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Conservative Accounting and Linear Information Valuation Models

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Conservative Accounting and Linear Information Valuation Models

Abstract

Prior research using the residual income valuation model and linear information models has generally found that estimates of firm value are negatively biased. We argue that this could result from the way in which accounting conservatism effects are reflected in such models. We build on the conservative accounting model of Feltham and Ohlson (1995) and the Dechow, Hutton and Sloan (1999) (DHS) methodology to propose a valuation model that includes a conservatism-correction term, based on the properties of past realizations of residual income and other information. Other information is measured using analyst-forecast-based predictions of residual income. We use data comparable to the DHS sample to compare the bias and inaccuracy of value estimates from our model and from models similar to those used by DHS and Myers (1999). Valuation biases are substantially less negative for our model, but valuation inaccuracy is not markedly reduced.

Keywords: Accounting; Capital markets; Valuation models; Linear information models

JEL classification: M41

Conservative Accounting and Linear Information Valuation Models

1. Introduction

The residual income valuation model expresses the intrinsic value of a firm's equity as the sum of book value of equity and the present value of expected future residual income (RI) (Edwards and Bell, 1961; Peasnell, 1982). Linear information models (LIMs) project expected future RI as a linear function of prior-period RI and other information (OI) not yet reflected in accounting numbers (Ohlson, 1989, 1995, 2001; Feltham and Ohlson, 1995, 1996).[1] Such models are appealing because they give closed-form valuation expressions in terms of currently observable information on which RI expectations are conditioned. However, empirical implementations suggest model misspecification because value estimates are substantially lower than market values on average. For example, Dechow, Hutton and Sloan (1999) (DHS) implement the Ohlson (1995) model and report that estimated intrinsic value is on average 25.9% lower than market value. Similarly Myers (1999) implements an empirical version of the Feltham and Ohlson (1995) model and reports that the median ratio of estimated intrinsic value to observed market value is 0.644, corresponding to an undervaluation of 35.6%. In this paper we argue that such negative bias in intrinsic value estimates may result from failure to deal fully with the implications of conservative accounting for RI projections. Building on methods used previously, we propose a LIM-based valuation model that accommodates conservative accounting effects, and we test it using data similar to those used by DHS.

Following Ohlson (1995) and Feltham and Ohlson (1995) (FO), we denote accounting as unbiased (conservative) when book value is asymptotically equal to (less than) intrinsic value. The RI valuation model implies that, when accounting is conservative, the net present value of expected future RIs is positive. The Ohlson (1995) model assumes that the net present value of expected future RIs is asymptotically equal to zero, and this implies unbiased accounting. However, the non-zero intercept parameters from DHS's LIM-estimation equations suggest that scaled RI has a negative mean and that OI, calculated by reference to analyst forecasts of earnings, has a positive mean.[2] This is consistent with conservative accounting. We show that by ignoring the intercepts from LIM-estimation equations, the DHS implementation of Ohlson (1995) neglects an economically important component of expected RI and of intrinsic value.

We show the implications for valuation models of non-zero means in RI and OI, implied by non-zero intercept parameters from empirical estimates of LIMs. Our analysis may be viewed as an empirical extension of the FO model. This model introduces accounting conservatism by assuming that expected future RI depends positively on the current book value of equity, in addition to current RI and OI. However, our analysis suggests that, if the assumed dependence between book value and expected future RI does not reflect information about the mean of OI, this characterization of accounting conservatism will not capture the anticipated unwinding of conservatism that is implied when average RI in the estimation period is negative and average OI is positive. In this case, intrinsic value estimates contain a conservatism-related bias. Results in Myers (1999, 18-20) are consistent with this analysis.

Building on the FO conservative accounting model and DHS's LIM-based empirical methodology, we propose a modified LIM-based valuation model containing a conservatism-correction term that captures the effects of non-zero means for both RI and an analyst-forecast-based measure of OI. We implement this model using data similar to

DHS. We compare the valuation errors from this model with those from two restricted models. The first includes OI but, similar to DHS, assumes unbiased accounting and has no conservatism-correction term. The second has a conservatism-correction term but, similar to Myers (1999), the correction ignores analyst-forecast-based OI and is based wholly on the properties of available realizations of accounting numbers.

We find that correcting LIM-based valuation models for accounting conservatism has a large effect on bias in value estimates. Further, the degree of bias differs substantially depending upon whether or not the conservatism-correction term includes OI. If it includes OI, value estimates are less negatively biased than in the valuation model with no conservatism-correction. In contrast, if it does not include OI, value estimates are even more negatively biased than in the model with no conservatism correction. We also find that, while conservatism correction can improve model performance in terms of bias, it does not markedly reduce the inaccuracy of value estimates.

Inclusion of OI is important in mitigating conservatism-related valuation bias because the analyst-forecast-based predictions of RI used to estimate OI dynamics parameters are higher on average than the past RI realizations used in estimation of the RI dynamics parameters. We attribute this, at least in part, to analyst anticipation of the unwinding of accounting conservatism. Nevertheless, we carry out two sensitivity tests motivated by alternative explanations of the properties of our OI proxy. First, we consider the possibility that results are affected by inclusion in the RI dynamics estimation sample of firm-years for which no analyst forecast (and hence OI measure) is available. Our results are robust when the sample is restricted to firms for which OI measures are available. Second, we consider the effect of adjusting for bias in analyst earnings forecasts. Our conservatism correction to valuation estimates remains economically significant when analyst forecasts are adjusted mechanistically by reference to the median of prior forecast errors. The economic significance of the conservatism correction is largely eliminated when forecasts are adjusted by reference to the mean of prior forecast errors. However, we note recent empirical evidence in Abarbanell and Lehavy (2003) that questions whether rational forecasts will be obtained through mechanistic adjustment of forecasts based on mean forecast errors, given that forecast errors are highly skewed empirically.

The remainder of the paper is structured as follows. In Section 2, we describe our conservative accounting model, together with two restricted versions similar to models used in prior literature, which serve as benchmarks for comparison in empirical analysis. In Section 3, we describe our empirical procedures for generating and comparing value estimates for the three valuation models. In Section 4, we describe our sample selection and data. In Section 5, we report the results of implementing the valuation models. In Section 6, we conclude.

2. LIM-based valuation models

Our proposed LIM-based valuation model

Assuming the dividend discount model and clean surplus accounting, the value of equity can be expressed as follows (Edwards and Bell, 1961; Peasnell, 1982):

$$V_t = b_t + \sum_{\tau=1}^{\tau=\infty} E_t[\tilde{x}^a_{t+\tau}]R^{-\tau} \ , \qquad \text{(RIVM)}$$

where V_t is the value of equity at time *t*, b_t is the book value of equity at time *t*, $E_t[.]$ denotes expectations at time *t*, x_t^a is RI at time *t* from an equity perspective, and *R* is one plus the cost of equity. RI is defined as $x_t^a \equiv x_t - (R-1)b_{t-1}$, where x_t is accounting earnings at time *t* from an equity perspective. In LIM-based valuation models, the second term of RIVM is estimated by combining (i) LIM parameters that characterize the RI generating process, (ii) a cost of capital estimate and (iii) current realizations of information variables, including RI, OI and book value.

We propose the following adaptation of the FO LIM:

$$
\begin{aligned}
\tilde{x}_{t+1}^a &= \omega_0 b_t + \omega_1 x_t^a + \nu_t + \tilde{e}_{1,t+1} \\
\tilde{\nu}_{t+1} &= \gamma_0 b_t + \gamma_1 \nu_t + \tilde{e}_{2,t+1} \\
\tilde{b}_{t+1} &= G b_t + \tilde{e}_{3,t+1},
\end{aligned}
\qquad \text{(LIM1)}
$$

where ω_0, ω_1 $(0 \le \omega_1 < 1)$, γ_0, γ_1 $(0 \le \gamma_1 < 1)$ and G $(1 \le G < R)$ are LIM parameters, ν_t denotes OI at time *t* and e_1, e_2 and e_3 are zero-mean unpredictable disturbance terms.

