year t-1 times $X_{j,h}$. If $X_{j,h}$ is negative we set $DIV_{j,h}$ equal to common stock dividends in year t-1 divided by 6% of firm j's assets in year t-1 (as in Frankel and Lee [1998]).

II.2. Sample and Descriptive Information

To be included in the year t=1976-1997 sample, a firm must have at least 12 years of annual, primary before extraordinary items, earnings-per-share and book value of equity observations on Compustat and at least two years of monthly returns on CRSP preceding each of these 12 years. Financial data are adjusted for stock splits using the adjustment factors provided by Compustat.[10] We exclude firms with negative or extremely small book values of equity (less than $1) at the valuation date; our results are not, however, sensitive to this restriction. The total sample contains 28,909 firm-year observations, or an average of 1,314 firms per year. Note that because each firm-year observation has the necessary data to estimate *both* the mechanical residual income model *and* the mechanical earnings model, we can perform *within-firm* comparisons each year of the value estimates based on the mechanical models. This within-firm design eliminates firm-specific effects as explanations for any differences between value estimates.

To avoid overstating significance levels by pooling the data over time, we perform our tests on each cross-section of j firms in each year t=1976-1997. To avoid outlier concerns, we use the median of the j estimates in each year t as the observation for year t; we then report statistical tests of the mean of these 22 yearly observations, using the time-series standard errors (Fama and MacBeth [1973]). This research design gives equal weight to each sample year, and by not pooling the data over time, it avoids overstating significance levels. Our inferences are not sensitive to how we aggregate the data or whether we use the mean, median or raw value as the unit of observation.

[10] For a random sample of firms, we verify the adjustment calculations using these factors.

Table 1, Panel A reports selected financial information about the sample; here we show the average values, across the 22 years, of the cross-sectional mean, median and standard deviation of the selected financial variables. These data show that across all years, the mean (median) market value of equity is about $1.4 billion ($253 million) and mean (median) book value of equity is $816 million ($175 million). Panel A also shows mean, median and standard deviation information about firm-specific discount rates, estimated as follows:

$$r_{j,t} = r_f + \beta_{j,t}[E(r_m) - r_f] \tag{5}$$

where $r_{j,t}$ = firm j's discount rate applicable to valuation year t.

r_f = risk-free rate, calculated as the long-term Treasury bond yield minus the historical premium on Treasury bonds over Treasury bills. Data on Treasury bond and Treasury bill yields are taken from Ibbotson and Sinquefield [1998].

$\beta_{j,t}$ = estimate of the systematic risk of firm j in year t. Firm-specific betas are calculated using a minimum of 24 (historical) monthly returns.

$E(r_m)$- r_f = expected market risk premium, measured as the mean realized premium over 1963 to year t-1. Data on risk premia are from Ibbotson and Sinquefield [1998].

The mean and median cost of equity for the time-series sample is 11.4%, with a sample standard deviation of 1.5%. Individual year data (not reported) show that the average cost of equity ranges from 7.9% in 1994 to 20.3% in 1981; with the exception of 1981, no year's average cost of equity exceeds 15%. In the valuation formulae (equations (2) and (4)), we assume that the estimated discount rate calculated for firm j in year t is constant, $r_{j,t} = r_j$, across the 5-year forecast horizon.

For each firm in year t, we use maximum likelihood estimation methods to estimate equations (1) and (3) using all available annual earnings and book value realizations prior to year t. The mean, median and maximum number of yearly observations for the estimations is 18, 17 and 35. These numbers are similar to the time series used by Myers [1999, who reports using 15-22 annual observations] and Finger [1994, who uses 15 annual observations].

Table 1, Panel B summarizes the yearly distributions of the firm-specific parameter estimates and the R^2s from these regressions. Turning first to the RI-AR1 model, we note that the explanatory power varies greatly across the sample firms, with 80% of the firms ranging between 1% and 60%; the mean adjusted R^2 is 27%. The median value of the intercept, $\omega_{j,0}$=0.03 (significant at the .00 level, not reported) is consistent with the unconditional mean value of residual income being positive for the typical sample firm.[11] The 10% and 90% values of the distribution indicate that at least 80% of the persistence parameters lie between 0 and 1; in unreported results, we find that $0<|\omega_{j,1}|<1$ for all 28,909 estimations of equation (1). The sample median value of $\omega_{j,1}$=0.49 (mean=0.46) and the standard deviation of 0.31 indicate considerable cross-sectional variation in the persistence of residual income; we interpret this result as supporting firm-specific estimations of the mechanical models.

Given that our paper focuses on the value of *firm-specific* estimations of the residual income and earnings models, we test whether the estimated persistence parameters differ across the sample firms. We take the yearly value of each statistic, e.g., mean, 10th percentile, etc., and calculate a t-statistic using the over time mean and standard error of that statistic (similar to the Fama-MacBeth [1973] procedure). This approach avoids problems with cross-sectional dependence that could distort statistical inference. Panel C, Table 1 reports the resulting standard errors, t-statistics and confidence intervals. The standard errors (t-statistics) for each statistic are small (large), and none of the confidence intervals for any statistic is overlapping. These results indicate that the sample persistence parameter estimates are significantly different from each other. In unreported tests, we also find no evidence of any trend in the parameter estimates.

The difference between our mean persistence parameter and that reported by Dechow et al. [1999], 0.46 versus 0.62, is potentially driven by the estimation approach (firm- and time-specific versus pooled cross-sectional and over-time), the proxy for cost of capital (we use firm- and time-specific estimates whereas they assume a constant 12%), and differences in sample composition (we require a minimum of 12 years of historical data to estimate a firm's persistence parameter, while Dechow et al. do not impose this assumption). In unreported tests, we find that the difference is driven by the estimation

[11] Myers [1999] finds a negative median intercept using 1996 data. In unreported results, we also find a negative median intercept for 1996 (as well as for 1997); for all other sample years, the intercept is positive.

approach. This result is also consistent with Myers [1999] who reports smaller persistence than Dechow et al. (0.23 versus 0.62) using firm-specific estimations for 1996.

Panel B also reports information on the yearly distributions of the firm-specific parameter estimates for the X-AR2 model. The median value of the intercept, $\phi_{j,0}$=0.14 (significant at the .00 level, not reported) is consistent with a positive unconditional mean value of earnings for the typical sample firm. The sample median value of $\phi_{j,1}$=0.79 (mean=0.82, standard deviation of 0.48) and of $\phi_{j,2}$=-0.16 (mean=-0.17, standard deviation of 0.35) indicate considerable cross-sectional variation in the parameter estimates on the first and second order lags in earnings. In unreported tests (similar to those shown in Panel C, Table 1 for the RI-AR1 persistence parameters), we find that the persistence parameters for the X-AR2 model differ significantly from each other. Finally, we note that the explanatory power of the X-AR2 model also varies substantially across the sample firms, with 80% of the firms ranging between 12% and 85%; the mean adjusted R^2 is 51%. (We do not compare the R^2s of the RI-AR1 and X-AR2 models since the distributions of residual income and earnings differ.)

<u>II.3. Comparing the Reliability of Value Estimates Based on Mechanical Forecasts</u>

In this section, we compare the signed prediction errors (SPE's which measure bias) and the absolute prediction errors (APE's which measure accuracy) of V(RI-AR1) versus V(X-AR2), where the prediction error equals the value estimate minus observed price, scaled by observed price measured at the end of firm j's fiscal year t. We also contrast the ability of each value estimate to explain variation in share prices, captured by the R^2 in a regression of observed price on each value estimate.

