THE RELIABILITY AND THE APPLICABILITY OF THE RESIDUAL INCOME-BASED VALUATION MODEL:

Theoretical Augmentation of the Linear Information Dynamics Model and its Validity Compared with Ohlson (1995) and Edwards-Bell-Ohlson Approaches

Thesis Submitted to Lancaster University in Fulfilment of the Requirements

for the Degree of Doctor of Philosophy in Accounting and Finance

by

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To my dearest

Jung-Hyun, Hee-Rin and Woo-Seok

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ABSTRACT

Following the seminal theoretical works of Ohlson (1995) and Feltham and Ohlson (1995, 1996), many researchers have tried to investigate the linear information dynamics (LID) model's validity empirically. However, empirical applications of the LID approach to residual income-based equity valuation, such as Dechow, Hutton and Sloan (1999) (DHS) and Myers (1999b), have produced estimates of firm value that are substantially lower on average than corresponding observed market values.

DHS's results that show the quite large downward bias of the value estimates based on Ohlson (1995), together with the work of Myers (1999b) that includes the RI intercept term in the pricing model, motivate me to augment the Ohlson model in order to capture the impact of the intercept terms on the residual income forecasts and firm values. I argue that the large negative bias in LID-based value estimates might be attributable to failure to deal fully with the effects of conservative accounting in projecting residual income. I term the augmented model, which incorporates residual income (RI) and 'other information' (OI) intercepts into the linear information dynamics, as the 'intercept-inclusive' LID model. I also show that the Feltham and Ohlson (1995) LID model as well as the Ohlson (1995) LID model are special cases of the 'intercept-inclusive' LID model.

The main objective of the thesis is thus to examine whether the 'intercept-inclusive' LID model produces more reliable value estimates than the extant RI-based valuation

models: the Ohlson (1995) LID-type and the EBO-type valuation models. Using U.S. (Chapter 4) and U.K. (Chapter 6) data, I show that use of a LID that impounds the effects of conservative accounting, as reflected in analyst forecast-based residual income projections, produces value estimates that are substantially less biased than those extant RI-based models. The thesis also addresses a potentially important issue of the different applicability under different conditions of different RI-based valuation models in Chapter 7. This is based on the idea that the models' relative applicability can differ across various firm-specific characteristics and properties, because the implementation procedures and underlying assumptions of competing models are apparently different. Among some firm-specific ex-ante variables, earnings-to-price ratio, market-to-book ratio and analyst-based one-year ahead RI forecast-to-book ratio seem to be influential with regard to the applicability of models.

Despite some contributions of this study, there are also several limitations that need to be explored in further research. In particular, value estimates based on the 'intercept-inclusive' LID approach are very sensitive to the assumed discount rate and growth rate. Moreover, the 'intercept-inclusive' LID model does not appear to improve the overall accuracy of value estimates. Together with the evidence of different applicability across firm-specific characteristics, how some firm-specific ex-ante variables can be used to modify the models and how to estimate firm-specific discount rates and growth rates could be important issues in further research.

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ABBREVATION AND NOTATION

AEX	all abnormal items (i.e., exceptional items plus extraordinary items)
AFE	absolute forecast error (AFE_{sp} : absolute forecast error of stock price, AFE_{ri}: absolute forecast error of residual income)
AR(*n*)	*n*th order auto-regression
ARR	accounting rates of return
b_t	book value of equity at year *t*
$\bar{b}_{t+i}$	*i*-year ahead expected book value of equity at year *t*
bg	book value growth rate
BG	one plus book value growth rate
BIN	'basic industries' sector classified by FTSE (level 3)
CA	current assets
CASH	cash and cash equivalents
CGD	'cyclical consumer goods' sector classified by FTSE (level 3)
CL	current liabilities
CSR	clean surplus relation
CSV	'cyclical services' sector classified by FTSE (level 3)
d_t	net dividends at year *t*
DEP	depreciation and amortization expense
DHS	Dechow, Hutton and Sloan (1999)
div	dividend payout ratio
DS	Datastream item
$E_t[\cdot]$	expectation operator conditional on the year *t* information
EBD	earnings, book value and dividend (model)
EBO	Edwards-Bell-Ohlson (model)
E/P	earnings-to-price ratio
EXC	exceptional items

EXT	extraordinary items
f_{t+i}	*i*-year ahead analysts' earnings forecasts at year *t*
f^{a}_{t+i}	analyst-based *i*-year ahead residual income forecasts at year *t*
FCF	discounted free cash flow (model)
FE	signed forecast error (FE_{sp} : signed forecast error of stock price)
FRI/B	analyst-based one-year ahead residual income forecast-to-book ratio
GIN	'general industries' sector classified by FTSE (level 3)
g_r	residual income growth rate
IIMR	Institute of Investment Management and Research
IMT	'information technology' sector classified by FTSE (level 3)
ind	industry-specific residual income persistence measure
LID	linear information dynamics
LMV	logarithm of market value (used as a proxy for firm size)
Ltg	long-term earnings growth estimate
MBE	meeting or beating earnings expectations
MOI	mean 'other information'
MRI	mean residual income
MV	market value
NCG	'non-cyclical consumer goods' sector classified by FTSE (level 3)
NS	the number of ordinary shares in issue (adjusted for subsequent capital actions)
NSV	'non-cyclical services' sector classified by FTSE (level 3)
OA	operating accruals
OI	'other information'

P_t	stock price of equity at year t
$P_t^{c,n}$	observed stock price at n months after the end of the fiscal year t
P/B	market-to-book ratio
PV	present value
PVED	present value of expected dividend (model)
$q1$	magnitude of residual income
$q2$	magnitude of exceptional items (or special items in DHS)
$q3$	magnitude of extraordinary items (or operating accruals in DHS)
$q4$	magnitude of all abnormal items
$q5$	magnitude of operating accruals
r	discount rate
R	one plus discount rate (r)
RD	research and development expenditures
RD/B	R&D-to-book ratio
RI	residual income
RIV	residual income valuation (model)
ROA	return on asset
ROE	return on equity
$r\bar{o}e_{t+i}$	i-year ahead expected return on equity at year t
RSR	'resources' sector classified by FTSE (level 3)
S	scaling variable
SA	full-tax adjustments after SSAP 15
sg	growth rate of scaling variable
SG	one plus growth rate of scaling variable
SGP	sequential generating process (of future residual income)
$SMOI_E$	mean of scaled 'other information' used as an explanatory variable
$SMRI_D$	mean of scaled residual income used as a dependent variable
$SMRI_E$	mean of scaled residual income used as an explanatory variable
STD	debt included in current liabilities

T (in EBO)	forecast horizon
TA	total assets
TP	income taxes payable
TV	terminal value
UTL	'utilities' sector classified by FTSE (level 3)
V_t	intrinsic value of equity at year t
x_t	earnings for the period (t-1, t)
x_t^a	residual income for the period (t-1, t)
X1	earnings before exceptional and extraordinary items
X2	full-tax adjusted earnings before exceptional and extraordinary items
X3	earnings after exceptional and extraordinary items
X4	earnings after exceptional items, but before extraordinary items
γ	'other information' parameter in the linear information dynamics
γ_0	'other information' intercept parameter
γ_1	'other information' persistence parameter
ε, e	unpredictable, zero mean disturbance term
v_t	'other information' at year t about future residual income not in current residual income
ω	residual income parameter in the linear information dynamics
ω_0	residual income intercept parameter (in most cases)
ω_1	residual income persistence parameter (in most cases)
^ (hat)	symbol indicating a parameter estimate
′ (prime)	symbol indicating a parameter based on scaled data
˜ (tilde)	symbol indicating an unobservable (future) variable
¯ (bar)	symbol indicating realised mean or expected value

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DECLARATION

I hereby declare that this thesis is my own work, and has not been submitted in substantially the same form for the award of a higher degree elsewhere.

Young-Soo Choi
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CHAPTER 1. INTRODUCTION

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CHAPTER 1

INTRODUCTION

1.1. Introduction

Recently, much empirical literature has emerged on the residual income valuation (RIV) model. From these empirical studies, value estimates based on the RIV model seem to be superior to traditional value estimates (i.e., those based on earnings, dividends, book value or free cash flows). In fact, it is very attractive that we can value a firm using tractable accounting information. Especially, if current residual income and current book value can capture much of the market's expectations as Ohlson's (1995) simple model suggests, it must be a breakthrough in accounting and finance.

Ohlson's (1995) accounting-based valuation model has been received enthusiastically by many researchers. The Ohlson model is based on the RIV relationship and the residual income (abnormal earnings) linear information dynamics (LID). The RIV relationship is just a restatement of the dividend discounting model, and it has been 're-discovered' regularly by academics. Thus, strictly speaking, the RIV relationship *per se* is not Ohlson's contribution.[1] Ohlson's original contribution is the information dynamics, which includes a modified AR(1) residual income generating process. This information dynamics is still controversial among researchers empirically.

[1] For example, theoretical development of the residual income valuation model can be found in Preinreich (1938) and Peasnell (1982).

Recent studies have assessed the empirical validity of the RIV relationship and of Ohlson's development of the relationship (Dechow, Hutton and Sloan, 1999; Hand and Landsman, 1998; Hand and Landsman, 1999; Frankel and Lee, 1998; Myers, 1999a; Myers, 1999b; Lee, Myers and Swaminathan, 1999; Francis, Olsson and Oswald, 2000). The approach used in Frankel and Lee (1998), Myers (1999a), Lee *et al.* (1999), and Francis *et al.* (2000) is to estimate future residual income from analysts' earnings forecasts, and to use these forecasts together with assumptions about terminal value to estimate firm value.[2] This is often called the Edwards-Bell-Ohlson (EBO) valuation approach. Dechow *et al.* (1999) (hereafter DHS) and Myers (1999b) specifically focus on the information dynamics, with its persistence parameters, which are central to Ohlson's development of the RIV relationship. The persistence parameters are not only the most difficult to estimate practically, but also the most crucial part of the Ohlson model in order to measure a firm's value. Actually, the Ohlson model's ability to summarize the present value of future residual income in terms of observable accounting variables and 'other information' follows directly from the linear information dynamics (Pope and Wang, 1999). On the other hand, Hand and Landsman (1998, 1999) test the Ohlson model without estimating persistence parameters, and compare the sign of regression coefficients with the theoretically predicted sign of them.

This research is motivated by this growing literature, particularly by the work of DHS and Myers (1999b), and addresses and develops the issues raised by these studies. Even though both empirical tests using U.S. data do not firmly support the validity of the

[2] Myers (1999a) specifically focuses on the terminal income (liquidation price less book value) for the estimation of terminal value, under the assumption that a firm's life is finite.

Ohlson model, they contribute to the empirical implementation of the RIV model in terms of the estimation of persistence parameters and the comparison of alternative models' forecasting ability for contemporaneous stock prices.

DHS estimate the persistence parameters of residual income (RI) and 'other information (OI)' first, and compare the relative forecasting ability of alternative models for explaining contemporaneous stock prices. They use pooled time-series and cross-sectional regression analysis to estimate RI and OI persistence parameters. Following a suggestion in Ohlson (2001), DHS estimate unobservable OI from observable analysts' earnings forecasts. The definition of OI using observable analysts' earnings forecasts gives a very important contribution to the practical implementation of the LID-based valuation models.[3]

DHS's results are generally supportive of Ohlson's information dynamics, but suggest that the application of those dynamics to equity pricing provides only minor improvements over traditional and much simpler valuation models that capitalise short-term earnings forecasts in perpetuity. That is, Ohlson's general model is outperformed in terms of explanation of contemporaneous stock prices by a special case of the model involving the capitalisation of analysts' forecasts in perpetuity. Moreover, there are inconsistencies between the predictive ability for future residual income of assumed residual income generating processes and the ability of pricing models based on those generating processes to explain contemporaneous stock prices.

[3] Liu and Ohlson (2000) and Begley and Feltham (2002) also use analysts' earnings forecasts as a means of estimating OI variable for the Feltham and Ohlson (1995) model and the Feltham and Ohlson (1996) model, respectively.

DHS's result that show the quite large downward bias of the value estimates based on Ohlson (1995), together with the work of Myers (1999b) that includes the RI intercept term in the pricing model, motivate me to augment the Ohlson model in order to capture the impact of the intercept terms on the residual income forecasts and firm values. I show that the large negative bias reported in DHS and Myers (1999b) might be attributable to a key assumption of the underlying Ohlson model. The Ohlson model, which assumes zero mean RI and OI reverting processes, seems to fail to capture the effects of conservative accounting. Because a non-zero mean reverting process for RI and OI could be observed in practice, the intercept terms might have a significant impact on forecasting future RI and valuing a firm. In the AR(1) RI (OI) process, the mean RI (OI) is approximately the same as the corresponding intercept over one minus the corresponding slope coefficient, so the non-zero intercept implies the non-zero mean RI (OI). I term the augmented model, which incorporates RI and OI intercepts into the linear information dynamics, as the 'intercept-inclusive' LID model.

I also show that the Feltham and Ohlson (1995) model is a special case of the 'intercept-inclusive' LID model. Feltham and Ohlson (1995) try to deal with conservative accounting, but the empirical implementation of the Feltham and Ohlson model as in Myers (1999b) provides evidence that it is also unlikely to cope well with conservatism. The most important difference between the 'intercept-inclusive' model and the Feltham and Ohlson model is the assumption of mean scaled OI. The 'intercept-inclusive' model allows for non-zero mean scaled OI, indicating that the mean of future RI could be different from the mean of past realised RI, but the Feltham and Ohlson model assumes zero mean OI.

In this study, I examine the reliability of various RI-based valuation models using large U.S. and U.K. samples. The U.S. study is motivated by the substantial negative bias, reported by DHS. It investigates whether the 'intercept-inclusive' LID model produces less biased value estimates compared to the Ohlson (1995) model and a simple model in which 1-year ahead earnings forecast is capitalised as a flat perpetuity.[4] In order to facilitate comparison with DHS's results, I use data that are very similar to those used in DHS. Empirical evidence shows that value estimates based on the 'intercept-inclusive' LID approach are substantially less biased than those based on the other two approaches.

I also replicate and extend the work of DHS using U.K. data. This enables a comparison to be made between the results for two countries. The results show that the patterns of residual income persistence in my U.K. data are similar to those reported in both U.S. studies (DHS and my U.S. study), even though there are some differences in the sign and the magnitude of regression coefficients. In terms of the models' validity, the Ohlson model seems to be outperformed by the 'intercept-inclusive' LID model and some EBO models. Thus, the U.K. study provides evidence similar to that from the U.S. study. The superiority of the 'intercept-inclusive' LID model over the Ohlson model in terms of bias and accuracy of value estimates is confirmed by various sensitivity tests.

[4] Note that the capitalisation of analysts' earnings forecasts in perpetuity is the same as 1-year forecast horizon EBO model with zero residual income growth in the post-horizon period.

Moreover, using U.K. data, I explore the important issue of differences in the applicability of valuation models. Despite the potential importance in equity valuation, there has been little concern about the issue of the conditions under which one model might dominate others. Because firms' accounting methods/systems and economic properties are different from each other, it is possible for a valuation model to have different applicability to different firms. In other words, bias and accuracy of value estimates might be different across firm-specific characteristics such as earnings persistence, conservatism, future potential growth and profitability, and a valuation model might not dominate other models in all circumstances. If the usefulness of a model consistently depends on some properties or characteristics, it would be evidence that the model cannot be applied universally. Thus, to explore which properties and characteristics affect the applicability of a model would be important, especially for practitioners. In general, the 'intercept-inclusive' LID model seems to perform well for firms with moderate earnings-to-price (E/P) ratio, market-to-book (P/B) ratio and one-year ahead RI forecasts-to-book (FRI/B) ratio. On the other hand, the Ohlson model (the EBO model) is likely to give relatively reliable value estimates for firms with low (high) E/P, P/B and FRI/B.

Although the LID and the EBO approaches to RI-based valuation are particular objects of interest to researchers in equity valuation, there is no explicit research on the comparison of the LID and the EBO approaches, to my knowledge. Motivated by the lack of research on the comparison of the LID and the EBO approaches, my U.K. study includes the Ohlson LID, the 'intercept-inclusive' LID and the EBO approaches for the overall reliability test and the applicability test. It must be of interest to examine whether a certain model dominates the others. If the simpler EBO model dominates the LID models in all cases, the process for estimating persistence parameters may offer few benefits and the LID models need to be further modified.

1.2. Structure of the Thesis

This thesis is made up of following chapters. Chapter 2 reviews literature related to residual income-based equity valuation. The chapter reviews the development of the RIV model and its empirical content, including some recent empirical research. In particular, since the seminal Ohlson (1995) LID approach, which has had a major influence on research, is a starting point of this thesis, its information dynamics, other information and persistence parameters are discussed from an empirical perspective. In addition with the LID approach, the EBO approach, which is simpler but still an issue of great interest to many researchers, is briefly discussed. For examples of the LID-based empirical research, DHS, Myers (1999b) and Hand and Landsman (1998, 1999) are reviewed, while Frankel and Lee (1998), Lee *et al.* (1999) and Francis *et al.* (2000) are reviewed as examples of the EBO-based empirical research. Due to recent academic efforts that enable us to use observable analysts' earnings forecasts for the construction of 'other information', which is unobservable, the ability of the LID approach to value a firm could be improved. Analysts' earnings forecasts are also a crucial component of the EBO models, with evidence of its superiority as a proxy for market's expectations over time-series forecasts. The last section of this chapter, therefore, reviews usefulness and attributes of analysts' earnings forecasts in the context of equity valuation.

Chapter 3 presents the development of the 'intercept-inclusive' LID model, which is innovative and central to my thesis. Because Ohlson's (1995) assumption that accounting is unbiased is unlikely to be appropriate in the presence of conservative accounting, the intercepts of AR(1) RI and OI generating equations in the Ohlson (1995) linear information dynamics seem to be non-zero. In other words, the non-zero mean expected RI, which corresponds to the accounting conservatism, is captured by the non-zero intercepts of both RI and OI generating equations in the linear information dynamics. From the relaxation of Ohlson's implicit assumption that the unconditional mean of RI and OI are zero, I derive the 'intercept-inclusive' LID model and show its potential impact on valuation biases. Then, some LID-based valuation models that have appeared in earlier studies, including the Feltham and Ohlson (1995) and Ohlson (1995) models, are shown to be special cases of the 'intercept-inclusive' LID model. There could be various LID-type and EBO-type valuation models according to the assumptions of LID in the first case, and various sets of forecast horizon and terminal value assumptions in the second case. In this thesis, I consider 9 Ohlson (1995) LID-based models and 7 'intercept-inclusive' LID-based models according to the assumption of OI and/or the restriction of RI and OI persistence parameters. According to the combination of 3 forecast horizons (1-year to 3-year) and 2 future RI growth assumptions (zero and non-zero), 6 EBO models are considered as well.

Chapter 4 examines the reliability of the 'intercept-inclusive' LID model in terms of bias and accuracy metrics, compared to the Ohlson (1995) LID model and the 1-year horizon EBO model with the assumption of zero future RI growth. RI and OI parameters are estimated using DHS's empirical procedure and using U.S. data from 1950 to 1995, which are very similar to those used by DHS. However, practical implementation of the 'intercept-inclusive' LID approach requires a fundamental change in the scaling variable from that used by DHS. DHS deflate RI and OI variables in the linear information dynamics by price to control for size. Because this causes the scaling variable to be an input to the 'intercept-inclusive' LID model, it causes circularity. In order to avoid this circularity problem, I use book value as a scaling variable. For a supplementary test, I investigate the effects of alternative trimming and winsorising criteria on LID parameters and value estimates.

Chapters 5 to 7 report the results of an analysis based on U.K. data from 1969 to 1998. Chapter 5 contains the definition of four alternative earnings measures together with other variables, sample selection and descriptive statistics. I use two measures of 'ordinary earnings', one measure comprising ordinary earnings and all abnormal items, and one measure comprising ordinary earnings and exceptional items. This enables me to test the robustness of the empirical results to the use of alternative earnings measures and to explore the effect of exceptional and/or extraordinary items on LID parameters and value estimates. All variables used in the U.K. study except the I/B/E/S analysts' earnings forecasts are defined in terms of Datastream items.

Chapter 6 provides the empirical results of the partial replication and extension of the DHS study relating to the estimation of LID parameters and the examination of competing models' reliability. I investigate the relative reliability of 22 competing valuation models in terms of three performance metrics - bias, accuracy and explainability - using each of four alternative earnings measures. Various sensitivity tests are then conducted by assuming different book value growth rates, residual income growth rates, and discount rates, and by using different benchmarking stock prices and consensus earnings forecasts. If the reliability of value estimates considerably varies by the change of a component in the valuation model, the component should be carefully estimated or assumed.

Chapter 7 investigates alternative models' applicability across various firm-specific characteristics. The issue of the conditions under which one model dominates the other models and a model performs best is explored using three approaches to RI-based equity valuation - the Ohlson (1995) LID, the 'intercept-inclusive' LID, and the 2-year horizon EBO with the assumption of 4% future RI growth. I address differences in the implementation procedures and the underlying assumptions of three competing models first, and then develop predictions about models' applicability across firm-specific characteristics – earnings attributes, conservatism, future potential growth, firm size, future profitability, and industry membership. Bias and accuracy of value estimates in portfolios partitioned by each ex-ante proxy variable for a certain firm-specific characteristic are compared by applying statistical tests for the equality and by use of graphical illustration. Regressions of bias and accuracy on various firm-specific ex-ante variables are also conducted in order to identify determinants of models' applicability.

Finally, Chapter 8 concludes the thesis with a summary of empirical results. Implications and limitations of the thesis are also discussed.

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CHAPTER 2

LITERATURE REVIEW

2.1. Development of the Residual Income Valuation (RIV) Model

The development of Ohlson's (1995) accounting-based valuation model starts from the assumption that firm value is 'the present value of expected dividends (PVED)', which is a widely accepted fundamental finance concept. A basic long-known accounting concept, the clean-surplus relation (CSR), is assumed as well. Under CSR, all changes in the balance sheet value of shareholders' funds other than transactions with shareholders are included in earnings. This is an important concept because it integrates the bottom-line items in the balance sheet and income statement (i.e., book value and earnings) so that all changes in assets/liabilities unrelated to dividends must pass through the income statement (Ohlson, 1995).

PDM

CSR

$$V_t = \sum_{\tau=1}^{\infty} R^{-\tau} E_t\left[\tilde{d}_{t+\tau}\right] \qquad \text{(Ass. 1: PVED)}$$

$$d_t = x_t - (b_t - b_{t-1}) \qquad \text{(Ass. 2: CSR)}$$

where V_t is intrinsic value of equity at date t, d_t is net dividends at date t, R is 1 plus the discount rate (r), x_t is earnings for the period (t-1, t), b_t is book value at date t, and $E_t[\cdot]$ is the expectation operator conditional on the date t information.

The definition of residual income (x_t^a), which is accounting earnings less a capital charge based on the opening book value of equity, allows PVED to be re-expressed as the sum of book value and the present value of future residual incomes. That is, Ass. 1, Ass. 2 and the definition of residual income (RI) yield the residual income valuation (RIV) model.

$$x_t^a = x_t - rb_{t-1} \tag{RI}$$

$$V_t = b_t + \sum_{\tau=1}^{\infty} R^{-\tau} E_t\left[\tilde{x}_{t+\tau}^a\right] \tag{RIV}$$

Thus, valuing a firm depends on how to estimate the second term in the right hand side of the RIV model – the present value of future cash flows not captured by the current book value (i.e., unrecorded goodwill). That is, the accuracy of estimated firm value comes from the accuracy of the estimated present value of expected future residual income. Two approaches have been developed for the estimation of the present value of future residual income. One is the future residual income generating information dynamics, and the other is the simpler Edwards-Bell-Ohlson (EBO) technique. Ohlson (1995) uses information dynamics to estimate the future residual income. The dynamics include a modified AR(1) auto-regressive process for residual income, which is called as 'residual income generating linear information dynamics (LID)'.

$$\begin{aligned} \tilde{x}_{t+1}^a &= \omega x_t^a + v_t + \tilde{\varepsilon}_{1,t+1} \\ \tilde{v}_{t+1} &= \gamma v_t + \tilde{\varepsilon}_{2,t+1} \end{aligned} \tag{Ass. 3: LID}$$

where v is information about future residual income not in current residual income (i.e., 'other information'), ε is the unpredictable, zero mean disturbance term, ω and γ are fixed persistence parameters that are non-negative and less than one.

In contrast, the EBO approach is to forecast residual income for the first few years and then estimate a 'terminal value (TV)' relating to periods beyond the forecast horizon. Consensus analysts' earnings forecasts and a long-term growth rate rather than the past earnings and book values are often used for forecasting residual income. If we assume that a firm's dividend payout ratio (div) is constant over the years, and we can get one and two year ahead analysts' earnings forecasts and a long-term earnings growth estimate (Ltg), then the future residual income can be estimated by a sequential generating process (denoted SGP) as follows:

Step 1: $f_{t+1}^{a} = E_t\left[\tilde{x}_{t+1}^{a}\right] = (r\bar{o}e_{t+1} - r)b_t$

where $r\bar{o}e_{t+1} = E_t\left[r\tilde{o}e_{t+1}\right] = f_{t+1} / b_t$

Step 2: $f_{t+2}^{a} = E_t\left[\tilde{x}_{t+2}^{a}\right] = (r\bar{o}e_{t+2} - r)\bar{b}_{t+1}$

where $\bar{b}_{t+1} = E_t\left[\tilde{b}_{t+1}\right] = \left[1 + r\bar{o}e_{t+1}(1-div)\right]b_t$ and $r\bar{o}e_{t+2} = E_t\left[r\tilde{o}e_{t+2}\right] = f_{t+2} / \bar{b}_{t+1}$

Step 3: $f_{t+i}^{a} = E_t\left[\tilde{x}_{t+i}^{a}\right] = (r\bar{o}e_{t+i} - r)\bar{b}_{t+i-1}, \quad i = 3,4,\cdots,T$

where $\bar{b}_{t+i-1} = E_t\left[\tilde{b}_{t+i-1}\right] = \left[1 + r\bar{o}e_{t+i-1}(1-div)\right]\bar{b}_{t+i-2}$

and $r\bar{o}e_{t+i} = E_t\left[r\tilde{o}e_{t+i}\right] = f_{t+2}(1+Ltg)^{i-2} / \bar{b}_{t+i-1}$

Step 4: $f_{t+i}^{a} = E_t\left[\tilde{x}_{t+i}^{a}\right] = f_{t+T}^{a}(1+g_r)^{i-T}, \quad i \geq T+1$ (SGP)

where f_{t+1} and f_{t+2} are respectively one-year-ahead and two-year-ahead analysts' earnings forecasts, f_{t+i}^{a} is i-year-ahead expected residual income, $r\bar{o}e_{t+i}$ is i-year-ahead expected return on equity, $\bar{b}_{t+i}$ is i-year-ahead expected book value, div is dividend payout ratio, Ltg is long-term growth rate, g_r is average future residual income growth rate, and T is forecast horizon.[5, 6]

Given the Ohlson's information dynamics in Ass. 3, the RIV model can be rewritten in terms of current book value, current residual income and 'other information' (Eq. 1). Equivalently, given CSR, this equation can be restated in terms of current book value, current earnings, dividends and 'other information'. This is why the Ohlson model is also said to be the EBD (Earnings, Book Value, Dividends) model. It is worth noting that market value is expressed partly by a weighted average of book value and capitalized current earnings (adjusted for dividends). So this equation is also called Ohlson's weighted average model (Eq. 2). Ass. 1, Ass. 2 and Ass. 3 also lead to the returns model given in Eq. 3. On the other hand, firm value can be estimated using SGP in the EBO framework (Eq. 4). Here, terminal value is often assumed to be the present value of year-T residual income in perpetuity (i.e., $TV = R^{-T}(f^a_{t+T}/r)$), although expected post-horizon growth could also be incorporated.

$$V_t = b_t + \alpha_1 x^a_t + \alpha_2 v_t \qquad \text{(Eq. 1)}$$

$$V_t = (1-k)b_t + k(\frac{R}{r}x_t - d_t) + \alpha_2 v_t \qquad \text{(Eq. 2: WAEBD)}$$

$$\frac{V_t + d_t}{V_{t-1}} = R + \frac{(1+\alpha_1)\varepsilon_{1t}}{V_{t-1}} + \frac{\alpha_2 \varepsilon_{2t}}{V_{t-1}} \qquad \text{(Eq. 3)}$$

---

[5] Lee *et al.* (1999) suggest a linear fade rate to the industry median ROE instead of a long-term earnings growth rate (*Ltg*) for calculating $\overline{roe}_{t+i}, i = 3,4,\cdots,T$ in Step 3.

[6] In Step 4, expected average residual income growth rate (g_r) is assumed for the post-horizon residual income. If g_r is assumed to be zero, $f^a_{t+i} = f^a_{t+T}$ so that terminal value is $R^{-T}(f^a_{t+T}/r)$.

$$V_t = b_t + \frac{(r\bar{o}e_{t+1} - r)b_t}{R} + \frac{(r\bar{o}e_{t+2} - r)\bar{b}_{t+1}}{R^2} + \cdots + \frac{(r\bar{o}e_{t+T} - r)\bar{b}_{t+T-1}}{R^T} + TV$$

(Eq. 4: EBO)

where $\alpha_1 = \frac{\omega}{R - \omega}$, $\alpha_2 = \frac{R}{(R-\omega)(R-\gamma)}$, $k = r\alpha_1$, and TV is terminal value.

2.2. Empirical Content of the RIV Model

2.2.1. Usefulness of the RIV model

As mentioned above, the RIV model is an equivalent form of the PVED model, given CSR. Dechow *et al.* (1999), therefore, insist that "the RIV model is interpretable in the context of the original PVED model, and the appeal to the residual income formulation of the PVED model is redundant. Thus, it provides no new empirical implications in and of itself". Ohlson (2001) also says that RIV should not be thought of as the formula necessary to derive conclusions bearing on values and returns. He argues that key implications of the Ohlson model do not substantially depend on the RIV framework.

Theorical equal.

However, RIV can usefully integrate with Ass. 1, 2, and 3 and in the process enhance our economic intuition as to how value relates to accounting numbers. Given the clean surplus relation, RIV implies that firm value does not depend on accounting procedures (e.g., historical cost accounting, fair value accounting), because all changes in book value flow through the profit and loss account. The empirical tests of Francis *et al.* (2000) find that differences in firms' accounting practices and policies have little impact

advantage

on the reliability of value estimates based on RIV.[7] This gives a theoretically justifiable basis for using accounting concepts in firm valuation. Even if the intrinsic values based on PVED, FCF (the discounted free cash flow model), and RIV are identical in theory, the estimated values will differ in practice because the forecasted attributes and the forecasting procedures for those value estimates are different. Francis *et al.* (2000), Penman and Sougiannis (1998), and Courteau *et al.* (2000) compare these alternative value estimates to observed prices. They conclude that RIV value estimates dominate the other two theoretically equivalent value estimates in terms of their ability to approximate to observed prices and in terms of their ability to explain observed prices. Their study supports the usefulness of the RIV model from the practical viewpoint.[8] Furthermore, RIV is advantageous because it compresses and streamlines the mathematics. Conclusively, the role of RIV in the Ohlson model ought not to be neglected, even if PVED and RIV theoretically yield the same solution (Ohlson, 2001).

empirical evidence

2.2.2. Information dynamics of the LID model

In order to perform valuation using the RIV model, future residual income should be estimated. One approach for the estimation is to construct the appropriate linear information dynamics (LID). That is, the link between current accounting and 'other' information and future residual income is an essential part of firm valuation, because it

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[7] There is no difference in the accuracy of RIV value estimates for high vs. low R&D firms and high vs. low accrual firms, although there is some evidence that RIV value estimates is a little different in terms of the explainability of variation in stock prices according to the level of accounting discretion.

[8] Lundholm and O'Keefe (2001a, 2001b) and Penman (2001) give an interesting debate recently about whether value estimates arising from theoretically equivalent valuation models (RIV, PVED and FCF) are different in practice or not.

determines the valuation formula.

However, information dynamics is still the most controversial part of the Ohlson model. Which information dynamics is most appropriate in order to make economic and accounting sense?

Ohlson (2001) says Ass. 3 is based on accounting concepts rather than analytical advantage. Even though Ass. 3 does not explicitly say anything about dividends, it implies that "dividends reduce current book value, but not current earnings" and "the evolution of 'other information' is independent of dividends", which make sense in the economic and accounting concepts. The incorporation of 'other information' also allows for the additional information in forecasting future residual income beyond the historical accounting information in the financial statements. Consequently, the valuation implications of Ass. 3 combined with Ass.1 and Ass. 2 have some attraction beyond mere simplicity in derivations via the RIV model.

In addition to Ohlson's simple information dynamics (Ass. 3), some complex information dynamics have been developed to explain better the complicated business world. Ohlson (1999) extends the simple information dynamics to permit two earnings' components – core earnings and transitory earnings, and mentions that one can introduce any information other than accounting data in the information dynamics without loss of generality. Barth *et al.* (1999) utilizes the Ohlson (1999) framework by decomposing earnings into cash flows and accruals. They conclude that both cash flows and accruals have future residual income forecasting relevance and value explaining relevance incremental to residual income and book value. Similarly but more generally, Pope and Wang (1999) establish the information dynamics with decomposed earnings to investigate whether the earnings components are informative and value-relevant. They contend that lagged book value and earnings components are generally relevant in predicting aggregate residual income and in valuing the firm. A bit surprisingly, even a value irrelevant earnings component can have an informative role in the information dynamics according to their analysis.

While Ohlson's (1995) information dynamics make a very important contribution to the RI-based valuation literature, it has limitations in its ability to explain a firm's accounting and economic reality by assuming 'unbiased accounting' and making future potential growth irrelevant. Amended information dynamics that allow conservative accounting are proposed by Feltham and Ohlson (1995, 1996). Because conservative accounting understates the value of operating assets systematically, Feltham and Ohlson (1995) split a firm's activities into operating and financial activities. Thus, the information dynamics assume that future residual operating income is generated by current residual operating income and operating assets, and operating assets grow. The influence of operating assets on future residual operating income captures accounting conservatism. Here, two types of 'other information' relevant to the forecasting of future residual income are incorporated in the linear information dynamics as well. The evolution of each 'other information' follows an AR(1) process. Feltham and Ohlson (1996) is similar to Feltham and Ohlson (1995), but more explicit about the sources of accounting conservatism. Two sources of accounting conservatism included in Feltham and Ohlson's (1996) information dynamics are i) the accounting depreciation rate greater than the economic depreciation rate and ii) future positive NPV investment opportunities not reflected in current accounting numbers. Consequently, future residual operating income is generated by current residual operating income, current capital investment, lagged operating assets and 'other information'.

Meanwhile, Biddle *et al.* (2000) proposes non-linear information dynamics based on the economic intuition that capital follows profitability. They assume that current profitability guides a firm's capital investment decisions so that future residual income is generally a convex function of both current profitability and capital investment informed by current profitability.

2.2.3. Other information in the LID model

In the empirical tests of the Ohlson (1995) and the Feltham and Ohlson (1995, 1996) model, 'other information (OI)' is often ignored by researchers because of the unobservable nature of 'other information'. However, Ohlson (2001) contends that "equating v to zero may be of analytical interest, but it severely reduces the model's empirical content" and "no apparent reasons suggest that one must eliminate 'other information' from the model, as long as one grants the observability of expected earnings".

From this point of view, one of the greatest challenges relates to the estimation of the 'other information' variable (v) when we apply the linear information dynamics model in practice. 'Other information' is information that is available to market actors but which is not capable of being inferred from historical earnings numbers and their time series properties. If 'other information' can be adequately incorporated into the linear information dynamics, it should be possible to improve the model's ability to forecast the next period's residual income and to explain firm value. Possible components of 'other information' are new patents, regulatory approval of a new drug for pharmaceutical companies, new long-lived contracts and order backlog (Myers, 1999b).

Despite the unobservable nature of 'other information', Ohlson (2001) suggests that analysts' consensus forecasts of next-year earnings would seem to be a reasonable proxy for expected earnings. Thus, 'other information' can be expressed as the expected residual income based on analysts' consensus earnings forecasts minus current residual income multiplied by ω (Eq. 5).

If we use analyst's consensus forecasts as next-year earnings forecasts, Eq. 1 and Eq. 2 can be restated as Eq. 6 and Eq. 7, respectively;

$$v_t = f_{t+1}^a - \omega x_t^a \qquad \text{(Eq. 5)}$$

$$V_t = b_t + (\alpha_1 - \omega\alpha_2)x_t^a + \alpha_2 f_{t+1}^a \qquad \text{(Eq. 6)}$$

$$V_t = \beta_1 b_t + \beta_2(\frac{R}{r}x_t - d_t) + \beta_3(\frac{1}{r}f_{t+1}) \qquad \text{(Eq. 7)}^9$$

where f_{t+1} is one-year-ahead analysts' consensus earnings forecasts, $f_{t+1}^a = E_t\left[\tilde{x}_{t+1}^a\right] = f_{t+1} - rb_t$ (i.e., one-year-ahead expected residual income), $\beta_1 = \dfrac{R(1-\omega)(1-\gamma)}{(R-\omega)(R-\gamma)}$,

[9] See Ohlson (2001) and Hand and Landsman (1998, 1999). See Appendix 2.1 for the derivation of Eq. 7.

$$\beta_2 = \frac{-r\omega\gamma}{(R-\omega)(R-\gamma)}, \text{ and } \beta_3 = \frac{Rr}{(R-\omega)(R-\gamma)}.$$

Eq. 6 states that equity market value is a linear function of current book value of equity, current residual income and next year's expected residual income. And Eq. 7 expresses equity market value as a linear function of current book value, current net income, net dividends and one-year-ahead net income. Here, it is worth noting that $\beta_1 + \beta_2 + \beta_3 = 1$, indicating that the dividend displacement property (i.e., $\partial V_t / \partial d_t$ = -1) holds in the Ohlson model (Ohlson, 2001).[10] For practical purposes, we can use Eq. 6 or Eq. 7 in place of Eq. 1 or Eq. 2 when 'other information (ν)' is incorporated for testing the Ohlson model.

Following a suggestion in Ohlson (2001), Dechow *et al.* (1999) uses I/B/E/S one-year ahead analysts' earnings forecasts to estimate OI in their empirical implementation of the Ohlson (1995) model. Liu and Ohlson (2000) apply this idea to the Feltham and Ohlson (1995) model. They suggest that one type of OI at year *t*, which is a component of the expected operating assets at year *t*+1, can be estimated using analysts' intermediate-term earnings growth rate forecasts.[11] The other type of OI at year *t*, which is a component of the expected residual operating income at year *t*+1, is estimated as in Dechow *et al.* (1999) and Ohlson (2001) (i.e., using one-year ahead analysts' earnings forecasts). On the other hand, Begley and Feltham (2002) use analyst-based one- and

[10] See Appendix 2.1 for the proof of $\beta_1 + \beta_2 + \beta_3 = 1$.

[11] Analysts' intermediate-term (five years) earnings growth rate forecasts are assumed to be closely tied with the expected growth rates in operating assets.

two-year ahead RI forecasts to estimate two kinds of OI included in the Feltham and Ohlson (1996) information dynamics. These efforts in estimating unobservable 'other information' by using observable analyst-based forecasts are an important contribution to the empirical implementation of the linear information dynamics model.

2.2.4. Persistence parameters of the LID model

In Ohlson's information dynamics (Ass. 3), ω reflects the extent to which the current level of residual income is likely to persist into the future, and γ reflects the extent to which 'other information' is likely to persist in the future. These persistence parameters are restricted to be non-negative and less than one, so that future residual income and 'other information' are assumed to asymptote to its mean, respectively. The unconditional means of residual income and 'other information' are zero in the Ohlson (1995) model (i.e., zero intercepts). Dechow *et al.* (1999) and Myers (1999b) state that the long-run residual income seems to follow a stationary and mean reverting process as Ohlson (1995) assumes. This means that the mean of the expected residual income does not depend on time, and the long-run residual income asymptotes to the mean.

For empirical purposes, we can measure ω and γ using their historical unconditional sample estimates. ω_1, obtained by running AR(1) regression in Eq. 8, is used as an estimate of ω in Ass. 3. Because Ohlson (1995) assumes independence between current RI and current OI, ω_1 can be an appropriate estimate for the real coefficient ω in Ass. 3. Given any ω, we can estimate a related γ if v_t ($f_{t+1}^a - \omega x_t^a$) is assumed to satisfy a simple auto-regressive process with parameter γ (Eq. 9).

$$x_{t+1}^{a} = \omega_0 + \omega_1 x_t^{a} + \varepsilon_{1,t+1} \qquad \text{(Eq. 8)}$$

$$v_{t+1} = \gamma_0 + \gamma_1 v_t + \varepsilon_{2,t+1} \qquad \text{(Eq. 9)}$$

Dechow *et al.* (1999) also suggest the conditional estimation of ω. Actually, in the Ohlson model, ω (as well as γ) should be a firm-specific parameter. However, instead of running a time series regression (Eq. 8) firm by firm like Myers (1999b), Dechow *et al.* (1999) modify the regression equation and include some firm-specific attributes in Eq. 8. They state that ω (the persistence of residual income) is affected by five determinants - the magnitude of residual income (*q1*), the magnitude of non-recurring special items included within residual income (*q2*), the magnitude of operating accruals (*q3*), the dividend payout ratio (*div*) and industry specific persistence measures (*ind*). Thus, a firm-specific persistence parameter can be estimated using these five conditioning variables as well as the level of residual income. An advantage of this approach over time-series-based approaches is that it is possible to allow the estimated persistence parameter to vary from period to period.

The estimation of conditional ω follows a two-step process. They first allow these 5 determinants of persistence to enter as interactive variables in Eq. 8 (Eq. 10). This might be an intuitively appealing challenge in the context that the interactive effects can also determine firm-specific persistence. Next, a firm-year specific persistence parameter (ω_t^f) is calculated by using the coefficients measured in the first step and firm-year specific attributes (Eq. 11).

$$x_t^a = \omega_0 + \omega_1 x_{t-1}^a + \omega_2(x_{t-1}^a q1_{t-1}) + \omega_3(x_{t-1}^a q2_{t-1}) + \omega_4(x_{t-1}^a q3_{t-1}) + \omega_5(x_{t-1}^a div_{t-1}) + \omega_6(x_{t-1}^a ind_{t-1}) + \varepsilon_t$$

(Eq. 10)

$$\omega_t^f = \omega_1 + \omega_2 q1_t + \omega_3 q2_t + \omega_4 q3_t + \omega_5 div_t + \omega_6 ind_t \qquad \text{(Eq. 11)}$$

However, Myers (1999b) criticizes this effort to estimate a firm-specific persistence parameter. He argues that simply adding other variables to Eq. 8 and summing the coefficients for the conditional persistence parameter gives rise to internal inconsistency with theory and inequilibrium price. That is, to be consistent with the theory, the time series of the additional 5 variables ($x_t^a q1_t, \cdots, x_t^a ind_t$) should also be estimated, and the equilibrium price should be a linear function of book value and 6 variables in Eq. 10 with complex coefficients containing up to 42 parameters.

2.3 Recent Empirical Research on the RIV Model

2.3.1. LID approach

Dechow, Hutton and Sloan (1999)

Dechow *et al.* (1999), first of all, consider several accounting-based valuation models through restricting ω and γ, and classify the models into 2 groups – one which ignores 'other information', and the other which includes it.