The important difference between LIM1 and the FO LIM is the $\gamma_0 b_t$ term in the second line of LIM1, which describes the OI dynamics. The role of this term is explained as follows. The first equation of LIM1 describes the RI dynamics. Ignoring for the moment OI (ν_t), this equation models expected future RI as the sum of (i) the product of ω_0 and book value and (ii) an autoregressive component.[3] Thus, asymptotically, RI expectations depend on ω_0. Because of the properties assumed for their OI dynamics, specifically that OI is purely autoregressive around a zero mean, FO require $\omega_0 > 0$ in order for long-run expected RI to exceed zero, and hence for accounting to be conservative.[4] However, consistent with DHS and Myers (1999), results reported below indicate that estimated values of ω_0 are *negative* over our estimation period. Since, under reasonable assumptions, an empirical estimate of ω_0 is of the same sign as the mean of the RI data from which it is estimated, this problem is likely to be due to negative-mean RI in the estimation period.[5] LIM1 mitigates the problem by introducing a potentially positive component to long-run expected RI through the $\gamma_0 b_t$ term from the OI dynamics. As with ω_0, under reasonable assumptions, γ_0 is of the same sign as the mean of the data from which it is estimated. Therefore, assuming that book value is positive, $\gamma_0 b_t$ is positive if the mean of OI in the estimation period is positive. Even if negative-mean RI in the estimation period gives rise to a negative estimate of ω_0, long-run expected RI exceeds zero and accounting is conservative if γ_0 is sufficiently large.[6] In summary, LIM1 is rich enough to capture two consequences of conservative accounting: (i) negative-mean past RI realizations and (ii) positive expected future RI, consistent with expected unwinding of accounting conservatism.

From RIVM and LIM1, it is straightforward to derive the following valuation model:

$$V1_t = b_t + \beta_1 x_t^a + \beta_2 \nu_t + (\beta_3 + \beta_4) b_t, \tag{V1}$$

where

$$\beta_1 = \frac{\omega_1}{R - \omega_1},$$

$$\beta_2 = \frac{R}{(R - \omega_1)(R - \gamma_1)},$$

$$\beta_3 = \frac{R\omega_0}{(R - \omega_1)(R - G)}, \text{ and}$$

$$\beta_4 = \frac{R\gamma_0}{(R-\omega_1)(R-\gamma_1)(R-G)} \; .$$

(See the appendix for details.)

The first three terms on the right-hand side of V1 correspond directly to terms in the Ohlson (1995) valuation model. The final term in V1, $(\beta_3 + \beta_4)b_t$, is a conservatism-correction term that depends importantly on ω_0 and γ_0. For $b_t > 0$, this conservatism-correction term is positive if $\omega_0 + \gamma_0 /(R-\gamma_1) > 0$.[7]

Benchmark models

We compare the valuation errors from V1 with valuation errors obtained from two restricted versions. The first assumes unbiased accounting and therefore contains no conservatism-correction term. The second omits OI, which results in the conservatism-correction term being based entirely on available realizations of past accounting numbers.

No conservatism correction (Model V2)

A restricted form of LIM1 that assumes unbiased accounting is

$$\begin{aligned} \tilde{x}^a_{t+1} &= \omega_1 x^a_t + \nu_t + \tilde{e}_{1,t+1} \\ \tilde{\nu}_{t+1} &= \gamma_1 \nu_t + \tilde{e}_{2,t+1} \; . \end{aligned} \qquad \text{(LIM2)}$$

RIVM and LIM2 give the following valuation model:

$$V2_t = b_t + \beta_1 x^a_t + \beta_2 \nu_t \; . \qquad \text{(V2)}$$

This is the unbiased-accounting Ohlson (1995) model implemented by DHS.

Conservatism correction based on RI realizations only (Model V3)

In order to observe the effect of forcing the conservatism-correction term to be determined wholly by the properties of realized accounting numbers, we drop OI from LIM1:

$$\begin{aligned} \tilde{x}^a_{t+1} &= \omega_0 b_t + \omega_1 x^a_t + \tilde{e}_{1,t+1} \\ \tilde{b}_{t+1} &= G b_t + \tilde{e}_{3,t+1} \ . \end{aligned} \tag{LIM3}$$

RIVM and LIM3 give the following valuation model:

$$V3_t = b_t + \beta_1 x^a_t + \beta_3 b_t \ . \tag{V3}$$

This is similar to the Myers (1999) implementation of the conservative-accounting FO model.[8]

3. Procedures for generating and comparing value estimates

Our procedure for estimating the parameters of LIM1 follows closely that used by DHS in implementing the Ohlson (1995) unbiased accounting model, differing only as required by the wider scope of our LIM and because we scale our data by book value rather than by stock price.[9] We also use a very similar dataset, details of which are provided in section 4. For each year t, we estimate RI dynamics parameters, $\omega_{0,t}$ and $\omega_{1,t}$ corresponding to ω_0 and ω_1 in LIM1, using all available data up to t as follows:

$$\frac{x^a_{j,s}}{b_{j,s-1}} = \omega_{0,t} + \omega_{1,t} \frac{x^a_{j,s-1}}{b_{j,s-1}} + e_{1j,s} \ . \tag{1}$$

In (1), j is a firm index, s is a time index ranging from the second year for which RI data are available up to t, $x^a_{j,s}$ is the RI per share for company j at year s, $b_{j,s-1}$ is the book value per share for company j at year s-1, and $e_{1j,s}$ is a disturbance term. RI per share is equal to $x_{j,s} - (R_s - 1)b_{j,s-1}$, where $x_{j,s}$ is the earnings per share of company j at year s and R is one plus the cost of equity. The cost of equity is assumed to be a cross-sectional constant but varies each year.

At each valuation date t, we measure OI using an adaptation of the procedure proposed by Ohlson (2001) and used by DHS. Consistent with LIM1, OI is measured as the difference between predicted one-year ahead RI based on the consensus analyst forecast and a forecast derived by applying equation (1) to current realizations of book value and RI:

$$\nu_{j,t} = f_{j,t}^{a,t+1} - (\omega_{0,t} b_{j,t} + \omega_{1,t} x_{j,t}^{a}) \ , \qquad (2)$$

where $\nu_{j,t}$ is OI per share for company j at year t and $f_{j,t}^{a,t+1}$ is the analyst-forecast-based prediction at year t of RI per share in year t+1 for firm j, defined as

$$f_{j,t}^{a,t+1} = f_{j,t}^{t+1} - (R_t - 1)b_{j,t} \ ,$$

where $f_{j,t}^{t+1}$ is the consensus analyst forecast at year t of earnings per share in year t+1 for firm j.[10] At each valuation date t, we estimate year-specific parameters, $\gamma_{0,t}$ and $\gamma_{1,t}$ corresponding to γ_0 and γ_1 in LIM1, as follows using all OI measures up to t:

$$\frac{\nu_{j,s}}{b_{j,s-1}} = \gamma_{0,t} + \gamma_{1,t} \frac{\nu_{j,s-1}}{b_{j,s-1}} + e_{2j,s} \ , \qquad (3)$$

where $e_{2j,s}$ is a disturbance term. In equation (3), the time index, s, ranges from the second year for which OI is available up to t.