Table 2, Panel A reports information on the signed and absolute prediction errors for V(RI-AR1) and V(X-AR2). To benchmark these results, we report similar information for value estimates based on book value of equity alone, V(B). Mean signed prediction errors indicate that V(X-AR2) and V(B) understate observed price by 29% and 17%, respectively (each significantly different from zero at the .00 level); this compares to mean understatement by V(RI-AR1) of 13% (significant at the .05 level). Within-firm comparisons reported in the last three rows of Panel A show that V(RI-AR1) exhibits statistically (at the .00 level) less bias than V(X-AR2) or V(B). For descriptive purposes, Panel A also reports summary information on the standard deviations and skewness of the SPE's of the value estimates. The smaller skewness for the signed prediction errors based on V(RI-AR1) versus V(X-AR2), 3.06 versus 8.74 (difference significant at the .03 level), indicates that the V(RI-AR1) distribution is less long tailed than is the distribution of V(X-AR2). Results for APE's show that V(RI-AR1) is the most accurate of the three value estimates considered, with a mean absolute misstatement of 38% of share price. Within-firm comparisons indicate that V(RI-AR1) is significantly more accurate than V(B) but only marginally (at the 0.13 level) more accurate than V(X-AR2).[12]

The results of the explainability tests are reported in Panel B; here we show the mean, calculated across the 22 yearly regressions, of the coefficient estimates, p-values and adjusted R^2s for regressions of observed price on each value estimate. The results show that V(RI-AR1) explains 71% of the cross-sectional variation in observed prices compared to 58% for V(B) and 68% for V(X-AR2), differences significant at the .00 level. The statistical significance of the difference in R^2s is assessed by calculating the difference in R^2s between each pair of models for each sample year t=1976-1997, averaging these difference over the 22 years, and then calculating the time-series standard error of the difference. Because it focuses on annual differences in R^2s, this method for assessing overall differential explainability is robust to potential over-time fluctuations in R^2s.

Given potential concerns with the levels regressions reported in Panel B, we also examine the ability of value estimates to explain market-to-book ratios. Our test follows Easton's [1998] recommendation to scale the dependent and independent variables by the book value of equity per share; for our analysis, this scaling results in the following regressions:

$$\frac{P_0}{B_0} = \frac{V(RI-AR1)}{B_0} = \frac{B_0 + \sum_{t=1}^{5} \frac{RI_t}{(1+r)^t} + \frac{RI_5}{r(1+r)^5}}{B_0} = 1 + \frac{\sum_{t=1}^{5} \frac{RI_t}{(1+r)^t} + \frac{RI_5}{r(1+r)^5}}{B_0} \tag{6a}$$

[12] The variances (both cross-sectional and over-time) of the reliability metrics based on V(X-AR2) are significantly larger than the variances of the reliability metrics based on V(RI-AR1) or V(B). The larger variances of the V(X-

$$\frac{P_0}{B_0} = \frac{V(X-AR2)}{B_0} = \frac{B_0 + \sum_{t=1}^{5}\frac{(X_t - rB_{t-1})}{(1+r)^t} + \frac{(X_5 - rB_4)}{r(1+r)^5}}{B_0} = 1 + \frac{\sum_{t=1}^{5}\frac{(X_t - rB_{t-1})}{(1+r)^t} + \frac{(X_5 - rB_4)}{r(1+r)^5}}{B_0} \tag{6b}$$

Equations (6a) and (6b) relate the market-to-book ratio to the increment in the value estimate, above current book value of equity, provided by the mechanical forecasts of residual income and earnings, respectively. OLS regression results, reported in Table 2, Panel C, show that mechanical residual income forecasts explain 35% of the variation in market-to-book ratios, compared to 33% for mechanical earnings forecasts (difference not significant at the .10 level). These results emphasize the direct incremental contribution, over book value of equity, of the mechanical forecasts to explaining share prices.

II.4. Extensions

Given our objective of assessing the reliability of mechanical-based value estimates for firms not followed by analysts, we repeat the tests in Table 2 for the subset of sample firms with no analyst coverage. If the Zacks data base contains at least one EPS forecast for that firm-year, we label the firm as analyst-followed that year, and as unfollowed otherwise. For the period 1981-1997, 23% on average, of the sample firms each year are unfollowed.[13] The results of repeating the analysis on the followed and unfollowed firms (Table 3) generally show more bias for followed firms than for unfollowed firms (mean understatements are 27-41% for followed firms versus 5-34% for unfollowed firms), larger APEs for followed firms than for unfollowed firms (36-44% versus 38-41%), and smaller explained variation for followed firms than for unfollowed firms (53-66% versus 73-79% for price regressions). With the exception of the market-to-book regressions where we observe significantly smaller explained variation for unfollowed firms, these results are consistent with investors placing more weight on accounting information when less other information (such as analysts' forecasts) is available.

AR2) metrics make it difficult to reject (at conventional levels) statistical equivalence with V(RI-AR1) or with V(B).

[13] We begin the analysis in 1981 when the number of firms with earnings forecasts is significantly larger than in 1978 when Zacks first began reporting forecasts. Because of the exclusion of 1976-1980, the combined results for followed and unfollowed firms differ from those reported in Table 2.

The within-sample results in Table 3 show that V(RI-AR1) is less biased, more accurate and has greater explainability than V(X-AR2), with most differences significant at the .00 level (the exception is the finding of no difference in the accuracy of V(RI-AR1) and V(X-AR2) for unfollowed firms). Comparisons of V(RI-AR1) and V(B) show that V(RI-AR1) is more biased and less accurate, but explains more of the variability in price. Overall, these results suggest that the choice of value estimate for unfollowed firms depends on the reliability metric being studied, e.g., a focus on bias suggests using V(B) for these firms while a focus on explaining price variation suggests using V(RI-AR1).

Based on Collins, Pincus and Xie's [1999] evidence that book value of equity and earnings have different meanings for loss firms than for profit firms, we also examine the sensitivity of the results to whether the firm reported a loss in the valuation year (Loss Firms, n=3,917) or a profit (Profit Firms, n=24,992). The results of this partitioning, shown in Table 4, indicate that V(X-AR2) and V(RI-AR1) tend to be less biased, more accurate and explain more of the variation in observed prices for profit firms than for loss firms. These differences are most pronounced for V(RI-AR1) prediction errors, where we observe 41% (11%) average understatements for loss (profit) firms and 69% (36%) APEs. Overall, we believe these results are consistent with the difficulty of predicting losses using mechanical models. That is, given that we require a time series of 12 years of data, it is unlikely many firms have losses for 12 years *and* survived; rather most of the firms report profits (some losses) in the estimation years, implying that linear extrapolation of this trend is unlikely to predict a loss.

Our third sensitivity check is based on recent research which questions whether the *realized* equity risk premium (r_m-r_f) is a reasonable proxy for the *expected* equity premium. Fama and French [2001], for example, show that realized stock returns over 1950-1999 are much higher than expected: the average annual realized equity premium is 8.3%, whereas their estimates of the expected equity premium range from 3.4% to 4.8% depending on the estimation approach.[14] Using too high a measure of the equity premium induces a downward bias in V(RI-AR1) and V(X-AR2). We expect this downward bias to increase the understatement indicated by signed prediction errors, but to have little or no effect on the explained variability measures, since the regressions allow for bias in both the intercept and the slope coefficient. A priori it is not clear what effect the downward bias has on absolute prediction errors. To assess the sensitivity of our results to measurement of the equity premium, we repeat out tests using Fama and French's revised equity risk premium of 4.03%. The results (not tabulated) show that the mean SPE for V(RI-AR1) is –15% compared to –13% (Table 2, Panel A), difference not significant at the .10 level. The mean APE for V(RI-AR1) is 37%, and is statistically indistinguishable from the 38% reported in Table 2, Panel A. As expected, the R^2 metrics are unchanged from those reported in Table 2: 71% explained variation for the observed price on value estimate regression and 35% for the market-to-book regression. Given the similarity between these results and those reported in Table 2, we conclude that measurement of the equity premium does not significantly affect our inferences.