Generally, their test shows that the models incorporating 'other information' are better than the models ignoring it, in terms of prediction of next period residual income and explanation of contemporaneous stock prices. But of the models incorporating 'other information', the model using ($\omega = 1$, $\gamma = 0$) or ($\omega = 0$, $\gamma = 1$) – a model that effectively capitalizes analysts' earnings forecasts for next year in perpetuity – provides the most accurate forecasts of stock prices, while the unrestricted general Ohlson model is the second most accurate.[12]

This result is somewhat surprising because it makes the estimation of future residual income unnecessary in firm valuation. That is, since the model using ($\omega = 1$, $\gamma = 0$) or ($\omega = 0$, $\gamma = 1$) gives the closest approximation to the observed stock price, rational expectations of future residual income might not be reflected in stock prices. Subsequent tests suggest that the superior explanatory power of the simple capitalization model may arise because investors over-weight information in analysts' earnings forecasts and under-weight information in current earnings and book value.

Another test is the regression of stock prices on the variables used in the valuation models. But in the case of regressions of price on book value and earnings (i.e., ignoring v), stock prices appear to place too low a weight on book value and too high a weight on earnings, compared with the value of coefficients using the historical averages of ω, γ, and r. In the case of regressions of price on book value, earnings and the consensus

[12] When we include 'other information' in pricing models, the model when $\omega = 1$ and $\gamma = 0$ is equivalent with the model when $\omega = 0$ and $\gamma = 1$, because Eq. 7 becomes $V_t = f_{t+1} / r$ in both cases.

analysts' forecasts of next year's earnings, stock prices place too low a weight on book value and too high a weight on the analysts' forecast of next year's earnings as well.

One interpretation of these results is that stock prices do not reflect rational expectations, because investors overestimate the persistence of residual income and short-term earnings forecasts. Another possibility is that the underlying theoretical model, which assumes that residual income is a (zero) mean reverting and is generated by auto-regressive process, is mis-specified.

Myers (1999b)

This study examines how well four different residual income valuation models, which are internally consistent with theory, show the predicted coefficients and the market price. In contrast to Dechow *et al.* (1999), Myers (1999b) estimates the firm-specific persistence parameters using a firm-specific time-series model. Before conducting his analyses, he argues that recent studies by Frankel and Lee (1998) and Dechow *et al.* (1999) modify the information dynamics, so violate internal consistency and the no arbitrage assumption. He then suggests four models preserving consistency with theory.

Four information dynamics used in this study are Eq. 8 (the Ohlson (1995) LID without OI, LIM1), Eq. 8 with current book value (the Feltham and Ohlson (1995) LID without OI, LIM2), Eq. 8 with current book value and the capital investment (the Feltham and Ohlson (1996) LID without OI, LIM3), and Eq. 8 with current book value and order backlog (the Feltham and Ohlson (1995) LID with OI, LIM4).[13] LIM2 is for capturing the conservative effect of book value, and LIM3 is for capturing the book value and income effects of conservatism. In LIM4, order backlog is added as one of 'other information' components to incorporate non-accounting information.

While the auto-regressive parameters of residual income in all models support the hypothesized sign and magnitude, which are positive and less than one respectively, they are small (median coefficients are 0.013 to 0.234). On the other hand, the efforts to capture the conservatism effect using LIM2 and LIM3 fail to describe the time series of residual income, even when the conservative sub-sample is used. Although conservatism models (LIM2 and LIM3) tend to explain market value better than a simple model (LIM1), the value estimates of all models understate market value in a similar fashion to the results of most previous empirical studies. These results mean that these 4 models do not explain a large portion of the market's expectations of future residual income. Finally, the inclusion of order backlog (LIM4) has a trivial effect on future residual income, and is not likely to improve the accuracy of value estimates.

He explains that the failure of empirical models might come from 1) too few observations for the time-series parameters and/or 2) nonstationary time series properties. Specifically, he states that nonstationarity of time series in the residual income valuation model might be due to changes in growth rates, accounting procedures

[13] Of course, LIM2 includes a AR(1) process to capture the evolution of book value, LIM3 includes a equation to capture the effect of book value and capital investment on next year's book value and a AR(1) process to capture the evolution of capital investment, and LIM4 includes two AR(1) processes to capture the evolution of book value and order backlog.

and production technologies.

Hand and Landsman (1998, 1999)

The objective of Hand and Landsman (1998)'s paper is to test whether v is zero or not in an empirical application of the Ohlson model. Their estimating equations are Eq. 2 omitting the last term for the test without v and Eq. 7 for the test with v. Their testing results show that both cases have anomalies. If v is assumed to be zero, the regression coefficients of book value, earnings, and dividends in Eq. 2 are predicted to be positive ($0 \leq 1\text{-}k \leq 1$), positive ($kR/r \geq 0$), and negative ($-1 \leq -k \leq 0$), respectively. However, their results show that the regression multiple relating dividends to equity market value is reliably positive. On the other hand, if v impacts future residual income via Ohlson's information dynamics, the regression coefficients of book value, earnings, dividends, and one-year-ahead forecasted earnings in Eq. 7 are respectively predicted to be positive ($\beta_1 \geq 0$), negative ($\beta_2 R/r \leq 0$), positive ($-\beta_2 \geq 0$), and positive ($\beta_3/r > 0$). However, the regression results also show that the signs on the multiples on current earnings and net capital stock outflows (they divided net dividends into common dividends and net capital stock outflows) are opposite to the predicted ones.

In their later version of the paper (Hand and Landsman, 1999), they focus on the role of dividends in equity valuation, and find that dividends are always positively priced. These results sharply contrast with Miller & Modigliani's dividend displacement property implied in the Ohlson model. Hand and Landsman (1999) also calculate the partial derivative of the market value of equity with respect to dividends ($\partial V_t / \partial d_t$) to compare with its predicted value of minus one, and reject the dividend displacement property once more.

Taken together, these results conflict with value irrelevancy of dividends that the Ohlson model asserts. Hand and Landsman (1998, 1999) try to explain their empirical results through the profitability-signaling role of dividends. They also find that the positive pricing of dividends is much larger for loss firms than for profit firms. It means that managers of loss firms use dividends to signal future profitability. These further tests firmly support their assertion for the profitability-signaling hypotheses. Overall, they conclude that dividends seem to be one component of 'other information' that is available to market actors but is not yet captured by current financial statements.

2.3.2. EBO approach

Frankel and Lee (1998)

Frankel and Lee (1998) investigate the relation between accounting numbers and firm value using the EBO technique (Eq. 4) rather than the information dynamics. They directly use analysts' consensus earnings forecasts as a proxy for market expectations of future earnings and estimate future residual income through SGP.[14] They then measure the firm's fundamental value by means of the estimated future residual income.

Through cross-sectional correlation coefficients with stock prices (*P*), they first show the superiority of the analysts' earnings-based EBO value measures (V_f) over the

[14] See Section 2.1 for SGP (Sequential Generating Process).

historical earnings-based EBO value measures (V_h). Values based on analysts' forecasts explain more than 64% of the variation in prices during the sample period, while historical earnings-based values and book value explain about 49% and 36%, respectively. Next, they state that the value-to-price ratio (V_f/P) is better than firm size and the book-to-price ratio (*B*/*P*) in terms of the predictability of cross-sectional returns, especially over longer time horizons. That is, firms that have higher V_f/P are predicted to earn higher long-term returns. Additionally, the predictive power of V_f/P for long-term returns remains strong, even when we consider its correlation with firm size and B/P.

Overall, this study shows the usefulness of the EBO model based on analysts' earnings forecasts. Thus, in addition to the estimation of persistence parameters using the information dynamics, the EBO technique also needs to be considered, when the residual income valuation model is assessed empirically.

Lee, Myers and Swaminathan (1999)

While recent empirical studies on the residual income valuation model investigate the explainability of cross-sectional prices and/or expected returns, Lee *et al.* (1999) focus on the time-series relation between value and price as a cointegrated system. They compare several competing measures of intrinsic value in terms of their tracking ability of price variation and their predictive power for future returns. Basically, they measure value estimates using the EBO approach (*V*), and compare it with traditional value estimates – dividends (*D*), earnings (*E*), and book value (*B*). For *V*, some factors that can affect value estimates are considered. Those factors include i) forecast horizon (3 to 18 years), ii) earnings forecasting method (a historical time-series model vs. a model based on analysts' consensus forecasts), iii) risk premia (a market-wide time-varying risk premium, a Fama-French one or three factor industry risk premium), and iv) risk free rate (short-term T-bill yield vs. the long-term treasury bond yield).

For evaluating of the tracking ability, they first examine the autocorrelations of dividend yield (*D/P*), earnings-to-price ratio (*E/P*), book-to-market ratio (*B/P*) and value-to-price ratio (*V/P*). The results show that traditional value metrics have high first-order autocorrelations, indicating that they are either nonstationary or long-term mean reverting. On the other hand, *V/P* measures have a lower standard deviation and a faster rate of mean-reversion (i.e., smaller first-order autocorrelations). Especially, *V/P* using the short-term interest rate (i.e., T-bill rate) and analysts' earnings forecasts has the lowest first-order autocorrelations, indicating that the choice of the riskless rate and earnings forecasting method play an important role for the success of *V*.

Next, Lee *et al.* (1999) examine the predictive power for future returns of alternative value estimates through a regression-based forecasting method. In this method, the average return over the next few periods is regressed on one or more explanatory variables from the current period. By means of univariate and three multivariate regressions, they show that *V/P* measures have much more significant forecasting power than traditional measures, and the predictive power of *V/P* is robust to the inclusion of other intrinsic value estimates or business cycle-related variables in the forecasting regression.

In addition to the evidence about the superiority of *V*, they rank alternative measures of *V/P* in terms of two dimensions – predictive ability and tracking error. Alternative measures of *V* are estimated using several factors mentioned above. Conclusively, the inclusion of time-varying interest rates and analysts' earnings forecasts improve the performance of the *V/P* measures, while the choice of alternative forecast horizons and risk premium are of secondary importance.

Francis, Olsson and Oswald (2000)

The objective of Francis *et al.*'s (2000) study is to examine whether three theoretically equivalent valuation models - the discounted dividend (DIV) model, the discounted free cash flow (FCF) model and the discounted abnormal earnings (AE) model - give rise to the same value estimates in practice. The motivation is related to the typical situation in which an investor has to decide which series of forecasts to use to value a firm. They argue that intrinsic value estimates derived from three models can differ because of the different attributes of forecasted DIV, FCF and AE.[15]

The relative reliability of value estimates arising from the three models is compared in terms of their accuracy and explainability. The accuracy is defined as the absolute difference between the value estimate and the current stock price, scaled by the current stock price, while the explainability is defined as the ability of value estimates to explain cross-sectional variation in current stock prices. For the calculation of value

[15] This study is in line with Penman and Sougiannis (1998), but uses ex-ante forecasted attributes rather than ex-post realised attributes to estimate a firm's intrinsic value.

estimates corresponding to each model, Francis *et al.* (2000) use the Value Line database to get the market's expectations of the relevant elements in three models.[16]

The results show that the AE value estimates are more accurate and explain more of the variation in stock prices than the other two value estimates. The authors mention that the superiority of the AE value estimates might come from the more reliance of value estimates on book value and/or the greater precision of AE forecasts, and the superiority is robust regardless of different accounting practices and policies. Thus, they suggest that, under the circumstances where earnings forecasts and book values are available, there is little motivation to use DIV or FCF model by manipulating accounting data.

2.4. Analysts' Earnings Forecasts

2.4.1. Usefulness of analysts' earnings forecasts in accounting research

Since the underlying principle that the share price of a firm is the embodiment of the market's expectations about its future prospects seems to be true, knowing and quantifying market expectations is one of the most important factors in the investment process (Rosen, 2000). In this context, the quantification of market's expectations has long been a main concern of both practitioners and capital market researchers. Following the development of databases that collect and process brokerage earnings estimates (i.e., I/B/E/S, First Call, Value Line, Zacks), it has been getting much easier

[16] Value Line database is preferred to other sources because it provides a more comprehensive set of forecasted attributes over longer horizons (Francis *et al.*, 2000, p. 51).

for both practitioners and researchers to access analysts' earnings forecasts for investment decisions and research. The usefulness and the attributes of analysts' earnings forecasts have been widely studied for the last three decades,[17] and this section reviews some of these studies in the context of equity valuation.

As mentioned in the above section, even for the LID-based equity valuation research, analysts' earnings forecasts can play an important role as an input when defining the 'other information' variable in the linear information dynamics. Recall that analysts' earnings forecasts can be used directly in the EBO-type models. Thus, analysts' earnings forecasts appear as one of crucial components in many valuation models. In addition with U.S. evidence, some European studies have found that forecasts of future earnings are an important factor in equity valuation (Capstaff *et al.*, 2001).

Earlier studies about analyst-based earnings forecasts examine whether analysts' earnings forecasts are superior to time-series model-based earnings forecasts that rely solely on past information. Many studies show evidence that analysts' earnings forecasts are more accurate than time-series forecasts (Brown and Rozeff, 1978; Fried and Givoly, 1982; Brown *et al.*, 1987b; Brown, 1993). Capstaff *et al.* (1995) also provides similar results for the U.K. Brown *et al.* (1987b) show that the superior accuracy of analysts' forecasts over time-series forecasts is not an artifact of i) chronological subperiods, ii) forecast horizon, iii) forecast error definition or treatment of outliers, iv)

[17] I/B/E/S Research Bibliography: Sixth Edition, edited by Lawrence Brown in 2000, consists of 579 studies related to analyst expectations.

conditioning quarter, or v) the statistical test statistic on which inferences are drawn.[18] Instead, Brown *et al.* (1987b) contend that the superior accuracy of analysts' forecasts is attributable to i) better utilization of information existing at the forecast initiation date for the time-series models (termed as a contemporaneous advantage), and ii) use of information acquired after the time-series model's forecast initiation date (termed as a timing advantage). In other words, the higher accuracy of analysts' forecasts over time-series forecasts generally stems from analysts' broader information set.

In terms of explainability of stock returns, Brown *et al.* (1987a) indicate that analyst-based earnings forecasts are generally more highly associated with abnormal stock returns than various time-series model-based earnings forecasts. However, O'Brien (1988) gives contradictory findings. Although her results are consistent with the higher accuracy of analysts' forecasts over time-series forecasts, she finds that autoregressive model forecasts explain abnormal stock returns better than analysts' forecasts. Despite some conflicting evidence on the accuracy and the explainability of analysts' earnings forecasts, it is common practice to implicitly assume that analyst-based earnings forecasts are a better surrogate for market's expectations than time-series model-based earnings forecasts (Kothari, 2001).

[18] There is some extant literature that show findings against the superiority of analysts' forecasts over time-series forecasts. These conflicting findings have led some researchers to attribute the superiority of analysts' forecasts to an artifact of certain experimental design issues (Brown *et al.*, 1987b).

2.4.2. Attributes of analysts' earnings forecasts

Evidence of optimism

Besides studies that demonstrate the higher accuracy and explainability of analysts' forecasts over time-series forecasts, many researchers have also studied the attributes of analysts' earnings forecasts. An important question related to the properties of analysts' earnings forecasts is whether analysts overestimate or underestimate earnings in a systematic way. This is the question about the bias of analysts' earnings estimates. If there is a systematic positive (negative) difference between forecasts and actuals, we call it as optimism (pessimism).

Notwithstanding the research design differences,[19] numerous past academic studies provide evidence that analysts tend to be optimistic and the optimistic bias is evident for most years and forecast horizons (O'Brien, 1988; De Bondt and Thaler, 1990; Brown, 1997; Brown, 1998; Richardson *et al.*, 1999; Easterwood and Nutt, 1999). Some studies even argue that analysts seem to be too optimistic for investors to rely on their forecasts (Dreman and Berry, 1995; Chopra, 1998). Chopra (1998) finds that the average earnings growth forecast is more than twice the actual growth rate. However, the median bias seems to be quite small or unbiased, indicating that the extreme outliers hugely influence on measures of optimism (O'Brien, 1988; Abarbanell and Lehavy, 2000a).

[19] Research design across studies can be different in terms of the use of earnings forecasts (source of forecasts (e.g. I/B/E/S or Value Line), median or mean, consensus or individual, quarterly or yearly, first or last), the use of actual earnings (same or different source with forecasts), and/or the treatment of outliers (trimming or winsorising, scaled or non-scaled forecast errors).

Determinants of optimism

There are several possible explanations for the presence of an optimistic bias in analysts' forecasts of earnings per share. These explanations generally fall in two categories. One is economic incentives-based explanations, and the other is behavioral cognitive-bias explanations. Among incentives-based explanations, some possible reasons why analysts tend to bias their true predictions toward a more optimistic view could be because i) analysts fear jeopardizing potential investment banking business, ii) analysts fear losing access to management as a source of information, and/or iii) analysts seek to generate trading commissions (McNichols and O'Brien, 1997). Consistent with these explanations, affiliated analysts seem to forecast earnings more optimistically than unaffiliated analysts, and managers tend to penalize analysts who produce negative reports about their firms by limiting or cutting off analysts' future contact with them (Das *et al.*, 1998).

On the other hand, De Bondt and Thaler (1990) and Capstaff *et al.* (2001) propose a cognitive-bias explanation for analysts' forecast optimism. They argue that analysts systematically over-react to new earnings information and the overreaction results in the optimistic forecasts. On the contrary, Abarbanell and Bernard (1992) find evidence that analysts under-react to earnings information, which is consistent with the post-earnings-announcement drift phenomenon. Recent research by Easterwood and Nutt (1999) shows that analysts underreact to negative information and overreact to positive information. They argue that these findings are consistent with analysts' optimism and bring together the apparently disparate conclusions of De Bondt and Thaler (1990) and Abarbanell and Bernard (1992).

McNichols and O'Brien (1997) provide another explanation for analysts' optimism. They argue that analysts choose not to publish unfavourable forecasts. That is, some portion of the pervasive analysts' optimism is due to analysts' self-selection of stocks for the coverage. Herding behavior among analysts could be one of other explanations for analysts' optimism as well (Brown, 1998).

Revisions

A deterrent to analysts from issuing optimistic forecasts could be the trade-off with their reputation. Optimistic analysts could be compensated by their employers and/or their targeting firms, but they may face difficulty of losing their reputation and job if they keep issuing incorrect forecasts to investors. Mikhail *et al.* (1999) provides evidence that there is a significantly negative relationship between analyst turnover and relative (not absolute) forecast accuracy. This issue is related to forecast revisions.

Bartov *et al.* (2000), Kasznik and McNichols (1999) and Lopez and Rees (2001) address that the meeting or beating earnings expectations (MBE) phenomenon is partly due to firms' earnings and expectation management, and the rewards to MBE are significant. Thus, even though firms' general management of analysts' expectations leads analysts to issue favorable (i.e., optimistic) forecasts, the expectation management as the fiscal year end approaches seems to encourage analysts to closely meet the following actual earnings because of MBE phenomenon. From this point of view, analysts are likely to revise their forecast downward in order to get credibility from the market. Chopra (1998) and Richardson *et al.* (1999) also report that analysts' forecasts are revised downward continuously in the course of the year.

Decline in optimism

Analysts' optimism appears to be waning in recent years. Brown (1997) shows that analysts' optimistic bias has decreased over time and was absent for S&P 500 firms from 1993 to 1996. Brown (1998) and Richardson *et al.* (1999) also provide evidence that the bias has turned from optimism to pessimism in recent years.

Kothari (2001) summarises three hypotheses that are possibly consistent with the decline in analysts' optimism. First, as Clement (1999), Jacob *et al.* (1999) and Mikhail *et al.* (1999) documented in their studies, analysts' experience seems to be positively associated with forecast accuracy. That is, by learning from past biases, analysts could reduce their optimistic bias. Second, as shown above, analysts' incentives may have changed. Because MBE is likely to be strongly associated with stock price, analysts have incentives to alter their initial optimistic forecasts to the most plausible figures as the earnings announcement date approaches. Third, the quality of data used in the research examining analysts' forecast properties has improved. Abarbanell and Lehavy (2000b) argue that the development of earnings definition that forecast data providers require analysts to forecast is a main factor in explaining the recent declines in analysts' optimism.

2.5. Conclusions

The residual income valuation relationship has long been known, but a voluminous body of studies on the RIV relationship has just recently done extensively by both empirical and theoretical researchers. Even though the RIV relationship is merely a restatement of the long-known dividend discounting model in finance, it appeals from the point that market values are directly linked to accounting numbers. In other words, we consider historical accounting numbers to be useful, in combination with 'other information' not yet reflected in accounting numbers, in doing firm valuation.

Two approaches to the residual income-based valuation have been developed. The EBO approach explores the relation between market value and the book value of equity, residual income forecasts in the forecasting horizon and an estimate of the terminal value for the post-horizon period. The LID approach explores the relation between market value and observable accounting numbers and unobservable 'other information' by using the linear information dynamics originally proposed by Ohlson (1995) and Feltham and Ohlson (1995, 1996). Because the essential task in the residual income-based valuation is forecasting future residual income streams, the EBO and the LID approaches try to do so through the appropriate forecast horizon assumption and terminal value estimation in the former case and the appropriate linear information dynamics in the latter case.

Thanks to some of the research that try to estimate unobservable 'other information' using observable analysts' earnings forecasts, the LID approach has evolved and analysts' earnings forecasts have been considered as one of important elements in the LID-based valuation as well as in the EBO-based valuation. However, most empirical studies show evidence that both approaches systematically give biased and inaccurate value estimates, although they are relatively superior to the traditional valuation approaches. The unsatisfactory evidence keeps opportunities and challenges in the valuation research wide open.

Appendix 2.1: Derivation of Eq. 7

$$V_t = b_t + (\alpha_1 - \omega\alpha_2)x_t^a + \alpha_2 f_{t+1}^a \qquad \text{(Eq. 6)}$$

Residual income and one-year-ahead expected residual income are represented as follows:

$$x_t^a = x_t - rb_{t-1} \qquad \text{(RI)}$$
$$f_{t+1}^a = f_{t+1} - rb_t \qquad \text{(ERI)}$$

Replacing x_t^a and f_{t+1}^a with $x_t - rb_{t-1}$ and $f_{t+1} - rb_t$, respectively, Eq. 6 can be restated as Eq. 6a:

$$V_t = b_t + (\alpha_1 - \omega\alpha_2)(x_t - rb_{t-1}) + \alpha_2(f_{t+1} - rb_t) \qquad \text{(Eq. 6a)}$$

From clean surplus relation (CSR), $b_{t-1} = b_t + d_t - x_t$.

Replacing b_{t-1} with $b_t + d_t - x_t$ using CSR, Eq. 6a can be expressed as an equivalent equation with 4 variables (b_t, x_t, d_t and f_{t+1}):

$$V_t = b_t + (\alpha_1 - \omega\alpha_2)\left[x_t - r(b_t + d_t - x_t)\right] + \alpha_2(f_{t+1} - rb_t) \qquad \text{(Eq. 6b)}$$

Rearranging Eq. 6b in terms of b_t, x_t, d_t and f_{t+1}, Eq. 7 is derived:

$$\begin{aligned} V_t &= \left[1 - r(\alpha_1 - \omega\alpha_2) - r\alpha_2\right]b_t + (\alpha_1 - \omega\alpha_2)(Rx_t - rd_t) + \alpha_2 f_{t+1} \\ &= \beta_1 b_t + \beta_2\left(\frac{R}{r}x_t - d_t\right) + \beta_3\left(\frac{1}{r}f_{t+1}\right) \end{aligned} \qquad \text{(Eq. 7)}$$

where

$$\beta_1 = \left[1 - r(\alpha_1 - \omega\alpha_2) - r\alpha_2\right] = 1 - r\alpha_1 + (r\omega - r)\alpha_2 = \frac{(R-\omega)(R-\gamma) - r\omega(R-\gamma) + (r\omega - r)R}{(R-\omega)(R-\gamma)}$$

$$= \frac{R^2 - R\omega - R\gamma + \omega\gamma - Rr\omega + r\omega\gamma + Rr\omega - Rr}{(R-\omega)(R-\gamma)} = \frac{R - R\omega - R\gamma + R\omega\gamma}{(R-\omega)(R-\gamma)} = \frac{R(1-\omega)(1-\gamma)}{(R-\omega)(R-\gamma)}$$

$$\beta_2 = r(\alpha_1 - \omega\alpha_2) = \frac{r\left[\omega(R-\gamma) - \omega R\right]}{(R-\omega)(R-\gamma)} = \frac{-r\omega\gamma}{(R-\omega)(R-\gamma)}$$

$$\beta_3 = r\alpha_2 = \frac{Rr}{(R-\omega)(R-\gamma)}$$

because $\alpha_1 = \dfrac{\omega}{(R-\omega)}$, $\alpha_2 = \dfrac{R}{(R-\omega)(R-\gamma)}$

In addition, note that

$$\beta_1 + \beta_2 + \beta_3 = \frac{R - R\omega - R\gamma + R\omega\gamma - r\omega\gamma + Rr}{(R-\omega)(R-\gamma)} = \frac{R^2 - R\omega - R\gamma + \omega\gamma}{(R-\omega)(R-\gamma)} = \frac{(R-\omega)(R-\gamma)}{(R-\omega)(R-\gamma)} = 1$$

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CHAPTER 3

DEVELOPMENT OF THE 'INTERCEPT-INCLUSIVE' LINEAR INFORMATION DYNAMICS (LID) MODEL AND RESEARCH DESIGN

3.1. Development of the 'Intercept-inclusive' LID Model

3.1.1. The potential need to allow for intercepts in LID models

Ohlson's linear information dynamics (LID) assumes that residual income (RI) follows a zero mean reverting process. This implies that the intercept term (ω_0) of the AR(1) RI generating equation is statistically zero so that long-run average RI is zero. However, in practice, this assumption may prove to be too restrictive. That is, it may not hold if the long-run average return-on-equity (ROE) is different from the long-run average discount rate, and the accounting system is not completely unbiased. This is supported by Dechow *et al.*'s (1999) (hereafter DHS) empirical results in that ω_0 (-0.02) is significantly different from zero. However they ignore the intercept term when they forecast RI and value a firm.

Similarly, it is possible to assume a non-zero mean reverting OI process, even if Ohlson (1995), Feltham and Ohlson (1995) and most literature based on these two outstanding works assume that the unconditional mean of OI is zero (i.e., the intercept of the AR(1) OI generating equation, γ_0, is zero). In DHS, OI is defined as one-year ahead analysts' RI forecasts less the model's forecasted RI based only on current RI and its parameter estimates. Then, the OI persistence parameters are estimated using the AR(1) OI generating process. In fact, like the issue of ω_0, this is also a matter of what assumptions one makes. It means that γ_0 is not necessarily zero practically, because analysts' RI forecasts might be different from the model's forecasted RI based only on current RI and its parameter estimates, on average. In other words, mean OI (*MOI*) is average analysts' RI forecasts (i.e., mean of f_{t+1}^a) less average first-cut estimate of expected RI (i.e., mean of $\omega_0 + \omega_1 x_t^a$) so that *MOI* represents mean bias which might be non-zero in practice. Thus, if we presume that a long-run average OI is not zero, γ_0 could impact on the value estimates. The possibility of non-zero γ_0 is supported by DHS's empirical result, in which γ_0 (0.01) is significantly different from zero. Note that γ_0 in DHS would be greater than 0.01 if ω_0 were considered in calculating OI.

In fact, if the stock market processes information efficiently and has unbiased expectations, the substantial downward biases reported in prior research suggest that the linear information dynamics used in prior research may be mis-specified. In the presence of conservative accounting, it is unlikely to be appropriate to work with a linear information dynamics that projects future RIs under the assumption that accounting is unbiased, as in the case of DHS. Non-zero RI and OI intercepts reflect the effect of conservative accounting on RI expectations, as deducible from analysts' earnings forecasts.

In short, Ohlson's (1995) assumption that the unconditional mean of RI and OI are zero is just an assumption, which could be relaxed. The persistent deviations from unity in market-to-book ratios suggest that Ohlson's implicit assumption may be inappropriate.

Furthermore, a non-zero mean RI might be practically sensible in the context of firms being going concerns and their maintenance of sustainable competitive advantage. One more important point is that the additional effect of these intercept terms on value estimates could be significant (see the numerical examples in Section 3.1.3).

3.1.2. The derivation of the 'intercept-inclusive' LID model

The above section suggests that it may be inadvisable to omit the intercepts from RI and OI generating processes and firm valuation equations. In this section, I include the intercepts in Ohlson's (1995) linear information dynamics and derive the 'intercept-inclusive' LID model from the empirical perspective.[20] In the empirical test, regression variables are often deflated by a scaling variable to control for size. For example, DHS use regression variables on a per-share basis scaled by current market value, when the parameters in the linear information dynamics are estimated through the pooled time-series and cross-sectional regression analyses. Under the assumption of a non-zero mean reverting process for RI and OI, these *scaled* ω_0 and γ_0 could be an important issue. If we use the scaled per-share data for the purpose of estimating LID parameters, while using the per-share data for the value estimates, *scaled* ω_0 (γ_0) cannot be used solely for estimating a firm's intrinsic value on the per-share basis. This is because the *scaled* ω_0 (γ_0) is a proportion of the scaling variable, not the actual contribution to future per-

[20] The 'intercept-inclusive' LID model using the *unscaled* RI and OI variables in the linear information dynamics has been developed in Appendix 3.3. This 'intercept-inclusive' LID model can be used for firm-by-firm parameter estimation and firm valuation, as in Myers (1999b). On the other hand, the practical implementation of the 'intercept-inclusive' LID model using the *scaled* RI and OI variables in the linear information dynamics has to be used for the pooled time-series cross-sectional parameter estimation and firm valuation, as in DHS, in order to deal with 'the size effect'.

share RIs and value estimates on the per-share basis. In other words, the contribution to future RIs and value estimates from incorporating intercepts in LID in which variables are scaled is not *scaled* ω_0 (γ_0) itself, but *scaled* ω_0 (γ_0) times the scaling variable. If I set all accounting variables to be on the per-share basis, the practical estimating equations for the LID parameters will be as in Eq. 1:

$$\begin{aligned}\frac{\tilde{x}^a_{t+1}}{S_t} &= \omega_0' + \omega_1\frac{x^a_t}{S_t} + \frac{v_t}{S_t} + \varepsilon_{1,t+1}' \\ \frac{\tilde{v}_{t+1}}{S_t} &= \gamma_0' + \gamma_1\frac{v_t}{S_t} + \varepsilon_{2,t+1}'\end{aligned} \qquad \text{(Eq. 1)}$$

where S_t is the scaling variable (e.g., stock price, book value) at the end of year t, ω_0' and ω_1 ($0 \le \omega_1 < 1$) are intercept and slope (persistence) parameters for scaled RI, v_t is OI at time t, γ_0' and γ_1 ($0 \le \gamma_1 < 1$) are intercept and slope (persistence) parameters for scaled OI and ε' terms are random error terms. Prime denotes a parameter based on scaled RI and OI per-share data, which is different from a parameter based on the corresponding levels data of RI and OI per-share.[21]

Multiplying both sides by S_t, Eq. 1 will be restated as Eq. 2.

$$\begin{aligned}\tilde{x}^a_{t+1} &= \omega_0' S_t + \omega_1 x^a_t + v_t + \varepsilon_{1,t+1} \\ \tilde{v}_{t+1} &= \gamma_0' S_t + \gamma_1 v_t + \varepsilon_{2,t+1}\end{aligned} \qquad \text{(Eq. 2)}$$

[21] I do not put the prime symbol on the slope coefficients because the slope parameters using *scaled* and *unscaled* per-share data are the same.

As we can notice from both equations, there is no problem when applying ω_1 (γ_1) estimated from Eq. 1 into the pricing formula, because ω_1 (γ_1) is just a multiple which is the same as the real slope coefficient in Eq. 2. However, in the case of the intercept terms, it is not that simple. Here, three important issues should be considered. First, ω_0' (γ_0') estimated from Eq. 1 is a proportion of the current scaling variable, not the level corresponding to the per-share RI (OI). That is, since the real contribution to future RIs and value estimates from incorporating intercepts is $\omega_0' S_t$ ($\gamma_0' S_t$), not ω_0' (γ_0'), it is obvious that the scaled intercept term (i.e., ω_0' and γ_0') *per se* should not be employed for the value estimates directly.

Secondly, $\omega_0' S_t$ is not constant over time so that future residual income series are the function of current scaling variable as well as current RI and OI. For example, stock price or book value as candidates for a scaling variable tend to grow generally. So, if the annual growth rate of the scaling variable is denoted as *sg*, the pricing formula will be as follows.[22]

$$\begin{aligned} V_t = b_t &+ \left[\frac{R\omega_0'}{(R-SG)(R-\omega_1)} + \frac{R\gamma_0'}{(R-SG)(R-\omega_1)(R-\gamma_1)} \right] S_t \\ &+ \frac{\omega_1}{R-\omega_1} x_t^a + \frac{R}{(R-\omega_1)(R-\gamma_1)} v_t \end{aligned} \qquad \text{(Eq. 3)}$$

where *SG* is 1 plus the growth rate in the scaling variable (*sg*).

[22] See Appendix 3.1 for the derivation of the pricing model when regression variables are scaled.

Unlike the valuation model based on the unscaled per-share data (see Appendix 3.3), the practical valuation model in this study should include the current scaling variable and its projected average growth rate. Thus, finally, the estimation of the future average growth rate of the scaling variable becomes another important issue. Here, it is worth nothing that mean RI (*MRI*) grows and future RI asymptotes to *MRI* (see Appendix 3.2 for details).[23]

3.1.3. Implications for valuation biases reported by DHS

The key point in Eq. 3 is that the magnitude of the effect of the intercept is potentially large, and small errors in the estimate, or ignoring the intercept altogether, could induce large valuation errors. In this section, I provide a simple numerical example to illustrate the potential effect on value estimates of the scaled intercept parameters ω_0' and γ_0'. For this purpose, I consider the likely magnitude of the effect of such omitted items on the value estimates reported by DHS. I will describe DHS procedure in more detail later.

Note that, since the parameters reported by DHS were estimated on the basis of data scaled by price, the term in square brackets in Eq. 3 becomes a proportion of contemporaneous price. Also, note that this DHS-based example is based on 'rough' calculations using reported parameters based on DHS's total data set, which were reported with low precision.

[23] Appendix 3.2 rearranges Eq. 3 to express it with terms comprising mean values of scaled RI and OI, and illustrates graphically where future RI streams asymptote to. Appendix 3.3 shows the case where RI and OI variables are not scaled.

The parameter estimates reported by DHS are as follows: $\omega_0' = -0.02$, $\omega_1 = 0.62$, $\gamma_0' = 0.01$, $\gamma_1 = 0.32$. At this point, note that γ_0' and γ_1 are the estimated parameters without regard for ω_0'. I first calculate the effect of disregarding the ω_0' term, using DHS's assumed cost of equity of 12% and the 'conservative' assumption that growth in price is expected to be zero. Feeding the appropriate parameters into the first term in the square brackets of Eq. 3 yields (1.12 × (-0.02)) / ((1.12 – 1) × (1.12 – 0.62)) = –0.373 (i.e., -37.3% of price).[24]

Calculation of the effect of DHS's disregard of the OI intercept term is a little more complicated. In estimating their OI variable, DHS disregarded the ω_0' term. On the conservative assumption of zero growth in the parameter estimation period, I estimate that, had DHS used ω_0' in their measurement of OI, their OI intercept parameter estimate would have been of the order of 0.0236 (2.36% of price) instead of 0.01 (1% of price).[25] Feeding the appropriate parameters into the second term within the square brackets in Eq. 3 yields (1.12 × 0.0236) / ((1.12 – 1) × (1.12 – 0.62) × (1.12 – 0.32)) = 0.551 (i.e., 55.1% of price).

The sum of the first and second terms in the square brackets of Eq. 3, which respectively correspond to the effect of ω_0' and γ_0' (re-estimated using ω_0'-inclusive OI,

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[24] Myers (1999b) refers to the potential problem of failing to deal with intercept terms. However, he only refers to the ω_0 component. Also, Myers incorrectly states that the effect of incorporating DHS's ω_0 term is –49% of price instead of –37% of price. This appears to be due to an error in the derivation of the ω_0 term which, on a $SG = 1$ basis, he states to be $R\,\omega_0/(R-1)(1-\omega_1)$ instead of $R\,\omega_0/(R-1)(R-\omega_1)$.

[25] The ω_0'-exclusive mean of OI is $\gamma_0'/(1-\gamma_1) = 0.01/(1-0.32) = 0.0147$. The ω_0'-inclusive mean of OI is 0.0147 + 0.02 = 0.0347. The ω_0'-inclusive value of γ_0' is thus 0.0347 × (1 – 0.32) = 0.0236.

i.e., 0.0236), is 17.8% (of price), implying that failure to deal with the terms would cause value estimates to be understated by 17.8% of price. This figure of 17.8% is about two-thirds of the magnitude of the bias reported by DHS (25.9%).

The assumption of 5% growth would give omitted ω_0' and γ_0' effects of (1.12 × (-0.02)) / ((1.12 – 1.05) × (1.12 – 0.62)) = –0.640 and (1.12 × 0.0246) / ((1.12 – 1.05) × (1.12 – 0.62) × (1.12 – 0.32)) = 0.984 respectively (note the change to γ_0' = 0.0246).[26] Under this assumption, the sum of the two terms is 34.4% of price, which is about 30% larger than the bias reported by DHS.

3.1.4. Special cases of the 'intercept-inclusive' LID model

In this section, I consider a number of RI-based valuation models that have appeared in earlier studies, and show that they nest within the valuation model given by Eq. 3.

First, the 'intercept-inclusive' LID model, Eq. 3, developed for the practical purposes is the same as the Feltham and Ohlson (1995) model, if we use book value as a scaling variable, assume γ_0' = 0, ignore OI in their book value generating process, and employ total book value rather than operating book value. That is, S_t, SG, ω_0' and ω_1 in Eq. 3 (b_t, BG, ω_0' and ω_1 in Eq. 4) respectively correspond to b_t, ω_{22}, ω_{11} and ω_{12} in the

[26] If we assume 5% growth, the ω_0'-exclusive mean of OI is $\gamma_0'/(SG-\gamma_1) = 0.01/(1.05-0.32) = 0.0137$. The ω_0'-inclusive mean of OI is 0.0137 + 0.02 = 0.0337. Thus, the ω_0'-inclusive value of γ_0' is 0.0337 × (1.05 – 0.32) = 0.0246.

Feltham and Ohlson (1995) model (Proposition 3, p. 705).

$$V_t = b_t + \frac{R\omega_0'}{(R-BG)(R-\omega_1)} b_t + \frac{\omega_1}{R-\omega_1} x_t^a + \frac{R}{(R-\omega_1)(R-\gamma_1)} v_t \qquad \text{(Eq. 4)}$$

Second, the modification of Eq. 2 by (i) eliminating the second equation and the v_t term and (ii) replacing the S_t term by a constant value of one gives the empirical 'LIM1' generating process examined by Myers (1999b) in a time series estimation context. This results in the following special case of Eq. 3. ω_0' and ω_1 in Eq. 5 respectively correspond to ω_{10} and ω_{11} of Myers' LIM1 model (p. 8).[27, 28]

$$V_t = b_t + \frac{R\omega_0'}{(R-1)(R-\omega_1)} + \frac{\omega_1}{R-\omega_1} x_t^a \qquad \text{(Eq. 5)}$$

Third, the elimination from Eq. 2 of the ω_0' and γ_0' terms gives rise to the valuation model which appears in Ohlson (1995), and which is used as the basis for the OI-inclusive part of DHS's study.

$$V_t = b_t + \frac{\omega_1}{R-\omega_1} x_t^a + \frac{R}{(R-\omega_1)(R-\gamma_1)} v_t \qquad \text{(Eq. 6)}$$

[27] Myers (1999b) incorrectly gives the second term of Eq. 5 as $R\,\omega_0\ /\ (R-1)(1-\omega_1)$ instead of $R\,\omega_0\ /\ (R-1)(R-\omega_1)$.

[28] O'Hanlon (1994) presents a general residual income valuation model which allows for future residual income to be generated by any class of ARIMA time series process (i.e., ARIMA (*p,d,q*)). Eq. 5 is the special case of the general model – ARIMA (1,0,0) with constant.

3.2. Empirical Implementation Procedure

3.2.1. DHS procedure

Ohlson (1995) represents RI expectations as being generated by knowledge of (i) current RI, (ii) current 'other information' (OI) and (iii) the parameters of the RI and OI generating process, as described by the following linear information dynamics (LID):

$$\begin{aligned} \tilde{x}^a_{t+1} &= \omega_1 x^a_t + v_t + \tilde{\varepsilon}_{1,t+1} \\ \tilde{v}_{t+1} &= \gamma_1 v_t + \tilde{\varepsilon}_{2,t+1} \end{aligned} \qquad \text{(Eq. 7)}$$

In Eq. 7, v_t denotes OI, ω_1 and γ_1 are persistence parameters for RI and OI respectively, and the $\tilde{\varepsilon}$ terms are zero-mean random error terms. The persistence parameters are constrained to be non-negative and to be less than one. The LID in Eq. 7 thus implies that the mean value of RI is zero. Ohlson (1995) shows that the process in Eq. 7 gives rise to the following RI-based estimate of the value of equity:

$$V_t = b_t + \frac{\omega_1}{R-\omega_1} x^a_t + \frac{R}{(R-\omega_1)(R-\gamma_1)} v_t \qquad \text{(Eq. 8)}$$

DHS devise an OI-inclusive empirical application of the LID-based valuation approach depicted in Eq. 7 and Eq. 8. This comprises the following steps:

1. For each year (t), the following pooled (time-series cross-sectional) regression is estimated:

$$\frac{x^a_{j,s}}{P_{j,s-1}} = \hat{\omega}'_{0,t} + \hat{\omega}_{1,t}\frac{x^a_{j,s-1}}{P_{j,s-1}} + \hat{e}_{1j,s} \qquad \text{(Eq. 9)}$$

where the subscript s is a time index ranging from the first year of available data to year t, x^a_j is RI per share for firm j, P_j is market price per share for firm j, $\hat{\omega}'_{0,t}$ and $\hat{\omega}_{1,t}$ are year-specific LID parameter estimates and $\hat{e}_1$ is an error term (hats denote parameter estimates and prime denotes a parameter based on scaled RI data compared with that based on RI itself). $\hat{\omega}_{1,t}$ is used as an estimate of ω_1 in Eq. 7, and the intercept, $\hat{\omega}'_{0,t}$, is disregarded. On the basis of pooled data from 1976-1995, DHS report parameter estimates of $\hat{\omega}'_{0,t}$ equal to –0.02 and $\hat{\omega}_{1,t}$ equal to 0.62.

2. For each year (t), following a suggestion in Ohlson (2001), OI is defined as:

$$v_{j,t} = f^a_{j,t+1} - \hat{\omega}_{1,t}x^a_{j,t} \qquad \text{(Eq. 10)}$$

where $v_{j,t}$ is the OI for firm j at time t, $f^a_{j,t+1} = f_{j,t+1} - (R-1)b_{j,t}$ is the time t 'full information' analyst-based forecast of firm j's RI per share for t+1, $f_{j,t+1}$ is the time t analyst earnings per share forecast for firm j for time t+1, and $\hat{\omega}_{1,t}$ is obtained from estimates of Eq. 9. Note that if $\hat{\omega}'_{0,t}$ < 0 then the estimated value of $v_{j,t}$ is understated and the magnitude of the understatement is $\hat{\omega}'_{0,t}$ multiplied by the scaling variable, $P_{j,t}$.