At each valuation date *t*, we also estimate a year-specific book value growth parameter, G_t, corresponding to G in LIM1, using all available book value data up to *t*, as follows:

$$G_t = \frac{\sum_{s=k}^{s=t} \sum_{j=1}^{j=N_s} b_{j,s}}{\sum_{s=k}^{s=t} \sum_{j=1}^{j=N_s} b_{j,s-1}} , \tag{4}$$

where N_s is the number of firms for which data are available for year *s*, and *k* is the second year for which book value data are available.[11]

At each valuation date *t*, the year-specific estimates of ω_0, ω_1, γ_0, γ_1, *G* and *R* are used, together with the corresponding current realizations of book value, RI and OI, to generate intrinsic value estimates for V1.

For LIM2, ω_1 is estimated from equation (1) as above. However, OI is measured as follows, without regard to the ω_0 intercept parameter from (1):

$$v_{j,t} = f_{j,t}^{a,t+1} - \omega_{1,t} x_{j,t}^{a} \ . \tag{2.a}$$

The parameter γ_1 is then estimated from this ω_0-exclusive OI measure, as in (3) above. Estimates of ω_1, (ω_0-exclusive) γ_1 and *R* are used, together with current realizations of book value, RI and (ω_0-exclusive) OI, to generate intrinsic value estimates for V2. Apart from the use of book-value-scaled data rather than price-scaled data, this procedure is identical to that used by DHS in their implementation of Ohlson (1995).

V3 intrinsic value estimates are generated using estimates of ω_0 and ω_1 from equation (1), estimates of *G* from equation (4), and estimates of *R*, together with current realizations of book value and RI.

Following the prior literature, we compare the ability of the three valuation models to explain stock prices by examining the bias and inaccuracy of valuation errors. *Ceteris paribus*, one model is better specified than another if it produces less biased and less inaccurate estimates of intrinsic value. For each model, we calculate scaled valuation errors equal to the intrinsic value estimate less the stock price three months after the corresponding balance sheet date, scaled by the stock price. Valuation bias is measured as the mean (median) signed valuation error, and valuation inaccuracy is measured as the mean (median) absolute valuation error.

4. Sample selection and data

We use data very similar to those used by DHS. Initially, we obtain from *COMPUSTAT* all available observations for earnings before extraordinary items available for common stockholders (Compustat Item 237) and book value of common equity (Compustat Item 235) for U.S. industrial and financial firms from 1950 to 1995, and state these items on a per-share basis. Negative-book-value cases are excluded. We obtain from I/B/E/S all available matching median consensus forecasts of earnings per share from 1974 to 1995, as at the first month after the corresponding I/B/E/S-reported prior-year earnings announcements.[12] We obtain from *CRSP* stock prices three months after fiscal year-ends. We obtain from *Datastream* monthly observations of the yield on U.S. Treasury Bonds with maturities greater than ten years. The time-varying cost of equity used in measuring

RI and as a discount factor in valuation models is estimated as the mean of this yield for the relevant calendar year plus an assumed market risk premium of 5%.[13]

[INSERT TABLE 1 ABOUT HERE]

Table 1 contains details of the sample. Similar to DHS, we estimate year-specific RI LIM parameters, ω_0 and ω_1, from a pooled cross-section/time-series regression (equation (1)) for each year from 1975 to 1995, using all available RI data going back to 1951.[14] Raw financial statement data are available from *COMPUSTAT* from 1950 onwards and, because calculation of RI requires lagged book value, RI observations are available from 1951 onwards. After excluding negative-book-value cases, we have a maximum of 130,359 firm-year RI observations in 1995. Of these, 114,844 have a corresponding lagged observation and are usable as the dependent variable in estimation of RI LIM parameters. Corresponding book value data are used to estimate the growth parameters, G. OI is measured from equations (2) and (2.a) for years from 1975 to 1995, using RI, estimated RI LIM parameters and analyst forecast data. Similar to DHS, we estimate year-specific OI LIM parameters, γ_0 and γ_1, from a pooled cross-section/time-series regression (equation (3)) for each of the 19 years from 1977 to 1995. After eliminating cases prior to 1975 pre-dating the availability of I/B/E/S earnings forecasts and cases from 1975 onwards for which no matching analyst forecasts are available, 39,560 firm-year observations are available for this purpose. We have 41,297 cases for the period 1977-1995 for which book value, RI, OI and price are all available. We construct value estimates for V1, V2 and V3 for these 41,297 cases.

[INSERT TABLE 2 ABOUT HERE]

Since the impact of accounting conservatism is likely to differ between high-intangible and low-intangible industrial sectors (Francis and Schipper, 1999), as part of our analysis we estimate LIM parameters and intrinsic value separately for high-intangible firms and low-intangible firms. Table 2 provides details of the sectors included in the 'high-intangible' group. These sectors comprise those classified as 'high-technology' in Francis and Schipper (1999) and in Amir, Lev and Sougiannis (1999) plus some additional sectors from the publishing, communications and transport industries.

[INSERT TABLE 3 ABOUT HERE]

Table 3 panel A provides descriptive statistics for the book-to-price ratio, the earnings-to-price ratio, and earnings scaled by lagged book value for the 130,359 firm-year observations from 1951-1995. Row 1 of panel B reports descriptive statistics for RI scaled by beginning-of-year book value, used in estimating the LIM parameters ω_0 and ω_1. Row 2 gives details of the scaled RI realizations corresponding to cases for which analyst-forecast-based predictions of next-year RI are also available. Row 3 gives details of analyst-forecast-based predictions of next-year RI for these cases, scaled by book value at the forecast date. Row 4 gives details of the corresponding OI measures used in the estimation of γ_0 and γ_1 parameters, also scaled by book value at the forecast date. Because of the differences between the means and medians of data described in panel B of Table 3, the most extreme one percent of RI observations and OI measures are deleted as outliers for the purpose of estimating LIM parameters, but are retained for the purpose of constructing value estimates.[15] Panel B therefore also reports the means exclusive of observations deleted in the estimation of the LIM parameters. We note from panel B that the analyst-forecast-based predictions of RI used to estimate parameters of the OI dynamics (row 3) are higher on average than the past RI realizations used to estimate parameters of the RI dynamics (row 1).

5. Results

LIM parameter estimates and implied valuation multiples

Table 4 reports the median values of the cost of equity parameter, *R*, the LIM parameter estimates ω_0, ω_1, γ_0 and γ_1 used in V1, the associated R-squared statistics from regression models (1) and (3), and the growth parameter *G*. It also reports the medians of the valuation multiples β_1, β_2, β_3, β_4 and $\beta_3 + \beta_4$ used in V1. The estimates of ω_0, ω_1 and β_3 are used in V3. The estimate of ω_1 is used in V2, along with the ω_0-exclusive estimates of γ_1 and β_2 based on (2.a). The ω_0-exclusive estimates of γ_1 and β_2 are very similar to the ω_0-inclusive estimates reported in Table 4, and are not separately reported. For each parameter and valuation multiple, we report the number of years (out of 19) for which the item is positive or negative. Results are reported for all firms taken together (high- and low-intangible) with joint parameter estimation, and for high-intangible firms and low-intangible firms separately.

[INSERT TABLE 4 ABOUT HERE]

For both the full sample and the two sub-samples, the median value of the RI persistence parameter, ω_1, is about 0.50 and that of the OI persistence parameter, γ_1, is about 0.60. The overall sample median growth rate is 5.0%, but this masks a significant difference between the growth rates for high- and low- intangible firms (6.4% and 4.7%, respectively).[16]

Consistent with DHS and with the negative mean RI used in estimation (see Table 3), the median value of ω_0 is negative for the full sample and the two sub-samples. Annual estimates are significantly negative in 13 out of 19 years for the full sample, and in 11 and 14 cases, respectively, for the high- and low-intangible sub-samples. Consistent with DHS and with the positive mean OI reported in Table 3, the median value of γ_0 is positive for the full sample and the two sub-samples. Annual estimates are significantly positive in all 19 years for the full sample, and in 17 and 19 cases, respectively, for the high- and low-intangible sub-samples. These parameters indicate that the conservatism-correction term can be expected to be important. As expected, given the signs of the ω_0 and γ_0 parameters, β_3 is negative in a majority of cases and β_4 is positive in all cases. For $b_t > 0$, the sign of the conservatism-correction term is given by the sign of $\beta_3 + \beta_4$, and this is positive in all cases. For the full sample, the conservatism correction is +32.5% of book value. Consistent with conservative accounting effects being more important for high-intangible firms, the conservatism correction is +51.7% of book value for these firms compared to +27.9% for low-intangible firms.