Our last extension considers the sensitivity of the results to using *consistent* value estimates, derived from the linear earnings and residual income processes. The advantage of these estimates is they do no not require finite horizon assumptions or terminal value calculations.[15] Following Garman and Ohlson [1980] and Ohlson [1995], Myers [1999] shows that the AR1 process for residual income and a no-arbitrage assumption implies a valuation function that is linear in current information, equation (2'):

$$V(RI - AR1)_0 = \frac{\omega_0 (1+r)}{r(1-\omega_1)} + B_0 + \frac{\omega_1}{(1+r-\omega_1)} RI_0 \qquad (2')$$

Similar arguments can be used to derive a valuation function for X-AR2 that is linear in current information, equation (4'):

[14] Other studies find similar or lower estimates: Gebhardt, Lee and Swaminathan [1999] estimate an average risk premium of 2-3% for the period 1979-1995; Claus and Thomas [1999] find 3.4% for the period 1986-1996; and Vuolteenaho's [2000] results suggest a 1-3% annual equity premium for the first decade of the 21st century.

[15] There are two (main) disadvantages of the consistent value estimates. First, based on our reading of valuation manuals, financial statement analysis textbooks and analyst reports, market participants do not calculate consistent value estimates; rather, when they use valuation models, they use the finite horizon calculation method outlined in section II.1 (see Copeland, Koller and Murrin [2000], Stewart [1991], Palepu, Bernard and Healy [2000], Paine-Webber [2000], Morgan Stanley Dean Witter [1998] and Salomon Smith Barney [2000]). Second, the earnings-based perfectly consistent value estimate, given by equation (4'), is sensitive to firms' dividend payout ratios, and are, therefore, biased downwards for small or no dividend paying firms.

$$V(X-AR2)_0 = k\left[\frac{\phi_0(1+r)^2}{r[(1+r)^2-(1+r)\phi_1-\phi_2]} + \frac{(1+r)\phi_1+\phi_2}{(1+r)^2-(1+r)\phi_1-\phi_2}X_0 + \frac{(1+r)\phi_2}{(1+r)^2-(1+r)\phi_1-\phi_2}X_{-1}\right] \tag{4'}$$

where k = the firm's dividend payout ratio.

Using the firm-specific parameter estimates from equations (1) and (3), as well as information about B_0, RI_0, X_0, X_{-1} and k, we calculate the consistent values of V(RI-AR1) and V(X-AR2) for the sample firms. The results, reported in Table 5, show that in all cases the consistent value estimates yield similar or stronger inferences than those reported in Table 2. In particular, we find that relative to V(X-AR2), V(RI-AR1) is less biased (-19% versus –83%), more accurate (42% versus 83%), and explains more of the variation in observed prices (R^2 of 72% versus 37%) and in market-to-book ratios (37% versus 15%); all differences are significant at the .00 level. Comparisons of the results in Tables 2 and 5 show that the consistent value estimates of V(RI-AR1) perform about the same as the finite horizon estimates, while the consistent value estimates of V(X-AR2) perform significantly worse than their finite horizon counterparts (e.g., SPEs of –83% versus –29%, APEs of 83% versus 41%, explained variation of 37% and 15% versus 68% and 33%). The lower performance of the consistent V(X-AR2) estimates arises because equation (4') relies heavily on the dividend payout ratio. Our proxy for firm j's dividend payout ratio, the ratio of dividends to net income in year t-1, will understate value for firms which pay no, or very small, dividends.

II.5. Summary

Overall, the results in Tables 2-5 show that value estimates based on mechanical residual income forecasts are less biased, at least as accurate, and explain at least as much, if not significantly more, of the variation in observed prices and market-to-book ratios than value estimates based on mechanical forecasts of earnings. These results are robust to whether the firm experienced a loss or whether the firm is followed by analysts. Because these comparisons hold the valuation formula constant and vary only the estimation of the residual income attribute, we conclude that the stronger economic rationale for using linear residual income time series models translates into superior valuation reliability, relative to value estimates based on linear earnings time-series models.

We also find that firm-specific models of residual income produce value estimates that are significantly more reliable than value estimates based on book value alone. This result contrasts with Dechow et al.'s finding that setting the coefficient on residual income to zero (essentially producing a value estimate based on book value of equity) yields the least biased and most accurate value estimate. In unreported tests, we probe this difference in results, and find that it is driven by relaxing the assumption that the persistence in residual income is an over-time and cross-sectional constant.

III. How Much Valuation Reliability Do Analysts Add?

Given the results in section II, we next consider how much valuation reliability is lost by using mechanical forecasts instead of analysts' forecasts. That is, we consider the gain in valuation reliability arising from some combination of analysts' expertise and their timing/information advantages. We compare V(RI-AR1) and V(X-AR2) value estimates with value estimates based on analysts' forecasts, V(AN). By contrasting the reliability of mechanical-based value estimates calculated using historical data with the reliability of analyst-based value estimates calculated each quarter using analysts' revised forecasts (beginning with those available immediately following fiscal year end), we attempt to isolate analysts' timing advantage. We adopt a within-firm design to eliminate concerns that differences between mechanical-based value estimates and analyst-based value estimates are due to sample composition.

III.1. Sample and Data

The sample consists of all firm-year observations with at least 12 years of EPS Compustat data and at least two years of monthly CRSP returns preceding each of the 12 years (these data are necessary to estimate the mechanical earnings and residual income models) and with current year and 1-year ahead

EPS forecasts on Zacks for any year k=1981-1997.[16] Each of the quarterly samples contains between 13,698 and 14,795 observations. The firms comprising the quarterly analyst samples are larger than the firms included in the large sample tests. In untabulated results, we find that the mean (median) market value of equity of the analyst sample firms is $2.5 billion ($647 million) and have mean (median) book value of equity is $1.3 billion ($407 million). The mean share price of the analyst sample firms (measured at the date of the analyst forecast) is about $37, and the average firm has an estimated cost of equity of 11.2% (similar to the large sample firms).

For each firm in each quarter of year k, we use analysts' EPS forecasts for years k (F_k) and and k+1 (F_{k+1}) made at the start of the fiscal quarter to calculate V(AN). The terminal value in V(AN) allows for growth at an assumed g=4% expected rate of inflation:

$$V(AN)_0 = B_{k-1} + \frac{F_k - rB_{k-1}}{(1+r)^1} + \frac{(1+g)(F_{k+1} - rB_k)}{(r-g)(1+r)^2} \tag{7}$$

For each firm-year, we also estimate equations (1) and (3) and construct X-AR2 and RI-AR1 forecasts for years h=k, k+1; the distribution of parameter estimates from these firm-specific regressions (not reported) is similar to those reported in Table 1. Because the mechanical models use *annual* earnings and residual income measures, the time-series parameters are *not* updated each quarter. Thus, by the fourth quarter, analysts' forecasts of current year earnings incorporate realizations of earnings in quarters 1-3, while the mechanical forecasts do not; we refer to this as analysts' timing advantage. Our calculations of V(RI-AR1) and V(X-AR2) are similar to those in section II except we limit the forecast horizon to two years (k and k+1) rather than five years, to be comparable to the available analyst forecasts. (The results are not sensitive to using a 2-year or a 5-year forecast horizon for the mechanical forecasts.)

<u>III.2. Comparing the Reliability of Value Estimates Based on Analysts Forecasts and Mechanical Forecasts</u>

[16] Beginning in 1981, some analysts provide a long term (3-5 year) growth rate for earnings. Because these data are not available for many firms, we restrict our focus to current and 1-year ahead EPS forecasts.