3. For each year (t), the following pooled (time-series cross-sectional) regression is estimated:

$$\frac{v_{j,s}}{P_{j,s-1}} = \hat{\gamma}'_{0,t} + \hat{\gamma}_{1,t}\frac{v_{j,s-1}}{P_{j,s-1}} + \hat{e}_{2j,s} \qquad \text{(Eq. 11)}$$

where $\hat{\gamma}'_{0,t}$ and $\hat{\gamma}_{1,t}$ are year-specific parameter estimates, and $\hat{e}_2$ is an error term (hats denote parameter estimates and prime denotes a parameter based on scaled OI data compared with that based on OI itself). $\hat{\gamma}_{1,t}$ is used as an estimate of γ_1 in Eq. 7, and the intercept, $\hat{\gamma}'_{0,t}$, is disregarded. On the basis of pooled data from 1976-1995, DHS report parameter estimates of $\hat{\gamma}'_{0,t}$ equal to 0.01 and $\hat{\gamma}_{1,t}$ equal to 0.32. Note that if $\hat{\gamma}'_{0,t}$ is disregarded, the expected value of one-period-ahead OI based on Eq. 11 (i.e., $E[\tilde{v}_{j,t+1}]$) is understated and the magnitude of the understatement is equal to $\hat{\gamma}'_{0,t}$ multiplied by the scaling variable, $P_{j,t}$.

4. For each year (t), firm value is estimated for each firm based on the valuation expression Eq. 8 using book value, RI, estimated OI, the parameter estimates $\hat{\omega}_{1,t}$ and $\hat{\gamma}_{1,t}$, and an estimate of the cost of equity. Because the estimated OI at time t is a function of the observable analyst-based time t RI forecast for time t+1 (f^a_{t+1}) and current RI, the value estimate at time t is equivalently expressed as in Eq. 12 (firm subscript j for variables and time subscript t for parameters are suppressed).

$$V_t = b_t + \frac{-\hat{\omega}_1\hat{\gamma}_1}{(R-\hat{\omega}_1)(R-\hat{\gamma}_1)}x^a_t + \frac{R}{(R-\hat{\omega}_1)(R-\hat{\gamma}_1)}f^a_{t+1} \qquad \text{(Eq. 12)}$$

As shown in Eq. 9 and 11, LID parameters in DHS are estimated based on per-share data scaled by lagged stock price. However, scaling by stock price makes value estimates a function of stock price when applying the 'intercept-inclusive' LID approach, so a fundamental change in the scaling variable is required in this study in order to compare the Ohlson LID-based value estimates with the 'intercept-inclusive' LID-based value estimates. In this study, lagged book value of equity is used as a scaling variable (see Section 3.2.2 for details about the issue of scaling variable).

3.2.2. My procedure

I augment the DHS approach by exploiting the information contained in the estimated LID intercept parameters. As explained in Section 3.1.2, these intercepts capture information concerning average scaled RI. However, practical implementation for valuation requires a fundamental change in the scaling variable, if we are to avoid making value estimates a function of market price. Multiplying Eq. 9 by $P_{j,s-1}$ shows that the conditional expectation of $x^a_{j,s}$ is a linear combination of $x^a_{j,s-1}$ and the scaling variable $P_{j,s-1}$. Similarly, from Eq. 11 the conditional expectation of $v_{j,s}$ is a linear combination of $v_{j,s-1}$ and $P_{j,s-1}$. In each case, the weight applied to $P_{j,s-1}$ in forming the conditional expectation is equal to the respective intercept parameter. Introducing the intercept parameters into the valuation model will therefore cause price to be an input to the valuation model. In order to avoid this circularity, while preserving the scaling of data that is necessary in cross-sectional analysis, I scale by the book value of equity.[29]

Similar to Ohlson (1995), obtaining a closed form valuation expression for the 'intercept-inclusive' LID model requires me to express conditional expectations of the RI flows for all future time periods in terms of information observable at the valuation date. If the LID intercepts do not equal zero, the conditional expectation of RI for each future period will depend on expected book value at the beginning of the respective period. Therefore, the 'intercept-inclusive' LID requires a model describing the book value dynamics. For simplicity, I assume that book value grows at a constant rate.

My modification of the Ohlson (1995) LID to include intercept parameters for RI and OI, with scaling by book value, leads to the following LID (refer to Eq. 1 for the general LID that allows any scaling variable):

$$\begin{aligned} \frac{\tilde{x}_{t+1}^a}{b_t} &= \omega_0' + \omega_1 \frac{x_t^a}{b_t} + \frac{v_t}{b_t} + \tilde{\varepsilon}_{1,t+1} \\ \frac{\tilde{v}_{t+1}}{b_t} &= \gamma_0' + \gamma_1 \frac{v_t}{b_t} + \tilde{\varepsilon}_{2,t+1} \\ \frac{\tilde{b}_{t+1}}{b_t} &= BG + \tilde{\varepsilon}_{3,t+1} \end{aligned} \qquad \text{(Eq. 13)}$$

where BG is one plus the rate of growth in book value and the $\tilde{\varepsilon}$ terms are random error terms. From Eq. 13, I obtain the following expectations:

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[29] Scaling RI by lagged book value produces the following measure (firm subscript suppressed): $\frac{x_t^a}{b_{t-1}} = \frac{x_t - (R-1)b_{t-1}}{b_{t-1}} = ROE_t - (R-1)$, where ROE_t denotes Return on Equity at time t, and is equal to x_t / b_{t-1}. This measure is familiar in the managerial consulting literature as the 'spread', being the excess of accounting profitability over the cost of capital.

$$\begin{aligned} E\left[\tilde{x}^a_{t+1}\right] &= \omega_0' b_t + \omega_1 x^a_t + v_t \\ E\left[\tilde{v}_{t+1}\right] &= \gamma_0' b_t + \gamma_1 v_t \\ E\left[\tilde{b}_{t+1}\right] &= BG b_t \end{aligned} \qquad \text{(Eq. 14)}$$

The model setup closely resembles the Feltham and Ohlson (1995) LIM. However, one important difference is that, from the second equation in Eq. 14, expectations of OI may also depend on book value and may thus deviate from zero on average. The empirical analysis shows that this can be an important difference in practice. In fact, this intercept allows the possibility that expected future RI, conditional on OI, will differ from the average value of RI over the estimation period.[30]

From the RI valuation relationship and Eq. 14, it is straightforward to derive the following valuation expression (refer to Eq. 3 for the general 'intercept-inclusive' LID model that allows any scaling variable):

$$V_t = b_t + \beta_1 x^a_t + \beta_2 v_t + (\beta_3 + \beta_4) b_t \qquad \text{(Eq. 15)}$$

where

$$\beta_1 = \frac{\omega_1}{R - \omega_1}, \ \beta_2 = \frac{R}{(R - \omega_1)(R - \gamma_1)}$$

$$\beta_3 = \frac{R\omega_0'}{(R - BG)(R - \omega_1)},$$

[30] Recall that OI is defined to be the difference between the analyst-based forecast of RI and the forecast of RI derived from a univariate model of RI.

$$\beta_4 = \frac{R\gamma_0'}{(R-BG)(R-\omega_1)(R-\gamma_1)}$$

The coefficients β_3 and β_4 on book value in Eq. 15 include the estimated values of the intercepts in the first two lines of Eq. 13, and arise because book value is the scaling variable in Eq. 13. The Ohlson (1995) valuation model Eq. 8 is a special case: where $\omega_0' = 0 \;\; \rightarrow \;\; \beta_3 = 0$ and $\gamma_0' = 0 \;\; \rightarrow \;\; \beta_4 = 0$.

I estimate the parameters for the first two equations in the modified LID system Eq. 13 using a direct development of the procedures used by DHS. Similar to DHS's procedure shown in Eq. 9, in estimating the first LID equation of Eq. 13, I ignore OI and estimate the following regression:

$$\frac{x_{j,s}^a}{b_{j,s-1}} = \hat{\omega}_{0,t}' + \hat{\omega}_{1,t}\frac{x_{j,s-1}^a}{b_{j,s-1}} + \hat{e}_{1j,s} \qquad \text{(Eq. 16)}$$

where $\hat{\omega}_{0,t}'$ and $\hat{\omega}_{1,t}$ are year-specific parameter estimates, and $\hat{e}_1$ is a random error term.

As mentioned above, OI is defined as the difference between the full information analyst-based forecast of RI ($f_{j,t+1}^a$) and the implied conditional expectation of RI based on parameter estimates from the univariate model described in Eq. 16:

$$v_{j,t} = f_{j,t+1}^a - (\hat{\omega}_{0,t}' b_{j,t} + \hat{\omega}_{1,t} x_{j,t}^a) \qquad \text{(Eq. 17)}$$

Note that OI defined for the application of the 'intercept-inclusive' LID approach (Eq. 17) is different from that defined for the application of the Ohlson LID approach (Eq. 10), because $\hat{\omega}'_{0,t}$ is differently assumed (non-zero versus zero). Now, the OI dynamics parameters are estimated based on the following regression:

$$\frac{v_{j,s}}{b_{j,s-1}} = \hat{\gamma}'_{0,t} + \hat{\gamma}_{1,t}\frac{v_{j,s-1}}{b_{j,s-1}} + \hat{e}_{2j,s} \qquad \text{(Eq. 18)}$$

where $\hat{\gamma}'_{0,t}$ and $\hat{\gamma}_{1,t}$ are year-specific parameter estimates and $\hat{e}_2$ is a random error term.

Finally, value estimates ($V_{j,t}$) are constructed for each firm (*j*) at each valuation date (*t*) based on Eq. 15. The following information is required as inputs to the valuation model: RI per share ($x^a_{j,t}$), estimated OI per share ($v_{j,t}$), book value per share ($b_{j,t}$), the assumed cost of equity, estimates of the LID parameters ($\hat{\omega}'_{0,t}, \hat{\omega}_{1,t}, \hat{\gamma}'_{0,t}, \hat{\gamma}_{1,t}$) and assumed values of the book value growth rate parameter, BG. Because the estimated OI at time t is a function of observable analyst-based time t RI forecast for time t+1 (f^a_{t+1}), current RI and current book value, Eq. 15 is equivalently expressed as Eq. 19 (firm subscript j for variables and time subscript t for parameters are suppressed).

$$V_t = b_t + \frac{R(\hat{\omega}'_0 BG - \hat{\omega}'_0\hat{\gamma}_1 + \hat{\gamma}'_0)}{(R-BG)(R-\hat{\omega}_1)(R-\hat{\gamma}_1)}b_t + \frac{-\hat{\omega}_1\hat{\gamma}_1}{(R-\hat{\omega}_1)(R-\hat{\gamma}_1)}x^a_t + \frac{R}{(R-\hat{\omega}_1)(R-\hat{\gamma}_1)}f^a_{t+1}$$

(Eq. 19)

3.2.3. Special cases

Table 3.1, Panel A summarizes the Ohlson LID model and its special cases. LID9 is the general Ohlson LID model given by Eq. 12. The models shown in Panel A are the same as the models used in DHS except for the separation of (ω_1 = 0, γ_1 = $\hat{\gamma}_1$) and (ω_1 = $\hat{\omega}_1$, γ_1 = 0) cases. As DHS stated, the valuation model based on (ω_1 = 0, γ_1 = $\hat{\gamma}_1$) is theoretically identical to the model assuming (ω_1 = $\hat{\omega}_1$, γ_1 = 0). However, analyst-based RI forecasts are biased practically so that $\hat{\gamma}_1$ when ω_1 = 0 is different from $\hat{\omega}_1$ when γ_1 = 0. Note that for the estimation of γ_1 in LID7, OI is defined as analyst-based RI forecast. That is, $\hat{\gamma}_1$ is the estimated slope coefficient from $f_{t+1}^a = \gamma_0 + \gamma_1 lag(f_{t+1}^a)$, because $v_t = f_{t+1}^a$ in this case.

Note also that LID1 is the book value model in which current book value is sufficient for all expected future payoffs, and LID2 is the earnings model in which capitalized current earnings (adjusted for dividends) is sufficient for all expected future payoffs. LID6, which is reported by DHS as a more reliable model than the Ohlson LID model, is the same as the EBO model that assumes 1-year forecast horizon and zero RI growth.

Table 3.1, Panel B summarizes the empirically testable special cases of Eq. 19 used in this thesis. The special cases of the 'intercept-inclusive' LID model are defined according to the assumption of OI and/or the restriction of RI and OI persistence parameters (i.e., ω_1 and γ_1). In addition to some combinations of assumptions about ω_1 and γ_1 ruled out by DHS, I exclude 3 more cases – (ω_1 = 1, no OI), (ω_1 = 1, γ_1 =

0) and ($\omega_1 = 0$, $\gamma_1 = 1$) in Panel B. This is because these cases give rise to random walk models with drift so that RI streams are non-stationary. That is, these cases violate the assumption of mean reverting process.

In Table 3.1, Panel B, LID10, LID11 and LID12 are models when OI is ignored in the linear information dynamics, while LID13 to LID16 are models when OI is dealt with. LID16 represents a general 'intercept-inclusive' LID model given by Eq. 19, and LID10 to LID15 are special cases of LID16. Here, note that $\hat{\omega}'_0$, $\hat{\gamma}'_0$ and $\hat{\gamma}_1$ in LID10, LID13, LID14 and LID15 except $\hat{\omega}'_0$ in LID15 are different from the parameters estimated using the above procedures given by Eq. 16, Eq. 17 and Eq. 18. This is because the restriction of $\omega_1 = 0$ and/or $\gamma_1 = 0$ is conditional for the estimation of those parameters so that the parameters estimated using the above procedures given by Eq. 16, Eq. 17 and Eq. 18 cannot be employed directly to the corresponding pricing model.

Specifically, in LID10, LID13 and LID14, $\hat{\omega}'_0$ for year t is the mean of book value-scaled RI using data up to year t (i.e., $\overline{\left(x_t^a/b_{t-1}\right)}$), because the assumption of $\omega_1 = 0$ makes $\hat{\omega}'_0$ absorb the whole mean value of scaled RI. Similarly, the assumption of $\gamma_1 = 0$ in LID13 and LID15 makes $\hat{\gamma}'_0$ absorb the whole mean value of scaled OI so that $\hat{\gamma}'_0$ for year t is the mean of book value-scaled OI using data up to year t. Thus, $\hat{\gamma}'_0$ for year t in LID13 is $\overline{\left(f_{t+1}^a/b_{t-1}\right) - \hat{\omega}'_{0,t}\left(b_t/b_{t-1}\right)}$ and $\hat{\gamma}'_0$ for year t in LID15 is $\overline{\left(f_{t+1}^a/b_{t-1}\right) - \hat{\omega}'_{0,t}\left(b_t/b_{t-1}\right) - \hat{\omega}_{1,t}\left(x_t^a/b_{t-1}\right)}$. Finally, in LID14, $\hat{\gamma}'_0$ and $\hat{\gamma}_1$ are the estimated parameters based on the AR(1) OI regression where OI is analyst-based RI forecasts less $\hat{\omega}_0'$ times book value (i.e., $v_t = f_{t+1}^a - \hat{\omega}_{0,t}' b_t$).

3.2.4. Some EBO models

In addition to the LID models, some EBO models are considered in this study. Although Frankel and Lee (1998) and Lee *et al.* (1999) show the evidence that the choice of alternative forecast horizon has little effect on the results, I use three EBO models based on different forecast horizon (T) using I/B/E/S analysts' consensus forecasts for one-year (f_{t+1}) to three-year (f_{t+3}) ahead earnings.[31] Here, after the explicit forecasting period, terminal value is assumed to be the present value of year-T residual income in perpetuity. Then, I also consider three more EBO models that allow for growth in the post-horizon period. Note that EBO1 is the same as LID6.

The requirement of estimating terminal values usually applied in the EBO approach is not only from earnings power (i.e., growth in the post-horizon period) but also from measurement error consistently occurred in the measurement of earnings and book values of equity (Penman, 1997). In other words, a terminal value is needed to correct both errors occurring i) by truncating the horizon and ii) when forecasting attributes up to the horizon. The error arising by truncating the horizon is of course because forecasts of attributes beyond the horizon are omitted in the truncation. On the other hand, the error in the forecasts to the horizon is due to the accounting rules that allow for the

[31] Actually, f_{t+1}, f_{t+2}, and f_{t+3} are earnings forecasts for current fiscal year, next fiscal year and next but one fiscal year, respectively.

differences on recognition and measurement of forecasts. Such consistent measurement error prevents future RI streams from converging to zero and is usually the result of conservative accounting consistently applied (Sougiannis and Yaekura, 2000). Thus, it is essential to specify terminal value that correctly captures the effect of a firm's specific economic fundamentals including the degree of conservatism. Myers (1999a) argues that many reversals of accounting conservatism come about within 'terminal income' that arises when companies are taken over, and ignoring this 'terminal income' when estimating terminal value could be a source of unreliable intrinsic value estimates based on the EBO approach. I leave the issue of terminal value specification in future research, and just consider 6 EBO models generally adopted in the earlier studies.

EBO models assuming no growth in the post-horizon period:

$$V_t = b_t + \frac{f_{t+1} - rb_t}{r} = \frac{1}{r} f_{t+1} \qquad \text{(EBO 1)}$$

$$V_t = b_t + \frac{f_{t+1} - rb_t}{R} + \frac{f_{t+2} - r\bar{b}_{t+1}}{rR} \qquad \text{(EBO 2)}$$

$$V_t = b_t + \frac{f_{t+1} - rb_t}{R} + \frac{f_{t+2} - r\bar{b}_{t+1}}{R^2} + \frac{f_{t+3} - r\bar{b}_{t+2}}{rR^2} \qquad \text{(EBO 3)}$$

EBO models assuming growth in the post-horizon period:

$$V_t = b_t + \frac{f_{t+1} - rb_t}{(r - g_r)} \qquad \text{(EBO 4)}$$

$$V_t = b_t + \frac{f_{t+1} - rb_t}{R} + \frac{f_{t+2} - r\bar{b}_{t+1}}{(r - g_r)R} \qquad \text{(EBO 5)}$$

$$V_t = b_t + \frac{f_{t+1} - rb_t}{R} + \frac{f_{t+2} - r\bar{b}_{t+1}}{R^2} + \frac{f_{t+3} - r\bar{b}_{t+2}}{(r - g_r)R^2} \qquad \text{(EBO 6)}$$

where f_{t+i} is i-year ahead analysts' consensus earnings forecast, $\overline{b}_{t+i}$ is i-year ahead estimated book value, and g_r is the estimated growth rate of RI in the post-horizon period. EBO 1 (EBO 4), EBO 2 (EBO 5) and EBO 3 (EBO 6) are respectively 1-year, 2-year and 3-year horizon model.

3.2.5. Pricing test of competing valuation models

After measuring persistence parameters, the competing valuation models will be compared in order to show which provides the value estimates that accord most closely with current stock prices. At this stage, value estimates from Ohlson-type LID models, 'intercept-inclusive'-type LID models and EBO models will be computed and compared. It is of interest to examine whether and where the 'intercept-inclusive' LID model brings significant benefit over its special cases and other models. In contrast, if there is clear evidence that the simpler EBO model produces more reliable value estimates in all cases, linear information dynamics still need to be modified.

In order to run 'horse races' between different valuation models, I contrast the reliability of value estimates from the alternative models in terms of three performance dimensions. They are the bias metric, the accuracy metric and the explainability metric. The bias (the accuracy) is defined as the signed (absolute) difference between the value estimate and the current stock price, scaled by the current stock price, while the explainability is defined as the ability of value estimates to explain cross-sectional variation in current stock prices. Therefore, under the bias, the accuracy and the explainability metrics, value estimates with, respectively, the closest signed forecast errors to zero, the smallest absolute forecast errors and the highest OLS R^2 are the most reliable. The accuracy and bias of an estimated value can be of great concern to an investor who wants to determine whether to buy, hold, or sell a firm's stock, to an analyst who wants to provide, along with his/her earnings forecasts, a stock recommendation, to an investment banker who wants to determine the offer price of an IPO, or to a researcher who wants to use such a price in examining a specific research question (Sougiannis and Yaekura, 2000)

Given the fundamental firm value, the signed forecast error and the absolute forecast error, scaled by stock prices, can be calculated as in Eq. 20 and Eq. 21. Furthermore, the regression of stock price on value estimate is used to get R^2 as the explainability metric (Eq. 22).

$$FE_{sp} = (V_t - P_t^{c,n}) / P_t^{c,n} \qquad \text{(Eq. 20)}$$

$$AFE_{sp} = \left| V_t - P_t^{c,n} \right| / P_t^{c,n} \qquad \text{(Eq. 21)}$$

$$P_t^{c,n} = \lambda_0 + \lambda_1 V_t + u_t \qquad \text{(Eq. 22)}$$

where FE_{sp} is the forecast error of stock prices, AFE_{sp} is the absolute forecast error of stock prices, $P_t^{c,n}$ is the observed stock price at n months after the end of the fiscal year t, and V_t is the fundamental value estimated by the RI-based valuation model for year t. Note that in order to make comparable the value estimate and the stock price, I use stock price at a few months (usually 3 months) after the fiscal year end rather than stock price at the fiscal year end.

Table 3.1: The competing valuation models

Panel A: The Ohlson model and its variants

When 'other information' is ignored	
LID1: $\omega_1 = 0$	$E_t\left[\tilde{x}^a_{t+1}\right] = 0$ $V_t = b_t$
LID2: $\omega_1 = 1$	$E_t\left[\tilde{x}^a_{t+1}\right] = x^a_t$ $V_t = b_t + \frac{1}{r}x^a_t = \frac{R}{r}x_t - d_t$
LID3: $\omega_1 = \hat{\omega}_1$	$E_t\left[\tilde{x}^a_{t+1}\right] = \hat{\omega}_1 x^a_t$ $V_t = b_t + \frac{\hat{\omega}_1}{(R-\hat{\omega}_1)}x^a_t$
LID4: $\omega_1 = \hat{\omega}^f_1$	$E_t\left[\tilde{x}^a_{t+1}\right] = \hat{\omega}^f_1 x^a_t$ $V_t = b_t + \frac{\hat{\omega}^f_1}{(R-\hat{\omega}^f_1)}x^a_t$
When 'other information' is incorporated	
LID5: $(\omega_1 = 0, \gamma_1 = 0)$	$E_t\left[\tilde{x}^a_{t+1}\right] = f^a_{t+1}$ $V_t = b_t + \frac{1}{R}f^a_{t+1}$
LID6: $(\omega_1 = 1, \gamma_1 = 0)$ or $(\omega_1 = 0, \gamma_1 = 1)$	$E_t\left[\tilde{x}^a_{t+1}\right] = f^a_{t+1}$ $V_t = \frac{1}{r}f_{t+1}$
LID7: $(\omega_1 = 0, \gamma_1 = \hat{\gamma}_1)$	$E_t\left[\tilde{x}^a_{t+1}\right] = f^a_{t+1}$ $V_t = b_t + \frac{1}{(R-\hat{\gamma}_1)}f^a_{t+1}$
LID8: $(\omega_1 = \hat{\omega}_1, \gamma_1 = 0)$	$E_t\left[\tilde{x}^a_{t+1}\right] = f^a_{t+1}$ $V_t = b_t + \frac{1}{(R-\hat{\omega}_1)}f^a_{t+1}$
LID9: $(\omega_1 = \hat{\omega}_1, \gamma_1 = \hat{\gamma}_1)$	$E_t\left[\tilde{x}^a_{t+1}\right] = f^a_{t+1}$ $V_t = b_t + \frac{-\hat{\omega}_1\hat{\gamma}_1}{(R-\hat{\omega}_1)(R-\hat{\gamma}_1)}x^a_t + \frac{R}{(R-\hat{\omega}_1)(R-\hat{\gamma}_1)}f^a_{t+1}$

Table 3.1 (continued)

Panel B: The 'intercept-inclusive' LID model and its variants – scaled by book value

When 'other information' is ignored	
LID10: $\omega_1 = 0$	$E_t\left[\tilde{x}^a_{t+1}\right] = \hat{\omega}'_0 b_t$ $V_t = b_t + \frac{\hat{\omega}'_0}{(R-BG)} b_t$
LID11: $\omega_1 = \hat{\omega}_1$	$E_t\left[\tilde{x}^a_{t+1}\right] = \hat{\omega}'_0 b_t + \hat{\omega}_1 x^a_t$ $V_t = b_t + \frac{R\hat{\omega}'_0}{(R-BG)(R-\hat{\omega}_1)} b_t + \frac{\hat{\omega}_1}{(R-\hat{\omega}_1)} x^a_t$
LID12: $\omega_1 = \hat{\omega}^f_1$	$E_t\left[\tilde{x}^a_{t+1}\right] = \hat{\omega}'^f_0 b_t + \hat{\omega}^f_1 x^a_t$ $V_t = b_t + \frac{R\hat{\omega}'^f_0}{(R-BG)(R-\hat{\omega}^f_1)} b_t + \frac{\hat{\omega}^f_1}{(R-\hat{\omega}^f_1)} x^a_t$
When 'other information' is incorporated	
LID13: ($\omega_1 = 0$, $\gamma_1 = 0$)	$E_t\left[\tilde{x}^a_{t+1}\right] = f^a_{t+1}$ $V_t = b_t + \frac{\hat{\omega}'_0 BG + \hat{\gamma}'_0}{(R-BG)R} b_t + \frac{1}{R} f^a_{t+1}$
LID14: ($\omega_1 = 0$, $\gamma_1 = \hat{\gamma}_1$)	$E_t\left[\tilde{x}^a_{t+1}\right] = f^a_{t+1}$ $V_t = b_t + \frac{\hat{\omega}'_0 BG - \hat{\omega}'_0\hat{\gamma}_1 + \hat{\gamma}'_0}{(R-BG)(R-\hat{\gamma}_1)} b_t + \frac{1}{(R-\hat{\gamma}_1)} f^a_{t+1}$
LID15: ($\omega_1 = \hat{\omega}_1$, $\gamma_1 = 0$)	$E_t\left[\tilde{x}^a_{t+1}\right] = f^a_{t+1}$ $V_t = b_t + \frac{\hat{\omega}'_0 BG + \hat{\gamma}'_0}{(R-BG)(R-\hat{\omega}_1)} b_t + \frac{1}{(R-\hat{\omega}_1)} f^a_{t+1}$
LID16: ($\omega_1 = \hat{\omega}_1$, $\gamma_1 = \hat{\gamma}_1$)	$E_t\left[\tilde{x}^a_{t+1}\right] = f^a_{t+1}$ $V_t = b_t + \frac{R(\hat{\omega}'_0 BG - \hat{\omega}'_0\hat{\gamma}_1 + \hat{\gamma}'_0)}{(R-BG)(R-\hat{\omega}_1)(R-\hat{\gamma}_1)} b_t + \frac{-\hat{\omega}_1\hat{\gamma}_1}{(R-\hat{\omega}_1)(R-\hat{\gamma}_1)} x^a_t + \frac{R}{(R-\hat{\omega}_1)(R-\hat{\gamma}_1)} f^a_{t+1}$

Table 3.1 (continued)

Panel C: The EBO models

When zero RI growth is assumed	
EBO1: 1- year forecasting horizon	$E_t\left[\tilde{x}^a_{t+1}\right]=f^a_{t+1}$ $V_t = b_t + \frac{f_{t+1}-rb_t}{r} = \frac{1}{r}f_{t+1}$
EBO2: 2-year forecasting horizon	$E_t\left[\tilde{x}^a_{t+1}\right]=f^a_{t+1}$ $V_t = b_t + \frac{f_{t+1}-rb_t}{R} + \frac{f_{t+2}-r\bar{b}_{t+1}}{rR}$
EBO3: 3-year forecasting horizon	$E_t\left[\tilde{x}^a_{t+1}\right]=f^a_{t+1}$ $V_t = b_t + \frac{f_{t+1}-rb_t}{R} + \frac{f_{t+2}-r\bar{b}_{t+1}}{R^2} + \frac{f_{t+3}-r\bar{b}_{t+2}}{rR^2}$
When non-zero RI growth is assumed	
EBO4: 1-year forecasting horizon	$E_t\left[\tilde{x}^a_{t+1}\right]=f^a_{t+1}$ $V_t = b_t + \frac{f_{t+1}-rb_t}{(r-g_r)}$
EBO5: 2-year forecasting horizon	$E_t\left[\tilde{x}^a_{t+1}\right]=f^a_{t+1}$ $V_t = b_t + \frac{f_{t+1}-rb_t}{R} + \frac{f_{t+2}-r\bar{b}_{t+1}}{(r-g_r)R}$
EBO6: 3-year forecasting horizon	$E_t\left[\tilde{x}^a_{t+1}\right]=f^a_{t+1}$ $V_t = b_t + \frac{f_{t+1}-rb_t}{R} + \frac{f_{t+2}-r\bar{b}_{t+1}}{R^2} + \frac{f_{t+3}-r\bar{b}_{t+2}}{(r-g_r)R^2}$

Note:

1) The models in Panel A (B) are based on the assumption of zero (non-zero) mean reverting process of RI and OI.
2) Book value is used as a scaling variable for the 'intercept-inclusive' LID model and its variants.
3) $\hat{\omega}_1$ ($\hat{\gamma}_1$) is RI (OI) persistence parameter, $\hat{\omega}'_0$ ($\hat{\gamma}'_0$) is scaled RI (OI) intercept parameter, and $\hat{\omega}^f_1$ ($\hat{\omega}'^f_0$) is firm-specific conditional RI persistence (intercept) parameter based on DHS's methodology. All LID parameters are year-specific (time subscript suppressed). V_t is intrinsic value at year t, b_t is book value at year t, x^a_t is residual income for year t, f^a_{t+1} is analyst-based RI forecasts for the next year, f_{t+i} is i-year ahead analysts' earnings forecasts, and $\bar{b}_{t+i}$ is i-year ahead book value estimates. R is 1 plus the discount rate (r), BG is 1 plus future book value growth rate, and g_r is future RI growth rate.
4) LID7 and LID8 are theoretically identical, but practically different. In LID7, $\hat{\gamma}_1$ is the estimated slope coefficient from $f^a_{t+1} = \gamma_0 + \gamma_1 lag(f^a_{t+1})$, because $v_t = f^a_{t+1}$ in this case.
5) In LID10, 13 and 14, $\hat{\omega}'_0$ for year t is the mean of book value-scaled RI using data up to year t (i.e., $\overline{(x^a_t/b_{t-1})}$). In LID 13, $\hat{\gamma}'_0$ for year t is $\overline{(f^a_{t+1}/b_{t-1}) - \hat{\omega}'_{0,t}(b_t/b_{t-1})}$. In LID14, $\hat{\gamma}'_0$ and $\hat{\gamma}_1$ are the estimated parameters of AR(1) OI regression where $v_t = f^a_{t+1} - \hat{\omega}'_{0,t}b_t$. In LID15, $\hat{\gamma}'_0$ for year t is $\overline{(f^a_{t+1}/b_{t-1}) - \hat{\omega}'_{0,t}(b_t/b_{t-1}) - \hat{\omega}_{1,t}(x^a_t/b_{t-1})}$.

Appendix 3.1: Derivation of the 'intercept-inclusive' LID model when regression variables are scaled

The two equations in Eq. 2, with the average future growth rate (*sg*) of the scaling variable, can be combined into one equation in order to express the future residual income generating process.

$$
\begin{array}{llllll}
E\left[x^a_{t+\tau}\right] = \omega_0' S_t & + \omega_1 x^a_t & & + v_t, & \text{if } \tau = 1 \\
\underbrace{\omega_0' SG^{\tau-1} S_t}_{(a)} & + \underbrace{\omega_1 E\left[x^a_{t+\tau-1}\right]}_{(b)} & + \underbrace{\gamma_0' SG^{\tau-2} S_t}_{(c)} & + \underbrace{\gamma_1 E\left[v_{t+\tau-2}\right]}_{(d)} & \text{if } \tau = 2,3,4,\cdots,\infty
\end{array}
$$

(Eq. 2a)

where S_t is a scaling variable and SG is 1 plus the average future growth rate (*sg*) of the scaling variable. Eq. 2a is a function of current scaling variable, current RI and current OI. Note that (*b*) includes lagged (*a*) term, lagged (*c*) term and lagged (*d*) term, and (*d*) includes lagged (*c*) term. The expression for the present value of expected future residual income implied by expression Eq. 2a comprises the following terms:

1. PV of S_t terms arising from the inclusion of ω_0' is the sum of (*1-i*) and (*1-ii*).

(*1-i*) PV of (*a*) series $= \dfrac{\omega_0'}{R - SG} S_t$

(*1-ii*) PV of S_t terms arising from the inclusion of ω_0' in (*b*)

$=$ PV of (*1-i*) in declining perpetuity with the growth rate of ($\omega_1 - 1$)

$$= \frac{\omega_1}{R - \omega_1} \cdot \frac{\omega_0'}{R - SG} S_t$$

$\therefore$ PV of S_t terms arising from the inclusion of $\omega_0' = \left[1 + \dfrac{\omega_1}{R - \omega_1}\right]\left[\dfrac{\omega_0'}{R - SG}\right] S_t$

2. PV of S_t terms arising from the inclusion of γ_0' is the sum of (*2-i*), (*2-ii*) and (*2-iii*).

(*2-i*) PV of (*c*) series $= \dfrac{\gamma_0'}{R(R - SG)} S_t$

(*2-ii*) PV of S_t terms arising from the inclusion of γ_0' in (*d*)

$=$ PV of (*2-i*) in declining perpetuity with the growth rate of ($\gamma_1 - 1$)

$$= \frac{\gamma_1}{R - \gamma_1} \cdot \frac{\gamma_0'}{R(R - SG)} S_t$$

(*2-iii*) PV of S_t terms arising from the inclusion of γ_0' in (*b*)

$=$ PV of the sum of (*2-i*) and (*2-ii*) in declining perpetuity with the growth rate of ($\omega_1 - 1$)

$$= \frac{\omega_1}{R - \omega_1} \cdot \left(1 + \frac{\gamma_1}{R - \gamma_1}\right) \cdot \frac{\gamma_0'}{R(R - SG)} S_t$$

Appendix 3.1 (continued)

$\therefore$ PV of S_t terms arising from the inclusion of γ'_0

$$= \left[1+\frac{\omega_1}{R-\omega_1}\right]\left[1+\frac{\gamma_1}{R-\gamma_1}\right]\left[\frac{\gamma'_0}{R(R-SG)}\right]S_t$$

3. PV of v_t terms is the sum of (*3-i*) and (*3-ii*).

(*3-i*) PV of v_t terms in (*d*) $= \dfrac{1}{R-\gamma_1}v_t$

(*3-ii*) PV of v_t terms in (*b*)

= PV of (*3-i*) in declining perpetuity with the growth rate of ($\omega_1 - 1$)

$$= \frac{\omega_1}{R-\omega_1}\cdot\frac{1}{R-\gamma_1}v_t$$

$$\therefore \text{PV of } v_t \text{ terms} = \left[1+\frac{\omega_1}{R-\omega_1}\right]\left[\frac{1}{R-\gamma_1}\right]v_t$$

4. PV of x_t^a terms is PV of x_t^a in declining perpetuity with the growth rate of ($\omega_1 - 1$).

$$\therefore \text{PV of } x_t^a \text{ terms} = \left[\frac{\omega_1}{R-\omega_1}\right]x_t^a$$

Collection of the four terms derived above gives:

$$V_t = b_t + \left[\frac{R\omega'_0}{(R-SG)(R-\omega_1)} + \frac{R\gamma'_0}{(R-SG)(R-\omega_1)(R-\gamma_1)}\right]S_t$$
$$+\frac{\omega_1}{R-\omega_1}x_t^a + \frac{R}{(R-\omega_1)(R-\gamma_1)}v_t$$

(Eq. 3)

Appendix 3.2: Rearrangement of Eq. 3 to isolate mean RI and OI terms

In this Appendix, I describe the link between the intercept-related (second) term in Eq. 3 and terms corresponding to mean values of scaled RI and OI. For this purpose, I assume that the ratio of the mean of scaled RI (OI) used as a dependent variable and the mean of scaled RI (OI) used as an explanatory variable is Y (Z).

$$Y = \overline{\left(\frac{x_{t+1}^a}{S_t}\right)} \Big/ \overline{\left(\frac{x_t^a}{S_t}\right)} \qquad \text{(Eq. A3.2.1)}$$

$$Z = \overline{\left(\frac{v_{t+1}}{S_t}\right)} \Big/ \overline{\left(\frac{v_t}{S_t}\right)} \qquad \text{(Eq. A3.2.2)}$$

where the bar denotes mean.

From the second line of the generating process in Eq. 1,

$$\overline{\left(\frac{v_{t+1}}{S_t}\right)} = \gamma_0' + \gamma_1 \overline{\left(\frac{v_t}{S_t}\right)} \qquad \text{(Eq. A3.2.3)}$$

Substitution of Eq. A3.2.2 gives the following expression corresponding to the mean value of OI, as scaled by contemporaneous scaling variable:

$$\overline{\left(\frac{v_t}{S_t}\right)} = \frac{\gamma_0'}{Z - \gamma_1} \qquad \text{(Eq. A3.2.4)}$$

This corresponds to the mean of the scaled difference between 'full information' analyst-based RI forecasts and forecasts based solely on a univariate time series model of RI. From the first line of Eq. 1,

$$\overline{\left(\frac{x_{t+1}^a}{S_t}\right)} = \omega_0' + \omega_1 \overline{\left(\frac{x_t^a}{S_t}\right)} + \overline{\left(\frac{v_t}{S_t}\right)} \qquad \text{(Eq. A3.2.5)}$$

Substitution of Eq. A3.2.1 and Eq. A3.2.4 gives

$$\overline{\left(\frac{x_{t+1}^a}{S_t}\right)} = \frac{\left[\omega_0' + \dfrac{\gamma_0'}{Z - \gamma_1}\right]}{Y - \omega_1} \cdot Y \qquad \text{(Eq. A3.2.6)}$$

which is a term corresponding to the mean 'spread', and

$$\overline{\left(\frac{x_t^a}{S_t}\right)} = \frac{\left[\omega_0' + \dfrac{\gamma_0'}{Z - \gamma_1}\right]}{Y - \omega_1} \qquad \text{(Eq. A3.2.7)}$$

Appendix 3.2 (continued)

The following terms from Eq. 3

$$\frac{R\omega_0'}{(R-SG)(R-\omega_1)},$$
$$\frac{R\gamma_0'}{(R-SG)(R-\omega_1)(R-\gamma_1)},$$

can respectively be expanded to give

$$\frac{\omega_0'Y}{(R-SG)(Y-\omega_1)}+\frac{-\omega_0'\omega_1}{(R-\omega_1)(Y-\omega_1)}\cdot\frac{R-Y}{R-SG},$$
$$\frac{\gamma_0'Y}{(R-SG)(Y-\omega_1)(Z-\gamma_1)}+\frac{-\gamma_0'\omega_1}{(R-\omega_1)(Y-\omega_1)(Z-\gamma_1)}\cdot\frac{R-Y}{R-SG}+\frac{-\gamma_0'R}{(R-\omega_1)(R-\gamma_1)(Z-\gamma_1)}\cdot\frac{R-Z}{R-SG}$$

Substitution of these expanded terms into Eq. 3 gives Eq. A3.2.8

$$V_t=b_t+\frac{1}{R-SG}\left[\left(\frac{\omega_0'+\dfrac{\gamma_0'}{Z-\gamma_1}}{Y-\omega_1}\right)\cdot Y\cdot S_t\right]+\frac{\omega_1}{R-\omega_1}\left[x_t^a-\frac{R-Y}{R-SG}\cdot\left(\frac{\omega_0'+\dfrac{\gamma_0'}{Z-\gamma_1}}{Y-\omega_1}\right)\cdot S_t\right]$$
$$+\frac{R}{(R-\omega_1)(R-\gamma_1)}\left[v_t-\frac{R-Z}{R-SG}\cdot\frac{\gamma_0'}{Z-\gamma_1}\cdot S_t\right]$$

(Eq. A3.2.8)

It is convenient to make the simplifying assumption that SG can be expressed as the ratio of the mean value of RI (OI) as scaled by lagged scaling variable and the mean value of RI (OI) as scaled by contemporaneous scaling variable. That is,

$$SG=\overline{(x_t^a/S_{t-1})}/\overline{(x_t^a/S_t)}\approx\overline{(x_{t+1}^a/S_t)}/\overline{(x_t^a/S_t)}=Y$$
$$=\overline{(v_t/S_{t-1})}/\overline{(v_t/S_t)}\approx\overline{(v_{t+1}/S_t)}/\overline{(v_t/S_t)}=Z$$

(Eq. A3.2.9)

Thus, Eq. A3.2.8 can be simplified into Eq. 3.2.10.

$$V_t=b_t+\frac{1}{R-SG}(SMRI_D\cdot S_t)+\frac{\omega_1}{R-\omega_1}\left[x_t^a-(SMRI_E\cdot S_t)\right]$$
$$+\frac{R}{(R-\omega_1)(R-\gamma_1)}\left[v_t-(SMOI_E\cdot S_t)\right]$$

(Eq. A3.2.10)

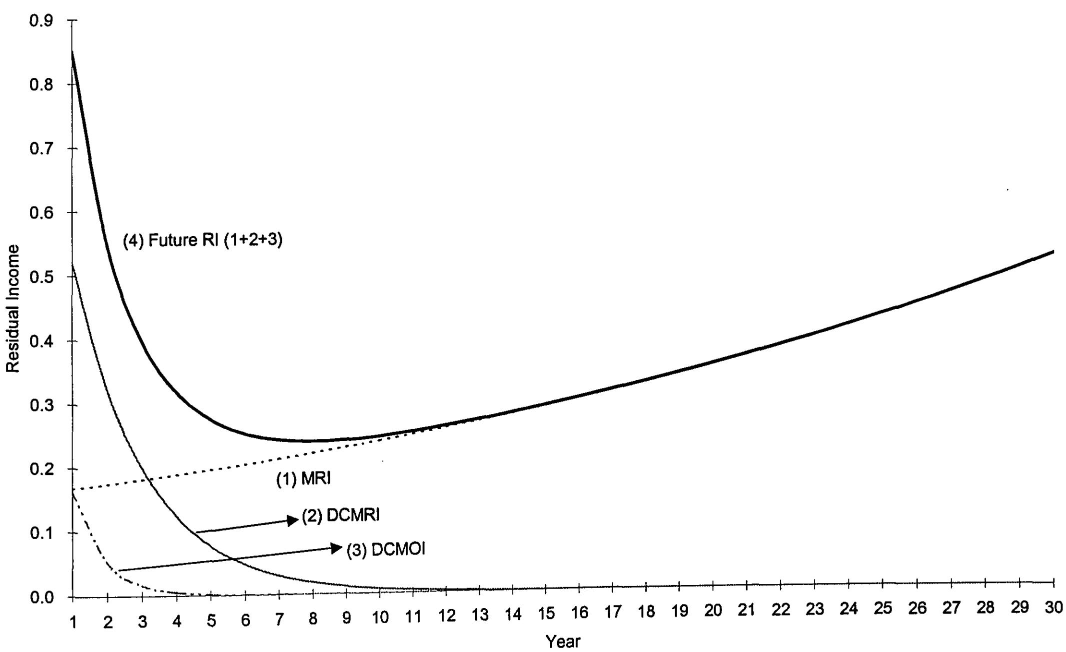
Appendix 3.2 (continued)

where $SMRI_E = \overline{\left(\frac{x_t^a}{S_t}\right)} = \frac{\omega_0'(SG-\gamma_1)+\gamma_0'}{(SG-\omega_1)(SG-\gamma_1)}$, $SMRI_D = \overline{\left(\frac{x_{t+1}^a}{S_t}\right)} = SMRI_E \cdot SG$,

$SMOI_E = \overline{\left(\frac{v_t}{S_t}\right)} = \frac{\gamma_0'}{SG-\gamma_1}$, $Y = \overline{\left(\frac{x_{t+1}^a}{S_t}\right)} \Big/ \overline{\left(\frac{x_t^a}{S_t}\right)} = SG$, $Z = \overline{\left(\frac{v_{t+1}}{S_t}\right)} \Big/ \overline{\left(\frac{v_t}{S_t}\right)} = SG$, and bar denotes mean.