The LIM parameter estimates provide an indication of how sensitive RI forecasts and value estimates are to the LIM specification employed in forecasting RI. When we use LIM3, we take account of ω_0 through the term $\omega_0 b_t$. In a majority of years this introduces a negative component to RI forecasts, given that b_t is positive. The capitalized value of this component is captured by the valuation multiple β_3. The values for β_3 reported in Table 4 indicate that value estimates in V3 are lower than V2 by over 20% of book value as a result of including β_3. However, V3 disregards OI entirely, and thereby eliminates the possibility that the RI forecasts can reflect any expected unwinding of the prior-period conservatism reflected in β_3. Table 4 reveals that the valuation consequences of ignoring the OI dynamics are substantial. For the full sample the median estimated value of β_4 is 0.574. For high-intangible firms the corresponding estimate is 0.813. Thus, ignoring this term in V3 reduces value estimates by 57% of book value for the full sample and by as much as 81% of book value for high-intangible firms.

Valuation errors from LIM-based valuation models

Table 5 reports the means and medians of the signed valuation errors (bias) and absolute valuation errors (inaccuracy) for valuation models V1, V2 and V3. Results are provided for the full sample of firms when LIM parameters are estimated jointly for all firms, for the full sample when LIM parameters are estimated separately for high- and low-intangible firms, and for each of the two groups when LIM parameters are estimated separately. For each of the V1, V2 and V3 bias metrics, we test the null hypothesis that the mean is zero, using a *t*-test, and the null hypothesis that the distribution is centred on zero, using a non-parametric signed-rank test. In all cases except for the mean bias metric for V1 for high-intangible firms, we reject the null hypothesis at the 1% level. For each of the V2 and V3 bias and inaccuracy metrics, we test the null hypothesis that the difference between that metric and the corresponding V1 metric is zero and the null hypothesis that the distribution of differences is centred on zero, again using a *t*-test and a non-parametric signed-rank test respectively. In all cases except for the mean inaccuracy metric for V2 for high-intangible firms, we reject the null hypothesis at the 1% level.

[INSERT TABLE 5 ABOUT HERE]

Valuation bias

It is evident from Table 5 that V1 gives a substantially smaller valuation bias than the unbiased-accounting V2. The overall mean (median) valuation bias for V1 with joint estimation of LIM parameters is +4.4% (-11.0%), compared to -23.1% (-33.9%) for V2.[17] The overall results when LIM parameters are estimated separately are almost identical. Similar qualitative differences in valuation bias are observed for the high-intangible and low-intangible sub-samples. The smaller valuation bias for V1 relative to V2 is unsurprising, given that $\beta_3 + \beta_4$ is systematically positive, and book value is required by our sample-selection procedure to be positive. Figure 1 plots the signed valuation errors from V1 and from V2, after sorting the sample based on the V2 errors.[18] It shows that the smaller bias in V1 relative to V2 arises because, across the whole range, intrinsic value estimates from V1 are systematically higher than those from V2.

For V3, which reflects the negative-mean realizations of RI in prior years but not the information in analyst-forecast-based predictions of RI, the overall mean (median) valuation bias with joint estimation of LIM parameters is -43.0% (-57.0%). The overall results when LIM parameters are estimated separately are again almost identical, but we note that the mean (median) valuation bias for high-intangible firms is highly negative at -59.0% (-72.4%). The explanation for V3 giving the most extreme negative valuation bias of the three models lies in our finding that RI realizations used in parameter estimation are negative on average, and that ω_0 and β_3 are therefore generally negative. In comparison with the unbiased-accounting V2, projections of future RI implied by LIM2 are being reduced and centered on mean RI in the estimation period.

The high negative bias for V3 illustrates the insufficiency of an FO-type conservatism-correction based on negative estimation-period RI realizations, when there is no provision in the OI dynamics for anticipated unwinding of accounting conservatism. LIM1 is similar to LIM3 in taking account of the negative-mean RI in the estimation period through the parameter ω_0 (via β_3). However, unlike LIM3, it includes a mechanism through which positive expected future RI is captured. Taking account of the LIM parameter γ_0 (via β_4) shifts conditional expectations of future RI. Since γ_0 is positive, the RI projections implied by LIM1 are higher than for both LIM2 and LIM3, and value estimates are correspondingly higher on average (less negatively biased).

Valuation inaccuracy

Table 5 reveals that, while the conservatism-correction in V1 significantly reduces valuation bias, its impact on valuation inaccuracy is more complex. Comparison of mean and median inaccuracy metrics reveals that all of the reported inaccuracy metrics are much lower for V1 than for V3, and that the differences are statistically significant. In contrast, comparison of inaccuracy metrics between V1 and V2 is less clear-cut. The mean inaccuracy metrics for V1 and V2 are quite similar, although statistical tests reveal that V2 is significantly less inaccurate for the full sample and for the low-intangibles sub-sample. The differences between the median inaccuracy metrics are larger, and suggest that V1 is less inaccurate than V2 for both the full sample and the two sub-samples.

[INSERT FIGURE 1 ABOUT HERE]

Figure 1 shows why the marked reduction in negative bias in V1 relative to V2 is accompanied by some reduction in the median-based inaccuracy metric but not by any reduction in the mean-based metric. The effect of using V1 rather than V2 is to bring about a general upward shift in signed valuation errors, which substantially reduces negative valuation bias. Inaccuracy-reducing cases, for which the V2 error is negative and the V1 error is less negative, make up approximately 58% of the sample. The median of the distribution of valuation errors is thus closer to zero for V1 than for V2. Inaccuracy-increasing cases, for which the V2 error is positive and the V1 error is more positive, make up only 22% of the sample.[19] However, the average magnitude of the differences between the V2 and V1 valuation errors is larger for the 22% of inaccuracy-increasing cases than for the 58% of inaccuracy-reducing cases, particularly at the extreme upper end of the distribution. The overall effect is that the mean-based inaccuracy metric is little changed from V2 to V1.[20]

Sensitivity checks

Sample composition

Our sampling procedure and estimation methodology closely follow DHS: our RI LIM parameters are estimated using all available RI observations from 1951 to 1995; our LIM parameters for analyst-forecast-based OI are estimated using cases for which forecasts are available from 1975 to 1995. As can be seen from Table 3, RI for the sample used in estimating RI LIM parameters (ω_0 and ω_1) is lower on average than the RI and RI forecasts for the sample used in estimating OI LIM parameters (γ_0 and γ_1). In order to ascertain whether differences between the sample used for RI parameter estimation and the sample used for OI parameter estimation account for differences in valuation bias, we implement all three valuation models by estimating all LIM parameters using only cases for which analyst-forecast-based predictions of RI are available. The results (not reported) are similar to those reported in Table 5 suggesting that differences in valuation bias are not an artifact of sample composition.