Our calculations of the reliability of V(RI-AR1) and V(X-AR2) are similar to those in section II, except we measure observed share price at the analyst forecast date. Comparisons of the SPEs and the APE's of V(AN), V(RI-AR1) and V(X-AR2) are reported in Panels A and B, Table 6.[17] The mean bias in V(AN) is indistinguishable from zero in every quarter; this compares to a mean understatement of price by V(RI-AR1) of 22-26% (significant at the .00 level). Both V(X-AR2) and V(B) understate observed price by 31% to 37%, significant at the .00 level. Data on the APE's indicate that V(AN) is significantly (at the .00 level) more accurate than V(X-AR2), but has similar accuracy to V(RI-AR1). In Panel C we contrast the value estimates in terms of their ability to explain observed prices. In general, V(AN) and V(RI-AR1) are similar in explaining variation in observed prices, with both value estimates outperforming V(X-AR2) and V(B) by about 1-10%. In terms of the market-to-book regression, the results in Panel D show that V(AN) dominates V(RI-AR1) and V(X-AR2), although the difference between the explained variability for V(AN) and V(RI-AR1) is much smaller than that between V(AN) and V(X-AR2).

Consistent with Dechow et al. [1999] and Frankel and Lee [1998], Table 6 shows that analyst-based value estimates are significantly less biased than mechanical based value estimates. In contrast to Dechow et al.'s results, however, we do not find that V(AN) is more accurate than V(RI-AR1).[18] In unreported tests, we replicated the Dechow et al. approach on our sample to determine whether the insignificant difference in accuracy (and in explained price variability) we document are due to our use of firm- and time-specific mechanical models, the way we use analyst information or sample differences. We find that the use of firm-specific RI-AR1 models (as opposed to Dechow et al.'s cross-sectionally constant RI-AR1 model) is the main reason for the smaller differences between V(RI-AR1) and V(AN).

[17] We do not tabulate data on the standard deviation and skewness in analyst-based value estimates. The mean standard deviation of the SPEs for V(AN) across sample years and quarters is 0.74, compared to 0.46 for V(RI-AR1) and 0.42 for V(X-AR2). The mean skewness of V(AN) is 5.37 compared to 3.66 for V(RI-AR1) and 4.79 for V(X-AR2).

[18] Dechow et al. report (Table 5) accuracy of 40% for their analyst-based value estimate and 46% for their mechanical residual income based value estimate. Frankel and Lee do not report comparisons of accuracy metrics for their value estimates.

There is some evidence in Table 6 that V(AN) becomes less biased as the year progresses (i.e., bias goes from 6% to –1%), but there are no meaningful within-year changes in accuracy or explainability. However, because the mechanical based value estimates also show reductions in bias during the year (e.g., the bias in V(RI-AR1) goes from –26% in quarter 1 to –22% in quarter 4), the declining bias in V(AN) cannot be attributed entirely to the analysts' timing advantage. We conclude that analysts' valuation superiority is likely driven by an information (not a timing) advantage.

As a sensitivity check, we investigate whether the relative reliability of valuations based on analysts' forecasts versus mechanical forecasts depends on the size of the firm. Prior studies predict that analysts' EPS forecasts are more accurate than mechanical EPS forecasts for large firms because these firms have richer information environments and offer greater benefits from acquiring information (e.g., Brown, Richardson and Schwager [1987]; Kross, Ro and Schroeder [1990]; and Wiedman [1996]).[19] The results of market association tests also indicate that the higher association between analysts' forecast errors and excess returns (measured relative to the association between mechanical forecast errors and excess returns) is positively related to firm size (Brown et al. [1987b]; Wiedman [1996]), suggesting that investors rely more on analysts' EPS forecasts of large firms than of small firms.

We repeat the analyses in Table 6 after ranking firms based on the market value of equity at the beginning of year t: we assign the largest 25% of firms to the top quartile ("Large Firms") and the smallest 25% to the bottom quartile ("Small Firms"). For brevity, Table 7 reports only results based on V(RI-AR1) and V(AN). We note that, in general, value estimates for Small Firms have smaller bias, greater accuracy and explain more of the variation in observed prices than value estimates for Large Firms (differences, not reported, are significant at conventional levels). However, the explained variability of the market-to-book regressions is significantly (at the .00 level) higher for Large Firms relative to Small Firms. Panel A, Table 7 also reveals that V(AN) is significantly less biased (at the .01 level) than V(RI-AR1) for both size partitions. Panel B shows, however, that this lower bias does not

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[19] Brown, Richardson and Schwager [1987] and Wiedman [1996] find a significant positive relation between analysts' relative accuracy and firm size; Kross, Ro and Schroeder [1990] do not.

translate into greater accuracy: for most quarters and size partitions, V(AN) and V(RI-AR1) have similar APE's. The price regression results reported in panel C show that, within each size sub-sample, V(RI-AR1) tends to explain more of the variation in observed price than does V(AN), with the exception of the 4th quarter. The results of the market-to-book regressions, panel D, are mixed: for some quarters and size partitions we find that book adjusted V(RI-AR1) explains significantly more of the variation in market-to-book ratios than does book adjusted V(AN) (Large Firms, Q1, Q2), but for other quarters and partitions we find the opposite result (Small Firms, all quarters; Large Firms Q4).

III.3. Summary

The results in Tables 6 and 7 suggest that, relative to V(RI-AR1), analyst-based value estimates are significantly less biased and explain more of the variation in market-to-book ratios; V(AN) is not, however, more accurate or able to explain more of the variability in observed prices. These results are generally consistent with, although not as extreme as, results reported by Dechow et al. and Frankel and Lee who find that analyst-based value estimates outperform mechanical-based value estimates. We find that the smaller differences in reliability metrics that we document between V(AN) and V(RI-AR1) are due to our use of firm-specific estimations of the persistence parameter in the RI-AR1 model. Finally, the absence of large and growing differences between analyst-based value estimates and mechanical-based value estimates throughout the year, suggests that the superiority of analyst-based value estimates stems from an information, not a timing, advantage

IV. Trading Rule Tests

Our tests of bias, accuracy and explained variability use observed price as the benchmark against which we evaluate mechanical-based and analyst-based value estimates. In this section, we evaluate the market efficiency assumption underlying this benchmark by examining the abnormal returns to trading rules formed for each value estimate. We rank firms each year, from high to low, on the ratio of the value estimate to price (V/P). For the large sample, we rank on the V/P ratio calculated at fiscal year end. For the analyst sample, we rank on the V/P ratio calculated using the first set of analyst forecasts available at the start of the second fiscal quarter, and we measure share price on this same date. The ranking is performed every fiscal year (1976-1997 for the large sample and 1981-1997 for the analyst sample).

If a firm is in the highest 30% of the ranked V/P distribution, we include that stock in the trading portfolio that begins four months after fiscal year end (for the large sample) and one month after the analyst forecast date (for the analyst sample); we wait to ensure that the information used to calculate the value estimate is available to the market. We hold that portfolio for a horizon of H months, H=12, 24 or 36 months. We roll the portfolio through the sample period plus the horizon for all observations with returns data. We regress the monthly portfolio return on the market return (CAPM) and separately on Fama and French's [1993] 3-factors. The intercepts from these regressions capture the abnormal returns generated by the trading strategy. This approach allows us both to incorporate firms with different fiscal year ends and to assess the statistical significance of any abnormal returns without introducing bias by compounding returns. Mitchell and Stafford [2000] show these calendar time portfolio regressions are preferred to other measures of abnormal returns, such as buy-and-hold abnormal returns and cumulative average abnormal returns. Lyon, Barber and Tsai [1999] find the calendar time portfolio regressions are also superior to a modified buy-and-hold abnormal return measure in the presence of cross-sectional dependence and/or a mis-specified asset pricing model.