In Eq. A3.2.10, the second term corresponds to the mean of scaled x_{t+1}^a, multiplied by the current scaling variable and capitalised (at R – SG) as a growing perpetuity. The third term corresponds to the current deviation of RI from the product of (i) the mean value of RI as scaled by contemporaneous scaling variable and (ii) current scaling variable, all capitalised as a declining perpetuity (at $\omega_1/(R-\omega_1)$). The fourth term corresponds to the current deviation of OI from the product of (i) the mean value of OI as scaled by contemporaneous scaling variable and (ii) current scaling variable, all capitalised as a declining perpetuity of declining perpetuities (at $R/(R-\omega_1)(R-\gamma_1)$). Since the third and the fourth terms converge to zero, total future RI streams are reverting to the growing product of the mean of scaled x_{t+1}^a and current scaling variable (i.e., $SG^{i-1} \cdot SMRI_D \cdot S_t$ where $i = 1,2,3,\cdots$). The below figure graphically illustrates an example about where future RI streams, when regression variables are scaled, asymptote to.

$\omega_0 = 0.02$, $\omega_1 = 0.62$, $\gamma_0 = 0.01$, $\gamma_1 = 0.32$, $\mathrm{R} = 1.12$, $x_t^a = 1$, $v_t = 0.1$, $\mathrm{S_t} = 2$, $SG = 1.04$



Appendix 3.2 (continued)

Note:

(1) The product of the mean of scaled x^a_{t+1} (*SMRI_D*) and current scaling variable for year *t+i* is

$$MRI_{t+i} = SG^{i-1} \cdot SMRI_D \cdot S_t \text{, where } SMRI_D = \overline{\left(\frac{x^a_{t+1}}{S_t}\right)}$$

(2) The difference between current RI and the product of the mean of scaled x^a_t (*SMRI_E*) and current scaling variable for year *t+i* is

$$DCMRI_{t+i} = \omega_1^i (x^a_t - SMRI_E \cdot S_t) \text{, where } SMRI_E = \overline{\left(\frac{x^a_t}{S_t}\right)}$$

(3) The capitalised difference between current OI and the product of the mean of scaled v_t (*SMOI_E*) and current scaling variable for year *t+i* is

$$DCMOI_{t+i} = \gamma_1^i \left[\left(\frac{R}{R-\omega_1}\right)\left(\frac{1}{\gamma_1}\right)\right](v_t - SMOI_E \cdot S_t) \text{, where } SMOI_E = \overline{\left(\frac{v_t}{S_t}\right)}$$

(4) Future RI for year *t+i* is the sum of MRI_{t+i}, $DCMRI_{t+i}$ and $DCMOI_{t+i}$.

Appendix 3.3: The 'intercept-inclusive' LID model when regression variables are unscaled

The 'intercept-inclusive' LID model when regression variables are *unscaled* is a special case of Eq. 3. That is, the scaling variable at time *t* is one and the annual growth rate of the scaling variable (*sg*) is zero (i.e., *SG* = 1) in Eq. 3. From the linear information dynamics in Eq. A3.3.1 and the similar derivation procedure in Appendix 3.1, the 'intercept-inclusive' LID model when regression variables are *unscaled* can be easily derived to Eq. A3.3.2. This model can be used for firm-by-firm parameter estimation and equity valuation in practice.

$$\begin{aligned}\tilde{x}^a_{t+1} &= \omega_0 + \omega_1 x^a_t + v_t + \tilde{\varepsilon}_{1,t+1}\\ \tilde{v}_{t+1} &= \gamma_0 + \gamma_1 v_t + \tilde{\varepsilon}_{2,t+1}\end{aligned} \qquad \text{(Eq. A3.3.1)}$$

$$\begin{aligned}V_t = b_t &+ \left[\frac{R\omega_0}{(R-1)(R-\omega_1)} + \frac{R\gamma_0}{(R-1)(R-\omega_1)(R-\gamma_1)}\right]\\ &+ \frac{\omega_1}{R-\omega_1}x^a_t + \frac{R}{(R-\omega_1)(R-\gamma_1)}v_t\end{aligned} \qquad \text{(Eq. A3.3.2)}$$

On the other hand, mean residual income (*MRI*) and mean 'other information' (*MOI*) can be approximately derived as follows. Here, if we assume non-zero ω_0 and γ_0, we can see that *MRI* and *MOI* are non-zero. Actually, residual income and 'other information' asymptote to *MRI* and *MOI*, respectively.

$\omega_0 = MRI - \omega_1 MRI - MOI$ .... (i)

$\gamma_0 = MOI - \gamma_1 MOI$ .... (ii)

where *MRI* and *MOI* are mean residual income and mean 'other information', respectively.

From (ii), $MOI = \dfrac{\gamma_0}{1-\gamma_1}$ (Eq. A3.3.3)

and from (i) and *MOI*, $MRI = \dfrac{\omega_0 + MOI}{1-\omega_1} = \dfrac{\omega_0(1-\gamma_1)+\gamma_0}{(1-\omega_1)(1-\gamma_1)}$ (Eq. A3.3.4)

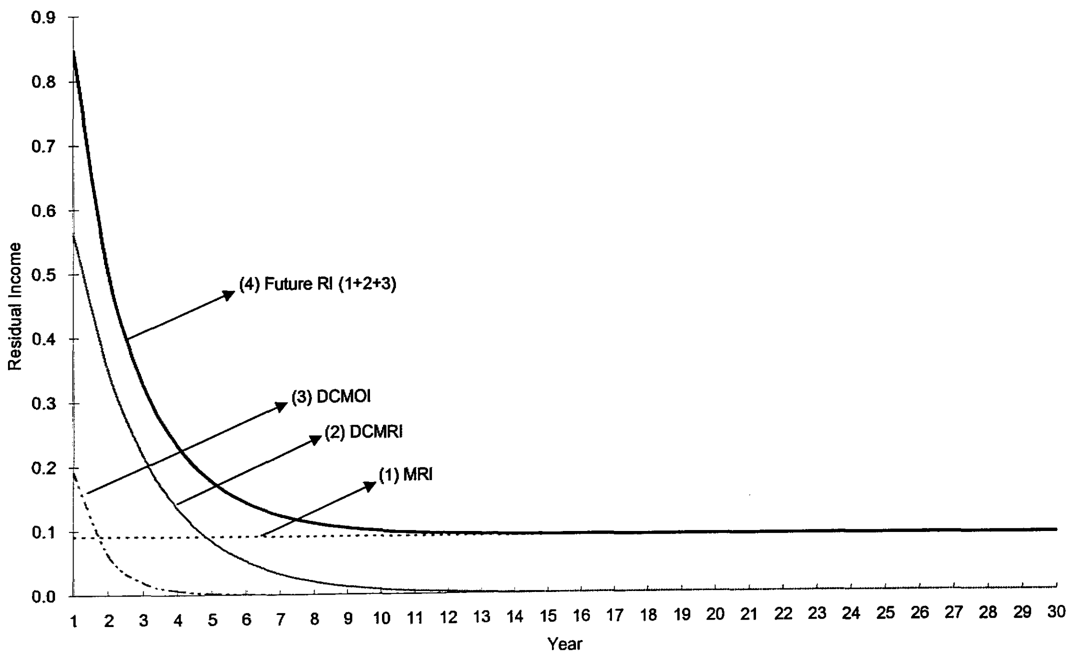
As we can see in Eq. A3.2.2, the pricing model now has a constant term in the square bracket, which composes 4 parameters and the discount rate. The first part of this constant term is the effect of non-zero ω_0 on the value estimates, while the second one is the additional effect from the incorporation of non-zero γ_0. That is, the constant term in the square bracket is the additional effect on firm's value from the incorporation of intercept terms ω_0 and γ_0, given the data for OI (v). Since *MRI* and *MOI* are approximately represented by Eq. A3.2.4 and Eq. A3.2.3, respectively, Eq. A3.2.2 can be restated as Eq. A3.2.5 below. Eq. A3.2.5 implies that firm value is the sum of current book value, the present value (PV) of mean RI in perpetuity, the PV of the difference between current and mean RI as a declining perpetuity with negative growth rate of ($\omega_1 - 1$), and the PV of the capitalized difference between current and mean OI (i.e., $\left(\dfrac{R}{R-\omega_1} \times \dfrac{1}{\gamma_1}\right)(v_t - MOI)$) in declining perpetuity with negative growth rate of (γ_1 -1):

Appendix 3.3 (continued)

$$V_t = b_t + \frac{MRI}{r} + \frac{\omega_1}{R-\omega_1}(x_t^a - MRI) + \frac{R}{(R-\omega_1)(R-\gamma_1)}(v_t - MOI) \qquad \text{(Eq. A3.2.5)}$$

The RI streams corresponding to the last three terms of the right-hand side of the pricing model Eq. A3.2.5 show where the total future RI streams asymptote. The figure below shows it graphically. A firm generates *MRI* every year in the future, and the difference between current and mean RI asymptotes to zero as time goes on. The capitalized difference between current and mean OI also converges to zero. Taken together, the total future RI streams asymptote to *MRI*.

$\omega_0 = 0.02,\ \omega_1 = 0.62,\ \gamma_0 = 0.01,\ \gamma_1 = 0.32, R = 1.12,\ x_t^a = 1,\ v_t = 0.1$



Note:

(1) *MRI* is mean residual income, and defined as

$$MRI = \frac{\omega_0(1-\gamma_1)+\gamma_0}{(1-\omega_1)(1-\gamma_1)}$$

(2) *i*-year ahead difference between current and mean RI ($DCMRI_{t+i}$) is defined as

$$DCMRI_{t+i} = \omega_1^i(x_t^a - MRI)$$

(3) *i*-year ahead capitalized difference between current and mean OI ($DCMOI_{t+i}$) is defined as

$$DCMOI_{t+i} = \gamma_1^i\left[\left(\frac{R}{R-\omega_1}\right)\left(\frac{1}{\gamma_1}\right)\right](v_t - MOI)$$

(4) Future RI for year $t+i$ is the sum of MRI, $DCMRI_{t+i}$ and $DCMOI_{t+i}$.

Appendix 3.3 (continued)

< Proof of the equality between Eq. A3.3.2 and Eq. A3.3.5 >

$$
\begin{aligned}
&\frac{MRI}{r} - \frac{\omega_1}{R-\omega_1} MRI - \frac{R}{(R-\omega_1)(R-\gamma_1)} MOI \\
&= \frac{\omega_0(1-\gamma_1)+\gamma_0}{(R-1)(1-\omega_1)(1-\gamma_1)} - \frac{\omega_0\omega_1(1-\gamma_1)+\omega_1\gamma_0}{(R-\omega_1)(1-\omega_1)(1-\gamma_1)} - \frac{R\gamma_0}{(R-\omega_1)(R-\gamma_1)(1-\gamma_1)} \\
&= \frac{(\omega_0-\omega_0\gamma_1+\gamma_0)(R-\omega_1)(R-\gamma_1)-(\omega_0\omega_1-\omega_0\omega_1\gamma_1+\omega_1\gamma_0)(R-1)(R-\gamma_1)-R\gamma_0(R-1)(1-\omega_1)}{(R-1)(R-\omega_1)(R-\gamma_1)(1-\omega_1)(1-\gamma_1)} \\
&= \frac{(\omega_0-\omega_0\gamma_1+\gamma_0)(R-\omega_1)(R-\gamma_1)-(\omega_0\omega_1-\omega_0\omega_1\gamma_1+\omega_1\gamma_0)(R-1)(R-\gamma_1)-R\gamma_0(R-\gamma_1)(1-\omega_1)}{(R-1)(R-\omega_1)(R-\gamma_1)(1-\omega_1)(1-\gamma_1)} \\
&+ \frac{R\gamma_0(R-\gamma_1)(1-\omega_1)-R\gamma_0(R-1)(1-\omega_1)}{(R-1)(R-\omega_1)(R-\gamma_1)(1-\omega_1)(1-\gamma_1)} \\
&= \frac{R\omega_0(R-\gamma_1)(1-\omega_1)(1-\gamma_1)}{(R-1)(R-\omega_1)(R-\gamma_1)(1-\omega_1)(1-\gamma_1)} + \frac{R\gamma_0(1-\omega_1)(1-\gamma_1)}{(R-1)(R-\omega_1)(R-\gamma_1)(1-\omega_1)(1-\gamma_1)} \\
&= \frac{R\omega_0(R-\gamma_1)+R\gamma_0}{(R-1)(R-\omega_1)(R-\gamma_1)} \\
&= \frac{R\omega_0}{(R-1)(R-\omega_1)} + \frac{R\gamma_0}{(R-1)(R-\omega_1)(R-\gamma_1)}
\end{aligned}
$$

CHAPTER 4. RELIABILITY OF THE 'INTERCEPT-INCLUSIVE' LINEAR INFOMRATION DYNAMICS (LID) MODEL: U.S. EVIDENCE

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CHAPTER 4

RELIABILITY OF THE 'INTERCEPT-INCLUSIVE' LINEAR INFORMATION DYNAMICS (LID) MODEL: U.S. EVIDENCE

4.1. Introduction and Motivation

Recent years have seen the latest rediscovery of a theoretical valuation relationship which expresses the economic value of a business as the sum of its accounting book value and the present value of all of its expected future residual incomes. This most recent rediscovery, often attributed to Ohlson (1995), follows previous rediscoveries by Preinreich (1938) and Peasnell (1982) and has prompted an explosion of interest in the role of residual income (RI) in valuation. Variants of RI are now regularly promoted by management consultants as aids to business valuation and 'value-based management'.[32]

A prominent strand of the academic literature on RI-based valuation is exemplified by the theoretical work of Ohlson (1995, 2001) and Feltham & Ohlson (1995, 1996). This combines the RI-based valuation relationship with an assumed generating process for RI, sometimes termed a 'linear information model' (LIM) (Feltham & Ohlson, 1995). LIMs (LIM is termed as LID (linear information dynamics) models through this thesis) project future RI by exploiting time series structure in RI in combination with exogenous 'other information (OI)' reflected in the accounting system with a lag.[33] Some

[32] Commercial versions of RI are Economic Value Added (EVA) by Stern Stewart & Co., Cash-Flow Return On Investment (CFROI) by Boston Consulting Group's HOLT Value Associates, Discounted Cash-flow Analysis (DCA) by Alcar, discounted Economic Profits (EP) by Marakon Associates, and Economic Value Management (EVM) by KPMG Peat Marwick (Biddle *et al.*, 1997).

[33] 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).

variants also include other accounting variables, such as book value, within the process that generates RI expectations. The intuition is fairly straightforward. The forecasting of RIs for the purpose of valuing a business is likely to involve the analysis of current and past accounting numbers, together with the analysis of other sources of information.

Dechow, Hutton & Sloan (1999) (hereinafter, DHS) devise a novel approach to application of the Ohlson (1995) 'other information'-inclusive linear information dynamics (hereinafter, LID) approach to RI-based valuation, and apply it to U.S. data. DHS compare LID-based value estimates, along with value estimates derived from simpler earnings-based valuation procedures, with observed share prices. A striking feature of DHS's results is that the OI-inclusive valuation approach undervalues shares by an average of about 26%.[34] This undervaluation is larger than that from a simple valuation model involving the capitalisation of one-year-ahead earnings forecasts. The OI-inclusive LID approach is also outperformed by this simple procedure on the criterion of mean absolute forecast error (accuracy). DHS's results have raised concerns about the reliability of LID-based valuation models.

This chapter is motivated by this substantial negative bias, reported by DHS, in value estimates from an OI-inclusive application to U.S. data of the LID approach to RI-based valuation. It explores one potential source of bias in the LID-based value estimates produced by approaches such as that used by DHS. DHS's LID-based value estimates are constructed in accordance with the Ohlson (1995) LID. The Ohlson (1995) LID is

[34] Myers (1999b) uses an OI-inclusive LID-based approach where order backlog is used to proxy for OI, and reports that the median ratio of value estimate to observed price is 0.648.

parameterised with no intercept parameters, implying that RI is expected to mean revert to zero. Therefore, DHS's value estimates do not reflect the intercept terms from their RI and OI generating process. Disregard for such intercept terms causes value estimates to be based on the possibly false implicit assumption that the mean of expected future scaled RI is zero. Casual observation of the persistent deviations from unity in market-to-book ratios suggests that it may be inappropriate to make such an implicit assumption. This chapter explores the impact of augmenting the procedure used by DHS such that value estimates impound the information in intercept terms from the RI and OI generating process. The analysis suggests that small LID intercept terms, such as those reported by DHS, could give rise to theoretical valuation effects of a similar order of magnitude to the bias reported by DHS. Using U.S. data similar to that used by DHS, this study illustrates empirically the impact of such terms. The evidence confirms that the impact can be comparable in size to, or larger than, the substantial valuation bias reported by DHS. Importantly, for those interested in applying LID model in practical accounting-based equity valuation, the magnitude of the intercept-related valuation component is highly sensitive to the assumed cost of capital and the expected rate of growth in the scaling variable.

The remainder of the chapter is structured as follows. Section 4.2 describes empirical methodology, data and descriptive statistics and Section 4.3 shows empirical results about the magnitude of the impact of the LID-based intercept terms in valuation models. Section 4.4 contains concluding remarks.

4.2. Empirical methodology and data

4.2.1. Methodology

DHS base their approach on Ohlson's (1995) LID-based valuation approach, and do not incorporate into their value estimates the intercept terms from their LID generating process for RI expectations. Disregard for such intercept terms would cause the omission from value estimates of the effect of non-zero means in expected RI, and could contribute to bias in value estimates. The possibility that omitted intercept terms contribute to bias in LID-based value estimates motivates me to augment the DHS approach by incorporating the intercept terms in LID and scaling data by book value. Scaling by book value rather than by stock price adopted in DHS is to avoid circularity, i.e., making value estimates a function of stock price. The 'intercept-inclusive' LID-based valuation formula is derived as follows (see Chapter 3 for details about the derivation of the 'intercept-inclusive' LID model):

$$V_t = b_t + \beta_1 x_t^a + \beta_2 v_t + (\beta_3 + \beta_4) b_t \qquad \text{(Eq. 1)}$$

where V_t is the value of equity at time t, b_t is the book value of equity at time t, and x_t^a and v_t are RI and OI at time t, respectively. $\beta_1 = \frac{\omega_1}{R-\omega_1}$, $\beta_2 = \frac{R}{(R-\omega_1)(R-\gamma_1)}$, $\beta_3 = \frac{R\omega_0'}{(R-BG)(R-\omega_1)}$ and $\beta_4 = \frac{R\gamma_0'}{(R-BG)(R-\omega_1)(R-\gamma_1)}$. ω_0' and γ_0' are the LID intercepts corresponding to AR(1) RI and OI equations, respectively (prime indicates parameters based on scaled data: see below for the parameter estimation procedure), and

ω_1 and γ_1 are the RI and OI persistence parameters, respectively. R is one plus the discount rate and BG is one plus the rate of growth in book value.

To enable comparison of my results about the 'intercept-inclusive' LID approach with the intercept-exclusive LID (the Ohlson LID) approach, as employed by DHS, I also construct value estimates by ignoring the LID intercept parameters and redefining OI as in DHS, but using book value as the scaling variable in estimation. Also, in order to facilitate comparison with DHS's results, I construct an additional value estimate in which the one-year ahead earnings forecast is capitalized as a flat perpetuity. Note that the Ohlson LID model is a special case of Eq. 1: where $\omega_0' = \gamma_0' = 0$. The model that capitalizes one-year ahead earnings forecasts as a flat perpetuity is also a special case of Eq. 1: where $(\omega_0' = \gamma_0' = \omega_1 = 0, \gamma_1 = 1)$ or $(\omega_0' = \gamma_0' = \gamma_1 = 0, \omega_1 = 1)$. Because this model is the same as the 1-year forecast horizon EBO model with the assumption of zero expected future RI growth, I term this model as the 1-year horizon EBO model. The Ohlson LID model and the 1-year horizon EBO model are as follows:

$$V_t = b_t + \beta_1 x_t^a + \beta_2 v_t \qquad \text{(Eq. 2)}$$

$$V_t = \frac{1}{(R-1)} f_{t+1} \qquad \text{(Eq. 3)}$$

where f_{t+1} is the time t analysts' earnings forecast for time t+1.

Similar to DHS, the LID parameters are estimated using the following AR(1) RI and OI generating (pooled time-series cross-sectional) regression equations:

$$\frac{x_s^a}{b_{s-1}} = \hat{\omega}'_{0,t} + \hat{\omega}_{1,t} \frac{x_{s-1}^a}{b_{s-1}} + \hat{e}_{1,s} \qquad \text{(Eq. 4)}$$

$$\frac{v_s}{b_{s-1}} = \hat{\gamma}'_{0,t} + \hat{\gamma}_{1,t} \frac{v_{s-1}}{b_{s-1}} + \hat{e}_{2,s} \qquad \text{(Eq. 5)}$$

where the subscript s is a time index ranging from the first year of available data to year t, $\hat{\omega}'_{0,t}$, $\hat{\omega}_{1,t}$, $\hat{\gamma}'_{0,t}$ and $\hat{\gamma}_{1,t}$ are year-specific parameter estimates, and $\hat{e}_1$ and $\hat{e}_2$ are random error terms. OI at time t (v_t) is defined as the full information analyst-based RI forecast ($f_{t+1}^a = f_{t+1} - (R-1)b_t$) less the implied conditional expectation of RI based on parameter estimates from the univariate model described in Eq. 4. Note that v_t in the 'intercept-inclusive' LID approach ($f_{t+1}^a - \hat{\omega}'_{0,t}b_t - \hat{\omega}_{1,t}x_t^a$) is different from v_t in the Ohlson LID approach ($f_{t+1}^a - \hat{\omega}_{1,t}x_t^a$), so the estimated OI parameters between two approaches are different.

In this study, Eq. 4 is estimated for each year (t) from 1975 to 1995, using available RI data going back to 1951.[35] The $\hat{\omega}'_{0,t}$ and $\hat{\omega}_{1,t}$ parameter estimates for 1975 and 1976 are used only for estimating OI, while those for 1977 to 1995 are used both for estimating OI and as direct inputs to the value estimates. The $\hat{\gamma}'_{0,t}$ and $\hat{\gamma}_{1,t}$ parameter estimates are estimated based on Eq. 5 for each year (t) from 1977 to 1995, using all available OI data from 1975 to time t. Using these parameter estimates, value estimates based on Eq. 1 and Eq. 2 are then obtained for each firm at each valuation date (t) from 1977 to 1995. I

[35] As in DHS, the range of years for which Eq. 1 is estimated is determined by the availability of earnings forecast data for use in constructing OI estimates.

obtain value estimates for a range of different assumed growth parameter values, and for a range of different assumed costs of equity (see the next section for details).

For each class of value estimate, I calculate scaled differences between the value estimates and the corresponding observed stock prices three months after the balance sheet date ($P_t^{c,3}$), as follows:

$$FE_t = \frac{V_t - P_t^{c,3}}{P_t^{c,3}} \qquad \text{(Eq. 6)}$$

$$AFE_t = |FE_t| \qquad \text{(Eq. 7)}$$

The signed differences (denoted as *FE*) as in Eq. 6 are used to measure bias in the value estimates. The absolute differences (denoted as *AFE*) as in Eq. 7 are used to measure accuracy in the value estimates.

4.2.2. Data

The empirical analysis employs U.S. data that is similar to that used by DHS, and that is drawn from a similar period. The data and the sources are detailed below.

Earnings per share and book value of equity per share

These data are collected from COMPUSTAT from 1950 to 1995. The earnings item is earnings before extraordinary items and discontinued operations available for common stockholders. The book value item is book value of common equity as adjusted by the preferred stockholders' legal claims against the firm. The accounting data relating to the periods prior to 1976 are used only for the purpose of estimating the LID parameters.

Data for 1976 to 1995 inclusive are used both for estimating LID parameters and as the basis for accounting inputs to the value estimates (RI and book value). Market prices of equity at balance sheet dates, to be used only for scaling purposes in the preliminary application of alternative LID procedures to price-scaled data, are also collected from COMPUSTAT.

Consensus analysts' forecasts of earnings per share

These are collected from I/B/E/S. Forecasts are available from January 1976, in respect of accounting periods ending in or after 1975, and forecasts issued up to and including 1995 are collected. Forecasts in respect of 1975, 1976 and 1977 are used exclusively for the purpose of estimating LID parameters. Forecasts in respect of 1978 and subsequent periods up to 1996 are used both for the purpose of estimating LID parameters and for the purpose of constructing value estimates.[36] As the measure of the period t forecast of the period t+1 earnings per share, I use the median forecast for period t+1 as at the first month after the I/B/E/S-reported period t earnings announcement.[37]

Share prices

In computing the *FE* and *AFE* measures, value estimates are compared with share prices at three months after the balance sheet date. Share price data are collected from CRSP from 1977 to 1995.[38]

[36] Analyst's forecasts made in 1977 (1995) in respect of 1978 (1996) are matched with RI realisations for 1977 (1995) for the purpose of estimating OI at 1977 (1995).
[37] The use of mean forecasts rather than median forecasts has no material effect on the results.
[38] In a preliminary test reported below, I follow DHS in constructing value estimates on the basis of parameters derived from data scaled by stock price at the fiscal year end. For the scaling purpose, I use fiscal year end stock prices provided by COMPUSTAT.

Cost of equity

For some versions of the tests, I assume a constant cost of equity capital, as DHS had done. I report results for three assumed values for the cost of equity: 10%, 12% and 14%. However, in another version, I allow the cost of equity capital to fluctuate year-by-year. I achieve this by assuming that, for each calendar year, the cost of equity capital is cross-sectionally constant and equal to the average risk-free rate for the calendar year plus an assumed constant market risk premium of 5%. The average risk-free rates are constructed from monthly observations of U.S. Treasury Bond yields for maturities over 10 years, collected from DATASTREAM. The average of the year-specific cost of equity estimates from 1976 to 1995 is approximately 14%, and ranges from 11.5% (1993) to 17.9% (1981).

Growth

Four values are assumed for the growth parameter, *SG*: 1.00, 1.02, 1.04 and 1.06 (i.e., assumed growth of zero, 2%, 4% and 6%, respectively). *SG* corresponds to the expected stock price growth (*PG*) when stock price is used as a scaling variable, while it corresponds to the expected book value growth (*BG*) when book value is used as a scaling variable. Note that the annual growth in aggregate book value in my data from 1976 to 1995 averaged 3.2%, implying an average growth parameter over the period of 1.032.[39]

[39] In arriving at this figure, I compare the aggregate book value for all observations for which a corresponding lagged book value is available with the corresponding aggregate lagged book value.

The data available from COMPUSTAT, CRSP and I/B/E/S are merged. Details of available data for firm-years from 1950 to 1995, and of the parts of this data used in the various stages of the analysis, are summarised in Table 4.1. Accounting data for a total of 148,712 firm-years for 1950 to 1995 are available from COMPUSTAT, after elimination of firm-years for which book value is negative. Some observations are lost due to the need to use lagged book value in constructing RI data, leaving 130,359 observations that could be used in LID parameter estimation. The accounting items that are input into the value estimates are drawn entirely from data from 1976-1995. The number of observations for periods from 1976 to 1995 for which analyst earnings forecast data from I/B/E/S and price data from CRSP are also available is 50,679. Of these observations, 9,382 are lost due to lack of lagged book value data, required in the construction of RI. This left 41,297 observations that are used in constructing value estimates for periods from 1977 to 1995.

Table 4.2 provides descriptive statistics on various scaled variables. Panel A gives descriptive statistics on the book-to-price ratio, the earnings-to-price ratio, earnings scaled by lagged book value and RI scaled by lagged book value for data from 1950-1995, which are used in arriving at LID parameter estimates. Panel B gives statistics for data from the sub-period 1976-1995, from which value estimates are constructed, including analyst-based RI forecasts (scaled by book value) and OI estimates (scaled by book value). Differences between the median and the mean of some variables indicate the existence of potentially influential outliers. In order to limit the impact of outliers, I delete from the RI and OI data used for estimation of the LID parameters the 1% most extreme observations. However, I retain all such outliers when constructing value estimates, and do not delete any of extreme value estimates. Supplementary tests reveal that the relative reliability of 3 competing models – the 'intercept-inclusive' LID model, the Ohlson LID model and the 1-year forecast horizon EBO model with no RI growth – are not sensitive to the method of dealing with outliers.

Table 4.2 suggests that the intercept parameters are likely to be important in LID-based valuation. The mean (median) value of scaled RI for 1951-1995, as reported in Panel A, is -4.6% (-1.5%) and both statistics are significantly different from zero at the 1% level. Since these statistics relate to the data used in estimating the $\omega_{0,t}$ and $\omega_{1,t}$ parameters, estimates of $\omega_{0,t}$ are likely to be negative.[40] Also, the mean (median) value of scaled OI for 1977-1995 is 13.8% (3.1%), and both statistics are significantly different from zero at the 1% level. Since these statistics relate to the data used in estimating the $\gamma_{0,t}$ and $\gamma_{1,t}$ parameters, estimates of $\gamma_{0,t}$ are likely to be positive.[41] The positive mean and median of OI suggest that analyst-based forecasts of scaled RI are higher on average

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[40] From Eq. 4, $\overline{\left(x_s^a/b_{s-1}\right)} = \omega_{0,t} + \omega_{1,t}\overline{\left(x_{s-1}^a/b_{s-1}\right)}$. Define g_t^{RI} to be $g_t^{RI} = \overline{\left(x_s^a/b_{s-1}\right)}/\overline{\left(x_s^a/b_s\right)} \approx \overline{\left(x_s^a/b_{s-1}\right)}/\overline{\left(x_{s-1}^a/b_{s-1}\right)}$, where the bar denotes 'mean', and g_t^{RI} is a measure of one plus the book value growth rate over the parameter estimation period, as implied by the scaled RI series. Rearranging the first expression with g_t^{RI} gives $\overline{\left(x_s^a/b_{s-1}\right)} \approx \omega_{0,t} + \left(\omega_{1,t}/g_t^{RI}\right)\overline{\left(x_s^a/b_{s-1}\right)} \approx g_t^{RI}\omega_{0,t}/(g_t^{RI} - \omega_{1,t})$. g_t^{RI} would normally be expected to exceed one. On the basis of evidence reported by DHS and in this study, $\omega_{1,t}$ would normally be expected to be less than one. Therefore, the sign of $\omega_{0,t}$ is likely to the same as that of the mean of scaled RI.

[41] As in footnote 40 for RI, from Eq. 5, $\overline{\left(v_s/b_{s-1}\right)} = \gamma_{0,t} + \gamma_{1,t}\overline{\left(v_{s-1}/b_{s-1}\right)}$. Define g_t^{OI} to be $g_t^{OI} = \overline{\left(v_s/b_{s-1}\right)}/\overline{\left(v_s/b_s\right)} \approx \overline{\left(v_s/b_{s-1}\right)}/\overline{\left(v_{s-1}/b_{s-1}\right)}$, where the bar denotes 'mean', and g_t^{OI} is a measure of one plus the book value growth rate over the parameter estimation period, as implied by the scaled OI series. Rearranging the first expression with g_t^{OI} gives $\overline{\left(v_s/b_{s-1}\right)} \approx \gamma_{0,t} + \left(\gamma_{1,t}/g_t^{OI}\right)\overline{\left(v_s/b_{s-1}\right)} \approx g_t^{OI}\gamma_{0,t}/(g_t^{OI} - \gamma_{1,t})$. g_t^{OI} would normally be expected to exceed one. On the basis of evidence reported by DHS and in this study, $\gamma_{1,t}$ would normally be expected to be less than one. Therefore, the sign of $\gamma_{0,t}$ is likely to the same as that of the mean of scaled OI.

than forecasts based on the univariate model Eq. 4. This is confirmed elsewhere in Table 4.2. The mean and median of scaled analyst-based RI forecasts for 1977-1995 (8.3% and 1.1%) are higher than the corresponding figures for the realized RIs for 1951-1995 (-4.6% and –1.5%), the latter being the sample on which the univariate model-based forecasts of RI are based.[42]

4.3. Empirical Results

4.3.1. Scaling by stock price

Purely in order to facilitate comparison with the study by DHS, I first report in Table 4.3 bias and accuracy statistics for value estimates using parameters obtained from price-scaled data. I recognise that scaling by price within an 'intercept-inclusive' value estimation procedure causes price to become an input to the value estimate. Such a procedure is not to be recommended as a means of estimating intrinsic value, and I include these results purely for the purpose of making the connection between this study and that by DHS. Table 4.3 reports bias and accuracy statistics for value estimates relative to price, for a constant assumed cost of equity of 12% (as used by DHS). Bias is

[42] The significant difference revealed here between the expectations of RI implied by analyst earnings forecasts and the RI realizations implied by the history of earnings suggests that it is unwise to infer RI expectations from the history of RI as recorded in archival databases. This problem could be due in part to bias in analyst earnings forecasts. Such bias is suggested by Table 4.2, which reports that the mean and median of analyst-based RI forecasts for 1977-1995 (8.3% and 1.1%) exceed those of RI realizations for 1977-1995 (2.2% and –0.7%). The existence of such a bias is confirmed by a direct comparison of analyst earnings forecasts with matching realized earnings for 1977-1995. Another potential contributory factor to the unreliability of archival databases as sources of expectations concerning RI is the possibility that the history of RI, as reflected in those databases, is downward biased. Myers (1999a) argues that many reversals of accounting conservatism come about within 'terminal income' that arises when companies are taken over, but that this 'terminal income', and its (normally positive) associated RI, is not reflected in the archival databases.

measured by reference to the median and mean of *FE*, and accuracy is measured by reference to the median and mean of *AFE*. I report results in respect of value estimates derived from (i) the intercept-exclusive approach (i.e., the Ohlson LID approach) employed by DHS and (ii) the 'intercept-inclusive' approach, using four assumed expected rates of growth in the scaling variable (0%, 2%, 4%, 6%).

For comparative purposes, I also report beneath my intercept-exclusive mean bias and mean accuracy statistics the corresponding figures reported by DHS. My statistics (-0.214 and 0.454) are similar to those reported by DHS (-0.259 and 0.419). It is notable that the incorporation of intercept terms eliminates the substantial negative bias (median 32.2%, mean 21.4%) that is present in the intercept-exclusive value estimates. Focusing on the results where the median of *FE* is used to measure bias, a small positive bias of less than 10% is observed for assumed growth rates of 0% and 2%, whilst more substantial positive biases of 15.6% and 30.1% are observed for assumed growth rates of 4% and 6% respectively. The use of the mean of *FE* to measure bias gives rise to a similar pattern, although the magnitudes of the estimated positive bias are larger. I also note that inclusion of intercept parameters has substantially less impact on the accuracy statistics than on the bias statistics.

4.3.2. Scaling by book value

As noted earlier, an 'intercept-inclusive' valuation procedure based on price-scaled data involves circularity, as price becomes an input to the valuation model. Therefore my main results are based on book value-scaled data. Table 4.4 reports LID parameter estimates derived from pooled (time series and cross-sectional) data for the periods 1977-1995. There are several points to note here. First, with the exception of the case in which cost of equity is assumed constant at 10%, the ω_0 parameter is negative, which suggests that, for these cases, the average value of the scaled RI used in deriving the ω_0 and ω_1 parameter estimates are negative. Second, the ω_1 parameter estimates are all in the region of 0.60, which is similar to that reported by DHS (0.62) on the basis of price-scaled data.[43] These estimates are rather higher than that reported by Myers (1999b) (0.234) on the basis of time series data. Third, estimates of γ_0 are all highly significant and positive, in the region of 0.025 (Panel C). The positive sign of γ_0 implies that the average value of the scaled OI used in deriving the γ_0 and γ_1 parameter estimates, as reported in Table 4.2, is positive (i.e., that analyst-based forecasts of scaled RI tend to be higher than forecasts based on the parameters of the univariate model Eq. 4). Fourth, OI persistence parameters (γ_1) are of a similar magnitude to RI persistence parameters (ω_1), but are rather higher than the corresponding OI persistence parameter estimate of 0.32 reported by DHS on the basis of price-scaled data where the OI intercept parameter is ignored in the definition of OI. Note that for the application of the Ohlson LID approach, γ_1 in Panel B, not γ_1 in Panel C, is used.

Bias and accuracy statistics for value estimates constructed on the basis of data scaled by book value are reported in Table 4.5. As in Table 4.3, four assumed rates of expected

[43] However, ω_1 parameters are very sensitive to the trimming or winsorising criteria. See Section 4.3.3 for the effect of trimming and winsorising on LID parameters. ω_1 parameters when estimated from price-scaled data using most extreme 1% trimming criteria are in the region of 0.55 (unreported).

growth are used: 0%, 2%, 4%, 6% (Annual growth in aggregate book value in the sample for 1976-1995 averaged 3.2%). In Table 4.5, four assumptions are made regarding the cost of equity. These assumptions are: (i) constant at 10%, (ii) constant at 12%, (iii) constant at 14%, and (iv) equal to the risk-free rate for the year plus an assumed constant market risk premium of 5% (As noted above, the average of the year-specific costs of equity for 1976-1995 is about 14%).

The pattern of results reported in Table 4.5 is similar to that observed in Table 4.3. Substantial negative biases are evident in the intercept-exclusive value estimates and in the one-year-ahead earnings forecast capitalisation-based estimates, particularly at the higher costs of equity and where the cost of equity varies by year. However, in the 'intercept-inclusive' value estimates, the negative biases are largely eliminated, sometimes being replaced by positive biases. Particularly high positive biases in excess of +100% are observed at the intersection of the lowest assumed cost of equity (10%) and the highest assumed rate of growth (6%). At the intersection of higher assumed costs of equity (14% and year-specific) and lower assumed rates of growth (0%, 2%, 4%), which accord more closely with the estimated costs of equity and realised growth in the sample period, the absolute values of the biases become much smaller. For the median-based results, the six bias statistics in this intersection are -14.0%, -11.3%, -7.6%, -17.7%, -15.3% and -11.8%. For the mean-based results, the six bias statistics in this intersection are 0.2%, 3.4%, 8%, -5.1%, -2.1% and 2.3%, compared with –25.9% in DHS. These results confirm that the incorporation into value estimates of the LID intercept parameters reflecting long run average RI and OI can mitigate valuation biases. However, it is also evident from Table 4.5 that bias in the 'intercept-inclusive' value estimates is very sensitive both to the assumed cost of equity and to the assumed rate of growth in the scaling variable. This is not surprising since the approach involves capitalising the mean RI term as a growing perpetuity (see Chapter 3 for details).

Although Table 4.5 shows that inclusion of intercept terms can significantly improve bias in LID-based value estimates, it provides little evidence of improvement in the accuracy of such estimates. Particularly, inaccurate value estimates are observed for the 'intercept-inclusive' model for the lowest assumed cost of equity (10%) and the highest assumed rate of growth (6%). Where the cost of equity is higher (14% and year-specific), the level of accuracy of the 'intercept-inclusive' model is very similar to that of the intercept-exclusive model. One explanation concerning the reasons for the lack of improvement in overall valuation accuracy could be the increased dispersion in valuation errors arising from capitalisation of mean effects as perpetuities. For example, for the year-specific cost of equity, the dispersion in the valuation errors for the intercept-exclusive model is 0.79, while for the 'intercept-inclusive' model it is 0.91 for $BG = 1.0$, 0.93 for $BG = 1.02$, 0.96 for $BG = 1.04$ and 1.01 for $BG = 1.06$. A similar pattern is observed for other assumed costs of equity. Particularly high dispersion in valuation errors is observed where the cost of equity is assumed to be 10% and BG is assumed to be 1.04 or 1.06.

However, the lack of improvement in overall valuation accuracy mainly arises from the poor applicability of the 'intercept-inclusive' LID approach for low stock price firms. In other words, although recognition of intercepts improves accuracy in one respect by shifting large negative valuation errors closer to zero for moderate and high stock price firms, it reduces accuracy in another respect because it also shifts valuation errors that are close to zero to be large positive valuation errors for low stock price firms. Interestingly, upward shifting occurs very consistently regardless of firm-years, and the distribution of valuation errors is highly related to stock price. Figure 4.1 illustrates this relationship graphically. Based on a book value growth rate of 4% and year-specific discount rates, I rank signed and absolute valuation errors by stock price and make 100 portfolios. Then, I depict the mean valuation errors (Panel A) and the mean absolute valuation errors (Panel B) of each portfolio. There are several noteworthy results in Figure 4.1. First, the bias pattern of the models based on the Ohlson LID and the 'intercept-inclusive' LID approaches is peculiar compared to the model based on the 1-year forecast horizon EBO approach. Valuation errors based on the former two models are negatively correlated with stock prices, whilst those based on the EBO model are unlikely to be correlated with stock prices. Second, the pattern of biases arising from the 'intercept-inclusive' LID approach is very similar to that arising from the Ohlson LID approach, but its biases are consistently shifted upward regardless of stock prices. Note that in the area of low stock price, the 'intercept-inclusive' LID approach gives rise to large positive bias, and is dominated by the Ohlson LID approach. Third, because of the poor applicability of the 'intercept-inclusive' approach for low stock price firms, its overall accuracy does not improve significantly compared to that based on the Ohlson LID approach. Panel B confirms this phenomenon. In the area of low stock price, the Ohlson LID approach dominates the 'intercept-inclusive' LID approach in terms of accuracy. Finally, a potentially important research issue arises from these results. Figure 4.1 just shows the different applicability of each valuation model along the dimension of stock price. One could also use other firm-specific characteristics (e.g., M/B ratio, firm size) in order to examine which firm-specific characteristics are determinants of a model's applicability.

In order to examine the reason why the 'intercept-inclusive' LID approach does not improve the overall accuracy considerably, I do a complementary test. This is to examine the effect of conservative accounting on value estimates. I do this by partitioning the pooled sample into 5 groups according to the market-to-book (M/B) ratio, which is often used as a proxy indicating the degree of conservatism. Then, I re-estimate LID parameters for each portfolio and feed them into pricing formula in order to get value estimates.[44] Table 4.6 shows bias and accuracy statistics when LID parameters are estimated separately for 5 groups partitioned by the M/B ratio. We see here that considering conservatism when constructing value estimates seems to improve the accuracy. Figure 4.2, Panel B also shows that in many areas of stock price, value estimates based on separate parameter estimation are more accurate than those based on pooled parameter estimation. These results encourage the possibility for further improvement of the overall accuracy of the 'intercept-inclusive' LID-based value estimates. That is, the elaborate application of the 'intercept-inclusive' LID approach could improve the accuracy more. I leave this to further research.