Analyst forecast bias

Our valuation methodology follows DHS's in that OI is measured as the difference between an analyst forecast-based prediction of RI and the prediction based on the first RI LIM equation. This procedure assumes that analyst forecasts are the best available source of earnings forecasts beyond the autoregressive model in the LIM. However, prior research shows that analyst forecast errors are positive on average (Brown, 1993). Several possible explanations for this empirical regularity have been proposed by prior research (Kothari, 2001). Forecast bias might reflect strategic reporting of deliberately biased forecasts (Lim, 2001) or selective reporting of truthful forecasts (McNichols and O'Brien, 1997). Alternatively, forecast bias might reflect systematic cognitive biases in analysts' information processing. Under these explanations, a better measure of the beliefs as at the forecast date might be obtained by correcting forecasts for bias based on observable prior forecast errors. However, more recent research suggests that positive forecast bias results from negative skewness in earnings. In particular, Abarbanell and Lehavy (2003) argue that apparent evidence on irrationality can be attributed to a relatively small number of extreme observations drawn from negatively skewed earnings distributions, which are unidentifiable ex-ante.[21] Under this explanation, it is not clear that a better measure of beliefs as at the forecast date will be obtained by mechanistic adjustment of original forecasts by the mean of observable prior forecast errors.

Nevertheless, we examine the sensitivity of our results reported earlier for V1 and V2 to bias-adjustment of earnings forecasts.[22]

We estimate bias adjustments from all available analyst forecast errors up to the OI measurement date. Because the distribution of analysts' forecast errors is highly skewed, we examine the effects of bias adjustments based on both the median of forecast errors and the mean of forecast errors. When bias adjustment is set equal to the median forecast error over the estimation period, the mean of the yearly adjustments is -1.7% of book value for high-intangible firms and -0.8% of book value for low-intangible firms. When it is set equal to the mean forecast error, the mean of the yearly adjustments is substantially larger in magnitude, being -5.6% of book value for high-intangible firms and -3.0% of book value for low-intangible firms. The magnitudes of these bias adjustments are consistent with the forecast errors reported by Das et al. (1998).[23]

[INSERT TABLE 6 ABOUT HERE]

The consequences of applying these bias adjustments in valuation are summarized in Table 6. This reports the overall mean and median of signed and absolute valuation errors for V1, V2 and V3 before bias adjustment, as given in Table 5, and the corresponding metrics for V1 and V2 after adjustment for median and mean forecast error. The metrics are for all firms (high- and low-intangible firms taken together) where LIM parameters are separately estimated for each group. The mean and median valuation biases in the median-bias-adjusted value estimates for V1 are –9.8% and –25.0%, respectively. The bias is more negative than from use of the unadjusted analyst forecast data for V1, but remains substantially less negative than the bias for V3. The application of the larger mean-based bias adjustment to V1 gives mean and median valuation biases of –45.1% and –58.1, respectively. The bias is substantially more negative than from use of the unadjusted analyst forecast data for V1, and is similar to that for V3. Because it lacks a conservatism-correction term, V2 is relatively insensitive to analyst-forecast-bias adjustment. Valuation inaccuracy is similarly affected by the forecast bias adjustments. For V1, adjustment based on median forecast error hardly affects inaccuracy, but adjustment based on mean forecast error leads to a large increase in inaccuracy. Again, V2 is little affected.

It is clear that the relative bias and inaccuracy of the valuation models is affected by adjustment for analyst-forecast-bias, and can vary substantially depending on the type of adjustment that is made. Adjustment by the median of past forecast errors has relatively little effect, but adjustment by the mean of past forecast errors has a more substantial effect. However, we emphasize that, in light of the evidence in Abarbanell and Lehavy (2003), it is questionable whether rational forecasts will be obtained through mechanistic adjustment of original forecasts by the mean of a skewed distribution of prior forecast errors

6. Conclusion

LIM-based valuation models are appealing in that they give closed form valuation expressions based on currently observable accounting information and other information. However, implementations of the LIM approach to estimating intrinsic values by DHS, based on the unbiased-accounting Ohlson (1995) model, and by Myers (1999), based on the conservative-accounting FO model, have reported large negative bias in value estimates. One explanation for this bias is that LIM-based valuation models, as implemented, do not fully accommodate the implications of conservative accounting for RI projections.

Building on FO and the empirical methodology of DHS, we propose a conservative-accounting valuation model that employs the properties of analyst-forecast-based OI, together with those of RI realizations, to forecast RI. Our results demonstrate that the inclusion of a conservatism-correction term reflecting the properties of RI realizations and of OI has a marked effect on value estimates, largely eliminating the substantial negative bias in prior research. However, the inclusion of this conservatism-correction does not markedly reduce the inaccuracy of value estimates. Our results also demonstrate that using negative-mean RI realizations alone to estimate the conservatism-correction term may reinforce the negative bias in value estimates. They suggest that LIM-based models will benefit from the inclusion of a term that allows the models to reflect information about expected future RI deducible from analyst forecasts.

Appendix

Valuation multiples in model V1

Valuation multiple on RI

$$\frac{\omega_1}{R}+\frac{\omega_1^2}{R^2}+\frac{\omega_1^3}{R^3}+......+\frac{\omega_1^\infty}{R^\infty}=\frac{\omega_1}{R-\omega_1}=\beta_1 \ .$$

Valuation multiple on OI

$$\left[1+\frac{\omega_1}{R-\omega_1}\right]\left[1+\frac{\gamma_1}{R-\gamma_1}\right]\frac{1}{R}=\frac{R}{(R-\omega_1)(R-\gamma_1)} \ =\beta_2 \ .$$

Valuation multiple on book value arising from the ω_0 *term*

$$\left[1+\frac{\omega_1}{R-\omega_1}\right]\left[1+\frac{G}{R-G}\right]\frac{\omega_0}{R}=\frac{R\omega_0}{(R-\omega_1)(R-G)}=\beta_3 \ .$$

Valuation multiple on book value arising from the γ_0 *term*

$$\left[1+\frac{\omega_1}{R-\omega_1}\right]\left[\frac{R\gamma_0}{(R-\gamma_1)(R-G)}\right]\frac{1}{R}=\frac{R\gamma_0}{(R-\omega_1)(R-\gamma_1)(R-G)}=\beta_4 \ .$$

Endnotes

1. Another approach uses explicit forecasts of RI over a finite horizon, together with an estimate of the present value of post-horizon RIs (Francis, Olsson and Oswald, 2000; Frankel and Lee, 1998; Lee, Myers and Swaminathan, 1999).
2. Expectations about future RI are conditioned both by RI realizations and by OI. Results reported in DHS indicate that neither of these items is zero-mean. The RI LIM intercept parameter reported by DHS (Table 1) is -0.02 and significantly different from zero (*t*-statistic: -29.04), and the OI LIM intercept parameter (Table 3) is 0.01 and significantly different from zero (*t*-statistic: 38.79). As explained in Section 2, this indicates that the RI realizations used in the estimation are negative on average and that the OI measures are positive on average.
3. In this study and in DHS, the RI LIM parameters, ω_0 and ω_1, are estimated from RI data without regard to OI.
4. In the FO model, a positive (negative) value of ω_0 (denoted ω_{12} in FO) would give rise to a positive (negative) value for the conservatism-correction multiple on book value (α_2 in FO).
5. From the first equation of LIM1 (ignoring OI), $\omega_0\overline{b_t} = \overline{x}^a_{t+1} - \omega_1\overline{x}^a_t$, where the bars denote 'mean'. In empirical estimation using pooled cross-section and time-series data, it is reasonable to assume that $\overline{x}^a_{t+1} \approx \overline{x}^a_t$. Thus, $\omega_0\overline{b_t} \approx (1-\omega_1)\overline{x}^a_{t+1}$ and, for $0 \le \omega_1 < 1$ and $\overline{b_t} > 0$, ω_0 has the same sign as the mean of RI. In the empirical estimation reported below, we scale RI by book value of equity. Similar reasoning applies to scaled data.