The results of the trading rules are shown in Table 8, Panels A-C for the large sample and in Panel D for the analyst sample. For each trading rule and horizon, we report the OLS coefficient estimates and t-statistics for the intercept and slope coefficients for the CAPM regression (first row) and the 3-factor regression (italics, second row). While all of the V/P trading rules show significant positive abnormal returns measured relative to the CAPM, none of the trading strategies exhibits significant abnormal returns measured relative to the 3-factor model. That is, consistent with the assumption of market efficiency which underlies our reliability metrics, we find no evidence that after controlling for market, size and book-to-market factors, mechanical-based or analyst-based value estimates earn abnormal returns. These results contrast with Frankel and Lee [1998], who report significant returns to their V(AN)/P strategy. In unreported tests, we determined that the difference in results stems from both the measurement of abnormal returns (we use calendar time portfolio regressions while they use buy-and-hold returns) and to sample differences (our sample firms have both analysts' forecasts and at least 12 years of Compustat data while their sample firms have analysts' forecasts and prior year data).

V. Conclusions

For a large sample of firms over 1976-1997, we find that intrinsic value estimates based on forecasts from firm-specific time-series models of residual income understate prices by 13%, are within 38% of observed prices, and explain 71% of the variation in observed prices. Statistically, they are more reliable than value estimates based either on book value alone or on forecasts from firm-specific time-series models of earnings. We interpret these results as suggesting that firm-specific mechanical models perform reasonably well at predicting residual income for purposes of equity valuation.

We also assess the effect on valuation reliability from using mechanical forecasts instead of analysts' forecasts by documenting the differential reliability between value estimates based on mechanical residual income forecasts, V(RI-AR1), and value estimates based on analysts' forecasts, V(AN). Within-sample tests show that while V(RI-AR1) is more biased than V(AN), it is similar in accuracy and explained variability. Examination of the quarterly trend in the properties of V(AN) and V(RI-AR1) indicates that analysts' timing advantage does not appear to increase the incremental reliability of value estimates based on their forecasts.

The result that firm-specific models of residual income perform about as well as analysts in generating a measure of intrinsic value has several implications for research. First, it raises questions about whether analysts' information advantage translates into meaningful differences in their intrinsic value estimates relative to mechanical-based value estimates. Second, it suggests that future valuation studies need not be limited to examining analyst-followed firms. Relatedly, research might consider modifications of the mechanical residual income model that allows for a broader set of firms (e.g., less restrictive data requirements) or alternative estimation procedures or model specifications that provide even more reliable estimates of intrinsic value.

In addition to the specific contributions noted above, this study adds to the literature on earnings prediction and residual income prediction in the context of equity valuation. Prior prediction studies focus on the accuracy of the forecast attribute over a short forecast horizon (usually one year) as the evaluation criterion (see, for example, the time-series earnings models evaluated by Ball and Watts [1972], Albrecht, Lookabill and McKeown [1977], Watts and Leftwich [1977], Lev [1983] and Finger [1994], or the evaluations of analysts' forecasts vis-à-vis mechanical earnings forecasts by O'Brien [1988] and Brown et al. [1987a]). The equity valuation criterion we use closely parallels Statement of Financial Accounting Concepts No. 1 "Objectives of Financial Reporting by Business Enterprises," which states that a primary objective of financial reporting is to provide information that is useful to present and potential investors in making investment decisions.

Our analyses also extend prior work that uses market return metrics as the evaluation criterion for evaluating mechanical versus analysts' forecasts. This literature includes studies examining the strength of the association between unexpected returns and mechanical versus analyst based measures of unexpected earnings (e.g., Hughes and Ricks [1987], O'Brien [1988]), Fried and Givoly [1982], Brown et al. [1987b]; Elgers and Murray [1992]; Walther [1997]) and studies examining the properties of mechanical earnings forecasts versus earnings forecasts inferred from price changes (e.g., Beaver, Lambert and Morse [1980] and Collins, Kothari and Rayburn [1987]). We use an alternative mechanism (residual income valuation) for evaluating the relation between equity valuation and residual income forecasts (mechanical or analyst) and consider direct and indirect approaches to mechanically forecasting the residual income attribute (residual income models versus earnings models).

Table 1
Descriptive Information on the Sample Firms and Their Time Series Models

Panel A: Selected financial information

Variable	mean	median	std. dev
Market value of equity ($mil)	1,414	253	4,282
Book value of equity ($ mil)	816	175	2,434
Earnings per share ($)	2.03	1.75	7.00
Observed share price ($)	28.44	20.82	151.59
Market-to-book ratio	1.64	1.29	1.36
Cost of equity	11.4%	11.4%	1.5%

Panel B: Distribution of firm-specific parameter estimates of mechanical time series models

	RI-AR1 model			X-AR2 model			
	ω_0	ω_1	R^2	ϕ_0	ϕ_1	ϕ_2	R^2
mean	-0.15	0.46	0.27	0.25	0.82	-0.17	0.51
Standard deviation	2.83	0.31	0.22	1.82	0.48	0.35	0.27
10%	-0.50	0.05	0.01	0.02	0.22	-0.65	0.12
25%	-0.16	0.27	0.07	0.05	0.48	-0.40	0.29
median	0.03	0.49	0.22	0.14	0.79	-0.16	0.55
75%	0.16	0.69	0.42	0.35	1.14	0.06	0.75
90%	0.35	0.85	0.60	0.74	1.50	0.26	0.85

Panel C: Differences in ω_1 estimates[c]

	Mean	10^{th} perc.	25^{th} perc.	Median	75^{th} perc.	90^{th} perc.
Mean	0.46	0.05	0.27	0.49	0.69	0.85
Standard error	0.01	0.01	0.01	0.01	0.01	0.01
t-statistic	76.1	6.8	39.6	68.2	86.7	125.5
95% confidence level, lower	0.45	0.03	0.26	0.48	0.68	0.83
95% confidence level, upper	0.47	0.06	0.28	0.51	0.71	0.86

[a] The sample contains all firm-year observations over t=1976-1997 with at least 12 years of Compustat historical earnings data. On average, 1,314 firms meet these requirements each year. Panel A shows summary information on selected financial variables of these firms, calculated as of the end of year t-1.

[b] The RI-AR1 model is: $RI_{j,t-1} = \omega_{j,0} + \omega_{j,1} RI_{j,t-2} + \varsigma_{j,t-1}$. The X-AR2 model is: $X_{j,t-1} = \phi_{j,0} + \phi_{j,1} X_{j,t-2} + \phi_{j,2} X_{j,t-3} + \upsilon_{j,t-1}$ where $X_{j,t}$ = firm j's reported EPS in year t. We estimate X-AR2 and RI-AR1 for each firm-year. Panel B shows summary statistics on the distributions of the parameter estimates and adjusted R^2s across the firms and sample years.

[c] We report the mean and standard error of each yearly statistic. The t-statistic is calculated using the over time mean and standard error of that statistic (similar to the Fama-MacBeth [1973] procedure).