[44] In order to re-estimate LID parameters, I actually classify firms rather than firm-years into 5 groups. For this, I rank all firms by the mean value of M/B.

4.3.3. Effects of winsorising and trimming

For the main results reported above, I trim the most extreme 1% cases of regression variables when LID parameters are estimated, and retain all such outliers for the purpose of constructing value estimates. In this sub-section, I investigate the effects of winsorising and trimming on LID parameters and value estimates by adopting some other approaches to dealing with extreme observations.[45] First, I delete outliers for the purpose of LID parameter estimation as for the main results (i.e., trimming the most extreme 1% regression variables), but construct bias and accuracy statistics after deleting the 1% most extreme values of *FE* and *AFE*, respectively. The purpose of this complementary test is to examine how much the overall bias and accuracy are affected by deleting extreme outputs (i.e., *FE* and *AFE*). Table 4.7 shows that the improvement in the overall accuracy arising by deleting extreme outputs is not much. Especially, the relative reliability (bias and accuracy) of the three models is qualitatively similar to the main results. One more interesting point is that the most extreme biases arising from the application of the Ohlson and the 'intercept-inclusive' LID models are positive. Of bias values deleted according to the 1% most extreme criteria, positive values are over 95% for both models, while they are about 35% for the 1-year forecast horizon EBO model.

Second, I use various trimming and winsorising criteria when estimating LID parameters, but use untrimmed (when trimming criteria are used) and winsorised (when winsorising criteria are used) data when constructing value estimates. Criteria used to

[45] For this supplementary test, only year-specific cost of equity capital is used. Data are scaled by book value as for the main results.

deal with extreme outliers are as follows: no trimming/winsorising, trimming 1%, trimming 2%, trimming 5%, winsorising 1%, winsorising 2%, and winsorising 5%. When trimming criteria are used, I truncate the most extreme cases of regression variables (i.e., scaled per-share data) at the stage of LID parameter estimation. On the other hand, the winsorisation is done at the outset by reference to scaled variables in their most primitive available form, and the winsorised values are then carried through the various stages of the analysis.

Table 4.8 shows RI and OI parameters estimated using various trimming and winsorising criteria. There are some points to note. First, the selection of trimming or winsorising criteria makes RI and OI persistence parameters quite different. Second, even in the same trimming or winsorising criteria, the percentage of outliers deleted or winsorised makes RI and OI persistence parameters sensitive. Third, even though the magnitude of RI and OI parameters are sensitive to the trimming and winsorising criteria, the statistical inferences from those parameters are the same: (i) RI intercept is negative (except for no trimming / winsorising criteria) and statistically significant, and OI intercept is positive and statistically significant. (ii) RI and OI persistence coefficient is greater than zero and less than one, and statistically significant.

From feeding these different parameters to pricing models, I now examine how much these different parameters affect the overall bias and accuracy. Table 4.9 summarizes median and mean statistics for both bias and accuracy. First, bias and accuracy statistics arising from the Ohlson LID approach are not sensitive to different LID parameters estimated using different trimming and winsorising criteria, and show large negative bias and low accuracy consistently. This indicates that RI and OI persistence parameters *per se* together with current RI and OI seem to fail to capture 'unrecorded goodwill'. Second, bias and accuracy statistics arising from the 'intercept-inclusive' LID approach are relatively sensitive. However, the relative reliability of competing value estimates produced by adopting different trimming and winsorising criteria does not differ substantially from the main results (i.e., results with criteria of trimming 1%). This supplementary test confirms the contribution of the 'intercept-inclusive' LID approach to equity valuation, especially in the context of significant elimination of large negative bias produced by applying the Ohlson LID approach. However, as discussed earlier, further research is needed for the improvement of the overall accuracy.

4.4. Conclusions

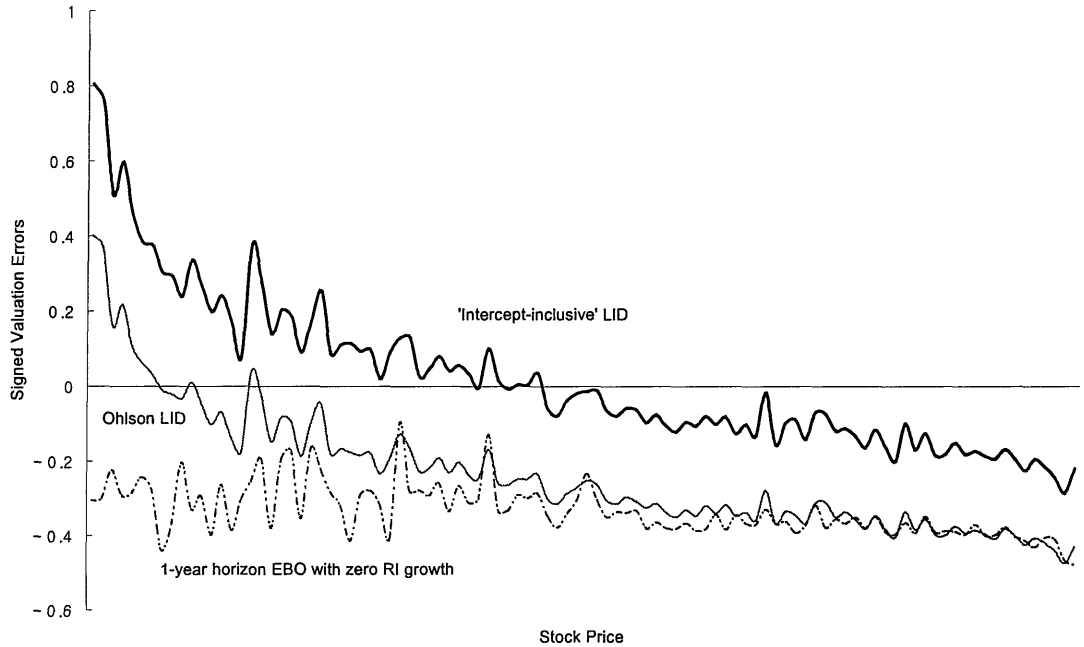
The Dechow, Hutton & Sloan (1999) (DHS) approach to the empirical application of the LID approach to residual income-based valuation is a novel one. It allows an empirical application of Ohlson's (1995) model of the joint role of accounting information and 'other information' in the determination of share prices. Motivated by the magnitude of the bias reported by DHS, I focus on one potential source of this bias. I explore the possibility that the large downward bias reported by DHS may be due in part to their non-recognition, following Ohlson (1995), of information about the mean value of expected future residual incomes contained in the intercept terms of the residual income generating process. In order to investigate this issue, I augment the DHS procedure such as to recognise all intercept terms from the residual income generating process.

Analysis based on the augmented procedure suggests that the valuation effects represented by such intercept terms could easily be of an order of magnitude comparable to, or larger than, that of the bias reported by DHS. This is confirmed by empirical analysis using a U.S. data set similar to that employed by DHS. I note, however, that biases in value estimates from such an 'intercept-inclusive' procedure are very sensitive to assumptions about the cost of equity and about growth. I also note that the 'intercept-inclusive' approach does not outperform the intercept-exclusive approach in terms of accuracy of value estimates.

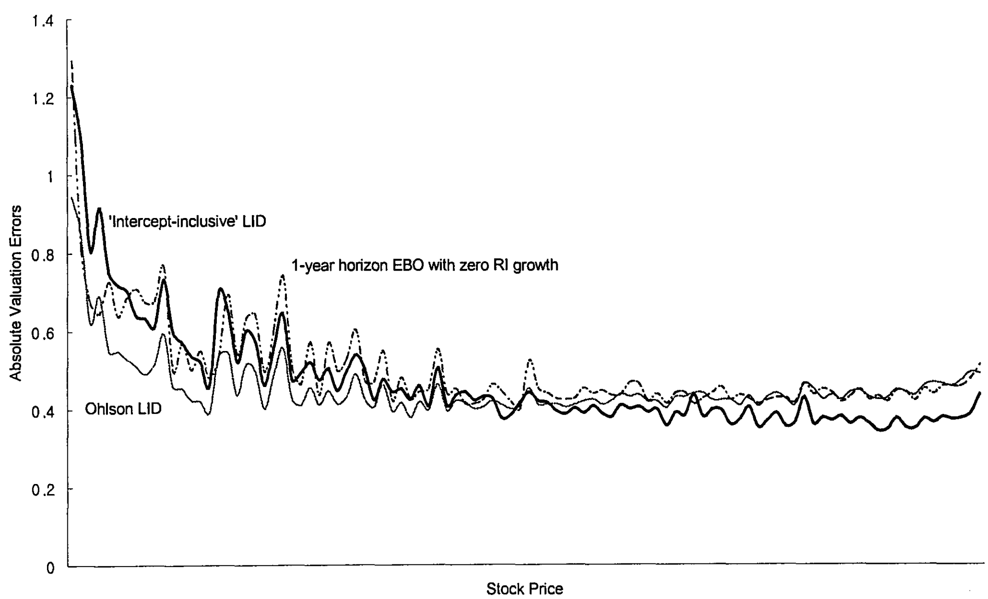
There are, of course, many ways in which the approach could be further augmented in order to improve the understanding of the joint role of accounting information and 'other information' in the determination of share prices. Such augmentations could incorporate such factors as time- and firm-specific estimation of the cost of equity, of expected growth and of LID parameters. These are potentially interesting avenues for further research.

Figure 4.1: Distribution of valuation errors arising from 3 different models

Panel A: Signed valuation errors ($FE_t = (V_t - P_t^{c,3}) / P_t^{c,3}$)



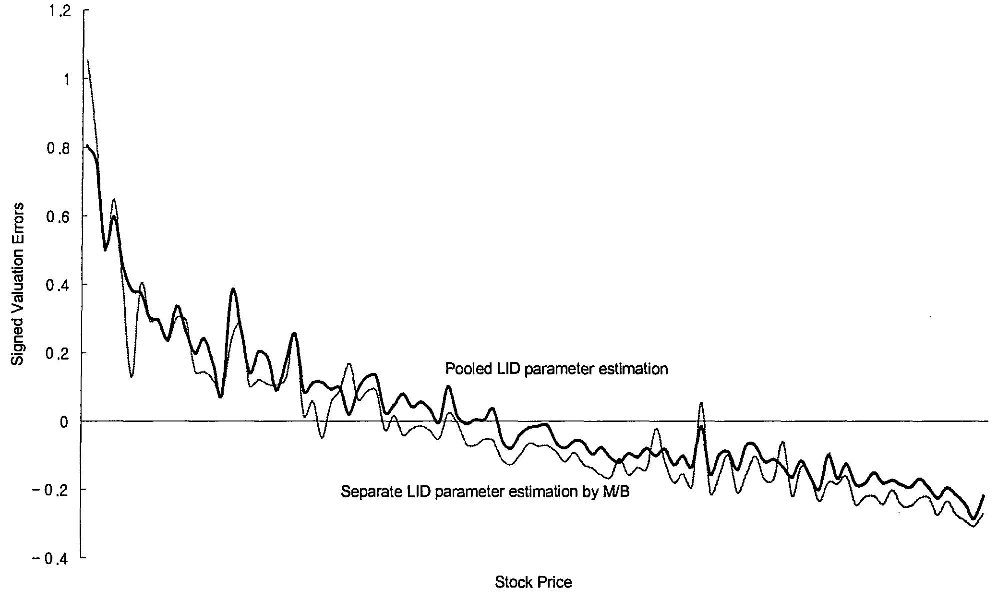
Panel B: Absolute valuation errors ($AFE_t = \left|V_t - P_t^{c,3}\right| / P_t^{c,3}$)



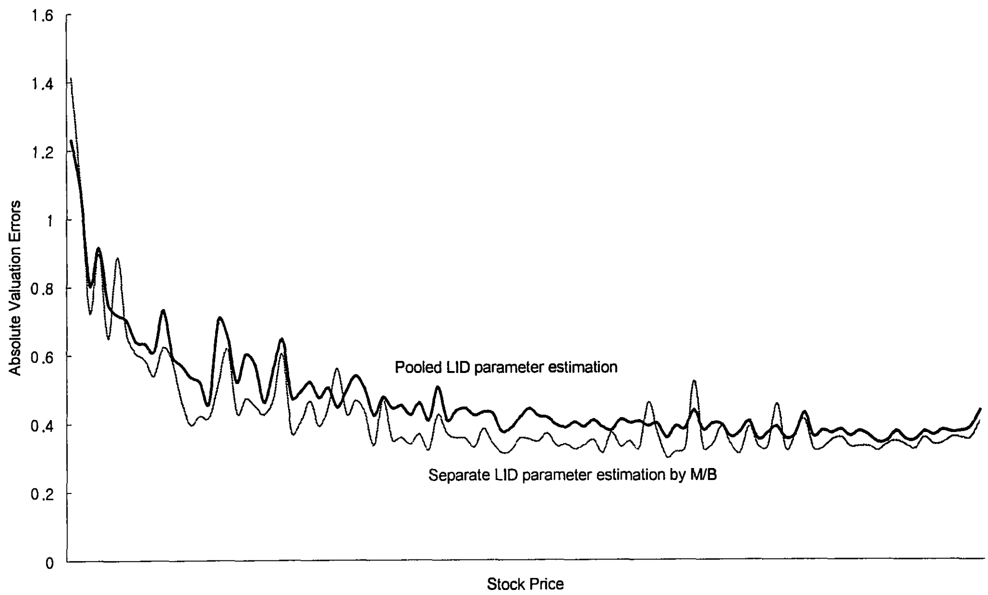
Note:
1) These graphs are based on the assumption of 4% expected rate of growth in book value and of year-specific cost of equity capital.
2) For each model (the 'intercept-inclusive' LID model, the Ohlson LID model and the 1-year forecast horizon EBO model with zero RI growth), total observations (41,297) used for the estimation of the intrinsic value are ranked by stock price and grouped into 100 portfolios, and the mean value of signed valuation errors (Panel A) and absolute valuation errors (Panel B) of each portfolio is depicted.

Figure 4.2: The effect of conservatism on the 'intercept-inclusive' LID-based value estimates: pooled vs. separate (by M/B) parameter estimation

Panel A: Signed valuation errors ($FE_t = (V_t - P_t^{c,3}) / P_t^{c,3}$)



Panel B: Absolute valuation errors ($AFE_t = \left|V_t - P_t^{c,3}\right| / P_t^{c,3}$)



Note:

1) These graphs are based on the assumption of 4% expected rate of growth in book value and of year-specific cost of equity capital.
2) For each model (the 'intercept-inclusive' LID model in which LID parameters are estimated using a pooled sample and are estimated separately for each of 5 sub-samples partitioned by market-to-book ratio), total observations (41,297) used for the estimation of the intrinsic value are ranked by stock price and grouped into 100 portfolios, and the mean value of signed valuation errors (Panel A) and absolute valuation errors (Panel B) of each portfolio is depicted.

Table 4.1: Number of available firm-years

	Number of firm-years
Available from Compustat data (1950-1995) after elimination of firm-year observations for which book value is negative (130,359 observations from 1951-1995 are used in year-specific LID parameter estimation. The remaining 18,353 observations could not be used because lagged book value, required for construction of RI, is missing)	148,712
Less: Observations from 1950-1975	41,686
Available observations from 1976-1995	107,026
Less: Missing I/B/E/S data	51,424
	55,602
Less: Missing CRSP data	4,923
	50,679
Less: Missing lagged book value data	9,382
Observations from 1977-1995 for LID value estimation (see note)	41,297

Note:
The RI inputs to the LID-based value estimates are based on financial statement data drawn from 1976-1995 only. Due to the need to use lagged book value to construct RI, the first RI inputs to the LID-based value estimates are from 1977. Also, an observation is lost wherever lagged book value is unavailable for a firm-year subsequent to 1977.

Table 4.2: Descriptive statistics

Panel A: Data from 1950-1995

	N	Mean	1%	Q1	Median	Q3	99%
Book / price (b_t/P_t)	148712	1.043	0.043	0.396	0.705	1.159	4.324
Earnings / price (x_t/P_t)	148712	-0.003	-1.621	0.017	0.064	0.108	0.351
Earnings / lagged book (x_t/b_{t-1})	130359	0.084	-1.033	0.031	0.112	0.174	0.670
RI / lagged book (x_t^a/b_{t-1})	130359	-0.046	-1.167	-0.103	-0.015	0.048	0.539

Panel B: Data from 1976-1995: used as the basis for accounting inputs to value estimates from 1997-1995

	N	Mean	1%	Q1	Median	Q3	99%
Book / price (b_t/P_t)	50679	0.738	0.073	0.379	0.622	0.946	2.602
Earnings / price (x_t/P_t)	50679	0.031	-0.776	0.032	0.066	0.102	0.250
Earnings / lagged book (x_t/b_{t-1})	41297	0.159	-0.659	0.061	0.132	0.192	0.636
RI / lagged book (x_t^a/b_{t-1})	41297	0.022	-0.789	-0.078	-0.007	0.054	0.503
Analyst-based RI forecast / book (f_{t+1}^a/b_t)	41297	0.083	-0.492	-0.036	0.011	0.069	0.534
OI / book (v_t/b_t)	41297	0.138	-0.191	0.000	0.031	0.073	0.839

Note:

1) N denotes the number of observations, 1% denotes the first percentile, Q1 denotes the 1st quartile, Q3 denotes the third quartile and 99% denotes the 99th percentile. See Table 4.1 for explanation of numbers of observation (N). In Panel A, descriptive statistics for book/price and earnings/price are given in respect of 1950-1995, and those for the remaining items requiring lagged book values are given for 1951-1995. In Panel B, descriptive statistics for book/price and earnings/price are given in respect of 1976-1995, and those for the remaining items are given for 1977-1995 and correspond to cases for which value estimates are constructed.

2) In constructing the data summarized in this table, year-specific costs of equity are used.

Table 4.3: Bias and accuracy - scaled by stock price, r = 12% (as in DHS)

	Ohlson LID	'Intercept-inclusive' LID			
		$SG = 1.00$	$SG = 1.02$	$SG = 1.04$	$SG = 1.06$
Median bias	-0.322	0.012	0.069	0.156	0.301
Mean bias	-0.214	0.130	0.190	0.281	0.433
(Mean bias reported by DHS)	(-0.259)				
Median accuracy	0.400	0.276	0.273	0.281	0.342
Mean accuracy	0.454	0.394	0.408	0.441	0.525
(Mean accuracy reported by DHS)	(0.419)				

Note:

1) Bias and accuracy statistics are based on the variable denoted *FE* and *AFE*, respectively, as described in Eq. 6 and Eq. 7. FE_t (AFE_t) is defined as the signed (absolute) difference between value estimate for time *t* and the observed stock price at three months after the time *t* balance sheet date, all scaled by the stock price at three months after the time *t* balance sheet date. The median and mean of each set of statistics are reported here.
2) The figures in the second column (Ohlson LID) relate to value estimates from an adaptation of the intercept-exclusive valuation procedure (Eq. 2) in which LID parameter estimates are derived from data scaled by stock price instead of book value. This valuation model was used by DHS.
3) The figures in the 3rd to 6th columns ('Intercept-inclusive' LID) relate to value estimates from an adaptation of the 'intercept-inclusive' valuation procedure (Eq. 1) in which LID parameter estimates are derived from data scaled by stock price instead of book value. *SG* is one plus the assumed expected rate of growth in the scaling variable (stock price, here). I report results for assumed expected rates of growth of zero, 2%, 4% and 6%.
4) The results reported above are based on an assumed constant cost of equity of 12%, as used by DHS.
5) These statistics are based on value estimates for 1977-1995. The number of observations used is 41,297 (see Table 4.1).

Table 4.4: LID parameter estimates – scaled by book value, using pooled data

Panel A: RI parameter estimates

$$\frac{x^a_{t+1}}{b_t} = \omega_0 + \omega_1 \frac{x^a_t}{b_t} + e_{1,t+1}$$

	ω_0	ω_1	Adj. R^2
$R = 1.10$	0.008 (10.69)	0.611 (130.60)	0.338
$R = 1.12$	-0.001 (-1.43)	0.598 (129.68)	0.334
$R = 1.14$	-0.010 (-13.99)	0.585 (128.72)	0.331
R = year-specific	-0.009 (-12.26)	0.586 (129.09)	0.332

Panel B: OI parameter estimates when ω_0 is ignored

$$\frac{v_{t+1}}{b_t} = \gamma_0 + \gamma_1 \frac{v_t}{b_t} + e_{2,t+1}, \text{ where } v_t = f^a_{t+1} - \omega_{1,t} x^a_t$$

	γ_0	γ_1	Adj. R^2
$R = 1.10$	0.027 (52.99)	0.602 (125.11)	0.318
$R = 1.12$	0.023 (45.27)	0.589 (121.56)	0.306
$R = 1.14$	0.017 (35.97)	0.575 (117.77)	0.293
R = year-specific	0.019 (38.23)	0.568 (115.88)	0.286

Panel C: OI parameter estimates when ω_0 is dealt with

$$\frac{v_{t+1}}{b_t} = \gamma_0 + \gamma_1 \frac{v_t}{b_t} + e_{2,t+1}, \text{ where } v_t = f^a_{t+1} - (\omega_{0,t} b_t + \omega_{1,t} x^a_t)$$

	γ_0	γ_1	Adj. R^2
$R = 1.10$	0.026 (50.78)	0.604 (125.98)	0.321
$R = 1.12$	0.026 (50.84)	0.601 (125.48)	0.320
$R = 1.14$	0.026 (51.07)	0.593 (123.47)	0.313
R = year-specific	0.024 (47.88)	0.593 (123.24)	0.312

Note:

1) t-statistics are given in parentheses.

2) The parameters reported in this table are estimated from all RI observations constructed from financial statement data drawn from 1976-1995, which is similar to the data period for which similar parameter estimates relating to pooled data are reported by DHS (their Tables 1 and 3). It corresponds approximately to the period for which I/B/E/S earnings forecasts for estimation of OI are available. Note that in deriving value estimates, I use year t-specific LID parameter estimates based on all available data prior to time t. (See Eq. 4 and Eq. 5, in which the parameter estimation dates are subscripted t and the data used in arriving at the time t parameter estimates are subscripted s).

3) x^a_t is the RI per share at time t, b_t is the book value per share at time t, R is one plus the cost of equity, v_t is the OI per share at time t, and e_1 and e_2 are random error terms. Four assumed values are used for R–1: 10%, 12%, 14% and year-specific.

Table 4.5: Bias and accuracy – scaled by book value

	1-year forecast horizon EBO (zero RI growth)	Ohlson LID	'Intercept-inclusive' LID			
			SG=1.00	SG=1.02	SG=1.04	SG=1.06
Median bias:						
R = 1.10	-0.145	-0.258	0.263	0.397	0.618	1.061
R = 1.12	-0.288	-0.304	0.025	0.088	0.182	0.337
R = 1.14	-0.390	-0.343	-0.140	-0.113	-0.076	-0.019
R = year-specific	-0.372	-0.339	-0.177	-0.153	-0.118	-0.064
Mean bias:						
R = 1.10	-0.080	-0.121	0.479	0.637	0.901	1.429
R = 1.12	-0.233	-0.184	0.197	0.272	0.384	0.571
R = 1.14	-0.343	-0.236	0.002	0.034	0.080	0.148
R = year-specific	-0.335	-0.235	-0.051	-0.021	0.023	0.091
Median accuracy:						
R = 1.10	0.340	0.383	0.458	0.523	0.669	1.065
R = 1.12	0.377	0.393	0.385	0.401	0.430	0.496
R = 1.14	0.429	0.408	0.369	0.371	0.373	0.382
R = year-specific	0.412	0.403	0.358	0.356	0.356	0.360
Mean accuracy:						
R = 1.10	0.526	0.471	0.724	0.842	1.056	1.526
R = 1.12	0.502	0.462	0.552	0.593	0.662	0.794
R = 1.14	0.513	0.461	0.476	0.486	0.502	0.532
R = year-specific	0.504	0.457	0.453	0.461	0.474	0.500

Note:

1) R is one plus the assumed cost of equity used in arriving at RI, OI and the value estimates. Four assumed values are used for (R–1): 10%, 12%, 14% and year-specific.
2) SG is one plus the assumed expected rate of growth in the scaling variable (book value, here). Results are reported under the four separate assumptions that SG is constant at 1.00, 1.02, 1.04 and 1.06.
3) Bias and accuracy statistics are based on the variable denoted FE and AFE in the text (Eq. 6 and Eq. 7). FE_t (AFE_t) is the signed (absolute) difference between the value estimate for time t and the observed share price three months after the time t balance sheet date, all scaled by the share price three months after the balance sheet date. The mean and median of each set of statistics are reported here.
4) The figures in the second column (1-year forecast horizon EBO with zero RI growth) relate to value estimates derived from the one-year ahead earnings forecast capitalized as a flat perpetuity. The figures in the third column (Ohlson LID) relate to value estimates derived from the intercept-exclusive valuation model (Eq.2). The figures in the 4th to 7th columns ('Intercept-inclusive' LID) relate to value estimates derived from the 'intercept-inclusive' valuation model (Eq. 1).
5) These statistics are based on value estimates from 1977-1995. The number of observations used is 41,297 (see Table 4.1).

Table 4.6: The effect of conservatism on bias and accuracy

	1-year forecast horizon EBO (zero RI growth)	Ohlson LID	'Intercept-inclusive' LID			
			SG=1.00	*SG*=1.02	*SG*=1.04	*SG*=1.06
Median bias:						
Separate by M/B	-0.372	-0.340	-0.210	-0.189	-0.156	-0.110
Pooled	-0.372	-0.339	-0.177	-0.153	-0.118	-0.064
Mean bias:						
Separate by M/B	-0.335	-0.242	-0.093	-0.061	-0.015	0.059
Pooled	-0.335	-0.235	-0.051	-0.021	0.023	0.091
Median accuracy:						
Separate by M/B	0.412	0.402	0.324	0.316	0.308	0.298
Pooled	0.412	0.403	0.358	0.356	0.356	0.360
Mean accuracy:						
Separate by M/B	0.504	0.456	0.428	0.426	0.428	0.443
Pooled	0.504	0.457	0.453	0.461	0.474	0.500

Note:

1) In this table, year-specific cost of equity capital is used in arriving at RI, OI and the value estimates.
2) *SG* is one plus the assumed expected rate of growth in the scaling variable (book value, here)
3) Bias and accuracy statistics are based on the variable denoted *FE* and *AFE* (Eq. 6 and Eq. 7). FE_t (AFE_t) is the signed (absolute) difference between the value estimate for time *t* and the observed share price three months after the time *t* balance sheet date, all scaled by the share price three months after the balance sheet date. The mean and median of each set of statistics are reported here.
4) The figures in the second column (1-year forecast horizon EBO with zero RI growth) relate to value estimates derived from the one-year ahead earnings forecast capitalized as a flat perpetuity. The figures in the third column (Ohlson LID) relate to value estimates derived from the intercept-exclusive valuation model (Eq.2). The figures in the 4th to 7th columns ('Intercept-inclusive' LID) relate to value estimates derived from the 'intercept-inclusive' valuation model (Eq. 1).
5) These statistics are based on value estimates from 1977-1995. The number of observations used is 41,297 (see Table 4.1).
6) 'separate by M/B' ('pooled') denotes the case in which LID parameters are estimated separately for 5 sub-samples partitioned by market-to-book ratio (are estimated using a pooled sample). Market-to-book (M/B) ratio is used as a proxy to represent the degree of conservatism applied to a firm's accounting system.

Table 4.7: The effect of trimming extreme FE (AFE) values on bias (accuracy)

	1-year forecast horizon EBO (zero RI growth)	Ohlson LID	'Intercept-inclusive' LID			
			SG=1.00	*SG*=1.02	*SG*=1.04	*SG*=1.06
Median bias:						
Trimming *FE*	-0.371	-0.343	-0.182	-0.157	-0.123	-0.069
No trimming *FE*	-0.372	-0.339	-0.177	-0.153	-0.118	-0.064
Mean bias:						
Trimming *FE*	-0.329	-0.275	-0.097	-0.068	-0.027	0.039
No trimming *FE*	-0.335	-0.235	-0.051	-0.021	0.023	0.091
Median accuracy:						
Trimming *AFE*	0.409	0.399	0.354	0.352	0.353	0.356
No trimming *AFE*	0.412	0.403	0.358	0.356	0.356	0.360
Mean accuracy:						
Trimming *AFE*	0.447	0.419	0.408	0.414	0.425	0.448
No trimming *AFE*	0.504	0.457	0.453	0.461	0.474	0.500

Note:

1) In this table, year-specific cost of equity capital is used in arriving at RI, OI and the value estimates.
2) *SG* is one plus the assumed expected rate of growth in the scaling variable. Book value is used as a scaling variable.
3) 'Trimming *FE* (*AFE*)' denotes the case in which the most extreme 1% of *FE* and *AFE* values are truncated. Note that the trimming criteria for the LID parameter estimation is the same as the case of 'no trimming *FE* (*AFE*)' (i.e., trimming the most extreme 1% regression variables in the scaled per-share form).
4) These statistics are based on value estimates from 1977-1995. The total number of observations used is 41,297 (see Table 4.1). Trimming the most extreme 1% of *FE* and *AFE* values gives 40,885 observations.

Table 4.8: The effect of trimming / winsorising on parameter estimation

Panel A: RI parameter estimates

$$\frac{x^a_{t+1}}{b_t} = \omega_0 + \omega_1 \frac{x^a_t}{b_t} + e_{1,t+1}$$

	ω_0	ω_1	Adj. R^2	N
No trimming / winsorising	0.040 (2.16)	0.468 (157.63)	0.423	33947
Trimming 1%	-0.009 (-12.26)	0.586 (129.09)	0.332	33485
Trimming 2%	-0.007 (-11.11)	0.644 (132.94)	0.349	32971
Trimming 5%	-0.006 (-11.77)	0.701 (135.43)	0.368	31487
Winsorising 1%	-0.012 (-14.30)	0.402 (108.53)	0.258	33947
Winsorising 2%	-0.010 (-12.49)	0.492 (122.11)	0.305	33947
Winsorising 5%	-0.007 (-11.38)	0.612 (139.63)	0.365	33947

Panel B: OI parameter estimates when RI intercept (ω_0) is ignored

$$\frac{v_{t+1}}{b_t} = \gamma_0 + \gamma_1 \frac{v_t}{b_t} + e_{2,t+1}, \text{ where } v_t = f^a_{t+1} - \omega_{1,t} x^a_t$$

	γ_0	γ_1	Adj. R^2	N
No trimming / winsorising	0.019 (2.66)	0.588 (388.57)	0.816	33947
Trimming 1%	0.019 (38.23)	0.568 (115.88)	0.286	33512
Trimming 2%	0.020 (45.05)	0.530 (100.45)	0.234	33007
Trimming 5%	0.020 (52.97)	0.454 (77.98)	0.162	31467
Winsorising 1%	0.010 (20.76)	0.721 (186.14)	0.505	33947
Winsorising 2%	0.013 (27.82)	0.659 (159.01)	0.427	33947
Winsorising 5%	0.018 (42.02)	0.534 (116.59)	0.286	33947

Panel C: OI parameter estimates when RI intercept (ω_0) is dealt with

$$\frac{v_{t+1}}{b_t} = \gamma_0 + \gamma_1 \frac{v_t}{b_t} + e_{2,t+1}, \text{ where } v_t = f^a_{t+1} - (\omega_{0,t} b_t + \omega_{1,t} x^a_t)$$

	γ_0	γ_1	Adj. R^2	N
No trimming / winsorising	0.021 (3.05)	0.588 (389.37)	0.817	33947
Trimming 1%	0.024 (47.88)	0.593 (123.24)	0.312	33512
Trimming 2%	0.025 (53.49)	0.551 (106.13)	0.254	33003
Trimming 5%	0.023 (59.36)	0.475 (82.51)	0.178	31481
Winsorising 1%	0.015 (29.50)	0.744 (195.43)	0.530	33947
Winsorising 2%	0.017 (35.54)	0.683 (167.98)	0.454	33947
Winsorising 5%	0.020 (47.31)	0.559 (124.18)	0.312	33947

Note:

1) Year-specific cost of equity capital is employed and book value is used as a scaling variable.
2) 'Trimming' denotes that the most extreme regression variables in the scaled per-share form are truncated for the purpose of LID parameter estimation, but are retained for the purpose of constructing value estimates.
3) 'Winsorising' denotes that the most extreme scaled per-share variables in their most primitive form are winsorised, and the winsorised values are then carried for both purposes of LID parameter and intrinsic value estimation.

Table 4.9: The effect of trimming / winsorising on bias and accuracy

	1-year forecast horizon EBO (zero RI growth)	Ohlson LID	'Intercept-inclusive' LID			
			SG=1.00	*SG*=1.02	*SG*=1.04	*SG*=1.06
Median bias:						
No T / W	-0.372	-0.354	-0.273	-0.272	-0.270	-0.267
Trimming 1%	-0.372	-0.339	-0.177	-0.153	-0.118	-0.064
Trimming 2%	-0.372	-0.336	-0.132	-0.100	-0.055	0.013
Trimming 5%	-0.372	-0.332	-0.098	-0.059	-0.006	0.076
Winsorising 1%	-0.373	-0.347	-0.276	-0.271	-0.265	-0.256
Winsorising 2%	-0.374	-0.345	-0.252	-0.242	-0.227	-0.203
Winsorising 5%	-0.374	-0.346	-0.208	-0.187	-0.157	-0.110
Mean bias:						
No T / W	-0.335	-0.272	-0.110	-0.086	-0.051	0.007
Trimming 1%	-0.335	-0.235	-0.051	-0.021	0.023	0.091
Trimming 2%	-0.335	-0.227	0.000	0.038	0.092	0.178
Trimming 5%	-0.335	-0.216	0.042	0.086	0.149	0.248
Winsorising 1%	-0.344	-0.269	-0.152	-0.136	-0.113	-0.078
Winsorising 2%	-0.341	-0.261	-0.128	-0.108	-0.079	-0.034
Winsorising 5%	-0.332	-0.254	-0.083	-0.054	-0.013	0.052
Median accuracy:						
No T / W	0.412	0.408	0.428	0.450	0.486	0.544
Trimming 1%	0.412	0.403	0.358	0.356	0.356	0.360
Trimming 2%	0.412	0.401	0.352	0.353	0.356	0.370
Trimming 5%	0.412	0.399	0.348	0.351	0.361	0.382
Winsorising 1%	0.412	0.401	0.393	0.396	0.400	0.404
Winsorising 2%	0.412	0.402	0.385	0.385	0.385	0.386
Winsorising 5%	0.411	0.405	0.371	0.369	0.367	0.369
Mean accuracy:						
No T / W	0.504	0.474	0.526	0.555	0.602	0.686
Trimming 1%	0.504	0.457	0.453	0.461	0.474	0.500
Trimming 2%	0.504	0.461	0.463	0.474	0.494	0.534
Trimming 5%	0.504	0.467	0.475	0.490	0.516	0.567
Winsorising 1%	0.484	0.437	0.459	0.469	0.484	0.508
Winsorising 2%	0.478	0.438	0.451	0.459	0.471	0.492
Winsorising 5%	0.463	0.434	0.439	0.446	0.459	0.484

Note:

1) Year-specific cost of equity capital is employed and book value is used as a scaling variable.
2) 'Trimming' denotes that the most extreme regression variables in the scaled per-share form are truncated for the purpose of LID parameter estimation, but are retained for the purpose of constructing value estimates.
3) 'Winsorising' denotes that the most extreme scaled per-share variables in their most primitive form are winsorised, and the winsorised values are then carried for both purposes of LID parameter and intrinsic value estimation.
4) No T / W denotes that neither trimming nor winsorising is applied.

CHAPTER 5. U.K. DATA AND VARIABLES

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CHAPTER 5

U.K. DATA AND VARIABLES

5.1. Earnings Measures

The clean surplus relation is one of the basic assumptions in the residual income valuation approach. However, it is difficult to get long time series of U.K. earnings numbers that completely satisfy the clean surplus relation. This is partly because it is only recently (1992) that the U.K. accounting standard FRS 3 required that all the information relating to changes in shareholders' funds be conveniently summarised as a note to the financial statements or in a primary statement. So for practical purposes, it is necessary to work with 'dirty surplus' earnings constructs. However, there are a number of dirty surplus earnings constructs that could potentially be used in valuation studies.

Therefore, instead of trying to get earnings numbers that satisfy the clean surplus relation, I try to investigate the sensitivity of my results to different earnings measures. In the study, I use two measures of 'ordinary earnings'. In addition, I use one measure comprising ordinary earnings plus exceptional and extraordinary items, and one measure comprising ordinary earnings plus exceptional items.[46] The empirical work is performed using each of these four measures. This enables me to test the robustness of the results to the use of alternative measures of 'ordinary earnings' and to explore the effect of exceptional and/or extraordinary items when I estimate persistence parameters

[46] The terms 'exceptional items' and 'extraordinary items' used through the thesis are as before FRS 3, unless otherwise stated. Reclassified exceptional items after FRS 3 consist of '(previous) exceptional items' and '(previous) extraordinary items'.

and form estimates of fundamental value.

5.1.1. Earnings before exceptional and extraordinary items (X1)

The first measure is pre-exceptional and pre-extraordinary earnings (denoted X1). X1 is Datastream item (DS henceforth) 210 (earned for ordinary–adjusted).[47] This is the net profit after tax, minority interests and preference dividends before exceptional and extraordinary earnings. Thus, this does not include any items not relating to the normal trading activities of the company. DS 210 is the adjusted figure using published and estimated accounting numbers, and is available for the sample period (1969-1998).[48] Even though there were some changes in U.K. income reporting standards, mainly through SSAP 6 (Extraordinary items and prior year adjustments) being superseded by FRS 3 (Reporting financial performance) with effect from 1993,[49] DS 210 appears to be consistent across both reporting regimes because it is stated on a pre-exceptional and pre-extraordinary basis.

A description of the relationship between published accounting numbers and DS 210, illustrated by examples drawn from companies' published numbers, is given in Appendix 5.3, Table A5.3.1. Unfortunately a number of cases were found in which Datastream had made clear errors in adjusting the published numbers to arrive at DS 210.[50] The existence of such errors has meant that, in collating my data, I have had to

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[47] See Appendix 5.1 for Datastream definition.
[48] Details of sample period and observations will be dealt with in a later section (Section 5.3).
[49] See Appendix 5.2 for the development of U.K. income reporting standards.
[50] See Appendix 5.4 for examples of Datastream errors.

incorporate screening procedures aimed at identifying and eliminating such errors. For details, see Section 5.3 in which I describe the data collation procedures in detail.

5.1.2. Full-tax adjusted earnings before exceptional and extraordinary items (X2)

DS 210 (X1) is potentially prone to a discontinuity due to a major change in tax accounting which occurred in the late 1970s with the introduction in SSAP 15 (Accounting for deferred tax) of partial recognition of the tax effect of timing differences.[51] In order to deal with this discontinuity, Datastream introduced an alternative measure of ordinary earnings: full-tax adjusted pre-exceptional and pre-extraordinary earnings (denoted X2). This is DS 182 (earned for ordinary – full tax). The definition of this earnings measure is the same as X1 except that, for periods after the implementation of SSAP 15, the earnings number is adjusted to reflect the tax charge as it would have been prior to SSAP 15. The total amount of the unprovided deferred tax balance must be disclosed in the notes to the financial statements, and DS 182 is the earnings adjusted to reflect a full provision for deferred tax. DS 182 is available for the sample period (1969-1998) and is consistent across the SSAP 6 and FRS 3 reporting regimes because it is stated on a pre-exceptional and pre-extraordinary basis like X1.[52]

However, the adjustment made by Datastream to arrive at DS 182 is itself inconsistent. As shown in Table 5.1, the Datastream adjustment to get from DS 210 to DS 182 has

[51] See Appendix 5.5 for SSAP 15.
[52] See Appendix 5.3, Table A5.3.2 for examples of the relationship between X2 (DS 182) and the published profit figure for (a) the pre-FRS 3 regime and (b) the post-FRS 3 regime.

not been made consistently over the years, even if relevant information on the tax charge has been disclosed consistently in the notes to the financial statements. Consequently, both of the 'ordinary earnings' items (DS 210 and DS 182) from Datastream are not completely consistent across the sample period. In order to ensure that my results are not dependent upon the choice of Datastream's measure of ordinary earnings, I use both of these measures (DS 210 and DS 182) in my subsequent analysis.

5.1.3. Earnings after exceptional and extraordinary items (X3)

While some people contend that net profit/loss should not be distorted by abnormal, unusual and non-recurring transactions, others advocate a more inclusive concept of income that reflects the effects of a larger proportion of all recorded transactions. Therefore, I also use post-exceptional and post-extraordinary earnings (denoted X3). This is the net profit after tax, minority interests and preference dividends after exceptional and extraordinary earnings. X3 is actually closer to Dechow *et al.*'s (1999) earnings definition (earnings before extraordinary items), because the definition of extraordinary items in the U.S. is similar to that used in the FRS 3 regime. That is, very few of the extraordinary items of the pre-FRS 3 regime in the U.K. are classified as extraordinary items under U.S. GAAP.

By the way, DS 625 (earned for ordinary), which is a key item for this measure, is inconsistent between the pre-FRS 3 and post-FRS 3 regimes, as well as being available only after the mid-1980s. DS 625 in the post-FRS 3 regime is the same as X3, because extraordinary items have effectively been abolished and reclassified into exceptional items after FRS 3, while DS 625 in the pre-FRS 3 regime is published post-exceptional and pre-extraordinary earnings. Accordingly, post-tax extraordinary items should be added to DS 625 to arrive at X3 in the pre-FRS 3 regime. DS 193 (extraordinary items – after tax) is the Datastream item corresponding to post-tax extraordinary items. For the period when DS 625 is not available (i.e., before the mid-1980s), X1 and exceptional items will be used in place of DS 625 (i.e., DS 625 = X1 + DS 194 (exceptional items) + DS 208 (exchange adjustments – any after-tax adjustments)).[53] See Appendix 5.3, Table A5.3.3 for examples of the relationship between X3 and the published profit figure.

5.1.4. Earnings after exceptional items, but before extraordinary items (X4)

My final measure, which is conceptually similar to the measure used in the U.S. study by Dechow *et al.* (1999), is earnings inclusive of exceptional items, but exclusive of extraordinary items.[54] Exceptional items are defined in SSAP 6 and FRS 3 as being 'material items which derive from events or transactions that fall within the ordinary activities of the reporting entity, and which need to be disclosed separately by virtue of their size or incidence'. Thus, this measure, X4, is considered as earnings inclusive of all ordinary activities of the company. As mentioned above, DS 625 is the same as X4 in the pre-FRS 3 regime, but includes items previously treated as extraordinary in the post-FRS 3 regime. Thus, to be consistent with DS 625 from the pre-FRS3 accounting

[53] See Appendix 5.6 for the relation between DS 625 and DS 210 (X1).