6. As shown below, this is so if $\gamma_0 > -\omega_0(R-\gamma_1)$.

7. Note that *R*, $(R-\omega_1)$, $(R-\gamma_1)$ and $(R-G)$ are all required to be positive.

8. Our LIM3 differs slightly from that used in Myers' (1999) implementation of FO (Myers' LIM2), which is as follows (our notation):

$$\tilde{x}_{t+1}^{a} = \omega_0 b_t + \omega_1 x_t^a + \omega_2 + \tilde{e}_{1,t+1}$$
$$\tilde{b}_{t+1} = Gb_t + \tilde{e}_{3,t+1} .$$

This contains an intercept term, ω_2, that is absent from our LIM3. However, a pooled cross-sectional estimation of this LIM uses the same information as our LIM3, and value estimates based on the resultant parameters are very similar to those given by our LIM3. It should also be noted that our empirical procedure described in Section 3 differs from Myers (1999) in that our LIM parameters are estimated from pooled cross-sectional/time-series regressions, as in DHS, rather than from company-specific time-series regressions, as in Myers (1999).

9. The use of price-scaled data will cause price to appear as an information variable in the associated valuation model, if the ω_0 and/or γ_0 parameters are not zero.

10. In DHS's implementation of the unbiased-accounting Ohlson (1995) model, the term corresponding to $\omega_{0,t} b_{j,t}$ is disregarded, and OI is defined as $f_{j,t}^{a,t+1} - \omega_{1,t} x_{j,t}^{a}$.

11. We recognize that the growth parameter, along with the other LIM parameters, could have a 'term structure'. However, in common with related literature, we do not build such a structure into the parameters of the generating process at each valuation date, but we do estimate the parameters separately at each valuation date.

12. The use of mean forecasts rather than median forecasts has no material effect on our results.
13. The assumed risk premium of 5% is approximately equal to the rate recommended in the practitioner-oriented valuation text by Copeland, Koller and Murrin (1996). It is also close to the mean of 5.3% of the yearly estimates of the U.S. equity risk premium reported by Easton, Taylor, Shroff and Sougiannis (2002, 671) for 1981 to 1998. We note that this figure is rather higher than the mean figure of 3.4% estimated by Claus and Thomas (2001, 1643) for the U.S. for the period 1985 to 1998, based on additional assumptions about post-horizon growth.
14. RI LIM parameters are used together with analyst-forecast-based predictions of RI to measure OI. 1975 is the earliest date for estimation of the RI LIM parameters, this being determined by the availability of analyst earnings forecasts in I/B/E/S. RI LIM parameters for 1975 and 1976 are used only for the purpose of measuring OI. Parameters for subsequent years are used for this purpose and within value estimates.
15. The deleted observations are those for which the absolute value of the difference between the observation and the median of the distribution are the greatest. Supplementary tests reveal that results are not sensitive to the method of dealing with outliers.
16. These growth rates are lower than the mean implied growth rate of 10.1% reported by Easton et al. (2002, 664). However, it should be noted that our growth parameter relates to book value, whereas Easton et al.'s relates to RI, and therefore impounds

beliefs about persistence in profitability (among other things) as well as those about growth in book value.

17. Our valuation bias of -23.1% for V2 with joint estimation of LIM parameters is very similar to the bias of -25.9% reported by DHS for a similar sample, but using price-scaled data to estimate LIM parameters. We find a very similar bias of -24.6% when we scale our data by price, suggesting that valuation bias with no conservatism correction is insensitive to the choice of deflator used in estimating LIM parameters.
18. The valuation errors depicted in Figure 1 are for all firms taken together, where LIM parameters are estimated separately for high- and low-intangible firms.
19. The remaining 20% of the sample is made up almost entirely of cases for which the V2 error is negative and the V1 error is positive, and the effect of these cases on the overall difference in inaccuracy between V2 and V1 is small.
20. We explore the possibility that inaccuracy might be affected by varying the assumed cost of capital. We vary the assumed cost of capital across the range from 10% to 20%, including setting the cost of capital equal to a level that eliminates bias. No marked reduction in inaccuracy is achieved.
21. Further analysis of the relationship between analyst-forecast-bias and earnings skewness can be found in Gu and Wu (2003) and Basu and Markov (2004). These studies suggest that forecast bias is a characteristic of optimal forecasts made by rational analysts when the distribution of earnings and earnings changes is skewed, and analysts attempt to maximize forecast accuracy.
22. Since V3 does not use analyst-forecast-based OI, no adjustment is made for this model.

23. For the period 1989-1993 and using a forecast horizon similar to that used in our study, Das et al. (1998, 286) report mean and median price-scaled analyst-forecast errors of -3.5% and -0.7%, respectively. We work with book-value-scaled forecast errors, but the mean and median of our forecast errors as scaled by price are -3.1% and -1.0%, respectively.

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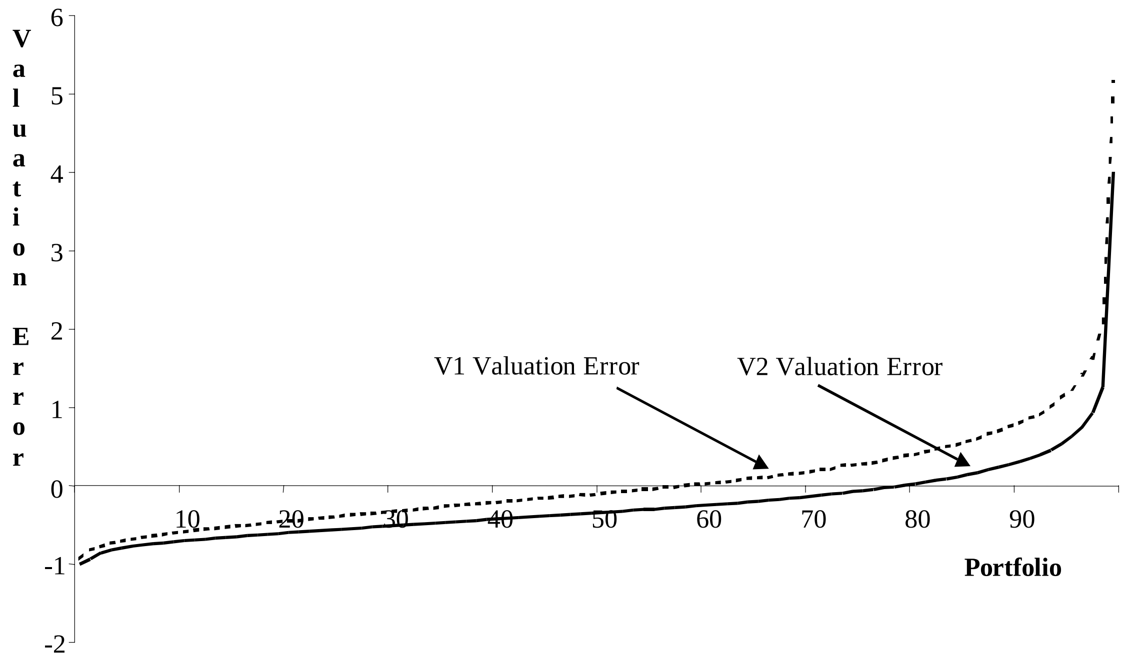
FIGURE 1
V1 signed valuation errors compared to V2 signed valuation errors*



Note:
* The valuation errors depicted here are for all firms taken together, where LIM parameters are estimated separately for high- and low-intangible firms. Valuation errors are measured as the intrinsic value estimate less the observed share price three months after the corresponding balance sheet date, all scaled by the share price. Observations are ranked based on V2 signed valuation errors, and are grouped into 100 portfolios on the basis of this ranking. Then the mean values of the V1 and V2 signed valuation errors of each portfolio are depicted.