Table 2
The Reliability of Mechanical-Based Value Estimates for the Large Sample, 1976-1997

Panel A: Prediction errors for value estimates[a]

Forecast source (V)	Signed prediction error (V-P)/P	Absolute Prediction error |(V-P)|/P	Std. dev. of prediction error (V-P)/P	Skewness of prediction error (V-P)/P
V(RI-AR1)	-0.13 (.05)	0.38 (.00)	0.51 (.00)	3.06 (.00)
V(X-AR2)	-0.29 (.00)	0.41 (.00)	0.68 (.00)	8.74 (.00)
V(B)	-0.17 (.00)	0.39 (.00)	0.62 (.00)	3.90 (.00)
V(RI-AR1) vs V(X-AR2)	0.16 (.00)	-0.03 (.13)	(.19)	(.03)
V(RI-AR1) vs V(B)	0.06 (.01)	-0.03 (.00)	(.00)	(.01)
V(X-AR2) vs V(B)	-0.13 (.00)	0.02 (.14)	(.62)	(.06)

Panel B: Univariate regressions of observed prices on value estimates[b]

Forecast source (V)	OLS intercept	OLS coefficient	OLS R^2
V(RI-AR1)	4.90 (.00)	0.98 (.69)	0.71 (.00)
V(X-AR2)	5.89 (.00)	1.13 (.08)	0.68 (.00)
V(B)	5.70 (.00)	1.02 (.77)	0.58 (.00)
V(RI-AR1) vs V(X-AR2)	(.00)	(.00)	(.00)
V(RI-AR1) vs V(B)	(.01)	(.02)	(.00)
V(X-AR2) vs V(B)	(.50)	(.00)	(.00)

Panel C: Univariate regressions of market-to-book ratio on the difference between the value estimate and book value of equity, scaled by book value of equity[c]

Forecast source (V)	OLS intercept	OLS coefficient	OLS R^2
V(RI-AR1)	1.42 (.00)	1.01 (.80)	0.35 (.00)
V(X-AR2)	1.58 (.00)	0.96 (.52)	0.33 (.00)
V(RI-AR1) vs V(X-AR2)	(.00)	(.21)	(.17)

See Table 1 for descriptions of the sample and the mechanical models. Variable definitions: V(RI-AR1) is the value estimate based on RI-AR1 forecasts; V(X-AR2) is the value estimate based on X-AR2 EPS forecasts; V(B) is the value estimate based on book value of equity. P = observed share price at fiscal year end t-1, t=1976-1997.

[a] Panel A reports mean signed and absolute prediction errors for the value estimates, calculated across the median prediction errors in each year t=1976-1997; significance levels for whether the mean prediction error differs from zero are shown in parentheses. The last three rows show the significance level for the t-test comparing the mean signed (or absolute) prediction errors between the noted two variables. We also report the standard deviation and skewness of the value estimates; these statistics are calculated for each sample year; we report the mean value of the 22 yearly values.

[b] Panel B reports mean (across year) intercepts, coefficient estimates and, in parentheses, significance levels for t-tests of whether the intercept equals 0 and the slope coefficient equals 1, for the regression of observed price on the noted value estimate. We also report the mean adjusted R^2 calculated across the 22 yearly regressions.

[c] Panel C reports mean (across year) intercepts, coefficient estimates and, in parentheses, significance levels for t-tests of whether the intercept equals 0 and the slope coefficient equals 1, for the regression of the market-to-book-ratio on the difference between the noted value estimate and the book value of equity, scaled by the latter. We also report the mean adjusted R^2 calculated across the 22 yearly regressions.

Table 3
The Reliability of Mechanical-Based Value Estimates for the Large Sample Partitioned by Analyst Following, 1981-1997

Forecast source (V)	Signed Prediction Error: Followed	Not Followed	Followed vs Not Followed	Absolute Prediction Error: Followed	Not Followed	Followed vs Not Followed
V(RI-AR1)	-0.27 (.00)	-0.25 (.00)	(.16)	0.36 (.00)	0.41 (.00)	(.00)
V(X-AR2)	-0.41 (.00)	-0.34 (.00)	(.00)	0.44 (.00)	0.43 (.00)	(.36)
V(B)	-0.30 (.00)	-0.05 (.28)	(.00)	0.40 (.00)	0.38 (.00)	(.26)
V(RI-AR1) vs V(X-AR2)	(.00)	(.00)		(.00)	(.23)	
V(RI-AR1) vs V(B)	(.00)	(.00)		(.00)	(.01)	
V(X-AR2) vs V(B)	(.00)	(.00)		(.00)	(.01)	

Forecast source (V)	Regression of price on value estimate, OLS R^2: Followed	Not Followed	Followed vs Not Followed	Market-to-book regression, OLS R^2: Followed	Not Followed	Followed vs Not Followed
V(RI-AR1)	0.66 (.00)	0.79 (.00)	(.00)	0.37 (.00)	0.09 (.00)	(.00)
V(X-AR2)	0.62 (.00)	0.75 (.00)	(.00)	0.31 (.00)	0.05 (.00)	(.00)
V(B)	0.53 (.00)	0.73 (.00)	(.00)	n/a	n/a	
V(RI-AR1) vs V(X-AR2)	(.01)	(.00)		(.01)	(.01)	
V(RI-AR1) vs V(B)	(.00)	(.00)		n/a	n/a	
V(X-AR2) vs V(B)	(.00)	(.30)		n/a	n/a	

See Table 1 for descriptions of the sample and the mechanical models. Variable definitions: V(RI-AR1) is the value estimate based on RI-AR1 forecasts; V(X-AR2) is the value estimate based on X-AR2 EPS forecasts; V(B) is the value estimate based on book value of equity. P = observed share price at fiscal year end t-1.

[a] We partition the sample observations by whether the firm was followed by an analyst in year t, t=1981-1997. We label a firm as analyst-followed in a given year if the Zacks data base contains at least one EPS forecast for that firm-year, and as not followed otherwise. On average, nearly one-quarter of the observations represent not followed firms. For each, we report mean signed prediction errors, mean absolute prediction errors and mean OLS R^2 of the price and market-to-book regressions, calculated across the median prediction errors or OLS R^2 in years 1981-1997.

Table 4
The Reliability of Mechanical-Based Value Estimates for the Large Sample
Partitioned by Firm Profitability, 1976-1997[a]

	Signed Prediction Error			Absolute Prediction Error		
Forecast source (V)	Profit firms	Loss firms	Profit vs loss	Profit firms	Loss firms	Profit vs loss
V(RI-AR1)	-0.11 (.09)	-0.41 (.00)	(.00)	0.36 (.00)	0.69 (.00)	(.00)
V(X-AR2)	-0.29 (.00)	-0.28 (.00)	(.75)	0.40 (.00)	0.56 (.00)	(.00)
V(B)	-0.20 (.00)	0.30 (.01)	(.00)	0.38 (.00)	0.60 (.00)	(.01)
V(RI-AR1) vs V(X-AR2)	(.00)	(.02)		(.07)	(.00)	
V(RI-AR1) vs V(B)	(.00)	(.00)		(.00)	(.76)	
V(X-AR2) vs V(B)	(.00)	(.00)		(.19)	(.34)	

	Regression of price on value estimate, OLS R^2			Market-to-book regression, OLS R^2		
Forecast source (V)	Profit firms	Loss firms	Profit vs loss	Profit firms	Loss firms	Profit vs loss
V(RI-AR1)	0.69 (.00)	0.66 (.00)	(.41)	0.41 (.00)	0.03 (.01)	(.00)
V(X-AR2)	0.66 (.00)	0.61 (.00)	(.15)	0.34 (.00)	0.03 (.01)	(.00)
V(B)	0.56 (.00)	0.69 (.00)	(.00)	n/a	n/a	
V(RI-AR1) vs V(X-AR2)	(.00)	(.01)		(.00)	(.61)	
V(RI-AR1) vs V(B)	(.00)	(.22)		n/a	n/a	
V(X-AR2) vs V(B)	(.00)	(.00)		n/a	n/a	

See Table 1 for descriptions of the sample and the mechanical models. Variable definitions: V(RI-AR1) is the value estimate based on RI-AR1 forecasts; V(X-AR2) is the value estimate based on X-AR2 EPS forecasts; V(B) is the value estimate based on book value of equity. P = observed share price at fiscal year end t-1.