[54] However, while FRS 3 effectively eliminates the occasion of any extraordinary items, U.S. GAAP recognises that there may be occasions when some items (e.g. result of an earthquake or expropriation) can be properly treated as extraordinary items.

regime, post-tax extraordinary items re-classified as exceptional in the post-FRS3 regime should be subtracted from DS 625 of the post-FRS 3 accounting regime. This item is approximately the same as DS 1083 (Total special items) less DS 1094 (Tax on special items) and DS 1097 (Minority interest in special items), which were newly created by Datastream after the implementation of FRS 3.[55] As the case of X3, X1 and exceptional items will be used for the period when DS 625 is not available (i.e., X4 = DS 625 = X1 + DS 194 + DS 208). Table 5.2 summarises 4 earnings measures defined in terms of Datastream items.

5.1.5. Other candidates for earnings measures

It may be worth searching for earnings measures that could be more relevant to firms' performance than the four earnings measures described above. Here, I suggest two candidates for future research.[56] One is a measure recommended by IIMR (Institute of Investment Management and Research) and the other is pro-forma earnings (or operating earnings) such as I/B/E/S actuals.

The IIMR has proposed in the wake of the requirement in FRS 3 that companies report a more all-inclusive measure of earnings. The objective of IIMR 'headline' earnings is to provide an unambiguous reference point for all users and the basis for more reliable forecasts. One motivation for using the IIMR measure in a further study could be that it

[55] See Appendix 5.3, Table A5.3.4 for examples of the relationship between X4 and the published profit figure.

[56] Because of the lack of data, it is difficult to do time-series cross-sectional analysis used in the study with these two other earnings measures. The selected firms who have enough data of these two other earnings measures can be used for further research, despite the possibility of selection bias.

is claimed to be a better concept of 'maintainable' earnings, and another reason is to have a number that is relatively likely to be consistent with I/B/E/S earnings forecasts, compared to earnings measures reported in other archival database such as Datastream. IIMR earnings include all the trading profits and losses for the year, but excludes profits and losses on capital items such as fixed assets. Specifically, items excluded from published FRS 3 earnings to arrive at IIMR earnings are (i) profit or loss on the sale or termination of an operation, (ii) profit or loss on the disposal of fixed assets, (iii) amortisation of goodwill, (iv) bid defence costs, (v) diminution in value of fixed assets, (vi) profit or loss on capital reorganisation of long term debt, and (vii) profit or loss on disposal of trade investments. Unfortunately, Datastream items for (iii) to (vii) do not exist separately. Therefore, only DS 1079 (Profit or loss on termination of operations) for (i) and DS 1081 (Profit or loss on sale of fixed assets) for (ii) can be used to define the IIMR earnings measure. And since the Datastream items required for constructing the IIMR numbers were not available prior to FRS 3, the IIMR earnings construct can be used only for the post-FRS 3 regime. For the post-FRS 3 regime, the proxy of the IIMR headline earnings is post-FRS 3 published earnings (DS 625) minus DS 1079 and DS 1081 after tax and minority interests. Another source of IIMR earnings is the Extel database, which offers IIMR EPS. Since some but not all firms present IIMR EPS as well as EPS required under the FRS 3 regime, the Extel database also has limitations for researchers seeking to adopt IIMR earnings because of the possibility of selection bias and the short time period available.

An alternative candidate for an earnings measure is the pro-forma I/B/E/S actual earnings. The I/B/E/S glossary (19^{th} ed.) defines its earnings as earnings after discontinued operations, extra-ordinary charges, and other non-operating items have been backed out. "I/B/E/S adjusts reported earnings to match analysts' forecasts. This is why I/B/E/S actuals may not agree with 'published actuals' obtained from other sources. Consequently, reported earnings on the I/B/E/S database may not exactly match earnings that appear in a company's earnings releases". Even though it is not clear yet whether most investors rely on this modified definition of earnings rather than earnings reported in the financial statements, it may be worth comparing this alternative earnings measure with GAAP earnings. Bradshaw, Moberg and Sloan (2000) contend that pro-forma I/B/E/S earnings are increasingly tracked by analysts and priced by investors.[57] However, as in the case of IIMR earnings, the I/B/E/S actual earnings data are not sufficient for the purpose of this study. So I also leave the potential usage of the I/B/E/S actual earnings measure to future research.

5.1.6. I/B/E/S earnings forecasts

Besides the four earnings measures discussed above, I use I/B/E/S earnings forecasts to produce approximate figures of 'other information (OI)' and to estimate future residual income directly for the EBO value estimates. Thus, I/B/E/S earnings forecasts play an important role in both equity valuation approaches, the linear information dynamics (LID) approach and the EBO approach. Because the I/B/E/S mean consensus forecasts may be affected by extreme values, I use median consensus forecasts for the main results. Then, mean forecasts will be used in order to test the sensitivity of alternative

[57] In the earlier research, Philbrick and Ricks (1991) report that the actual EPS numbers reported by COMPUSTAT are more accurate than those reported by I/B/E/S.

consensus earnings forecasts.

Despite the important role of analysts' consensus earnings forecasts in equity valuation, one critical limitation exists when employing these forecasts. As mentioned in the above sub-section, the I/B/E/S definition of earnings may be different from the definition of any earnings measure reported in Datastream. That is, it is difficult to find an earnings measure that exactly corresponds to I/B/E/S earnings from four earnings definitions used in this study. This gives rise to one potential problem when we calculate the proxy of 'other information' using I/B/E/S earnings forecasts. That is, as we can see in the definition of 'other information', i.e., $v_t = f_{t+1}^a - E_t\left[\tilde{x}_{t+1}^a\right]$, 'other information' contains one of the four Datastream earnings measures and the Datastream earnings relevant residual income (RI) persistence (and intercept) parameters as well as I/B/E/S earnings forecasts. So 'other information' is constructed using two kinds of earnings measures, whose definitions are not exactly consistent. In principle, it is possible to use the actual earnings numbers reported by I/B/E/S for current residual income and the relevant persistence (and intercept) parameters to estimate 'other information' and firms' intrinsic value. However, the relatively short time series of available I/B/E/S data limit the practicability of this approach.

5.2. Other Variables and Definitions

In order to calculate residual income, the discount rate *r* should be measured. Dechow *et al.* (1999) use the long-run U.S. industrial average discount rate (12%), but I adopt year-average discount rates that vary over the years. Specifically, I use 12-month average discount rates up to the fiscal year end month in order to allocate more reasonable year-average discount rates to each firm-year. For example, if a firm's fiscal year end month is January 1998, average discount rate from February 1997 to January 1998 is more suitable for the firm's business activity than that from January 1998 to December 1998. Even though some people (e.g. Frankel and Lee, 1998) find that varying the discount rate has little effect on this kind of research, I think a time varying rate is more reasonable.[58] In this thesis, r is considered to be approximately equal to 5% plus year-average of U.K. Gross Redemption Yield on 20 year Gilts, because U.K. average risk premium is supposed to be 5% or so. The average discount rate over the sample period (1969 – 1998) is 15.5%.[59] Table 5.3 shows U.K. Gross Redemption Yield on 20 year Gilts over the sample period.

Variables other than earnings measures are similar to Dechow *et al.* (1999), but are defined in terms of their Datastream items. In this study, all empirical analyses are based on the per-share data. Table 5.4 summarises variables used in the study.

P and b: Stock price (P) is market value (Datastream code MV) divided by the number of ordinary shares in issue (Datastream code NS). NS is the adjusted figure for subsequent capital actions (e.g., stock splits, stock dividends). Thus, P is the same as the adjusted stock price (Datastream code P). P is the fiscal year end price and is used as a scaling variable in some versions of my analysis. Note that P is differentiated from

[58] Lee *et al.* (1999) indicate that time-varying discount rates are an essential part of valuation models in their time-series applications. Furthermore, the firm-year specific discount rate would be most reasonable because equity valuation is a task applied on a firm-year basis (Sougiannis and Yaekura, 2000).
[59] If the annualized 3-month U.K. Treasury bill rate is used, the average discount rate over the sample period is about 15%.

$P^{c,n}$, which is used as a benchmark of the estimated intrinsic values (see below for details). Book value per share (b) is the total share capital and reserves excluding preference capital (DS 305, Equity capital and reserves) divided by NS.

q2 – q4: *q2*, *q3* and *q4* are respectively defined as absolute value of exceptional items (*EXC*), extraordinary items (*EXT*) and all abnormal items (*AEX*), divided by lagged book value. And each variable is used as one of the determinants of the firm-specific persistence parameter. However, since I use 4 different earnings measures in this study, the effect of exceptional and/or extraordinary items on residual income varies according to earnings measures. Firstly, in the case of X1 and X2, which exclude exceptional and extraordinary items, any exceptional and extraordinary items should not be used as a determinant of the firm-specific persistence parameter. Next, when we use X3 (X4), the magnitude of all abnormal items, *q4* (the magnitude of exceptional items, *q2*) will be a relevant determinant, accordingly *AEX* (*EXC*) will be.[60] In Datastream terms, *EXC* is [(DS 194 + DS 208) – (DS 1083 – DS 1094 – DS 1097)] / NS, *EXT* (extraordinary items) is [(DS 1083 – DS 1094 – DS 1097) + DS 193] / NS, and *AEX* is (DS 194 + DS 208 + DS 193) / NS.

q5: *q5* is defined as the magnitude of operating accruals, and is $|OA_t \;/\; TA_{t-1}|$ where *TA* is total assets (DS 392, Total assets).[61] As Sloan (1996) suggests, operating accruals (*OA*) is computed as follows: $OA_t = (\Delta CA_t - \Delta CASH_t) - (\Delta CL_t - \Delta STD_t - \Delta TP_t) - DEP_t$,

[60] In the case of X3, one can alternatively examine the effect of the magnitude of exceptional items (*q2*) and the magnitude of extraordinary items (*q3*) on residual income separately.
[61] All unadjusted accounting numbers reported in Datastream are divided by NS so that the adjusted per-share numbers are used through the study, even though it is not explicitly stated.

where *CA* is current assets (DS 376, Total current assets), *CASH* is cash/cash equivalents (DS 375, Total cash and equivalent), *CL* is current liabilities (DS 389, Total current liabilities), *STD* is debt included in current liabilities (DS 309, Borrowings repayable within 1 year), *TP* is income taxes payable (DS 381, Current taxation), and *DEP* is depreciation and amortization expense (DS 136, Depreciation).

div: The dividend payout ratio (*div*) is defined as dividends divided by earnings. For the dividend payout ratio of firm-years that have negative earnings, I divide dividends by total assets times median ROA for the year (i.e., $d_t/(TA_t \times R\overline{O}A_t)$, where $R\overline{O}A_t$ is median ROA for year *t*).[62] In addition, to ensure that the dividend payout ratio should not be greater than 100%, I set $div = 1$ if *div* is larger than 1. In Datastream terms, dividend (*d*) is DS 187 (Ordinary dividends – net).

ind: Industry-year specific persistence parameter (ind_t) is $\omega_{i,t,1}$ in the regression equation $x^a_{i,t+1} = \omega_{i,t,0} + \omega_{i,t,1} x^a_{i,t} + \varepsilon_{i,t+1}$, where *i* represents each industry. For industry *i* and year *t*, all available *i* industry data from 1969 to year *t* are used. However, in order to avoid getting unreasonable parameters arising from the insufficient pooled data, I set 1969 to 1978 industry-year specific parameters equal to 1979 industry-year specific parameter for every industry groups except 'information technology' industrial sector (denoted as

[62] Median ROAs for the year are shown in Appendix 5.7. In the U.K., the long-run median ROAs for alternative earnings are 5.1 to 5.7%. Similarly, the long-run mean ROA (earnings before extraordinary items divided by total assets) in the U.S. is 6% or so (Lee *et al.*, 1999).

IMT) and 'utilities' industrial sector (denoted as UTL).[63] For the same reason, I set 1969 to 1987 (1994) industry-year specific parameters equal to 1988 (1995) parameter for IMT (UTL).

RD: Research and development expenditures include regular write-offs to the P/L account of R&D capitalised in the balance sheet as well as amounts expended in the year that are not capitalised. This is DS 119 (Research and development).

$P_t^{c,n}$: In order to make comparable the stock price and the earnings announcement, I use stock prices observed at 3 to 7 months after the fiscal year end. A variety of reporting lags are used in order to test the sensitivity of my results to the assumed lag. Stock prices as reported 3 to 7 months after the end of the fiscal year, but adjusted for subsequent capital actions (e.g., stock splits, stock dividends), are obtained from Datastream (Datastream code P – adjusted price).

5.3. Data Collation and Sample Selection

All data used in this study were extracted from Datastream except consensus earnings forecasts from I/B/E/S. Firstly, all possible U.K. industrial companies were collected from Datastream - the sample includes the dead firms in order to avoid survivorship bias. The company list initially consists of total 2,641 firms over the sample period from

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[63] For industry-year specific persistence parameters, I use FTSE Level 3 classification. FTSE Level 3 industry groups are Resources (RSR), Basic industries (BIN), General industries (GIN), Cyclical consumer goods (CGD), Non-cyclical consumer goods (NCG), Cyclical services (CSV), Non-cyclical services (NSV), Utilities (UTL), and Information technology (IMT).

1969 to 1998. The 30-year period is chosen to get as much firm-year data as possible. Another reason to set the starting year as 1969 is that missing values (especially earnings data) are more common prior to the late 1960s in Datastream. Before obtaining total firm-year observations, I deleted some observations that have missing earnings, book value, or stock price, which are core variables in this study.

Furthermore, I found some clear errors that Datastream made, even though most of them are trivial and random. These trivial and random errors may have little effect on my results because this study is conducted with a large number of firm-year observations. However, I corrected as many errors as I could. First of all, I corrected large critical errors that Datastream made while adjusting the published numbers to arrive at DS 210, even though the corrections are likely to have little effect on the final results. Some critical errors were found in DS 981 (adjustments to operating profit) that has a large effect on DS 210. Firstly, I collected 39 firm-years for which the absolute value of DS 981 is greater than 100% of the absolute value of DS 625 (earned for ordinary), and 32 firm-years that have large negative DS 981 less than minus £10 million. I then investigated 11 firm-years from each set. Among 22 firm-years, 2 (Lasmo, 31/12/94 and Cadbury Schweppes, 31/12/94) have completely wrong numbers in DS 981.[64] But, fortunately, I can conclude that these errors do not occur systematically.

On the other hand, I corrected cases in which values were reported for DS 1083, DS

[64] DS 981 of Lasmo and Cadbury were –222,000 and –114,800, respectively. But I found that they should be respectively about –17,000 (Total exceptional profit for the year, note 3) and 23,000 (Exceptional item – Spain restructuring costs, note 2) from the Financial Statements.

1094 and DS 1097 in the pre-FRS 3 regime, for which these items should not be available. Especially, many dead companies had large numbers on DS 1094. Also, 7 firm-year observations had non-zero numbers on DS 193 in the post-FRS 3 regime, although after the introduction of FRS 3 in the U.K. GAAP, DS 193 has been effectively abolished (i.e., zero). Thus, I set these numbers to zero.

Finally, I found that some DS 210 and DS 182 that have zero values do not actually represent zero earnings. They represent missing values so that these cases were deleted as well.[65] I also found other data entry errors. Total assets (DS 392) should not be zero and current liabilities (DS 389) should not be negative. Also, there were some missing values in DS 376 (current assets), DS 375 (cash and equivalent), DS 389, DS 381 (current taxation), DS 136 (depreciation) and DS 187 (dividends). So I collated these data entry errors with the numbers in the financial statement and corrected them. Appendix 5.4 summarises the errors that Datastream had made.

After collating and correcting data, total 30,277 firm-year observations were obtained. Among these, 449 cases (1.5%) had negative book values so I deleted those cases, because some versions of my data analysis require book value as a scaling variable. Therefore, available data from Datastream during 1969 to 1998 after eliminating negative book values are 29,828 firm-years. This is one of the primary data sets that is used for estimation of RI persistence parameters.[66] Because RI is defined in terms of

[65] These cases were only found during 1969 to 1971.
[66] Note that because RI is defined in terms of lagged book value and AR(1) RI regression equation is used for the estimation of RI parameters, total observations available for RI persistence parameters are 25,187. It means that the first and second observations of each firm can not be used for the purpose of RI parameter estimation.

lagged book value, total observations for the calculation of RI is 27,435, and are available for the periods 1970-1998. Then, this data set is merged with I/B/E/S analysts' earnings forecasts data. Because I/B/E/S provides analysts' earnings forecasts for U.K. firms only for 1990 onwards, total observations for the calculation of OI are significantly reduced to 8,346. This is another primary data set that is used for the estimation of OI persistence parameters.[67] Note here that analysts' earnings forecasts made in respect of year *t*+1 are matched with RI realizations for year *t* for the purpose of estimating OI at year *t*. Finally, 6,835 observations from 1991 to 1998 are used for the purpose of the estimation of firms' intrinsic values, because the 1989 OI parameter cannot be estimated and the 1990 OI parameter is estimated with a small number of observations. Table 5.5 shows details of U.K. sample construction.

Also Appendix 5.8 shows the distribution of firm-year observations. As shown in Panel A, total firm-year observations vary according to variables included in the analysis. It means that the number of firm-year observations vary depending on the number of lags in the dependent and/or independent variables. Thus, if pooled AR(1) and AR(4) analyses based upon the residual income variable are conducted, total firm-year observations that can be used are 25,187 and 19,753, respectively. Note also that many firms have a small number of observations. In Panel A (B), 878 (546) firms have data points less than or equal to 5 (3) that is about 37% of the total firms in each set. The average number of observations per firm is 12.5 (5.7) for the periods 1969-1998 (1989-1998).

[67] Note also that because AR(1) OI regression equation is used for the estimation of OI parameters, total observations available for OI persistence parameters are 6,875. It means that the first observations of each firm can not be used for the purpose of OI parameter estimation.

5.4. Descriptive Statistics

Table 5.6, Panel A shows the descriptive statistics of the main raw variables in per-share form – 4 earnings measures, stock price and book value. The distribution of all these variables is long-tailed, which means that accounting variables and stock price tend to have high density around their median.[68] Conversely, there are potentially influential outliers in the data set. Therefore, the trimming or winsorising criteria should be applied in the data analysis in order to avoid the effect of extreme outliers. In this U.K. study, I delete the 1% most extreme outliers for the estimation of RI and OI persistence parameters. However, I retain all data for the test of reliability of value estimates.

On the other hand, mean values of each variable are much higher than median values, which means that the distribution of all variables tends to be right-skewed.[69] Right-skewness of stock price is because some firms have extremely large stock prices that dominate the stock market. Meanwhile, right-skewness of earnings variables and book value is because the accounting system is conservative. That is, the accounting system tends to postpone the recognition of revenues/gains and accelerate the recognition of expenses/losses (Myers, 1999a). Together with Table 5.6, Panel B, we can see that firms' stock price, earnings and book value have increased over time.

Table 5.6, Panel A also presents the descriptive statistics of RI. The negative median

[68] 90% of each variable is centrally dense within 0.2 – 0.5% of the corresponding range.
[69] Even though mean value of X3 is also much higher than median value of it, its skewness is negative. The negative skewness of X3 seems to be caused by large negative extraordinary items.

(mean) residual income regardless of earnings measures is consistent with previous research and is because ROE is smaller than the discount rate, on average.[70] There are two possible reasons why the median (mean) values of RI in Panel B are higher than those in Panel A. One is that the discount rate has fallen recently so that many ROE values exceed the discount rate. Based on 8,346 observations from 1989 to 1998, the median (mean) discount rate is just 13.3% (13.6%), while the median (mean) ROE is about 14% (16-17%). The other reason is that firms' earnings seem to have increased more than firms' book value, on average, over time. Compared to median values for the periods 1969-1998, median values of earnings for the periods 1989-1998 have increased more than 60%, while median values of book value have increased about 40%.

Table 5.6, Panel A also shows the relationship between alternative earnings measures. The mean of X1 is larger than the mean of X3 or X4, because the exceptional (*EXC*) and extraordinary (*EXT*) items, especially large items, tend to occur as losses rather than profits, in general, so that their mean values are negative, on average. We can see that *AEX* (all abnormal items), *EXC* and *EXT* tend to have large negative numbers. As described in Appendix 5.6, X1 is approximately X3 minus *AEX* (0.102 + 0.038), or X4 minus *EXC* (0.132 + 0.008). In addition, X1 is X2 plus *SA* (full tax adjustments after SSAP 15) (0.126 + 0.014), and X3 is X4 plus *EXT* (0.132 – 0.030).

On the other hand, Table 5.6, Panel B shows statistics of analysts' earnings forecasts and 'other information'. First, median (mean) value of one-year ahead analysts' earnings

[70] Long-run median (mean) ROEs are less than 13.4% (14.8%) regardless of earnings measures. Thus, these ROEs of U.K. industrial companies are less than the cost of capital (15-15.5%), on average.

forecasts are positive and greater than the median (mean) value of realized earnings, which means that analysts tend to forecast earnings optimistically. The optimistic behavior of analysts is consistent with evidence reported in prior studies (e.g., O'Brien, 1988; De Bondt and Thaler, 1990; Brown, 1997; Brown, 1998; Richardson *et al.*, 1999; Easterwood and Nutt, 1999).

Second, median (mean) value of analysts' earnings forecasts is increasing in forecasting windows. That is, two-year ahead analysts' earnings forecasts are larger than one-year ahead analysts' earnings forecasts, and three-year ahead analysts' earnings forecasts are larger than two-year ahead analysts' earnings forecasts. This indicates that analysts' tend to be more optimistic when they forecast earnings over a longer time horizon.[71] The tendency of the incremental optimism over forecasting windows is also consistent with previous research, and it may, at least partly, cause the superiority (in terms of bias and accuracy) of longer horizon EBO models reported in Sougiannis and Yaekura (2000).

Third, 'other information' is positive, on average,[72, 73] which means that analysts-based forecasts of RI are higher than RI forecasts based on the univariate AR(1) RI generating equation. The mean of analyst-based RI forecasts for 1989-1998 is –3.3% (unreported), while the corresponding figure for the realized RIs for 1969-1998 is –11.8% to –15.9%.

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[71] In order to make median (mean) values of 1 to 3-year ahead earnings forecasts comparable, the number of observations are reduced to 3,711, but the evidence of the incremental optimism over forecasting windows does not change. In this case, the median (mean) values of 1 to 2-year ahead earnings forecasts are respectively 0.151 (0.196) and 0.175 (0.226).

[72] The negative mean value of OI based on X1 is caused by one extremely large negative OI (-132). The numbers in parentheses show mean and standard deviation of OI when one extremely large negative OI is deleted.

[73] The intercept of AR(1) RI regression is incorporated into the calculation of OI. If the intercept parameter is ignored in the calculation of OI, and one extremely large negative OI is deleted, the median (mean) value of OI is still positive, but smaller than the corresponding figures in Table 5.6, Panel B.

Note that the sample for the periods 1969-1998 is used for the univariate AR(1) RI generating process.

Table 5.7 describes the properties of some main variables using ratios. Here, the earnings measure X4, which is conceptually similar to the earnings measure employed in Dechow *et al.*'s (1999) U.S. study, is used. Overall, magnitudes and signs of figures from the U.K. sample are very consistent with corresponding U.S. figures reported in Chapter 4, even though the sample period is different. Panel A is based on the sample from 1969 to 1998 and Panel B from 1989 to 1998. From these two panels, i) book-to-market ratio and earnings-to-price ratio have decreased over time, and ii) firms' profitability (earnings-to-lagged book ratio, i.e., ROE) and abnormal returns (RI-to-lagged book ratio, i.e., the spread between ROE and cost of capital) have increased over time. Also, as U.S. study in Chapter 4, 1) the median and mean value of scaled OI (2.9% and 15.6%) are positive, and 2) the median and mean of scaled analysts-based RI forecasts for 1989-1998 (2.2% and 11.1%) are higher than the corresponding figures of the realized RIs (-2.2% and –1%) for 1969-1998.

Table 5.1: Examples of inconsistency in Datastream's post-SSAP 15 adjustment

(£ ,000)

Example 1 : SCAPA Group

	91	92	93	94	95	96	97	98
Effect on P/L account tax charge of SSAP 15 (per note to Financial Statement)	384	-50	527	400	2400	400	2000	-500
SSAP 15 adjustment of Datastream	384	-50	0	0	0	0	2000	-500

Example 2 : Cadbury Schweppes

	90	91	92	93	94	95	96	97
Effect on P/L account tax charge of SSAP 15 (per note to Financial Statement)	6200	2200	1700	7900	3200	7000	-3000	-4000
SSAP 15 adjustment of Datastream	6200	2200	1700	0	0	7000	0	0

Note : Relevant notes in Financial statement of SCAPA Group (1998) and Cadbury Schweppes (1992) are respectively "Had full provision for deferred taxation been made for the whole Group then there would have been an additional credit of £0.5m (£2.0m charge in the case of 1997)" and "The charge of £94.2m has been reduced by £1.7m in respect of tax at the current year's rate on timing differences for which deferred tax has not been provided".

Table 5.2: Four earnings definitions and Datastream items[74]

	Pre-FRS3	Post-FRS3	General
X1	DS 210	DS 210	DS 210
X2	DS 182	DS 182	DS 182
X3	DS 625 + DS 193	DS 625[1)]	DS 625 + DS 193
X4	DS 625[2)]	DS 625 – (DS 1083 – DS 1094 – DS 1097)	DS 625 – (DS 1083 – DS 1094 – DS 1097)

Note:

1) DS 193 still exists after FRS 3, but its numbers are all zero.

2) DS 1083, 1094 and 1097 do not exist before FRS 3.

3) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings and X4 is post-exceptional and pre-extraordinary earnings.

[74] See Appendix 5.6 for relations and differences between 4 alternative earnings measures.

Table 5.3: U.K. Gross Redemption Yield on 20 year Gilts (%)

1969	1970	1971	1972	1973	1974	1975	1976	1977	1978
9.04	9.21	8.85	8.90	10.71	14.77	14.39	14.43	12.72	12.47
1979	1980	1981	1982	1983	1984	1985	1986	1987	1988
12.99	13.78	14.74	12.88	10.80	10.69	10.62	9.87	9.47	9.36
1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
9.58	11.08	9.92	9.12	7.87	8.05	8.25	8.10	7.09	5.47

Note: Redemption Yield shown in this table is year average from January to December. Note that year-specific Redemption Yield used in the study is 12 month average up to the fiscal year end month.

Table 5.4: Other variables and definitions

Variable	General Definition
x_t	Earnings per share for year t
	X1: Earnings before exceptional and extraordinary items
	X2: Full-tax adjusted earnings before exceptional and extraordinary items
	X3: Earnings after exceptional and extraordinary items
	X4: Earnings after exceptional, but before extraordinary items
f_{t+n}	Analysts' earnings forecasts at year t for year $t+n$
MV_t	Market value of equity at the end of year t
P_t	Stock price at the end of year t
b_t	Book value per share at the end of year t
x_t^a $(=RI_t)$	Residual income for year t.
f_{t+n}^a	Analyst-based residual income forecasts at year t for year $t+n$
$q1_t$	Magnitude of residual income (= $\lvert x_t^a / b_{t-1} \rvert$)
$q2_t$	Magnitude of exceptional items (= $\lvert EXC_t / b_{t-1} \rvert$)
$q3_t$	Magnitude of extraordinary items (= $\lvert EXT_t / b_{t-1} \rvert$)
$q4_t$	Magnitude of all exceptional and extraordinary items (= $\lvert AEX_t / b_{t-1} \rvert$)
$q5_t$	Magnitude of operating accruals (= $\lvert OA_t / TA_{t-1} \rvert$)
div_t	Dividend payout ratio (= d_t / x_t)
ind_t	Historical persistence of residual income for firms in the same industry
v_t $(=OI_t)$	Other information for year t (= $f_{t+1}^a - E_t\left[\tilde{x}_{t+1}^a\right]$)
RD_t	Research and development expenditures during year t
$P_t^{c,n}$	Contemporaneous stock price measured at n months after the end of fiscal year t

Table 5.5: Number of firms and firm-year observations

	Number of Firm-years
Available from Datastream for which all accounting data and market value exist (1969-1998)	30,277
Less: Observations for which book value was negative	449
Available from Datastream after elimination of firm-year observations for which book value was negative (1969-1998)	29,828
Less: First observation of each firm	2,393
Total observations available for the calculation of RI (1970-1998)	27,435
Less: Observations for which I/B/E/S data were unavailable	19,089
Total observations available for the calculation of OI (1989-1998)	8,346
Less: 1989 or 1990 observations	1,511
Total observations for the estimation of value estimates (1991-1998)	6,835
Total observations available for the estimation of RI persistence parameters (1971-1998) = 29828 – 2393 – 2248 (second observation of each firm)	25,187
Total observations available for the estimation of OI persistence parameters (1990-1999) = 8346 – 1471 (first observation of each firm)	6,875

Note:

1) If there is a discontinuity less than or equal to 24 months in a firm's data series, I consider the adjacent two data points continuous so that I apply the time-series cross-sectional analyses as normal. Otherwise, I treat the data series, separated at the discontinuity, as the data of two different firms.
2) Under this criterion, deleting negative book value causes 45 cases of discontinuity. In addition, there are 3 more cases of discontinuity where a firm's data series itself contains discontinuity.
3) Thus, even though the total number of firms from 1969 to 1998 is 2,345, I treat as if there are 2,393 firms. Similarly, even though the total number of firms from 1989 to 1998 used for the calculation of OI is 1,395, I treat as if there are 1,471 firms.

Table 5.6: Descriptive statistics (raw variables in per-share form)

Panel A: 1969 to 1998 (£)

	N	Mean	Std	Min	1%	Q1	Median	Q3	99%	Max
X1	29828	0.140	2.007	-81	-0.336	0.021	0.066	0.143	1.197	125
X2	29828	0.126	1.832	-81	-0.329	0.020	0.060	0.132	1.115	98
X3	29828	0.102	2.580	-161	-0.621	0.018	0.063	0.143	1.311	129
X4	29828	0.132	2.112	-123	-0.453	0.021	0.067	0.145	1.262	126
P	29828	1.905	17.497	0.001	0.024	0.305	0.758	1.700	12.460	1753
b	29828	1.691	14.214	0.00002	0.016	0.265	0.577	1.160	13.293	764
AEX	29828	-0.038	1.421	-131	-0.509	-0.006	0	0.003	0.316	71
EXC	29828	-0.008	0.439	-49	-0.198	-0.001	0	0.002	0.140	9.5
EXT	29828	-0.030	1.330	-123	-0.369	-0.001	0	0	0.232	71
SA	29828	0.014	0.419	-3.4	-0.025	0	0	0.004	0.155	58
RI1	27435	-0.118	2.692	-215	-1.486	-0.064	-0.009	0.021	0.309	89
RI2	27435	-0.132	2.713	-214	-1.517	-0.073	-0.014	0.014	0.283	89
RI3	27435	-0.159	3.651	-301	-1.729	-0.072	-0.009	0.022	0.400	89
RI4	27435	-0.126	2.847	-223	-1.520	-0.065	-0.008	0.022	0.319	89

Table 5.6 (continued)

Panel B: 1989 to 1998 (£)

	N	Mean	Std	Min	1%	Q1	Median	Q3	99%	Max
X1	8346	0.172	1.333	-8.5	-0.239	0.047	0.110	0.203	0.959	98
X2	8346	0.167	1.293	-8.5	-0.236	0.047	0.109	0.200	0.949	98
X3	8346	0.125	1.391	-41	-0.597	0.038	0.105	0.200	1.070	98
X4	8346	0.158	1.437	-22	-0.387	0.045	0.108	0.200	0.973	98
P	8346	2.576	19.935	0.001	0.120	0.797	1.571	2.828	11.721	1753
b	8346	1.523	7.609	0.002	0.039	0.425	0.801	1.447	9.858	545
RI1	8346	-0.040	1.209	-29	-0.986	-0.054	0.004	0.054	0.327	89
RI2	8346	-0.045	1.225	-29	-0.992	-0.057	0.002	0.052	0.319	89
RI3	8346	-0.087	2.006	-127	-1.325	-0.072	0.001	0.054	0.442	89
RI4	8346	-0.054	1.270	-36	-1.113	-0.061	0.003	0.053	0.321	89
f_{t+1}	8346	0.178	0.255	-2.197	-0.063	0.065	0.131	0.227	0.884	9.0
f_{t+2}	7424	0.206	0.301	-1.136	0.001	0.081	0.152	0.255	0.980	11.0
f_{t+3}	3711	0.237	0.244	-0.619	0.011	0.102	0.183	0.304	0.988	6.7
OI1	8346	-0.003	1.490	-132	-0.556	-0.004	0.018	0.048	0.405	7.2
	(8345)	(0.013)	(0.374)							
OI2	8346	0.010	1.451	-128	-0.476	0.002	0.024	0.056	0.434	7.3
	(8345)	(0.025)	(0.361)							
OI3	8346	0.023	1.464	-117	-0.595	-0.001	0.027	0.069	0.522	45
	(8345)	(0.037)	(0.716)							
OI4	8346	0.003	1.507	-131	-0.578	-0.004	0.019	0.054	0.479	16
	(8345)	(0.019)	(0.468)							

Note:

1) *P* is fiscal year end stock price, X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings, and *b* is book value per share.
2) *AEX* represents all exceptional and post-tax extraordinary items, i.e., (DS 194 + DS 208 + DS 193). *EXC* represents exceptional items defined in the pre-FRS regime, i.e., [(DS 194 + DS 208) – (DS 1083 – DS 1094 – DS 1097)]. *EXT* represents post-tax extraordinary items defined in the pre-FRS regime, i.e., (DS 1083 – DS 1094 – DS 1097) + DS 193. *SA* represents full-tax adjustments after SSAP15, i.e., DS 209. *RIi* is residual income based on X*i*.
3) f_{t+n} is *n*-year ahead median analysts' earnings forecasts from I/B/E/S.
4) *OI* is defined as analysts-based RI forecasts less RI forecasts based on the univariate AR(1) RI generating equation, when RI intercept is incorporated and book value is used as a scaling variable. That is, $OI_t = f_{t+1} - rb_t - \omega_{0,t}b_t - \omega_{1,t}RI_t$. *OIi* is 'other information' based on X*i*.
5) The numbers in parentheses reported in *OI* rows are results after deleting one extremely negative *OI* values – i.e., -132 of *OI1*, -128 of *OI2*, -117 of *OI3* and -131 of *OI4*.

Table 5.7: Descriptive statistics (ratios) – based on X4

Panel A: 1969 to 1998

	N	Mean	1%	Q1	Median	Q3	99%
Book / price (b_t/P_t)	29828	1.299	0.071	0.437	0.791	1.390	8.081
Earnings / price (x_t/P_t)	29828	0.086	-0.660	0.052	0.085	0.137	0.736
Earnings / lagged book (x_t/b_{t-1})	27435	0.145	-0.511	0.069	0.134	0.211	0.791
RI / lagged book (x_t^a/b_{t-1})	27435	-0.010	-0.658	-0.089	-0.022	0.057	0.650

Panel B: 1989 to 1998

	N	Mean	1%	Q1	Median	Q3	99%
Book / price (b_t/P_t)	8346	0.727	0.057	0.337	0.538	0.854	3.378
Earnings / price (x_t/P_t)	8346	0.050	-0.545	0.047	0.068	0.093	0.242
Earnings / lagged book (x_t/b_{t-1})	8346	0.164	-0.531	0.073	0.140	0.225	0.949
RI / lagged book (x_t^a/b_{t-1})	8346	0.028	-0.666	-0.064	0.006	0.089	0.807
Analyst-based RI forecast / book (f_{t+1}^a/b_t)	8346	0.111	-0.303	-0.039	0.022	0.107	1.442
OI / book (v_t/b_t)	8346	0.156	-0.142	-0.005	0.029	0.083	1.571

Note:

1) The earnings measure used here is earnings before extraordinary items (X4), which is similar to the earnings measure used in Dechow *et al.*'s (1999) U.S. study.
2) The mean of the discount rate based on 1969-1998 (1989-1998) sample is 15.5% (13.6%).
3) f_{t+1}^a is analysts-based RI forecasts. That is, $f_{t+1}^a = f_{t+1} - rb_t$ where f_{t+1} is one-year ahead median analysts' earnings forecasts from I/B/E/S.
4) *OI* (=*v*) is defined as analysts-based RI forecasts less RI forecasts based on the univariate AR(1) RI generating equation, when RI intercept is incorporated and book value is used as a scaling variable. That is, $OI_t = f_{t+1} - rb_t - \omega_{0,t}b_t - \omega_{1,t}RI_t$.

Appendix 5.1: Extracts from Datastream manual

1) Item 210 (Earned for ordinary – adjusted)

General: Net profit after tax, minority interests and preference dividends. This is the adjusted earnings using the adjusted pre-tax profit and taxation charge, i.e., excluding pre-tax extraordinary items, non-operating provisions and transfers to tax-exempt reserves, exchange gains/losses and any other items not relating to the normal trading activities of the company.
210 = 175 (After tax profit – adjusted) – 176 (Minority interests) – 177 (Other adjustments) – 180 (Preference dividend – gross) – 181 (Preference dividend for period) – 629 (Directors bonuses).
UK: 210 = 175 – 176 – 177 – 180 – 181 + 205 (Supplementary tax equalisation) + 206 (Adjustment to irrecoverable advance corporation tax) – 629 (for UK companies, item 629 is only applicable to miscellaneous financials).

2) Item 182 (Earned for ordinary – full tax)

General: This is the net profit after tax, minority interest and preference dividends.
182 = 175 – 176 – 207 (Minorities – supplementary tax) – 177 – 181.
UK: The definition is similar to that for item 210 (Earned for ordinary – adjusted) except that supplementary tax may have been deducted from item 210 to provide a comparable earnings figure between accounts published before and after 1980, when the UK accounting standard SSAP15 was issued.

3) Item 625 (Earned for ordinary)

General: This is the net profit after tax, minority interest and preference dividends, but before any post-tax extraordinary items, using the published unadjusted figures.
625 = 154 (Pre-tax profit) – 203 (Total tax charge) – [1086 (Minority interests) or 176 (Minority interests)] – 629 – 177 – 181 [+622(Associates after-tax profit)].

4) Item 193 (Extraordinary items)

General: Extraordinary items as defined by the company will be entered here. The item applies only for companies which show extraordinary items after tax.

5) Item 194 (Exceptional items)

General: This is the sum of all adjustments made to published pre-tax profit. Also included are the adjustments made to published tax (Notional tax adjustment, item 185) and prior year tax (item 199).
UK (IND:FRS3): 194 = 989 (Total tax adjustment) – 1097 – 981 (Adjustments to operating profit) + 1083 + 1091 (Other non-operating adjustments) – 1090 (Adjustments to associate profits)

6) Item 1083 (Total special items)

General: A Datastream created title reflecting the total of exceptional amounts shown in the published P&L statements between operating profit or loss and non-trading income/expense and individually highlighted at items 1079, 1080, 1081 and 1082.
1083 = 1079 (Profits of losses on termination of operations) - 1080 (Reorganization or restructuring costs) + 1081 (Profits or losses on sale of fixed assets) + 1082 (Other special gains/losses)

Appendix 5.1 (continued)

7) Item 1094 (Tax on special items)

General: This is the tax as specified by the company relating to amounts shown at item 1083.

8) Item 1097 (Minority interest in special items)

General: The share of 'special items' relating to minorities.

9) Item 208 (Exchange adjustments)

General: Any after-tax adjustments are included here.

10) Item 376 (Total current assets)

General: This includes stock, work in progress, debtors, cash and equivalent and any other current assets. Accounts receivable after 1 year are included.

11) Item 375 (Total cash and equivalent)

General: This includes cash, bank balances, short-term loans and deposits and investments shown under current assets.

12) Item 389 (Total current liabilities)

General: This includes current provisions, creditors, borrowings repayable within 1 year and any other current liabilities. It also includes trade accounts payable after 1 year.

13) Item 309 (Borrowings repayable within 1 year)

General: This shows bank overdrafts, loans and other short-term borrowings. The current portion of long-term loans is also included.

14) Item 381 (Current taxation)

General: Corporation tax due for payment in less than one year.
UK: This includes any advance corporation tax on dividends shown separately by the company.

15) Item 136 (Depreciation)

General: This represents provisions for amounts written off (AWO), and depreciation of fixed assets and assets leased in.

16) Item 392 (Total assets)

General: This relates to the total assets employed by the company.
392 = 339 (Total fixed assets – net) + 344 (Total intangibles) + 356 (Total investments including associates) + 359 (Other assets) + 376 (Total current assets)

17) Item 187 (Ordinary dividends)

General: This relates to net amounts paid on ordinary shares, and also includes the variable amount paid on participating preference shares.

18) Item 119 (Research and development)

General: This figure includes regular write-offs to the profit and loss account of research and development capitalised in the balance sheet. Also included are amounts expended in the year which are not capitalised.

Appendix 5.2: The development of U.K. income reporting standards

1) SSAP 6 (1974; Extraordinary Items and Prior Year Adjustments)
  - Prior to SSAP 6, unusual or non-recurring transactions were frequently accounted for as reserve movements. Moreover, there was the subjectivity in determining whether or not an event was unusual or non-recurring.
  - SSAP 6 required most extraordinary or prior year items to be accounted for through the P&L account, but not through reserves. It also required the separate disclosure of the profit/loss on extraordinary items after the profit/loss on ordinary activities.
  - However, there were significant inconsistencies between different companies on disclosing the effect of similar events in the P&L account, because SSAP 6 inadvertently caused the development of a multiplicity of items classified as extraordinary.

2) SSAP 6 (1986, revised)
  - The revised SSAP 6 was aimed at reducing the problem of inconsistency in classification of extraordinary items by means of defining 'ordinary activities', 'exceptional items' and 'extraordinary items' and giving the extended list of examples.
  - However, as the Research Committee of ICAS (Institute of Chartered Accountants in Scotland) identified later, there were some shortcomings in the UK income reporting standards such as the adherence to legal form rather than economic substance, the use of cost rather than value, the concentration on the past rather than the future, and the interest in profit rather than wealth.

3) FRS 3 (1992; Reporting Financial Performance)
  - The main objective of FRS 3 is to ameliorate some of these shortcomings. That is, it is 'to require reporting entities falling within its scope to highlight a range of important components of financial performance to aid users in understanding the performance achieved by a reporting entity in a period and to assist them in forming a basis for their assessment of future results and cash flows'.
  - A basic rule in FRS 3 is that all recognised gains and losses must appear on the face of the P&L account unless specifically permitted or required to be taken direct to reserves by law or by accounting standards.
  - The P&L account has been reshaped as a layered format. The new format highlights important components of firm's performance – 1) the results of continuing operations including the results of acquisitions, 2) the results of discontinued operations, 3) profits and losses on the sale or termination of an operation, costs of a fundamental reorganisation or restructuring, and profits or losses on the disposal of fixed assets, and 4) extraordinary items.
  - Extraordinary items are effectively abolished. Most items which were previously classified as extraordinary items are to be treated as exceptional items.
  - All exceptional items should be included under the statutory format headings to which they relate.
  - Especially, certain types of exceptional items should be shown separately on the face of the P&L account after operating profit and before interest. These are 1) profits or losses on the sale or termination of an operation, 2) costs of a fundamental reorganisation or restructuring, and 3) profits of losses on the disposal of fixed assets. These items represent most of items treated as extraordinary under SSAP 6 regime.
  - FRS 3 introduces a new primary financial statement in the form of a 'Statement of total recognised gains and losses' to reflect the reporting of changes in wealth.