TABLE 1
Summary of data used in LIM parameter estimation and construction of value estimates

	Estimation of ω_0 and ω_1 LIM parameters	Estimation of γ_0 and γ_1 LIM parameters	Construction of value estimates
Number of firm-years from 1951-1995 for which earnings per share and lagged book value per share observations are obtained from COMPUSTAT (excluding negative book value cases), and for which RI can be calculated	130,359	130,359	
Less: Cases for which there is no matching lagged RI observation	15,515		
RI observations from 1952-1995 used as dependent variable to estimate yearly ω_0 and ω_1 parameters[*†]	114,844		
Less: Earnings per share observations from 1951-1974		32,515	
Available earnings per share and RI observations from 1975-1995		97,844	
Less: RI observations for which there is no matching I/B/E/S forecast of the next year's earnings per share. (In these cases, it is not possible to arrive at an analyst-based measure of OI.)		50,373	
Number of OI measures from 1975-1995		47,471	47,471
Less: Cases for which there is no matching lagged OI measure		7,911	
Number of OI measures from 1976-1995 used as dependent variable to estimate yearly γ_0 and γ_1 parameters[†]		39,560	
Less: OI measures from 1975-1976 (used only in the estimation of γ_0 and γ_1 LIM parameters)[‡]			1,617
Available OI measures from 1977-1995			45,854
Less: Cases from 1977-1995 for which there is no matching price observation			4,557
Cases from 1977-1995 for which book value, RI, OI and price are all available, and for which value estimates are constructed			41,297

Notes:

* RI LIM parameters are estimated for each year from 1975 to 1995 using all available RI data going back to 1951. Parameters for 1975 and 1976 are used only for the purpose of measuring OI. Parameters for subsequent years are used for this purpose and in value estimates.

† Of the 114,844 RI observations and 39,560 OI measures, the most extreme 1% are deleted as outliers in estimating ω_0, ω_1, γ_0 and γ_1 parameters.

‡ OI measures prior to 1977 are used only in the estimation of γ_0 and γ_1 parameters, and are not used directly in value estimates.

TABLE 2
Sectors included in ‘high-intangible’ group

Three-digit SIC code	Sector name*
271	Newspapers: publishing
272	Periodicals: publishing
273	Books
274	Miscellaneous publishing
283	Drugs
284	Soap, detergents, and cleaning preparations, perfumes, cosmetics
357	Computer and office equipment
360	Electronic and other electrical equipment and components
361	Electric transmission and distribution equipment
362	Electrical industrial apparatus
363	Household appliances
364	Electric lighting and wiring equipment
365	Household audio and video equipment
366	Communications equipment
367	Electronic components and accessories
368	Computer hardware
371	Motor vehicles and motor vehicle equipment
372	Aircraft and parts
376	Guided missiles and space vehicles and parts
382	Laboratory apparatus
384	Surgical, medical and dental instruments and supplies
481	Telephone communications
482	Telegraph and other message communications
483	Radio and television broadcasting stations
484	Cable and other pay television services
489	Communications services not elsewhere classified
737	Computer programming, data processing and other computer-related services
873	Research, development and testing services

Note:

* These sectors comprise those classified as ‘high-technology’ in Francis and Schipper (1999) and in Amir, Lev and Sougiannis (1999) plus some additional sectors from the publishing, communications and transport industries. Of the 130,359 firm-year observations shown in Table 1 as being available for ω_0 and ω_1 LIM parameter estimation, 30,069 (23%) are categorized as high-intangible; of the 41,297 firm-year observations used in the construction of value estimates, 10,740 (26%) are categorized as high-intangible.

TABLE 3
Descriptive statistics[*]

Panel A: Raw data from 1951-1995	N	Mean	1%	Q1	Median	Q3	99%
Book-to-price ratio	130,359	1.085	0.054	0.427	0.737	1.193	4.329
Earnings-to-price ratio	130,359	0.000	-1.641	0.021	0.066	0.110	0.342
Earnings scaled by lagged book value	130,359	0.084	-1.033	0.031	0.112	0.174	0.670

Panel B: Data used in LIM parameter estimation	N	Mean including outliers	Mean excluding outliers[†]	1%	Q1	Median	Q3	99%
RI realizations used in ω_0 and ω_1 parameter estimation	130,359	-0.046	-0.050	-1.167	-0.103	-0.015	0.048	0.539
RI realizations where analyst-forecast-based predictions of RI are available	47,471	0.016	-0.025	-0.798	-0.076	-0.006	0.055	0.502
Analyst-forecast-based predictions of RI used in measuring OI	47,471	0.101	0.012	-0.480	-0.036	0.012	0.070	0.548
OI used in γ_0 and γ_1 parameter estimation	47,471	0.155	0.074	-0.185	-0.001	0.029	0.076	0.880

Notes:

[*] Panel A reports details of raw data for 1951-1995 corresponding to the 130,359 cases used in estimation of LIM1 parameters ω_0 and ω_1. Panel B reports details of RI and OI. These are scaled by previous-year book value in the case of RI realizations, and by forecast-date book value in the cases of RI forecasts and OI. Row 1 of panel B reports details of the RI realizations used in estimation of LIM1 parameters ω_0 and ω_1. Row 2 reports details of the subset of 47,471 RI realizations for which analyst-forecast-based predictions of next-year RI and measures of OI are available. Row 3 reports details of corresponding analyst-forecast-based predictions of RI used in measuring OI. Row 4 reports details of OI used in the estimation of LIM1 parameters γ_0 and γ_1. N denotes the number of observations, 1% denotes the first percentile, Q1 the 1st quartile, Q3 the third quartile and 99% the 99th percentile.

[†] For the purpose of estimating the LIM1 parameters ω_0 and ω_1, the most extreme 1% of RI observations are deleted. The first two rows of panel B report mean RI exclusive of outliers. Likewise, for the purpose of estimating the LIM1 parameters γ_0 and γ_1, the most extreme 1% of OI measures are deleted. Rows 3 and 4 include the means of the corresponding items exclusive of those deleted observations.

TABLE 4
Medians of yearly estimates of cost of equity, LIM parameters, and valuation multiples

	R	ω_0	ω_1	$R^2(\omega)$	γ_0	γ_1	$R^2(\gamma)$	G	β_1	β_2	β_3	β_4	$\beta_3+\beta_4$
Joint Parameter Estimation													
All firms*	1.136	-0.010	0.490	0.312	0.014	0.620	0.315	1.050	0.753	3.458	-0.219	0.574	0.325
		(-17.96)	(182.68)		(23.30)	(88.24)							
No. of positive estimates†		5	19		19	19			19	19	5	19	19
No. of negative estimates†		13	0		0	0			0	0	14	0	0
Separate Parameter Estimation													
High-intangible firms only*	1.136	-0.009	0.477	0.326	0.017	0.631	0.342	1.064	0.728	3.568	-0.241	0.813	0.517
		(-6.46)	(84.55)		(11.53)	(45.39)							
No. of positive estimates†		7	19		17	19			19	19	7	19	19
No. of negative estimates†		11	0		0	0			0	0	12	0	0
Low-intangible firms only*	1.136	-0.010	0.496	0.306	0.013	0.609	0.299	1.047	0.776	3.335	-0.218	0.510	0.279
		(-16.99)	(161.46)		(20.29)	(74.19)							
No. of positive estimates†		5	19		19	19			19	19	5	19	19
No. of negative estimates†		14	0		0	0			0	0	14	0	0

Note:

* This table reports the median of the 19 yearly estimates of the items for the years 1977-1995 inclusive, as used in valuation model V1:

$$V1_t = b_t + \beta_1 x_t^a + \beta_2 v_t + (\beta_3 + \beta_4) b_t \ , \qquad \text{(V1)}$$

where b_t is the book value of equity per share at year *t*, x_t^a is the RI per share at year *t*, v_t is the OI per share at year *t*, and the β items are valuation multiples (defined below).