[a] We partition the sample observations by whether the firm reported a loss in year t, t=1976-1997. Of the total 28,909 observations, there are 3,917 loss firms and 24,992 profit firms. For each partition, we report mean signed prediction error, mean absolute prediction errors and mean OLS R^2 of the price and market-to-book regressions. Mean values are calculated across the median prediction errors or OLS R^2 in years 1976-1997.

Table 5
The Reliability of Consistent Mechanical-Based Value Estimates for the Large Sample, 1976-1997

Forecast source (V)	Signed prediction error	Absolute prediction error
Consistent V(RI-AR1)	-0.19 (.00)	0.42 (.00)
Consistent V(X-AR2)	-0.83 (.00)	0.83 (.00)
V(RI-AR1) vs V(X-AR2)	(.00)	(.00)

Forecast source (V)	Regression of observed price on value estimate, OLS R^2	Market-to-book regression, OLS R^2
Consistent V(RI-AR1)	0.72 (.00)	0.37 (.00)
Consistent V(X-AR2)	0.37 (.00)	0.15 (.00)
V(RI-AR1) vs V(X-AR2)	(.00)	(.00)

.See Table 1 for descriptions of the sample and the mechanical models. Variable definitions: V(X-AR2) is the value estimate based on X-AR2 EPS forecasts; V(RI-AR1) is the value estimate based on RI-AR1 forecasts. V(B) is the value estimate based on book value of equity. P = observed share price at fiscal year end t-1.

[a] For each partition, we report mean signed prediction error, mean absolute prediction errors and mean OLS R^2 of the price and market-to-book regressions. Mean values are calculated across the median prediction errors or OLS R^2 in years 1976-1997.

Table 6

The Reliability of Mechanical-Based and Analyst-Based Value Estimates, 1981-1997[a]

Panel A: Signed prediction errors, by quarter[b]

Forecast source (V)	Quarter 1	Quarter 2	Quarter 3	Quarter 4
V(RI-AR1)	-0.26 (.00)	-0.24 (.00)	-0.23 (.00)	-0.22 (.00)
V(X-AR2)	-0.37 (.00)	-0.36 (.00)	-0.35 (.00)	-0.34 (.00)
V(B)	-0.34 (.00)	-0.32 (.00)	-0.31 (.00)	-0.31 (.00)
V(AN)	0.06 (.28)	0.03 (.54)	0.01 (.85)	-0.01 (.88)
V(RI-AR1) vs V(B)	(.00)	(.00)	(.00)	(.00)
V(X-AR2) vs V(B)	(.00)	(.00)	(.00)	(.00)
V(AN) vs V(B)	(.00)	(.00)	(.00)	(.00)
V(RI-AR1) vs V(AN)	(.00)	(.00)	(.00)	(.00)
V(X-AR2) vs V(AN)	(.00)	(.00)	(.00)	(.00)
V(X-AR2) vs V(RI-AR1)	(.00)	(.00)	(.00)	(.00)

Panel B: Absolute prediction errors, by quarter[b]

Forecast source (V)	Quarter 1	Quarter 2	Quarter 3	Quarter 4
V(RI-AR1)	0.35 (.00)	0.35 (.00)	0.36 (.00)	0.36 (.00)
V(X-AR2)	0.42 (.00)	0.41 (.00)	0.41 (.00)	0.41 (.00)
V(B)	0.41 (.00)	0.40 (.00)	0.41 (.00)	0.41 (.00)
V(AN)	0.33 (.00)	0.33 (.00)	0.33 (.00)	0.33 (.00)
V(RI-AR1) vs V(B)	(.00)	(.00)	(.00)	(.00)
V(X-AR2) vs V(B)	(.35)	(.07)	(.26)	(.75)
V(AN) vs V(B)	(.00)	(.01)	(.00)	(.00)
V(RI-AR1) vs V(AN)	(.20)	(.37)	(.28)	(.12)
V(X-AR2) vs V(AN)	(.01)	(.01)	(.00)	(.00)
V(X-AR2) vs V(RI-AR1)	(.00)	(.00)	(.00)	(.00)

Panel C: Explained variability from regressions of price on value estimate, by quarter[c]

Forecast source (V)	Quarter 1	Quarter 2	Quarter 3	Quarter 4
V(RI-AR1)	0.63 (.00)	0.59 (.00)	0.56 (.00)	0.55 (.00)
V(X-AR2)	0.55 (.00)	0.55 (.00)	0.53 (.00)	0.52 (.00)
V(B)	0.49 (.00)	0.51 (.00)	0.47 (.00)	0.47 (.00)
V(AN)	0.59 (.00)	0.56 (.00)	0.55 (.00)	0.57 (.00)
V(RI-AR1) vs V(B)	(.00)	(.01)	(.00)	(.00)
V(X-AR2) vs V(B)	(.00)	(.14)	(.00)	(.00)
V(AN) vs V(B)	(.00)	(.30)	(.06)	(.01)
V(RI-AR1) vs V(AN)	(.08)	(.17)	(.71)	(.40)
V(X-AR2) vs V(AN)	(.07)	(.84)	(.67)	(.20)
V(X-AR2) vs V(RI-AR1)	(.00)	(.00)	(.00)	(.08)

Panel D: Explained variability from market-to-book regressions of price, by quarter[c]

Forecast source (V)	Quarter 1	Quarter 2	Quarter 3	Quarter 4
V(RI-AR1)	0.49 (.00)	0.42 (.00)	0.38 (.00)	0.36 (.00)
V(X-AR2)	0.28 (.00)	0.24 (.00)	0.21 (.00)	0.20 (.00)
V(AN)	0.48 (.00)	0.47 (.00)	0.48 (.00)	0.47 (.00)
V(RI-AR1) vs V(AN)	(.77)	(.04)	(.00)	(.00)
V(X-AR2) vs V(AN)	(.00)	(.00)	(.00)	(.00)
V(X-AR2) vs V(RI-AR1)	(.00)	(.00)	(.00)	(.00)

Variable definitions: V(X-AR2) is the value estimate based on X-AR2 EPS forecasts; V(AN) is the value estimate based on analysts' earnings forecasts. V(RI-AR1) is the value estimate based on RI-AR1 forecasts. V(B) is the value estimate based on book value of equity. P = observed share price measured at the analyst forecast date. V(X-AR2) and V(RI-AR1) estimates are calculated using a 2-year forecast horizon.

[a] To be included in any quarterly sample for any year k=1981-1997, a firm must have at least 12 years of Compustat historical earnings data and current and 1-year ahead earnings forecasts in that fiscal quarter. The number of firm-year observations in each sample are: Q1, 13,698; Q2, 13,843; Q3, 14,617 and Q4, 14,795.

[b] Panel A (Panel B) reports mean signed (absolute) prediction errors for the value estimates, calculated across the median prediction errors in each year k=1981-1997; significance levels for whether the mean prediction error differs from zero are shown in parentheses.

[c] Panel C reports the mean adjusted R^2 across the 17 yearly regressions, 1981-1997.