Appendix 5.3: Examples of the relationship between four earnings measures and the published figure

Table A5.3.1: Examples of the relationship between X1 and the published figure

(a) Pre-FRS 3

Example 1: Cadbury Schweppes (29/12/90)		Terms in Financial Statement
Earned for ordinary (DS 625)	176000	Profit Attributable To Shareholders (P/L) – Preference Dividends (Note 10)
Prior year tax (DS 199)	(1200)	Under / (over) provision in previous years (Note 8)
X1 (DS 210)	174800	

Example 2: Glaxo Wellcome (30/6/90)		Terms in Financial Statement
Earned for ordinary (DS 625)	793000	Profit before extraordinary items (P/L)
Capital gains/losses (DS 198)	8000	Realised (losses) / gains (Note 6)
Other adjustments (DS 200)	(4000)	Market value adjustments (Note 6)
X1 (DS 210)	797000	

Note:
1) DS 625 (Earned for ordinary) – DS 194 (Exceptional items) – DS 208 (Exchange adjustments after tax) = DS 210 (Earned for ordinary – adjusted)
where
DS 194 = DS 198 (Capital gains/losses) + DS 199 (Prior year tax) + DS 185 (Notional tax adjustment) + DS 200 (Other adjustments)
– DS 197 (Additional depreciation) – DS 193 (Extraordinary items after tax)
DS 193 is subtracted here because the other items on the right-hand side include items classified as extraordinary as well as exceptional.
2) DS 625 is not available in Datastream before mid-1980s. However, the number is available from the Financial Statements.

Appendix 5.3 (continued)

Table A5.3.1 (continued)

(b) Post-FRS 3

Example 1: Cadbury Schweppes (30/12/95)				Terms in Financial Statement
Earned for ordinary (DS 625)			300000	Profit for the Financial Year (P/L)
Adjustments to pre-tax profit (DS 914)				
Adjustments to operating profit (DS 981)		49000		Acquisition related restructuring costs (P/L)
Total special items (DS 1083)				
Profit or losses on termination of operation (DS 1079)	(15000)			Profit on sale of investments in subsidiary undertakings (P/L)
Profit or losses of sale of fixed assets (DS 1081)	1000			Loss re properties (P/L)
		(14000)		
			35000	
Total Tax Adjustments (DS 989)				
Tax on adjustments to operating profits (DS 1093)		(17000)		Tax on acquisition related restructuring costs (P/L)
Tax on special items (DS 1094)		1000		The profit on sale of investment and the net loss re properties gave rise to tax payable of £1m & £nil, respectively (Note 4)
Prior year tax (DS 199)		2000		Under provision in previous years (Note 8)
			(14000)	
Minority interests in special items (DS 1097)			4000	The amount attributable to minorities of the net loss re Properties was a loss of £4m (Note 4)
X1 (DS 210)			325000	

Appendix 5.3 (continued)

Table A5.3.1 (continued)

(b) Post-FRS 3 (continued)

Example 2: SCAPA Group (31/3/98)			Terms in Financial Statement
Earned for ordinary (DS 625)		20400	Profit for the Year (P/L)
Adjustments to pre-tax profit (DS 914)			
Adjustments to operating profit (DS 981)	27800		Pre-tax exceptional items (P/L)
		27800	
Total Tax Adjustments (DS 989)			
Tax on adjustments to operating profits (DS 1093)	(6000)		Tax on exceptional items (P/L)
Prior year tax (DS 199)	(600)		Prior year adjustment (Note 5)
		(6600)	
X1 (DS 210)		41600	

Note:
DS 625 (Earned for ordinary) – DS 194 (Exceptional items) =
DS 625 + [DS 914 (Adjustments to pre-tax profit) – DS 989 (Total tax adjustments) + DS 1097 (Minority interests in special items)] =
DS 210 (Earned for ordinary – adjusted),
where
DS 914 = DS 981 (Adjustments to operating profit) – DS 1083 (Total special items) – DS 1091 (Other non-operating adjustments) + DS 1090 (Adjustment to associate profits),
DS 989 = DS 1093 (Tax on adjustment to operating profits) – DS 1094 (Tax on special items) – DS 1095 (Tax on other non-operating adjustments) + DS 1096 (Tax on adjustment to associate profits) + DS 199 (Prior year tax).

Appendix 5.3 (continued)

Table A5.3.2 : Examples of the relationship between X2 and the published figure

(a) Pre-FRS 3

Example 1: Cadbury Schweppes (29/12/90)		Terms in Financial Statement
X1 (DS 210)	174800	
Total SSAP 15 adjustments (DS 209)		
Supplementary tax equalisation (DS 205)	(6200)	The charge of £78m has been reduced by £6.2m in respect of tax at the current year's rate on timing differences for which deferred tax has not been provided. (Note 8)
X2 (DS 182)	168600	

Example 2: Glaxo Wellcome (30/6/90)		Terms in Financial Statement
X1 (DS 210)	797000	
Total SSAP 15 adjustments (DS 209)		
Supplementary tax equalisation (DS 205)	(34000)	Taxation has been reduced by £36m because of accelerated capital allowances for which no deferred taxation has been provided. If deferred taxation had been provided the taxation charge would have been increased by £2m. (Note 7)
X2 (DS 182)	763000	

Note: Prior to SSAP 15, DS 182 and DS 210 are identical.

Appendix 5.3 (continued)

Table A5.3.2 (continued)

(b) Post-FRS 3

Example 1: Cadbury Schweppes (30/12/95)		Terms in Financial Statement
X1 (DS 210)	325000	
Total SSAP 15 adjustments (DS 209)		
Supplementary tax equalisation (DS 205)	(7000)	The charge of £158m has been reduced by £7m in respect of tax at the current year's rate on timing differences for which deferred tax has not been provided. (Note 8)
X2 (DS 182)	318000	

Example 2: SCAPA Group (31/3/98)		Terms in Financial Statement
X1 (DS 210)	41600	
Total SSAP 15 adjustments (DS 209)		
Supplementary tax equalisation (DS 205)	500	Had full provision for deferred taxation been made for the whole Group then there would have been an additional credit of £0.5m. (Note 5)
X2 (DS 182)	42100	

Appendix 5.3 (continued)

Table A5.3.3 : Examples of the relationship between X3 and the published figure

(a) Pre-FRS 3

Example 1: Cadbury Schweppes (31/12/88)		Terms in Financial Statement
Earned for ordinary (DS 625)	140400	Profit Attributable To Shareholders (P/L) – Preference Dividends (Note 10)
Extraordinary items after tax (DS 193)	28400	Extraordinary items (P/L)
X3	168800	

Example 2: Glaxo Wellcome (30/6/91)		Terms in Financial Statement
Earned for ordinary (DS 625)	912000	Profit before extraordinary items (P/L)
Extraordinary items after tax (DS 193)	–31000	Extraordinary items (P/L)
X3	881000	

(b) Post-FRS 3

Example 1: Cadbury Schweppes (30/12/95)		Terms in Financial Statement
X3 (DS 625)	300000	Profit for the Financial Year (P/L)

Example 2: SCAPA Group (31/3/98)		Terms in Financial Statement
X3 (DS 625)	20400	Profit for the Year (P/L)

Appendix 5.3 (continued)

Table A5.3.4 : Examples of the relationship between X4 and the published figure

(a) Pre-FRS 3

Example 1: Cadbury Schweppes (31/12/88)		Terms in Financial Statement
X4 (DS 625)	140400	Profit Attributable To Shareholders (P/L) – Preference Dividends (Note 10)

Example 2: Glaxo Wellcome (30/6/91)		Terms in Financial Statement
X4 (DS 625)	912000	Profit before extraordinary items (P/L)

(b) Post-FRS 3

Example 1: Cadbury Schweppes (30/12/95)			Terms in Financial Statement
Earned for ordinary (DS 625)		300000	Profit for the Financial Year (P/L)
Total special items (DS 1083)			
Profit or losses on termination of operations (DS 1079)	(15000)		Profit on sale of investments in subsidiary undertakings (P/L)
Profit or losses on sale of fixed assets (DS 1081)	1000		Loss re properties (P/L)
		(14000)	
Tax on special items (DS 1094)		1000	The profit on sale of investment and the net loss re properties Gave rise to tax payable of £1m & £nil, respectively (Note 4)
Minority interest in special items (DS 1097)		4000	The amount attributable to minorities of the net loss re Properties was a loss of £4m (Note 4)
X4		291000	

Example 2: SCAPA Group (31/3/98)		Terms in Financial Statement
Earned for ordinary (DS 625)	20400	Profit for the Year (P/L)
Total special items (DS 1083)	0	
X4	20400	

Appendix 5.4: Examples of Datastream errors

Examples of Datastream errors that I found when I collected data from Datastream in November 1999 are as follows.

1) DS 981

When published earnings numbers (DS 625) were adjusted to arrive at DS 210, Datastream made some clear errors in DS 981 of some companies. But it was impossible to correct all of these errors because I had to manage thousands of firm-year data. So I investigated only large negative DS 981, and corrected some data using the numbers in the financial statements.

2) DS 1094 and DS 1097 before FRS 3

Lots of dead companies had numbers on DS 1094 and DS 1097 in the pre-FRS 3 regime. These items should be available only after the implementation of FRS 3. So I corrected these errors.

3) DS 1083 before FRS 3

DS 1083 before FRS 3 that had value zero were found in 46 firm-year observations. This item also should not be available before FRS 3. So I corrected these errors.

4) DS 193 after FRS 3

7 firm-year observations had non-zero value in DS 193 after FRS 3. I set this item to zero because this item was effectively abolished with the introduction of FRS 3.

5) No annualisation

I found some data that were not annualized, but I assumed these errors were made randomly. So I left these items as they were.

6) DS 210 and DS 182 that have zero values

I found that some zero earnings numbers actually represent missing values, not zero values. These cases were found during 1969 to 1971, and deleted.

7) Other data entry errors

Other data entry errors were found in DS 392 (total assets) and DS 389 (current liabilities) etc. For example, DS 392 should not be zero and DS 389 should not be negative. And I found some missing values in DS 376 (current assets), DS 375 (cash and equivalent), DS 389, DS 381 (current taxation), DS 136 (depreciation) and DS 187 (dividends). I collated these data entry errors with the numbers in the financial statements and corrected them. However, DS 381 in Datastream is a very noisy item. It represents just 'corporation tax' for some cases as its definition implies, but for some other cases it includes 'other taxation' and/or 'social security' because no item is categorised as 'corporation tax' in the financial statement.

Appendix 5.5: SSAP 15 (Accounting for deferred tax)

1) Need for a statement
   - Taxable profits are often substantially different from accounting profits because of the existence of 'permanent differences' and 'timing differences'.
   - Permanent differences come from non-taxable income or non-allowable expenditure (e.g., dividend income, government grant income, entertainment expenditure)
   - Timing differences arise when certain items of income or expenditure are included in the computation of taxable profit in one period and in the financial accounts in another. Deferred tax is the tax that relates to timing differences.

2) Three approaches to account for the tax effects of timing differences
   - Flow through approach: Only the tax payable in respect of a period should be charged in that period. So no provision for deferred tax would be made.
   - Full provision approach: Financial statements for a period should recognise the full tax effects of all timing differences.
   - Partial provision approach: Deferred tax should be accounted for to the extent that it is probable that a liability or asset will crystallise and should not be accounted for to the extent that it is probable that a liability or asset will not crystallise.

3) Two computation methods for deferred tax
   - Deferral method: The tax effects of timing differences are regarded as deferrals of taxation payable or recoverable to be allocated to future periods when the differences reverse. Balances on the deferred taxation account are regarded as deferred credits or charges, and are not revised on the changes in the rate of taxation.
   - Liability method: The tax effects of timing differences are regarded as liabilities for taxes payable in the future or as assets representing recoverable taxes. Whenever there is a change in the rate of taxation, there will be a revision of the opening balance of deferred taxation.

4) SSAP 15
   - Since the original publication of SSAP 15 in 1978, the basic rules of accounting for deferred tax have not changed significantly (i.e., partial provision approach and liability method).

< The development of accounting for deferred taxation in the U.K. >

	Approach for deferred tax provision	Computation method for deferred tax
ED 11 (1973)	- Full provision	- Deferral method
SSAP 11 (1975)	- Full provision	- Deferral or liability method
ED 19 (1977)	- Full provision generally - Partial provision under some conditions (not explained precisely)	- Liability method
SSAP 15 (1978)	- Partial provision generally - Full provision on short-term timing differences	- Liability or deferral method
ED 33 (1983)	- Partial provision	- Liability method implicitly
SSAP 15 (1985, revised)	- Partial provision	- Liability method
SSAP 15 (1992, amended)	- Partial provision generally - Full provision on post-retirement costs	- Liability method

Appendix 5.6: Relations and differences between 4 earnings measures

1) X1 vs. X2

X1 (DS 210, earned for ordinary – adjusted) and X2 (DS 182, earned for ordinary – full tax) are exactly the same before the issue of SSAP 15, while, subsequent to SSAP 15, X1 is different from X2 by the difference between full tax charge and tax charge after applying deferred taxation in the SSAP 15 regime. The two items differ by the amount of DS 209 (Total SSAP 15 adjustments)[75].

$$X1 = X2 + DS\ 209$$

2) X1 vs. DS 625

The relations between X1 and X3 or X4 depend on the relationship between X1 and DS 625 (earned for ordinary), a core item of X3 and X4. X1 should be the same as DS 625 less exceptional items (DS 194) according to their definitions. In other words, the only reconciling item between DS 210 and DS 625 is normally DS 194. This is true both before and after FRS 3. However, DS 208 (Exchange adjustments after tax) in pre-FRS 3 occasionally arose as an additional reconciling item, because DS 210 does not include after-tax exchange adjustments, while DS 625 does.[76]

$$X1 = DS\ 625 - DS\ 194 - DS\ 208$$

< Example for relations between X1 and DS 625 (Unilever) >

	1988	1989	1990	1991	1992	1993
DS 625	830000	1050000	1108000	1148000	1286000	1291000
DS 194	20000	66000	52000	32000	9000	-156000
DS 208	14000	23000	10000	3000	-2000	0
X1 (DS 210)	796000	961000	1046000	1113000	1279000	1447000

Note: FRS 3 has been applied from 1993.

3) X1 vs. X3

As X3 includes all exceptional and extraordinary items, but X1 excludes them, all *exceptional items and post-tax extraordinary items* should be taken away from X3 to reconcile it with X1.

$$X1 = X3 - (DS\ 194 + DS\ 208 + DS\ 193)$$

where DS 193 is extraordinary items after tax

[75] DS 209 is an additional charge or credit that would be adjusted if full provision for deferred taxation has been made.
[76] DS 208 is included in DS 1082 (Other special items) in the post-FRS 3 regime. In other words, DS 208 has been effectively eliminated after FRS 3, even if the item still exists in Datastream.

Appendix 5.6 (continued)

4) X1 vs. X4

As X4 includes exceptional items, but X1 does not, *exceptional items* defined in the pre-FRS regime should be deducted from X4 to reconcile it with X1.

$$X1 = X4 - (DS\ 194 + DS\ 208) + (DS\ 1083 - DS\ 1094 - DS\ 1097)$$

where DS 1083 is total special items, DS 1094 is tax on special items, and DS 1097 is minority interests in special items

5) X3 vs. X4

By definition, the difference between X3 and X4 should be *post-tax extraordinary items*, because X3 includes all exceptional and extraordinary items, while X4 includes only exceptional items. In the FRS 3 regime, DS 1083 – DS 1094 – DS 1097 represents most of former extraordinary items.

$$X3 = X4 + (DS\ 1083 - DS\ 1094 - DS\ 1097) + DS\ 193$$

< Relations and differences between 4 earnings measures >

	X2	X3	X4
X1	+209	– (194 + 208 + 193)	– [(194 + 208) – (1083 – 1094 – 1097)]
X2	-	– (194 + 208 + 193) – 209	– [(194 + 208) – (1083 – 1094 – 1097)] – 209
X3	-	-	+ [(1083 – 1094 – 1097) + 193]

Note:
1) All numbers indicate Datastream items.
2) Xi in the first column = Xj in the first row + Xij
3) DS 1083, 1094 and 1097 do not exist before FRS3.
4) DS 1083 = DS 1079 – DS 1080 + DS 1081 + DS 1082
5) DS 193 and 208 exist in Datastream after FRS3, but are effectively abolished (i.e., zero).
6) Generally, (DS 194 + DS 208 + DS 193) represents all exceptional and post-tax extraordinary items, [(DS 194 + DS 208) – (DS 1083 – DS 1094 – DS 1097)] represents exceptional items defined in the pre-FRS regime, and (DS 1083 – DS 1094 – DS 1097) + DS 193 represents post-tax extraordinary items defined in the pre-FRS regime.

Appendix 5.7: Median ROA for year in the U.K.

	X1	X2	X3	X4
69	4.7%	4.7%	4.9%	4.9%
70	4.8%	4.8%	5.0%	5.0%
71	5.5%	5.5%	5.6%	5.6%
72	6.1%	6.1%	6.4%	6.4%
73	6.5%	6.5%	6.7%	6.5%
74	5.2%	5.2%	5.2%	5.2%
75	4.8%	4.8%	4.8%	4.8%
76	5.1%	5.1%	5.3%	5.2%
77	5.8%	5.3%	5.9%	6.0%
78	6.4%	5.3%	6.4%	6.5%
79	6.5%	4.7%	6.8%	6.8%
80	5.3%	3.8%	5.6%	5.7%
81	4.2%	3.0%	4.6%	4.9%
82	4.1%	2.9%	3.9%	4.2%
83	4.6%	3.4%	4.4%	4.8%
84	5.4%	4.2%	4.8%	5.5%
85	5.5%	4.8%	5.6%	5.7%
86	6.3%	5.8%	6.3%	6.4%
87	7.1%	6.9%	7.2%	7.3%
88	7.7%	7.3%	7.9%	7.8%
89	7.0%	6.8%	7.4%	7.2%
90	6.1%	6.0%	6.2%	6.2%
91	4.7%	4.5%	4.5%	4.8%
92	4.4%	4.2%	4.0%	4.4%
93	4.7%	4.6%	4.6%	4.7%
94	5.6%	5.4%	5.5%	5.5%
95	5.9%	5.7%	5.8%	5.8%
96	5.8%	5.6%	5.6%	5.7%
97	6.0%	6.0%	5.6%	5.8%
98	6.1%	6.1%	5.6%	5.7%
Average	5.7%	5.1%	5.6%	5.7%

Note: ROA is defined as earnings (X1 to X4) divided by total assets (DS 392).

Appendix 5.8: Distribution of firm-year observations

Panel A: Data set from 1969 to 1998

No. of obs. per firm	No. of firms	Cumulative no. of firms	No. of obs.	1 year lagged obs.	2 year lagged obs.	5 year lagged obs.
31	8	8	248	240	232	208
30	197	205	5910	5713	5516	4925
29	36	241	1044	1008	972	864
28	29	270	812	783	754	667
27	134	404	3618	3484	3350	2948
26	49	453	1274	1225	1176	1029
25	35	488	875	840	805	700
24	24	512	576	552	528	456
23	16	528	368	352	336	288
22	20	548	440	420	400	340
21	24	572	504	480	456	384
20	36	608	720	684	648	540
19	47	655	893	846	799	658
18	57	712	1026	969	912	741
17	64	776	1088	1024	960	768
16	43	819	688	645	602	473
15	62	881	930	868	806	620
14	57	938	798	741	684	513
13	72	1010	936	864	792	576
12	73	1083	876	803	730	511
11	82	1165	902	820	738	492
10	81	1246	810	729	648	405
9	74	1320	666	592	518	296
8	52	1372	416	364	312	156
7	52	1424	364	312	260	104
6	91	1515	546	455	364	91
5	141	1656	705	564	423	0
4	126	1782	504	378	252	0
3	214	1996	642	428	214	0
2	252	2248	504	252	0	0
1	145	2393	145	0	0	0
Total	2393		29828	27435	25187	19753

Appendix 5.8 (continued)

Panel B: Data set from 1989 to 1998

No. of obs. per firm	No. of firms	Cumulative no. of firms	No. of obs.	1 year lagged obs.
11	6	6	66	60
10	313	319	3130	2817
9	167	486	1503	1336
8	108	594	864	756
7	69	663	483	414
6	62	725	372	310
5	76	801	380	304
4	124	925	496	372
3	164	1089	492	328
2	178	1267	356	178
1	204	1471	204	0
Total	1471		8346	6875

Note: Some companies changed their fiscal year end more than once during the sample period (1969-1998). Thus, those companies have more fiscal years than the number of calendar years. That is why the number of observations per firm more than 30 exists over the 30-year sample period (see Panel A). For the same reason, the number of observations per firm more than 10 exists over the 10-year sample period (see Panel B). However, the change of the fiscal year end does not affect the time-series analysis severely, because the annualized accounting data from Datastream have been used.

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CHAPTER 6

RELIABILITY OF COMPETING VALUATION MODELS: U.K. EVIDENCE

6.1. Introduction and Motivation

As equity valuation based on the residual income valuation (RIV) relationship is becoming standard in accounting-based capital market research, many researchers have tried to examine the validity of the RIV model empirically. However, both the Ohlson (1995)-type and the Feltham and Ohlson (1995)-type linear information dynamics (LID) approach and the Edwards-Bell-Ohlson (EBO) approach are unlikely to represent the market's expectations satisfactorily, even though those residual income-based valuation approaches generally outperform the traditional valuation approaches – e.g. book value-based valuation approach and earnings-based valuation approach (Dechow, Hutton and Sloan, 1999; Sougiannis and Yaekura, 2000).

In particular, the empirical results in which value estimates based on the RIV models produce large negative forecast errors can make practitioners suspicious of the practical usefulness of these valuation models. Dechow, Hutton and Sloan (1999) (hereafter DHS) report a negative bias of about 26% in value estimates derived by applying Ohlson's (1995) linear information dynamics model, and the median ratio of the value estimate to the observed stock price reported by Myers (1999b) is 0.411 for LIM1 (Linear information dynamics model (LIM) incorporating RI intercept, but not 'other information (OI)'), 0.644 for LIM2 (LIM incorporating RI intercept, book value and its growth, but not OI), 0.924 for LIM3 (LIM incorporating RI intercept, book value and its growth, and capital investment and its growth, but not OI), and 0.648 for LIM4 (LIM incorporating RI intercept, book value and its growth, order backlog and its growth).[77] Moreover, value estimates based on the EBO approach are also much lower than observed stock prices on average (e.g. Lee *et al.*, 1999; Sougiannis and Yaekura, 2000).

This study is motivated by the large negative bias of value estimates arising from the application of the RIV models reported in previous empirical studies. I suspect that this large negative bias may be caused by model mis-specification. The main objective is, thus, to examine the validity of the 'intercept-inclusive' LID model developed in Chapter 3 in comparison with the Ohlson (1995) LID model and the EBO model using all U.K. industrial firms. I gave some indication of the relative superiority of value estimates based on the 'intercept-inclusive' LID model in terms of bias and accuracy using U.S. data in Chapter 4. This chapter provides evidence for the U.K.

This study is different from the U.S. study in Chapter 4 in the following respects. First, I compare various valuation models, although the main focus is on the Ohlson LID model (denoted as LID9), the 'intercept-inclusive' LID model (denoted as LID16) and 2-year horizon EBO models (denoted as EBO2 and EBO5).[78,79] The competing valuation

[77] Note that Myers' (1999b) additional term in each pricing model related to RI intercept (i.e., α_0) is incorrectly derived. (1-ω_{11}) in LIM1's α_0 and ω_{10} in LIM2 and LIM3's α_0 should be (1+r-ω_{11}) and (1+r) ω_{10}, respectively.

[78] Precisely, the Ohlson LID model is the OI-inclusive general Ohlson (1995) model, the 'intercept-inclusive' LID model is the 'intercept and OI'-inclusive modified LID model and EBO2 (EBO5) is 2-year horizon EBO model under the assumption of zero (non-zero) RI growth.

[79] Among the total observations (6,835) for the pricing test, the observations that have 2-year ahead analysts' earnings forecasts are 5,958, while the observations that have 3-year ahead analysts' earnings forecasts are only 3,033. Thus, 2-year horizon EBO model seems to be more comparable with LID models than 3-year horizon EBO model.

models consist of the Ohlson LID and its variants (total 9 models: LID1 – LID9), the 'intercept-inclusive' LID and its variants (total 7 models: LID10 – LID16) and 6 EBO models (EBO1 – EBO6). See Chapter 3 for the details of 22 models. To my knowledge, there is little empirical research comparing the EBO-type and the LID-type valuation models, so this is an additional motivation of this study.

Second, I use four alternative earnings measures in order to examine the sensitivity of the results to different earnings measures. If the alternative earnings measures give significantly different value estimates, the choice of earnings measure would be an important issue in the residual income-based equity valuation research.

Third, in addition to two performance metrics – bias and accuracy – used in the U.S. study of Chapter 4, the association between value estimates and observed stock prices (explainability) is also examined. However, since those concerned with equity valuation seek to estimate a firm's intrinsic value correctly, the ability of value estimates to explain variation in observed stock prices is not as appropriate as bias and accuracy metrics. Francis *et al.* (1999) state that, of the three metrics, they believe accuracy best captures individual investors' loss functions, and bias assists in understanding the accuracy results. Also, Holthausen and Watts (2001) state that "choosing between the accuracy and association criteria requires an accounting and standard setting theory. If the FASB is interested in investors being able to use the information to generate their own estimates of value, association is the appropriate test. If the FASB is interested in income measuring value, accuracy might be the appropriate test". Thus, the accuracy and bias test seem to be more appropriate in this study, because we are interested in the valuation model measuring the intrinsic value. The explainability test is peripheral.

Finally, various sensitivity tests are also conducted. For the main results, valuation models are constructed as follows. 1) The future RI growth rate is assumed as 4% for EBO4 – EBO6. 2) The future book value growth rate is assumed as 4% for the 'intercept-inclusive' LID model and its variants (i.e., LID10 – LID16). 3) The cost of capital is assumed to be 5% plus the fiscal year average U.K. redemption yield on 20 year gilts. 4) To be comparable with value estimates, stock prices at 3 months after the fiscal year end are used as benchmarks. 5) For consensus earnings forecasts, median analysts' forecasts from I/B/E/S are used. Assumptions are varied in the subsequent analyses in order to investigate the sensitivity of the results to the assumptions made.

The remainder of this chapter is structured as follows. In the next section 6.2, some research questions and research design relevant to the LID parameter estimation and the pricing test are described. Section 6.3 shows the replicated results of DHS using the U.K. data. In Section 6.4, the reliability of value estimates derived from 22 competing valuation models is tested and compared. Section 6.5 contains the sensitivity test and Section 6.6 concludes.

6.2. Research Questions and Research Design

6.2.1. Research questions

Estimation of LID parameters

In the Ohlson Model, persistence parameters are very important because they determine the pricing formula. Estimation of persistence parameters is peculiar to all LID models. Even though analysts' earnings forecasts are commonly employed in the EBO approach, the estimation of future residual income for the EBO value estimates is not crystallized. It means that various approaches can be applied to the estimation of future residual income. On the other hand, the estimation of persistence parameters suggested by Ohlson (1995) is performed through the fixed framework called the linear information dynamics. Therefore, when the Ohlson model is criticized in terms of its validity, it is not the RIV model itself, but the assumed linear information dynamics. There is of course much room to modify Ohlson's (1995) linear information dynamics in order to better estimate the intrinsic value. One good example is the Feltham and Ohlson (1995) model, which incorporates conservative effects in the linear information dynamics. The inclusion of intercept terms in the Ohlson (1995) linear information dynamics is also a way to better estimate the intrinsic value.

My research starts from the replication of DHS's work for the estimation of persistence parameters using U.K. industrial data. This enables me to investigate whether the results of the two countries are consistent or not. At this stage, the same question as DHS's is also investigated: Is the AR(1) process sufficient for the forecast of future residual income? If it is proved that the AR(1) process is sufficient, the procedure to estimate a firm's value is very simple and straightforward.

More related questions about the parameters that are necessary for the LID models would be as follows. Are the sign and/or the magnitude of the parameters similar to the results of the U.S. study? Additionally, since I use four different earnings measures, whether different earnings measures give rise to different parameters will be another research question. If LID parameters significantly depend on earnings measures, it is worth investigating which earnings measure provides the persistence parameters that have quick mean reversion and high explanatory power, and why. A related question would be how much abnormal items impact on the forecast of future residual income.

Next, there may be differences in parameters according to scaling variables. In empirical research, it is common to deflate variables by a scaling variable in order to control for the effect of size. Since I use stock price as a scaling variable for the replication of DHS, but book value for the application of the 'intercept-inclusive' LID model, it may be worth examining whether different scaling variables cause large differences in the estimated LID parameters.

In addition, it may also be worth noting how much OI intercept and persistence parameters change according to the definition of OI. OI is defined as the difference between analyst-based RI forecasts and univariate AR(1) model-based RI forecasts. Thus, if we ignore intercept terms in the linear information dynamics, the univariate AR(1) model-based RI forecast equals the RI persistence parameter times current residual income, while if we incorporate intercept terms, the mechanical model-based RI forecast additionally includes the RI intercept parameter times the current scaling variable.

Pricing test

As most empirical research shows, the Ohlson model does not completely explain the market's expectations. There might be two possibilities. One is that Ohlson's model may be mis-specified or too restrictive, and the other is that the applicability of the Ohlson model may be different under different circumstances. If the second possibility is true in the real world, a pooled analysis including all industrial firms might give rise to misleading inferences on the validity of the Ohlson model. Thus, an important research question relates to the potentially differing level of applicability of the Ohlson model and other RIV models in different circumstances. I deal with this research question in Chapter 7.

As I mentioned before, the main objective of this chapter is to examine the validity of the various residual income-based valuation models. Thus, after estimating parameters for the LID models, I am going to provide U.K. evidence regarding which of the value estimates from the alternative RIV models generally gives the intrinsic value estimate which is closest to current stock prices using a pooled sample. In other words, my main research question is about the reliability of the RIV models. Specifically, the related questions would be as follows. 1) Which valuation model's value estimates dominate other models' value estimates in terms of bias, accuracy and explainability? 2) Is the superiority of a certain valuation model or the relative ranks of competing models consistent regardless of the choice of earnings measures? 3) Which earnings measure generally enhances the validity of the RIV models? 4) How much do exceptional and/or extraordinary items affect firm valuation?

6.2.2. Research design about the estimation of the LID parameters[80]

Estimation of unconditional RI persistence parameters (ω)[81]

To measure RI persistence parameters, I firstly use the pooled time-series and cross-sectional regression analysis by running an equation based on Ohlson's AR(1) information dynamics (Eq. 1). At this stage, all regression variables on a per-share basis are scaled by stock price or book value at the end of year t in order to control for size. Scaling by stock price or book value at the end of year t for all regression variables is adopted in all subsequent analyses related to the estimation of RI and OI parameters. As a scaling variable, stock price is used for the purpose of replicating DHS and of comparing the U.K. results with the DHS's U.S. study, while book value is used for the purpose of applying the 'intercept-inclusive' LID model and of comparing all competing valuation models used in this study.

$$x_{t+1}^{a} = \omega_0 + \omega_1 x_t^a + \varepsilon_{t+1} \qquad \text{(Eq. 1)}$$

$$x_{t+1}^{a} = \omega_0 + \omega_1 x_t^a + \omega_2 x_{t-1}^a + \omega_3 x_{t-2}^a + \omega_4 x_{t-3}^a + \varepsilon_{t+1} \qquad \text{(Eq. 2)}$$

$$x_{t+1}^{a} = \omega_0 + \omega_1 x_t^a + \omega_2 b_{t-1} + \varepsilon_{t+1} \qquad \text{(Eq. 3)}$$

---

[80] The estimation of the LID parameters is an extended replication of DHS.

[81] See Appendix 6.1 for the relevant practical issue when estimating RI parameters when OI is dealt with.

$$x_{t+1}^{a} = \omega_0 + \omega_1 x_t^{a} + \omega_2 b_t + \varepsilon_{t+1} \qquad \text{(Eq. 4)}$$

$$x_{t+1}^{a} = \omega_0 + \omega_1 x_t + \omega_2 b_{t-1} + \varepsilon_{t+1} \qquad \text{(Eq. 5)}$$

For the purpose of replicating DHS and of comparing the U.K. results with the DHS's U.S. study, the resultant persistence parameters from Eq. 1 are then compared with the persistence parameters of another model with 3 additional lagged residual income terms (Eq. 2) and with an additional book value term (Eq. 3). These analyses are exactly the same as DHS, so the objectives at this stage are to examine whether the results using U.K. data are consistent with those using U.S. data. The AR(4) model in Eq. 2 is applied to investigate whether the AR(1) process is sufficient for future residual income generation. Also, lagged book value, which is a component of current residual income, is added to check whether it affects the residual income generating process. If the AR(1) process is sufficient, the lagged book value should not play an informative role on the future residual income generation.

In addition, I try to explore other models with a book value term. In Eq. 4, current book value rather than lagged book value is employed as proposed by Myers (1999b).[82] Thus, ω_2 in Eq. 4 is a conservatism parameter, and is predicted to be greater than zero. On the other hand, Eq. 5 is the regression equation of future residual income on the components of current residual income – i.e., current earnings and lagged book value. The purpose of this equation is to examine the effect of the components separately, and

[82] Even though Feltham and Ohlson (1995) use operating income and operating assets to capture the conservative accounting, Myers (1999b) states that the empirical results using Feltham and Ohlson (1995) model and Eq. 4 are very similar.

to compare with ω_1 in Eq. 1.

Effects of abnormal items on RI persistence parameters

One of the objectives for which I try to use alternative earnings measures is how much exceptional and/or extraordinary items affect future residual income. Besides the direct comparison between parameters estimated by alternative earnings measures, multivariate regression of future residual income on current residual income and abnormal items are performed to specify the effects of those items.

Let X3 and X4 to be earnings inclusive of all abnormal items (*AEX*) and earnings inclusive of just exceptional items (*EXC*), respectively.[83] The multivariate regressions to investigate the effects of abnormal items are in the following Eq. 6, Eq. 7 and Eq. 8. All equations are driven to show how much current abnormal items included in earnings play an informational role for forecasting next-year aggregate residual income. Since abnormal profits and losses tend to occur once in a while so that next year's earnings (residual incomes) tend to return to the level that a firm can achieve normally, the corresponding regression coefficients are all predicted to negatively relate with future residual income. Thus, all coefficients that are related to abnormal items (ω_2 to ω_4) are predicted to be negative.

$$X3^a_{t+1} = \omega_0 + \omega_1 X3^a_t + \omega_2 EXC_t + \omega_3 EXT_t + \varepsilon_{t+1} \qquad \text{(Eq. 6)}$$

$$X3^a_{t+1} = \omega_0 + \omega_1 X3^a_t + \omega_4 AEX_t + \varepsilon_{t+1} \qquad \text{(Eq. 7)}$$

[83] For details of earnings definitions, see Chapter 5, Section 5.1.

$$X4^a_{t+1} = \omega_0 + \omega_1 X4^a_t + \omega_2 EXC_t + \varepsilon_{t+1} \qquad \text{(Eq. 8)}$$

where "*a*" denotes residual income (abnormal earnings). Eq. 6 and Eq. 7 are the same with respect to investigating the effect on future residual income of all abnormal items. Eq. 6 is just to separate the effect of all abnormal items using exceptional items and extraordinary items (*EXT*).

Estimation of conditional firm-specific ω

Next, firm-specific persistence parameters are estimated. I define 5 determinants for the conditional persistence parameter, and replicate as DHS suggests. However, since I use 4 alternative earnings measures (see Chapter 5, Section 5.1 for alternative earnings definitions), the item corresponding to special items (*q2* in DHS) needs to be varied according to the earnings measure that is used. General equations to estimate firm-specific persistence parameters are Eq. 9 and Eq. 10.

$$\begin{aligned} x^a_t = \omega_0 + \omega_1 x^a_{t-1} + \omega_2(x^a_{t-1}q1_{t-1}) + \omega_3(x^a_{t-1}q2_{t-1}) + \omega_4(x^a_{t-1}q3_{t-1}) + \omega_5(x^a_{t-1}q4_{t-1}) + \\ \omega_6(x^a_{t-1}q5_{t-1}) + \omega_7(x^a_{t-1}div_{t-1}) + \omega_8(x^a_{t-1}ind_{t-1}) + \varepsilon_t \end{aligned} \qquad \text{(Eq. 9)}$$

$$\omega^f_t = \omega_1 + \omega_2 q1_t + \omega_3 q2_t + \omega_4 q3_t + \omega_5 q4_t + \omega_6 q5_t + \omega_7 div_t + \omega_8 ind_t \qquad \text{(Eq. 10)}$$

where *q1* is the magnitude of residual income, *q2* is the magnitude of exceptional items, *q3* is the magnitude of extraordinary items, *q4* is the magnitude of all abnormal items, *q5* is the magnitude of accounting accruals, *div* is the dividend payout ratio, and *ind* is the industry-year specific persistence measures.[84]

[84] See Chapter 5, Section 5.2 for the details of variable definitions.

The variables in Eq. 9 are expected to have attributes to determine the degree of the persistence of residual income. The predicted signs of the corresponding coefficients are discussed below:

q1: The magnitude of residual income represents the absolute value of the abnormal accounting rates of return (ARR). Intuitively, it is difficult for a firm to sustain extremely high abnormal ARR because competition is likely to eliminate the firm's competitive advantage (O'Hanlon, 1997; Freeman *et al.*, 1982). Similarly, if a firm experiences extremely low abnormal ARR, the management may practice 'income manipulation' to maximize short-run abnormal ARR (Brooks and Buckmaster, 1976; Freeman *et al.*, 1982). Thus, the residual income for firms with large *q1* tends to be less persistent (i.e., mean revert more quickly) than for firms with small *q1*, so that ω_2 in Eq. 9 is expected to be negative.

q2 – q4: The abnormal items such as exceptional items, extraordinary items are likely to be more transitory than earnings from firms' normal activities. That is, the magnitude of such abnormal items is negatively related with the persistence of residual income, so the corresponding coefficients of *q2* to *q4* (i.e., ω_3 to ω_5) are all predicted to be negative.

q5: Residual income is less persistent when accruals comprise a large proportion of current earnings (Barth *et al.*, 1999). Thus the coefficient of the magnitude of accounting accruals (ω_6) is predicted to be negative.

div: This is the most controversial part in Eq. 9. DHS predict the corresponding coefficient of *div* to be negative, because firms with growth opportunities are considered to have lower dividend payout ratios. However, as Hand and Landsman (1998, 1999) show, dividend can be considered as a component of OI that plays a positive informational role for predicting future residual income.

ind: The relationship between industry-specific and firm-specific persistence parameters is predicted to be positive, because industry-specific factors are relatively stable over time so that historical persistence of a certain industry has the positive effect on the persistence of firms in the same industry (DHS).

Estimation of OI and its persistence

As Ohlson (2001) and DHS suggest, OI is measured by means of I/B/E/S analysts' consensus earnings forecasts. Since the estimated future residual income can be defined as one-year-ahead analysts' earnings forecasts less a capital charge based on the current book value, OI is reasonably estimated by the following equation (Eq. 11). That is, OI is defined as analyst-based RI forecast less mechanical AR(1) RI model-based RI forecast. Given OI (v), it is easy to estimate the persistence parameter, γ, using Eq. 12.

$$v_t = f_{t+1}^a - E_t\left[\tilde{x}_{t+1}^a\right] = f_{t+1} - rb_t - E_t\left[\tilde{x}_{t+1}^a\right] \qquad \text{(Eq. 11)}$$

$$v_{t+1} = \gamma_0 + \gamma_1 v_t + \varepsilon_{t+1} \qquad \text{(Eq. 12)}$$

where $E_t\left[\tilde{x}_{t+1}^a\right]$ is $\omega_1 x_t^a$ or $\omega_0 + \omega_1 x_t^a$ depending upon the assumption of ω_0.

6.3. Replication of Dechow, Hutton & Sloan (1999) – scaled by stock price

6.3.1. Estimation of ω and γ

Here, I present the estimating process and results of the U.K. RI and OI persistence parameters (ω and γ). The methodology is mainly based on DHS. All regression variables on the per-share basis are scaled by stock price at the end of year t in order to control for size,[85] because the analysis is conducted on a pooled basis, not on a firm-by-firm basis. Moreover, the most extreme 1% of each regression variable is deleted in all regression analysis to remove the effect of extreme data points.

Pooled ω with one lag

Since residual income variables are on a per-share basis, current stock price is used as a deflator. Thus, the variables in the estimating equation in Table 6.1 for residual income persistence parameters are implicitly the scaled per-share data. This equation can be used for the parameters of all LID models regardless of the incorporation of OI, as long as we assume that the OI variable is independent with the RI variable in the same time horizon.[86] This equation is equivalent to Ohlson (1995)'s linear information dynamics

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[85] Practically, Ohlson's AR(1) model will be equivalently $x_t^a = \omega_0 + \omega_1 x_{t-1}^a + \varepsilon_t$ when we estimate the persistence parameter with historical residual income. Thus, regression variables are scaled by lagged stock price so that a regression equation is like $x_t^a / P_{t-1}^c = \omega_0 + \omega_1 \, x_{t-1}^a / P_{t-1}^c + \varepsilon_t$.

[86] Even under the assumption of the independence between RI and OI, the estimated intercept ω_0 is the real intercept plus mean OI. Thus, it is difficult to estimate the real intercept in practice. In this study, the estimated intercept ω_0 is used as a proxy of the real intercept, despite the possibility of some noise.

without OI, except that regression variables in this equation are scaled. An empirical estimate of Ohlson's linear information dynamics should allow for a non-zero intercept if we assume that the discount rate differs from the average long-run ROE (Myers, 1999b).[87] Note that ω_0 estimated from this equation is a proportion of current stock price, not the level of (per-share) residual income.

Table 6.1 shows the persistence parameters for 4 different earnings measures. The intercepts (ω_0) of all earnings measures are negative and significantly different from zero. This is consistent with prior research (e.g. Dechow *et al.* 1999, Myers 1999b). Myers (1999b) states that this is because the average discount rate is higher than the average ROE. The persistence parameters (ω_1) are 0.502 to 0.667, and statistically significant. Thus, Ohlson's hypothesis that $0 < \omega_1 < 1$ is strongly supported.

More importantly, the persistence parameters of pre-exceptional and pre-extraordinary earnings (i.e., X1 and X2) have larger coefficients than other earnings, because they are more closely related to firms' normal trading activities which is supposed to be more permanent. From this viewpoint, it is not surprising that X3 has the lowest coefficient amongst the four earnings measures, because this includes all transitory earnings. And from the coefficient of X4, exceptional items seem to be much more permanent than extraordinary items. The relative magnitude of explanatory power (R^2) between alternative earnings measures has a similar pattern with that of RI persistence. Year-specific residual income persistence parameters that are estimated using all available

[87] The mean (median) ROE based on X1 to X4 in the U.K. are 14.8% (13.2%), 13.7% (11.9%), 13.5% (13.1%), and 14.4% (13.4%), respectively.

data from 1969 through the forecast year are shown in Panel B.

In order to examine the effects of abnormal items, 3 multivariate regressions with abnormal items are conducted. In the second equation in Table 6.2, X3 is earnings inclusive of all abnormal items so that the variable representing all abnormal items is included in the right-hand side of the equation. The purpose of conducting the first equation in Table 6.2 is to investigate the effects of the components (i.e., exceptional and extraordinary items) of all abnormal items separately. Similarly, the variable corresponding to exceptional items is included in the third equation, because X4 is earnings inclusive of exceptional items, but not extraordinary items.