R is one plus the cost of equity. ω_0 and ω_1 are RI LIM parameters estimated from regression model (1), using all available data back to 1951, and $R^2(\omega)$ is the R-squared statistic from that model. γ_0 and γ_1 are OI LIM parameters estimated from regression model (3) for use in V1, using all available data back to 1975, and $R^2(\gamma)$ is the R-squared statistic from that model. Median *t*-statistics from the 19 yearly regression models are in parentheses beneath the median regression parameter estimates. G is one plus the expected rate of growth in book value estimated from equation (4) using all available book value data back to 1950. $\beta_1 = \dfrac{\omega_1}{R-\omega_1}$, $\beta_2 = \dfrac{R}{(R-\omega_1)(R-\gamma_1)}$, $\beta_3 = \dfrac{R\omega_0}{(R-\omega_1)(R-G)}$, and $\beta_4 = \dfrac{R\gamma_0}{(R-\omega_1)(R-\gamma_1)(R-G)}$.

The estimates of ω_0, ω_1 and β_3 are also used in valuation model V3 (see text). The estimates of ω_1 are used in V2, along with ω_0-exclusive estimates of γ_1 and β_2 based on (2.a) (see text). The ω_0-exclusive estimates of γ_1 and β_2 are very similar to the corresponding ω_0-inclusive estimates reported above, and are not separately reported.

† Figures are the number of positive or negative estimates among 19 yearly estimates. In the cases of the ω_0, ω_1, γ_0 and γ_1 parameter estimates, an estimate is only designated as positive or negative if it is significantly different from zero at the 5% level. ω_0 was positive in the late 1970s and early 1980s, but became negative thereafter. The significance of this term tends to increase as time goes on. γ_0 and the RI and OI persistence parameters, ω_1 and γ_1, are systematically positive during the sample period.

TABLE 5
Bias and inaccuracy in value estimates*

	N	Conservatism correction based on realizations and forecasts (V1) †		No conservatism correction (V2) †		Conservatism correction based on realizations only (V3) †	
		Mean	Median	Mean	Median	Mean	Median
Bias (signed valuation errors)							
Joint Parameter Estimation (all firms)	41,297	0.044	-0.110	-0.231	-0.339	-0.430	-0.570
Separate Parameter Estimation							
All firms	41,297	0.044	-0.112	-0.232	-0.340	-0.431	-0.565
High-intangible firms only	10,740	-0.021‡	-0.207	-0.367	-0.475	-0.590	-0.724
Low-intangible firms only	30,557	0.067	-0.086	-0.185	-0.298	-0.375	-0.518
Inaccuracy (absolute valuation errors)							
Joint Parameter Estimation (all firms)	41,297	0.484	0.360	0.453	0.403	0.587	0.604
Separate Parameter Estimation							
All firms	41,297	0.478	0.355	0.453	0.403	0.587	0.599
High-intangible firms only	10,740	0.532	0.415	0.529‡	0.505	0.685	0.737
Low-intangible firms only	30,557	0.459	0.335	0.426	0.372	0.553	0.560

Notes:

* This table reports means and medians of bias and inaccuracy metrics for value estimates from 1977 to 1995. Bias and inaccuracy metrics are based on the signed and absolute values, respectively, of the valuation errors. Valuation errors are measured as the intrinsic value estimate less the observed share price three months after the corresponding balance sheet date, all scaled by the share price. Results are provided for the full sample of firms when LIM parameters are estimated jointly for all firms taken together (row one of each section of the table), for the full sample when LIM parameters are estimated separately for high- and low-intangible firms (row two), and for each of the two groups when LIM parameters are estimated separately (rows three and four).

† Value estimates from V1, from which valuation errors are measured, are as follows:

$$V1_t = b_t + \beta_1 x_t^a + \beta_2 \nu_t + (\beta_3 + \beta_4) b_t \ , \qquad \text{(V1)}$$

where b_t is book value of equity per share at time *t*, x_t^a is RI per share at time *t*, ν_t is OI per share at time *t*, $\beta_1 = \dfrac{\omega_1}{R-\omega_1}$, $\beta_2 = \dfrac{R}{(R-\omega_1)(R-\gamma_1)}$, $\beta_3 = \dfrac{R\omega_0}{(R-\omega_1)(R-G)}$, and $\beta_4 = \dfrac{R\gamma_0}{(R-\omega_1)(R-\gamma_1)(R-G)}$. In these expressions, ω_0 and ω_1 are RI LIM parameters, estimated from regression model (1) using all available data back to 1951, γ_0 and γ_1 are OI LIM parameters, estimated from regression model (3) using all available data back to 1975, and G is one plus growth in book value, estimated from (4) using all available book value data back to 1950.

Value estimates from V2, from which valuation errors are measured, are as follows:

$$V2_t = b_t + \beta_1 x_t^a + \beta_2 \nu_t \ , \qquad \text{(V2)}$$

where ν_t and β_2 are estimated excluding the parameter ω_0.

Value estimates from V3, from which valuation errors are measured, are as follows:

$$V3_t = b_t + \beta_1 x_t^a + \beta_3 b_t \ . \qquad \text{(V3)}$$

‡ For each of the V1, V2 and V3 bias metrics, we test the null hypothesis that the mean is zero, using a *t*-test, and the null hypothesis that the distribution is centred on zero, using a non-parametric signed-rank test. In all cases except for the mean bias metric for V1 for high-intangible firms, we reject the null hypothesis at the 1% level. For each of the V2 and V3 bias and inaccuracy metrics, we test the null hypothesis that the difference between that metric and the corresponding V1 metric is zero and the null hypothesis that the distribution of differences is centred on zero, again using a *t*-test and a non-parametric signed-rank test, respectively. In all cases except for the mean inaccuracy metric for V2 for high-intangible firms, we reject the null hypothesis at the 1% level.

TABLE 6
Summary of effects of bias adjustment on valuation errors*

	N	Conservatism correction based on realizations and forecasts (V1) Mean	Median	No conservatism correction (V2) Mean	Median	Conservatism correction based on realizations only (V3) Mean	Median
Bias (signed valuation errors)							
Before analyst-forecast-bias adjustment	41,297	0.044	-0.112	-0.232	-0.340	-0.431	-0.565
After analyst-forecast-bias adjustment:							
Based on median forecast error	41,297	-0.098	-0.250	-0.261	-0.370	N/a	N/a
Based on mean forecast error	41,297	-0.451	-0.581	-0.330	-0.433	N/a	N/a
Inaccuracy (absolute valuation errors)							
Before analyst-forecast-bias adjustment	41,297	0.478	0.355	0.453	0.403	0.587	0.599
After analyst-forecast-bias adjustment:							
Based on median forecast error	41,297	0.479	0.392	0.465	0.423	N/a	N/a
Based on mean forecast error	41,297	0.624	0.613	0.490	0.466	N/a	N/a

Note:
* This table summarizes the mean and median of valuation errors from 1977 to 1995 before and after adjustment of OI measures for prior analyst-forecast-bias, for all firms (high- and low-intangible firms taken together) where LIM parameters are separately estimated for each group. Bias and inaccuracy metrics are based on the signed and absolute values, respectively, of the valuation errors. Valuation errors are measured as the intrinsic value estimate less the observed share price three months after the corresponding balance sheet date, all scaled by the share price. The figures before bias adjustment are drawn from Table 5. When bias adjustment is done by reference to median forecast error, the mean of the yearly adjustments is -1.7% of book value for high-intangible firms and -0.8% of book value for low-intangible firms. When bias adjustment is done by reference to mean forecast error, the mean of the yearly adjustments is -5.6% of book value for high-intangible firms and -3.0% of book value for low-intangible firms. Statistical tests are carried out in respect of the differences between the metrics for valuation errors before analyst-forecast-bias adjustment and the metrics after analyst-forecast-bias adjustment. All differences are significant at the 1% level, except for that between the mean inaccuracy metric before analyst-forecast-bias adjustment for V1 and the corresponding metric after adjustment for median forecast error.