Table 7
Size-Partitioned Analysis of the Reliability of Mechanical-Based and Analyst-Based Value Estimates

Panel A: Signed prediction errors, by quarter[a]

	Quarter 1		Quarter 2		Quarter 3		Quarter 4	
Forecast source (V)	Small	Large	Small	Large	Small	Large	Small	Large
V(RI-AR1)	-0.23	-0.30	-0.22	-0.28	-0.21	-0.27	-0.19	-0.27
V(AN)	0.09	0.03	0.08	0.00	0.06	-0.01	0.03	-0.03
V(RI-AR1) vs V(AN)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)

Panel B: Absolute prediction errors, by quarter[a]

	Quarter 1		Quarter 2		Quarter 3		Quarter 4	
Forecast source (V)	Small	Large	Small	Large	Small	Large	Small	Large
V(RI-AR1)	0.34	0.37	0.34	0.37	0.35	0.38	0.35	0.38
V(AN)	0.30	0.35	0.31	0.36	0.31	0.36	0.30	0.36
V(RI-AR1) vs V(AN)	(.10)	(.49)	(.06)	(.55)	(.04)	(.59)	(.01)	(.35)

Panel C: Explained variability from regressions of price on value estimate, by quarter[b]

	Quarter 1		Quarter 2		Quarter 3		Quarter 4	
Forecast source (V)	Small	Large	Small	Large	Small	Large	Small	Large
V(RI-AR1)	0.63	0.55	0.65	0.50	0.59	0.43	0.57	0.42
V(AN)	0.57	0.48	0.63	0.42	0.59	0.41	0.62	0.44
V(RI-AR1) vs V(AN)	(.07)	(.03)	(.57)	(.02)	(.92)	(0.54)	(.10)	(.73)

Panel D: Explained variability from market-to-book regressions, by quarter[b]

	Quarter 1		Quarter 2		Quarter 3		Quarter 4	
Forecast source (V)	Small	Large	Small	Large	Small	Large	Small	Large
V(RI-AR1)	0.29	0.60	0.20	0.55	0.17	0.49	0.15	0.47
V(AN)	0.44	0.57	0.45	0.49	0.48	0.51	0.51	0.53
V(RI-AR1) vs V(AN)	(.00)	(.09)	(.00)	(.00)	(.00)	(.37)	(.00)	(.06)

See Table 5 for descriptions of the quarterly analyst samples. We rank firms in each sample based on market value of equity at the end of year k-1, and define the largest 25% as Large Firms, and the smallest 25% as Small Firms. Variable definitions: V(AN) is the value estimates based on analysts' earnings forecasts. V(RI-AR1) is the value estimate based on RI-AR1 forecasts. P = observed share price at the analyst forecast date. V(X-AR2) and V(RI-AR1) estimates are calculated using a 2-year forecast horizon.

[a] For each sample, we report mean signed prediction errors (Panel A) and mean absolute prediction errors (Panel B) calculated across the median prediction errors in each year k=1981-1997. We report significance levels for whether prediction errors differ between value estimates, holding constant the sample.

[b] For each sample, Panel C reports the mean R^2s across the 17 yearly regressions of observed price on the noted value estimate. Panel D reports similar information for the market-to-book regressions.

Table 8
Abnormal Returns to Trading Rules Using Mechanical-Based and Analyst-Based Value Estimates

Horizon:	a	t(a)	b	t(b)	s	t(s)	h	t(h)	R2	Mean monthly return
Panel A: Strategy based on V(B)										
12 months	0.33	1.81	0.99	23.18					0.66	1.07%
	-0.11	*-1.26*	*1.02*	*45.91*	*0.95*	*27.53*	*0.61*	*16.06*	*0.92*	
24 months	0.38	2.10	1.00	23.87					0.68	1.13%
	-0.05	*-0.53*	*1.02*	*46.41*	*0.95*	*28.28*	*0.58*	*15.63*	*0.93*	
36 months	0.38	2.15	1.01	24.58					0.69	1.14%
	-0.03	*-0.34*	*1.02*	*47.77*	*0.94*	*28.63*	*0.55*	*15.30*	*0.93*	
Panel B: Strategy based on V(X-AR2)										
12 months	0.40	2.85	0.86	26.50					0.72	1.04%
	-0.01	*-0.22*	*0.93*	*55.46*	*0.65*	*25.31*	*0.60*	*21.61*	*0.94*	
24 months	0.43	3.15	0.89	27.89					0.74	1.09%
	0.05	*0.68*	*0.94*	*59.21*	*0.67*	*27.40*	*0.56*	*21.04*	*0.95*	
36 months	0.42	3.11	0.90	28.73					0.75	1.09%
	0.05	*0.75*	*0.95*	*59.66*	*0.67*	*27.40*	*0.53*	*20.01*	*0.95*	
Panel C: Strategy based on V(RI-AR1)										
12 months	0.43	3.09	0.88	27.27					0.73	1.08%
	0.02	*0.28*	*0.94*	*55.35*	*0.63*	*24.19*	*0.60*	*20.99*	*0.94*	
24 months	0.43	3.14	0.91	28.86					0.75	1.10%
	0.04	*0.67*	*0.96*	*59.93*	*0.65*	*26.71*	*0.55*	*20.53*	*0.95*	
36 months	0.42	3.11	0.92	29.42					0.76	1.10%
	0.05	*0.78*	*0.96*	*60.87*	*0.67*	*27.46*	*0.53*	*19.83*	*0.95*	
Panel D: Strategy based on V(AN)										
12 months	0.33	2.29	0.87	26.04					0.77	0.97%
	0.06	*0.47*	*0.98*	*29.79*	*0.35*	*7.04*	*0.44*	*7.76*	*0.84*	
24 months	0.29	2.13	0.89	27.89					0.79	0.95%
	0.04	*0.34*	*0.99*	*32.26*	*0.37*	*7.98*	*0.42*	*7.89*	*0.86*	
36 months	0.27	2.02	0.90	28.92					0.80	0.93%
	0.03	*0.28*	*0.99*	*33.39*	*0.38*	*8.38*	*0.39*	*7.76*	*0.87*	

Variable definitions: V(X-AR2) is the value estimate based on X-AR2 EPS forecasts; V(B) is the value estimate based on book value of equity. V(RI-AR1) is the value estimate based on RI-AR1 forecasts. V(AN) is the value estimate based on analysts' earnings forecasts. P = observed share price measured at fiscal year end (for the mechanical-based estimates) and at the forecast date (for the analyst-based estimates).

[a] We report the abnormal returns to value-to-price strategies according to the CAPM (first line for each horizon) and, in italics, the Fama-French 3-factor model (second line for each horizon). The three factors are the excess return on the market portfolio, SMB (a zero-cost portfolio capturing the difference between large and small stocks) and HML (a zero-cost portfolio capturing the difference between high and low book-to-market stocks). The portfolio contains the top 30% of V/P ratios ranked each year. Portfolio positions are taken 4 months after year end for mechanical-based trading rules and 1-month after the forecast date for analyst-based trading rules, to ensure that all information is known to the market. OLS coefficient estimates and t-statistics are presented.

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Residual income, is common concept used in valuation and can be defined as the excess return generated over the minimum rate of return (often referred to as the cost of capital) of the amount of net income. Residual Income Formula = Net Income of the Firm â€“ Equity Charge. Where, Equity Charge = Cost of Equity Capital x Equity Capital.Â Residual Income can be calculated using the below formula as, Residual Income = Net Income of the firm â€“ Equity charge: = us$4,700,500 â€“ us$4,800,000. As seen from the negative economic profit it can be concluded that AEW has not to earn adequate to cover the equity cost of capital. The Residual Earnings Model (REM) is used and applied to three private equity case studies in Brazil and three private equity cases in China The regression model draws its data from Bloomberg terminals as well as Thomson Reuters Eikon. All amounts are in USD.Â 1.1 Private Equity in the 21st Century. The motivation of understanding private equity comes from the fact that private equity can shape the spheres of influence of a country by attracting investment, bridging key strategic entities, and improve the overall economy. By understanding how to make more accurate forecasts of private equity deals, one can make better investment decisions. The PE landscape is ever developing and unique in each of the BRICS countries, and a cookie cutter approach is not ideal.