The results of these multivariate regression analyses are summarized in Table 6.2. Note that controlling for exceptional and extraordinary items causes ω_1 to rise to a level that is similar to that for ω_1 (X1) and ω_1 (X2) in Table 6.1. Here, the coefficients of variables corresponding to abnormal items (i.e., ω_2, ω_3 and ω_4) are all statistically significant and negative as expected, and the magnitude of these numbers is relatively large. Thus, the smaller persistence parameters of X3 and X4 compared to those of X1 and X2 in Table 6.1 arise because the abnormal items included in X3 and X4 give rise to a decline in residual income persistence. Especially, we see that extraordinary items have a larger decremental effect than exceptional items. These results from multivariate regressions make sense and are consistent with the pattern of coefficients in Table 6.1.

Pooled ω with four lags

DHS also run the auto-regression model with four lags in order to explore whether Ohlson's AR(1) process is sufficient to describe the generation of residual income. Table 6.3 presents the same analysis. The intercepts of all earnings measures are negative and significant, and the coefficients of lag one residual income are significant. And, in the case of X3 that is most similar to DHS's earnings definition, the coefficient of 2 year lagged residual income is significant and positive as in DHS's results. However, in the case of other earnings measures, those coefficients are negative. Moreover, somewhat differently from DHS's results, some coefficients of 3 and 4 year lagged residual income are significant. Nonetheless, the magnitude of the coefficients of these additional lags suggests that the lags have negligible impact on future residual income in general.[88] Thus, the AR(1) process proposed by Ohlson (1995) is relatively sufficient to forecast the future residual income.

Pooled ω with book value

Here, I include book value as another explanatory variable, because the assumption that only current residual income has an informational role to forecast future residual income is too restrictive. Table 6.4, Panel A is just the replication of DHS. Consistent with DHS, the book value has a negative and significant coefficient, and its addition causes a decline in the coefficient on residual income. The higher R^2 compared to that of Table 6.1 also shows that book value gives additional information to the future residual

[88] If I extend to include up to 5 year lagged residual income, the coefficient of 4 year lagged residual income becomes non-significant, but the coefficient of 5 year lagged residual income becomes significant. Moreover, because the correlation between dependent variable and 4 year lagged residual income is too low, 4 year lagged residual income seems to have little effect on future residual income.

income generating process.

The model in Table 6.4, Panel B is similar to that in Panel A, but it is based on Myers (1999b) which includes current book value rather than lagged book value in order to capture the conservative accounting effect on the future residual income. The results are also consistent with Myers (1999b). Firstly, the intercepts of all cases are 0.032 or so and significantly positive (median 0.07, Myers (1999b)). Secondly, the conservatism parameters (ω_2) are significantly negative in all cases when they are predicted to be positive (i.e., $0 < \omega_2 < 1$), which means that this model does not explain the conservatism effect on information dynamics either. This is really to do with the fact that RI used to estimate the model is negative on average.[89] Compared to Panel A, all coefficients and explanatory powers are larger and more significant. It makes sense that the current book value has more ability to forecast future residual income than the past book value.

Panel C of Table 6.4 shows the regression of future residual income on the components of current residual income (i.e., current earnings and one year lagged book value). We see that earnings have an incremental effect on future residual income, while lagged book value has a decremental effect. Compared to Table 6.1, the explanatory power is larger in all cases, which means that the decomposition of current residual income describes future residual income more accurately, even though the cost of equity is the missing component here. Since the cost of equity is cross-sectionally constant for each

[89] Although expected future negative RI would indicate 'aggressive accounting' (i.e., book value > market value), this is not happening here.

year, its omission seems to have a small effect. Taken together with Panel A, B, and C, the inclusion of book value to the Ohlson's information dynamics and the decomposition of residual income are likely to have more ability to explain future residual income. Note that in this study, the 'intercept-inclusive' LID approach in which the regression variables are scaled by book value actually incorporates the effect of book value on the future residual income.

Firm-specific ω (ω^f)

Using the determinants of DHS for firm-specific conditional ω, I run the equation in Table 6.5, Panel A. The only difference is that DHS uses just one earnings measure, while I use four different earnings measures. Thus, instead of the magnitude of special items used in DHS, I need the magnitude of the abnormal items corresponding to each earnings measure. That is, I have to define the magnitude of all abnormal items for X3 and the magnitude of exceptional items for X4. In the case of X3, I try to run two regressions. One is with the magnitude of all abnormal items, and the other is with the components of all abnormal items (i.e., after decomposing it into exceptional and extraordinary items).

As shown in Table 6.5, Panel A, the coefficients of residual income (ω_1) are significant in all cases, and range from 0.68 to 0.72 (0.61 in DHS). And as predicted, the coefficients of the magnitude of residual income (ω_2), the coefficients of the magnitude of abnormal items (ω_3, ω_4, and ω_5) and the magnitude of accounting accruals (ω_6) are significantly negative for all earnings constructs. Moreover, industry-specific RI persistence seems to be positively related to the RI persistence of a firm that belongs to the industry, as predicted. These results are consistent with DHS. However, the coefficients of dividend payout ratio are large and significantly positive when it is predicted to be negative, so are very inconsistent with DHS. As Hand and Landsman (1998, 1999) says, dividend payout policy seems to play a positive informational role for future residual income.

Table 6.5, Panel B shows the distribution of the conditional firm-specific persistence parameters (ω^f). The mean (median) of ω^f is 0.70 to 0.79 (0.78 to 0.93). And more than 92% of firm-years have persistence parameter greater than zero and less than 1 regardless of earnings measures. It is also worth noting that most firm-years (more than 86%) have a high persistence parameter that is greater than 0.5.

Estimation of γ

Here, I produce the estimates of the OI persistence parameter. The estimation process of OI persistence is like that of RI persistence, even though there is an inconsistency problem when analysts' earnings forecasts from I/B/E/S are used for the calculation of OI. This is because none of the four earnings constructs matches exactly the I/B/E/S earnings forecasts. Leaving this limitation to further research, I here use all four earnings measures and book value from Datastream.

In Table 6.6, Panel A, all intercepts are significantly positive, and similar to DHS's result (0.01). OI persistence parameters are also significant, and range from 0.32 to 0.37 (0.32 in DHS). Thus, OI persistence using the U.K. data is quite similar to that using the

U.S. data. To be consistent with DHS's approach, I assume zero-mean residual income reversion and define OI as analyst-based RI forecasts minus the mechanical model-based RI forecasts ignoring the RI intercept. Panel B shows the year-specific OI persistence parameters that are estimated using all available data from 1989 through the forecast year.

6.3.2. Reliability of alternative value estimates

Before conducting a reliability test on alternative value estimates, I examine the RI forecasting ability of those valuation models. The RI forecasting ability of the assumed LID process, reported in Table 6.7, shows that the magnitude of absolute forecast errors is somewhat different to DHS, but the pattern is consistent. As with DHS, the LID process incorporating OI produces the most accurate RI forecasts, and the absolute RI forecast errors derived by applying such LID process (i.e., the LID process for LID5-LID9 models) are significantly lower than other LID processes (i.e., the LID process for LID1-LID4 models) at 1% level. Note that the next year's RI forecasts are just analyst-based RI forecasts when OI is incorporated in the LID process.

Table 6.8 presents the reliability of alternative valuation models in terms of bias, accuracy and explainability. In Panel A, the relative ranks of median bias among competing value estimates are exactly the same as DHS,[90] but mean bias suggests that the Ohlson LID model (LID9) seems to dominate most of its special cases. I believe that

[90] DHS only reported the mean values of bias and accuracy.

the median value is more appropriate for the comparison of value estimates than the mean value, because the mean value can be considerably affected by the extreme outliers. So I will mainly focus on the median values in this study. Panel B shows the statistical test for differences of median and mean bias. For the test of median (mean) differences, the sign test and the Wilcoxon signed rank test (student's t test) are used for the paired sample.[91] Even though the median bias of LID9 is significantly different from that of LID6, two median figures are very similar, indicating that LID9 together with LID6 performs well among 9 models. However, the value estimates based on LID9 substantially underestimate the observed stock prices by about 29% (mean) or 43% (median) of the price (mean 26% in DHS).

On the other hand, median and mean accuracy, reported in Panel C, shows very consistent results with DHS. LID6 and LID7 significantly dominate LID9 in terms of accuracy. Note that DHS ignored LID7 that assumes (ω_1 = 0, γ_1 = $\hat{\gamma}_1$), because it is theoretically identical to LID8 that assumes (ω_1 = $\hat{\omega}_1$, γ_1 = 0). But LID7 can be different from LID8 practically, so I include it in the set of competing valuation models.[92] In Panel E, LID9 is also outperformed by LID6 and LID7 in terms of explainability. Thus, as DHS conclude, Table 6.8 generally suggests that value estimates just capitalising one-year ahead earnings forecasts in perpetuity (LID6) seem to dominate the Ohlson LID model-based value estimates in terms of all performance

[91] I believe that the sign test is most appropriate in this study because almost all test variables (the difference between forecast errors of 2 different model-based value estimates) are not normally distributed and are not symmetric.
[92] As shown in the note to Table 6.6, γ_1 for LID7 is 0.735 to 0.835, and it is different from ω_1 for LID8 (0.502 to 0.693).

metrics.

Overall, the replication for the estimation of RI and OI persistence parameters and the examination of the models' relative reliability using the U.K. data gives quite similar results with DHS's U.S. study. The choice of alternative earnings measures is unlikely to make any significant difference in the relative validity of alternative valuation models.

6.4. Reliability of Competing Valuation Models – scaled by book value

In Section 6.3, stock price is used as a scaling variable in order to make the replicated results comparable with those reported in DHS. DHS ignored intercept terms, which contains information about the mean. I wish to explore the effect of taking account of these. If I include intercept terms, then the scaling variable appears in the pricing model. Thus, scaling by stock price causes stock price to be an input to the pricing model, so that the pricing model is unlikely to be useful to practitioners or to academics. Therefore, for the subsequent analysis, I use book value as an alternative scaling variable.

6.4.1. Estimation of ω and γ

Table 6.9 reports the RI and OI persistence parameters when book value is used as a scaling variable. The pooled unconditional RI persistence parameters (ω_1), reported in Panel A, show a similar pattern and magnitude to those in Table 6.1, but the intercepts

(ω_0) seem to be getting closer to zero. Based on X1 earnings measures, ω_0 is not statistically different from zero. And the magnitude of ω_0 based on X2, X3 and X4 is very small compared to that in Table 6.1. The relative magnitude of explanatory power (adjusted R^2) between models based on alternative earnings measures has a similar pattern with that of RI persistence. Year-specific RI persistence parameters that are fed to the pricing formula as well as the calculation of OI are shown in Panel B.

Table 6.10, Panel A presents the coefficients on the determinants of firm-specific persistence parameters using exactly the same method as was used in Table 6.5, but using regression variables scaled by book value rather than stock price. The sign of all coefficients except ω_2 (the coefficient of the magnitude of residual income) is consistent with that reported in Table 6.5, but the magnitude is very different. Especially, the coefficients of residual income (ω_1) are much smaller than the corresponding coefficients in Table 6.5. However, as shown in Table 6.10, Panel B, the distribution of the resultant firm-specific persistence parameters is not much different from that in Table 6.5. The mean (median) of ω^f is 0.71 to 0.80 (0.74 to 0.80). And most of firm-specific persistence parameters (more than 89%) are in the range of zero and one, which is Ohlson's (1995) hypothesis.

Panel A and Panel C in Table 6.11 respectively report OI persistence parameters when ω_0 is ignored and incorporated. The OI intercepts (γ_0) and persistence coefficients (γ_1) in both panels are very similar regardless of the assumption for RI reverting process. This is because the estimated ω_0 in Table 6.9 is very small so that its inclusion for the calculation of OI has little effect on the OI numbers. By the way, scaling by book value rather than stock price (see Table 6.6, Panel A) seems to induce larger γ_0 and γ_1. As we mentioned earlier in Chapter 3, a small change in γ_0 as well as ignoring or incorporating it could give rise to large difference in the value estimates.

Table 6.12 reports parameters under the restriction of ω_1 and/or γ_1. Because the restriction of ω_1 and/or γ_1 make the equations in linear information dynamics different from the original equations, the RI and OI persistence parameters estimated in Table 6.9 and Table 6.11 cannot be used directly for the corresponding pricing model. For example, if intercepts are not incorporated and ω_1 is assumed as zero (i.e., LID7), OI is defined as one-year ahead analyst-based RI forecasts (f_{t+1}^a) rather than f_{t+1}^a minus ω_1 times RI. Therefore, OI persistence parameters are estimated from the regression of scaled f_{t+1}^a on lagged scaled f_{t+1}^a. For the same reason, ω_0 for LID10, LID13 and LID14 (Panel B), γ_0 for LID13 (Panel C), γ_0 and γ_1 for LID14 (Panel D), and γ_0 for LID15 (Panel E) should be estimated separately. Notes 6 to 10 describes the estimating process or the estimators briefly.[93]

6.4.2. Reliability of alternative value estimates

The reliability tests of 22 valuation models are summarized in Table 6.13. First, Panel A shows the bias of models' value estimates from the observed stock prices. Regardless of

[93] For details of the estimating process or the estimators, see Chapter 3.

earnings measures, the relative ranks of median (mean) signed forecast errors of alternative value estimates are very consistent. Most notably, the development of the 'intercept-inclusive' LID model (LID16) in order to capture the effect of intercept terms on the value estimates removes most of the downward bias of the value estimates based on the Ohlson LID model (LID9). And LID16 also dominates the EBO models by large difference in the bias. The median (mean) bias of LID16 ranges from -17.6% to -22.5% (-0.3% to 7.7%) of price according to earnings measures. A little bit surprisingly, LID13, which is a special case of LID16 that assumes ($\omega_1 = 0$, $\gamma_1 = 0$) and incorporates OI, also generates quite good value estimates in terms of bias. The median (mean) bias of LID13 is about -20% (5%) of price and is very similar to that of LID16. On the other hand, LID15, which is another special case of LID16 that assumes ($\omega_1 = \hat{\omega}_1$, $\gamma_1 = 0$) and incorporates OI, gives rise to almost zero median bias, but quite large upward mean bias. Note that just assuming non-zero mean RI reversion without incorporating OI in the pricing model (i.e., LID10 – LID12) gives more downward bias (i.e., performs worse) than that caused by the implementation of the Ohlson model.

Panel B reports the test for differences of median and mean bias. It is based on earnings measure X4, but the results based on the other 3 earnings measures are very similar in terms of the significance of differences. If 2 samples (i.e., forecast errors of 2 different model-based value estimates) are paired, the sign test and the student t test are respectively used for median and mean differences. If 2 samples have different observations (e.g. forecast errors of LID16 vs. EBO5), the Mann-Whitney U test (i.e., Wilcoxon rank sum test) and two-sample t test are respectively used for median and mean differences. From Panel B, we see that median and mean bias of LID16 are significantly different from those of other models at 1% level.

Panel C in Table 6.13 reports the absolute forecast errors of alternative value estimates as a metric of accuracy. The median values of accuracy also evidence that LID16 gives quite accurate value estimates. As shown in Panel D, the median accuracy of LID16 is statistically outperformed by that of EBO5 and EBO6, but the differences are small. Moreover, the development of LID16 gives rise to about 7% improvement in accuracy against LID9. The median accuracy figures show that the EBO models, the 'intercept-inclusive' LID model and some of its variants (LID13 and LID15) generally outperform the Ohlson LID model and its variants. However, LID10, LID11 and LID12, which are also variants of the 'intercept-inclusive' LID model that assume non-zero mean RI reversion and no OI, have the worst accuracy.

On the other hand, the mean accuracy of LID16 is not good. I guess this is partly because the additional term included in LID16 from the incorporation of the intercepts is sensitive so that LID16 tends to produce more extreme value estimates than the Ohlson model. In other words, although recognition of intercepts improves accuracy in one respect by shifting the centre of the distribution of valuation errors closer to zero, it reduces it in another respect because capitalization of mean effects as perpetuities increases the dispersion in valuation errors.

In order to examine why the mean accuracy of LID16 does not improve much, I plot forecast errors based on LID9, LID16, EBO2 and EBO5 in Figure 6.1. Here, the dark line depicts observed stock prices, and the pale line represents forecast errors as a percentage of observed stock prices. A large number of valuation errors of LID9, EBO2 and EBO5 are located below stock prices, indicating that those valuation models produce large negative bias overall. On the other hand, LID16 shifts the distribution of valuation errors upward so that it eliminates most of the negative bias resulting from applying LID9. However, we see that in the area of low stock prices, LID16 produces large positive forecast errors much more than LID9, EBO2 and EBO5. This could be one explanation for the poor mean accuracy of LID16. Unreported tests show that if we just focus on stock prices (scaled by lagged stock price) greater than 0.66 (about 80% of total firm-years), the mean accuracy of LID16 improves from 0.557 to 0.481 and dominates that of other LID models. LID9 improves its mean accuracy only by 0.01 (from 0.509 to 0.499).

Finally, Panel E in Table 6.13 presents the explainability of the competing value estimates. Unlike the relative superiority of LID16 in terms of bias and (median) accuracy, the ability of its value estimates to explain cross-sectional variation in current stock prices is not high. The explainability of LID16 is outperformed by the Ohlson model and some of its variants (LID6 and LID7) as well as all EBO models. As mentioned above, however, the explainability seems to be less appropriate than bias and accuracy for this kind of valuation research.

Figure 6.2 graphically illustrates the reliability of alternative valuation models. Regardless of earnings measures, the graphs are very similar to each other, so I present only the case of X4. Here, the bias in the X axis is 1 minus absolute values of median signed forecast error and the accuracy in the Y axis is 1 minus median absolute forecast error. So, the upper right point represents the most reliable value estimates. The graph illustrates that there is a relatively strong relation between bias and accuracy. That is, if a model generates value estimates that have low bias, its value estimates seem to have high accuracy. There is little difference in accuracy between LID16 and EBO5 (EBO6), but the difference in the bias between two models is significant. Consequently, LID16 seems to produce quite reliable value estimates in bias and accuracy metrics.

Taken together, value estimates based on the EBO models are generally likely to be reliable in all performance metrics (bias, accuracy and explainability). However, since the bias and accuracy metric might be more appropriate in the reliability test of the valuation models, the 'intercept-inclusive' model (LID16) seems to have superior reliability to most of other models. LID 16 considerably improves the high bias and the low accuracy arising from the implementation of the Ohlson model. Especially, my effort to improve the large downward bias of the value estimates based on the Ohlson model seems to be very successful.

6.5. Sensitivity Test

This section provides some sensitivity tests. If the reliability of value estimates considerably varies according to the change of an ingredient in the residual income valuation model, the ingredient must be carefully estimated or assumed. Estimation errors or unreasonable assumptions of a critical ingredient can lead to serious errors in value estimates.

6.5.1. Sensitivity to book value growth rate

In Table 6.14, I report results for 5 assumed values of the book value growth rate: 0%, 2%, 4%, 6% and 8%. Here, earnings before extraordinary items (X4) are used, but results when other earnings measures are used are very similar. Value estimates based on the 'intercept-inclusive' LID model and its variants (i.e., LID10 – LID16) vary according to different assumptions on book value growth, because only those pricing models contain book value growth as an ingredient of the pricing formula. Note that value estimates of LID10 – LID16 reported in Table 6.13 are based on 4% book value growth rates. The assumption of 4% growth rate for the main results is ad hoc so that investigating the extent to which results are sensitive to book value growth rate is important.[94]

As shown in Table 6.14, Panel A, value estimates of LID10 – LID12 and LID14 are not very sensitive to book value growth in terms of bias, while value estimates based on LID13, LID15 and LID16 are likely to be sensitive. Especially, LID15-based value estimates are so sensitive to book value growth that there is large positive bias at 6% and 8% book value growth. However, the deviation of LID16-based value estimates from zero seems to be still less than that of other value estimates for all assumed book value growth rates, indicating that LID16-based value estimates outperform other value

[94] The median (mean) value of book value to lagged book value from 1991 to 1998 is 4.0% (11.7%). While, the median (mean) book value to the median (mean) lagged book value in the same period is 1.4% (-2.6%).

estimates in terms of bias. It is interesting that bias of relatively high performers (i.e., LID13, LID15 and LID16) moves upward in book value growth, while bias of other models moves downward.

As with the bias metric, Table 6.14, Panel B shows that the superiority of median accuracy of LID16-based value estimates persists regardless of what assumption is made regarding the book value growth rate. The change in median accuracy of those value estimates in response to variation in the assumed book value growth is small. On the other hand, the association between LID16-based value estimates and observed stock prices is still low, and the EBO models and the Ohlson LID and some its variants (LID6 – LID8) outperform this model. Overall, the assumption of book value growth rate has little effect on the relative ranking of various models' value estimates in terms of all performance metrics – bias, accuracy and explainability.

6.5.2. Sensitivity to residual income growth rate

In this study, 6 different EBO models are used for the test of reliability of value estimates. EBO1 – EBO3 (EBO4 – EBO6) are constructed under the assumption of zero (non-zero) residual income growth rate, so the first, second and third figures of the second column in each panel of Table 6.15 (i.e., g_r = 0%) respectively represent corresponding figures of EBO1, EBO2 and EBO3. The assumption of 0% or 4% for future residual income growth rate is also ad hoc, so that it is worth examining the effect of different residual income growth on the reliability of value estimates.

Table 6.15, Panel A provides bias figures. All median and mean bias figures except for the mean bias of EBO4-based value estimates show that negative bias seems to improve in line with increases in the assumed residual income growth rate. The median bias of EBO5-based value estimates is -26% of stock price. However, this figure is still outperformed by LID16-based bias figures reported in Table 6.14, Panel A. Accuracy reported in Table 6.15, Panel B also shows that the median accuracy figures of EBO-based value estimates does not change much according to the assumption of residual income growth. Especially, when the 2 or 3-year horizon EBO model assuming non-zero residual income growth is used, the maximum change in median accuracy in the assumed four residual income growth rates is just 2.2% (EBO5) and 2.5% (EBO6). However, the mean accuracy of EBO-based value estimates seems to be sensitive to the assumed residual income growth rate.

EBO5 and EBO6 give the best median accuracy when the residual income growth rate is 6%. But EBO models assuming zero residual income growth seem to outperform corresponding EBO models assuming non-zero residual income growth in terms of mean accuracy. Similar to the pattern of mean accuracy, the ability of EBO1 – EBO3 models to explain variation in the observed stock prices is better than that of the same horizon EBO models with the non-zero residual income growth assumption (i.e., EBO4 – EBO6). We see that the explainability of the EBO-based value estimates is quite sensitive to the assumed residual income growth rate.

6.5.3. Sensitivity to discount rate

For the main results reported in Table 6.13, year-specific discount rates are used. Even though I believe that time-varying discount rates are more reasonable than constant discount rates in equity valuation, I report results for 5 assumed values of the discount rate (10%, 12%, 14%, 16% and 18%) and compare them with results for time-varying discount rates. Theoretically, the firm-year specific discount rates should be applied, because equity valuation is a task performed on a firm at a specific point in time. However, in practice, especially in pooled cross-sectional time-series analyses such as this study, there is little consensus as to how the discount rate should be determined. Frankel and Lee (1998) used 3 different constant discount rates (11%, 12% and 13%) and 2 industry-specific discount rates based on a one-factor and a three-factor model of Fama and French (1997), and stated that varying the discount rate had little effect on their results. By contrast, Lee *et al.* (1999) indicated that time-varying discount rates are an essential part of valuation models in their time-series applications. Sougiannis and Yaekura (2000) also found that different assumptions about discount rates made their results differ. Specifically, the constant discount rate of 12% had the best performance in terms of bias and accuracy of value estimates, with second the year-specific, third the industry-specific and last the firm-specific discount rates.

In Table 6.16, Panel A, most models' value estimates deviate from the observed stock prices least of all when discount rates are assumed as a constant 10%. The constant discount rate of 12% also gives better performance in terms of bias than year-specific discount rates in most models. However, the purpose of equity valuation is not seeking for best discount rates that gives best value estimates. If unreasonable discount rates had the best performance, it rather raises a suspicion that a model may be mis-specified. Even if value estimates arising from LID16 give bias figures that are very sensitive to discount rates, they less deviate from the observed stock prices when assuming reasonable discount rates (12 – 16% as well as year-specific discount rates), compared to most models.

Accuracy figures in Panel B also have a similar pattern to bias figures. Most models' value estimates are most accurate when discount rates are assumed constant at 10% or 12%, but LID16-based value estimates are most accurate when discount rates are assumed constant at 14% or when year-specific rates are used. In terms of relative accuracy ranking of various valuation models, EBO models seem to dominate LID models at a discount rate of 10% and 12%, and LID16 seems to outperform other models at a discount rate of 14% and 16%. In terms of explainability, EBO models except EBO4 have the best ability to explain variation of stock prices regardless of the different assumption about the discount rate, and LID16 explains less than LID9 in most of cases. Overall, value estimates of LID16 are quite sensitive to discount rates in all performance metrics, but the relative ranking at reasonable discount rates (12-16%) is very similar to the results when year-specific discount rates are used.

6.5.4. Sensitivity to benchmarking stock price

For the main results reported in Table 6.13, the observed stock prices at 3 months after the fiscal year end are used as a benchmark, because investors can acquire the firms' information through the issue of the financial statements at 3 months after the fiscal year end in most cases. Here, I use other benchmarking stock prices of 4 to 7 months after the fiscal year end in order to investigate the robustness of the results.

As shown in Table 6.17, Panel A, B and C, value estimates are not sensitive in terms of their bias, accuracy and explainability according to different benchmarking stock prices. And regardless of benchmarking stock prices, their relative ranking is similar to that when stock prices at 3 months after the fiscal year end are used. However, even if differences in bias, accuracy and explainability figures for a certain model are not significantly different from each other according to different benchmarks, there are some interesting points. First, in terms of bias, most models' value estimates have the best performance in bias metric when stock prices at 3 and 7 months after the fiscal year end are used. On the other hand, when stock prices at 3 and 4 months after the fiscal year end are compared to value estimates, most models give the most accurate value estimates. The most inaccurate value estimates are observed in all valuation models except the 'intercept and other information-inclusive' models (i.e., LID13 – LID16) when stock prices at 5 months after the fiscal year end are used as a benchmark. Finally, in terms of explainability, most models' value estimates provide the best ability to explain variation of stock prices when stock prices at 3 and 5 months after the fiscal year end are used. Thus, regardless of performance metrics, stock prices at 3 months after the fiscal year end seems to be a reasonable benchmark for the purpose of testing the reliability of value estimates.

6.5.5. Sensitivity to consensus earnings forecasts

For the main results in Table 6.13, median consensus earnings forecasts from I/B/E/S are used because median values are less affected by extreme outliers. Here, results using mean consensus earnings forecasts are reported in order to examine how different results are. From Table 6.18, we see that the differences of bias, accuracy and explainability figures are trivial, indicating that the choice of consensus earnings forecasts from I/B/E/S does not matter. Actually, the distribution of median and mean consensus earnings forecasts (not reported) is almost identical.

6.6. Conclusions

This study provides the relative reliability test of 22 competing valuation models. The main objective of the study is to examine whether the incorporation of RI and OI intercepts in the Ohlson (1995) linear information dynamics improves the quality of value estimates in terms of three performance metrics – bias, accuracy and explainability. DHS investigated the validity of the Ohlson (1995) LID model, but concluded that the Ohlson model is outperformed by its special case that capitalizes just one-year ahead earnings forecasts in perpetuity. More strikingly, the Ohlson model produces a large negative bias of about 26%. This study is motivated by this large negative bias based on the Ohlson model. The DHS implementation disregards intercept terms from linear information dynamics, which assumes that expected future RI is zero on average. This study relaxes the assumption of zero mean RI reversion, and investigates the validity of the 'intercept-inclusive' LID model by comparison with other LID and EBO models.

This study starts from the replication of DHS using the U.K. data. The replicated results are very consistent with DHS's U.S. study in terms of the estimated RI and OI parameters and the relative validity of the Ohlson LID model and its variants. Four earnings measures used in this study in order to test the robustness of the results are unlikely to make any significant difference in the relative validity of various valuation models.

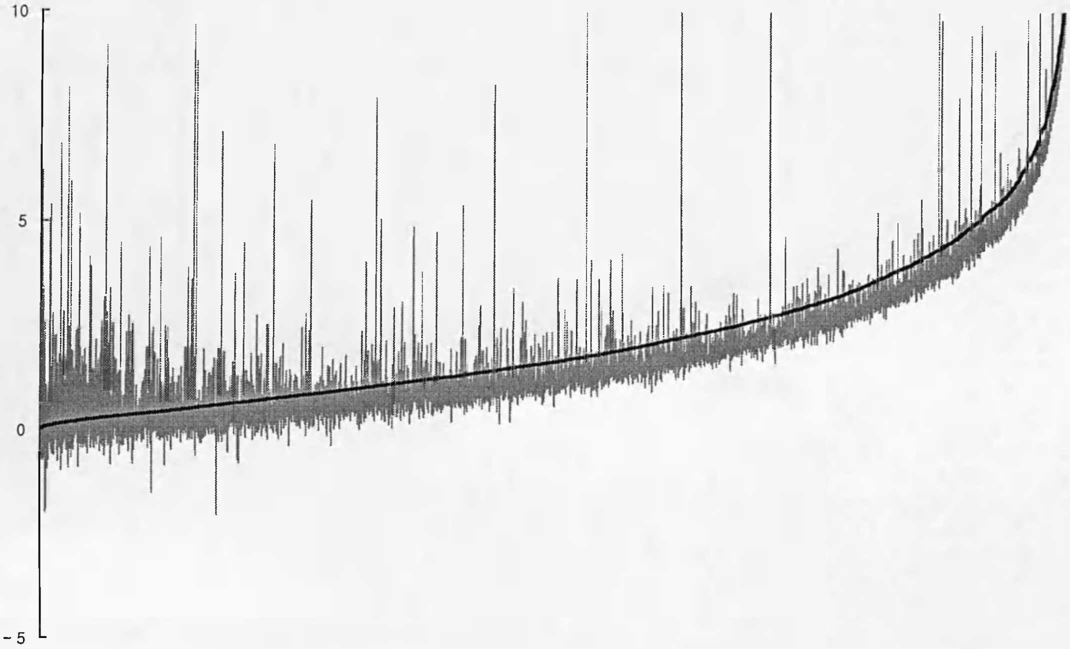
Next, in order to investigate the reliability of the 'intercept-inclusive' LID model, book value rather than stock price is used as a scaling variable, because the scaling variable appears in the pricing formula and the pricing model is therefore unlikely to be useful if stock price is used as a scaling variable. The test results show that the 'intercept-inclusive' LID model eliminates most large negative bias derived by applying the Ohlson LID model, and gives quite good median accuracy. However, the mean accuracy of the 'intercept-inclusive' LID model does not improve much. I guess that this may be caused partly by more outliers produced by the model and partly by high sensitivity of the additional term comprising intercept parameters, especially to low price stocks.

Finally, some sensitivity tests show that the relative ranking of competing valuation models in terms of bias, accuracy and explainability is not very sensitive to the assumption of future book value and residual income growth and to the use of alternative benchmarking stock prices and consensus analysts' earnings forecasts. However, bias, accuracy and explainability figures of models are very sensitive to some ingredients, especially to the discount rate.

Overall, the development of the 'intercept-inclusive' model seems to give quite good value estimates in terms of bias and median accuracy. However, the reasons why the model fails to improve the mean accuracy needs to be explored in further research.

Figure 6.1: Distribution of forecast errors – scaled by book value, based on X4

Panel A: LID9-based value estimates



Panel B: LID16-based value estimates

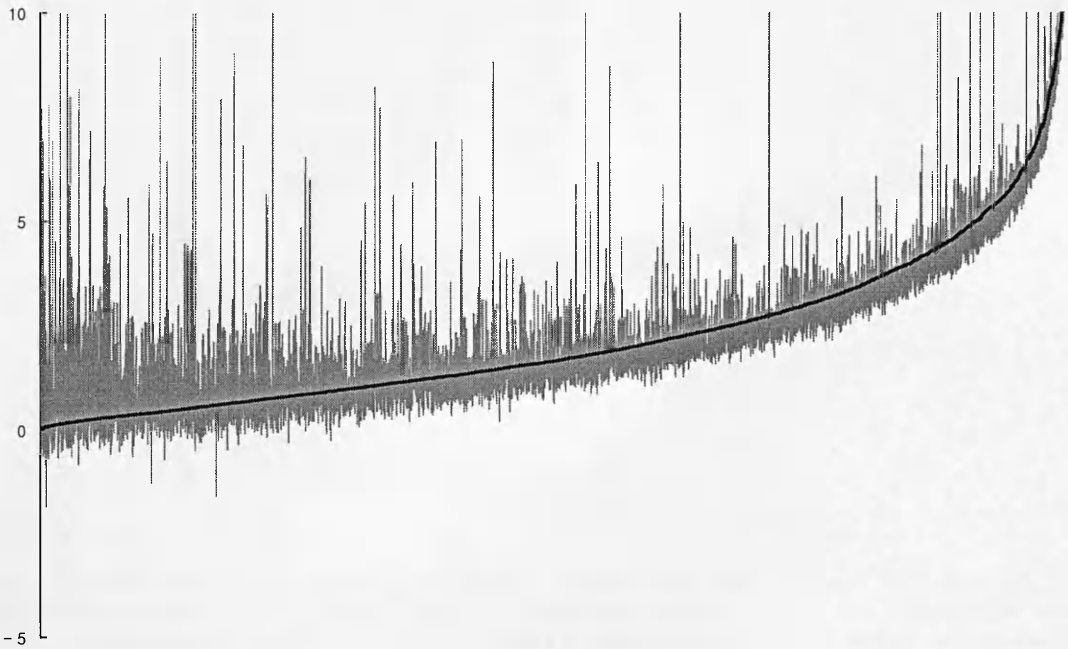
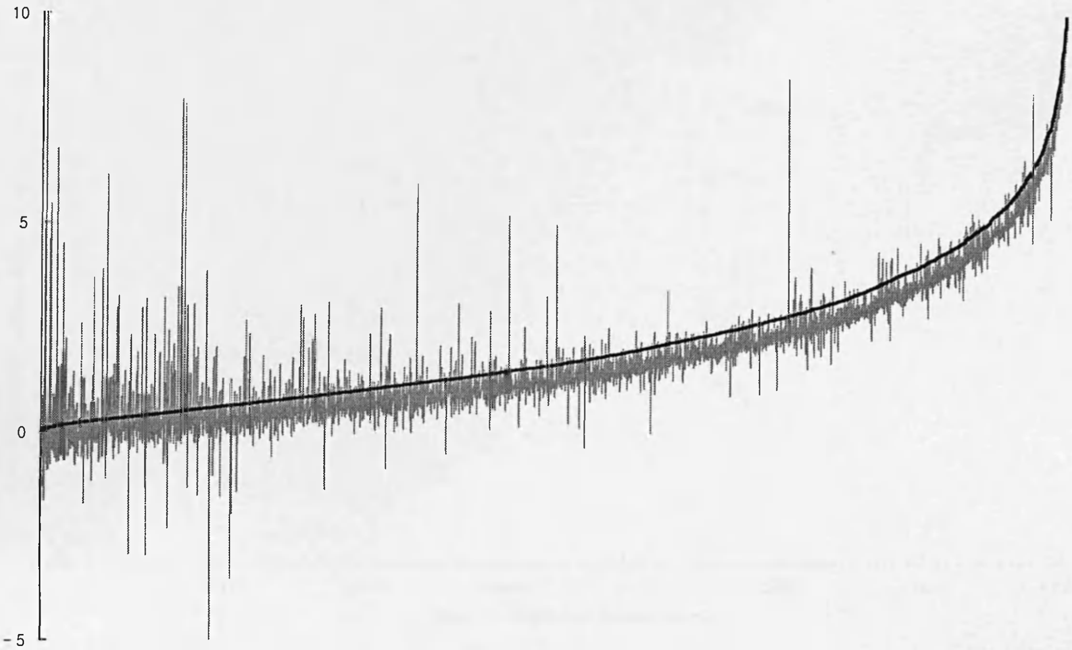
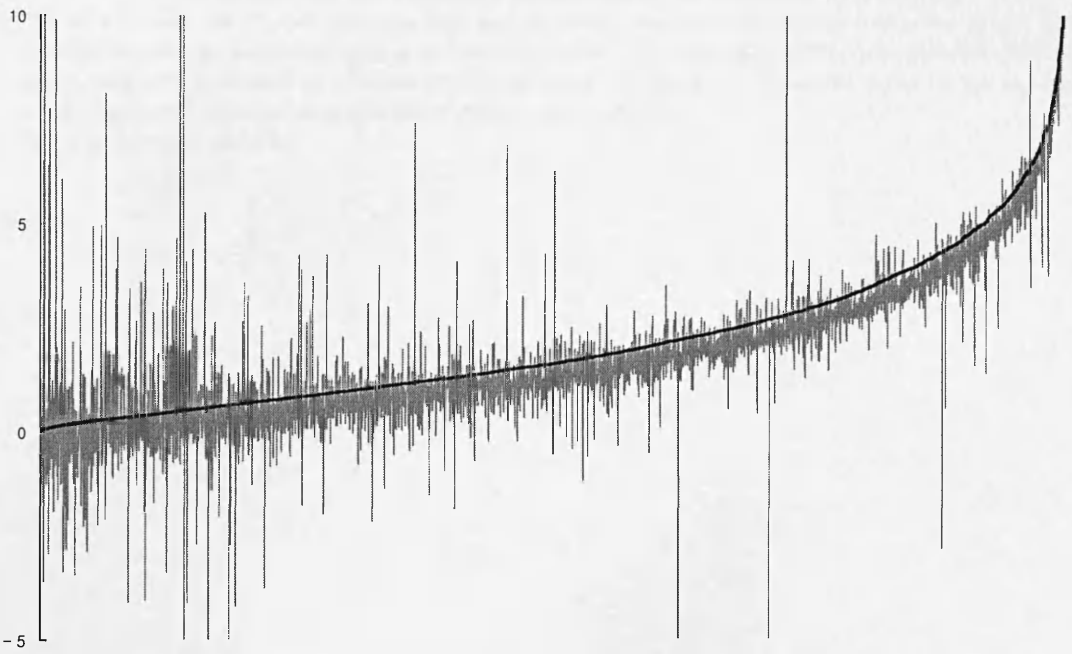


Figure 6.1 (continued)

Panel C: EBO2-based value estimates

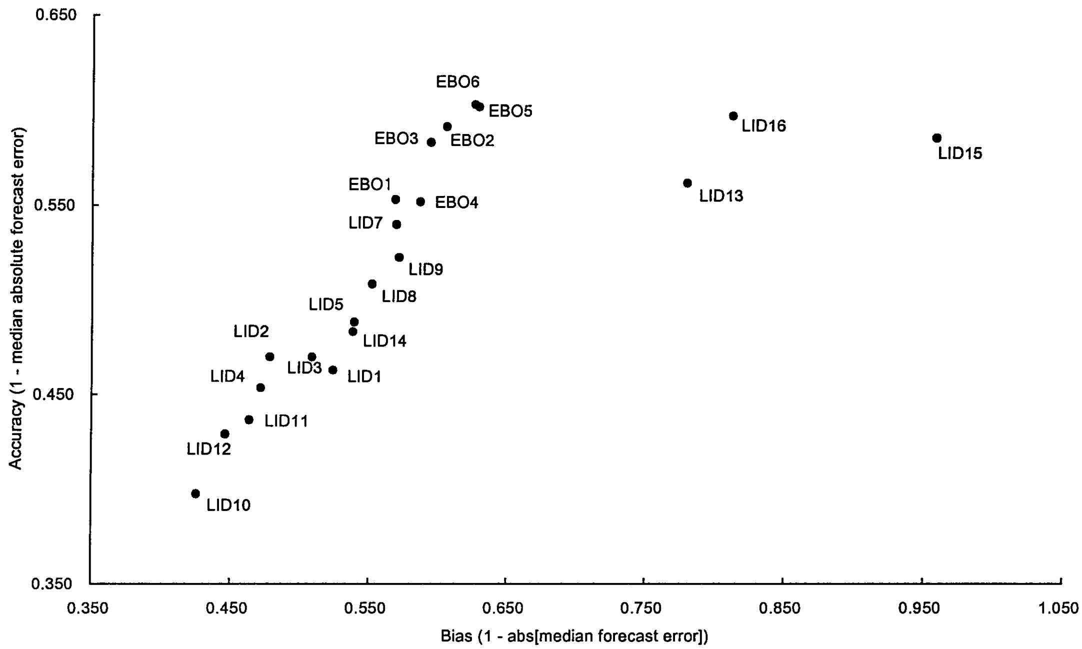


Panel D: EBO5-based value estimates



Note: The dark line depicts observed stock prices, and the pale lines represent forecast errors as a percentage of observed stock prices. The pale lines above (under) the dark line indicate that value estimates are overestimated (underestimated). In order to focus on forecast errors around stock prices, the Y axis is adjusted to range from –5 to 10. So some extremely large positive or negative forecast errors are cut off at 10 and –5, respectively.

Figure 6.2: Reliability of value estimates – scaled by book value, based on X4



Note:

1) This graph is based on median bias and median accuracy of value estimates when earnings measure X4 is used. The plots based on four alternative earnings measures are similar to each other.
2) The X axis and the Y axis indicate bias and accuracy respectively, but to make the graph more understandable, the horizontal axis is defined as 1 minus absolute value of median forecast error and the vertical axis is defined as 1 minus median absolute forecast error. Thus, the point on the top-right corner represents the most accurate and unbiased value estimate.
3) EBO1 is the same as LID6.

Table 6.1: Unconditional ω with one lag – scaled by stock price

$$x_{t+1}^{a} = \omega_0 + \omega_1 x_t^{a} + \varepsilon_{t+1}$$

Panel A: Pooled ω

	X1	X2	X3	X4
ω_0	-0.018***	-0.021***	-0.032***	-0.021***
	(-18.92)	(-23.36)	(-24.61)	(-20.33)
ω_1	0.631***	0.667***	0.502***	0.590***
	(148.31)	(168.15)	(103.62)	(132.83)
Adj. R^2	0.470	0.533	0.302	0.416
N	24813	24816	24773	24802

Panel B: Year-specific ω

	X1		X2		X3		X4	
	ω_0	ω_1	ω_0	ω_1	ω_0	ω_1	ω_0	ω_1
89	-0.023	0.649	-0.028	0.693	-0.033	0.542	-0.023	0.611
90	-0.023	0.649	-0.028	0.693	-0.033	0.540	-0.024	0.611
91	-0.024	0.648	-0.029	0.691	-0.035	0.536	-0.026	0.609
92	-0.024	0.649	-0.028	0.690	-0.036	0.535	-0.026	0.608
93	-0.023	0.642	-0.027	0.681	-0.036	0.529	-0.026	0.603
94	-0.022	0.636	-0.026	0.673	-0.035	0.518	-0.024	0.597
95	-0.021	0.633	-0.025	0.670	-0.034	0.514	-0.023	0.594
96	-0.020	0.632	-0.024	0.668	-0.033	0.511	-0.023	0.591
97	-0.019	0.633	-0.022	0.669	-0.032	0.509	-0.022	0.592
98	-0.018	0.631	-0.021	0.667	-0.032	0.502	-0.021	0.590

Note:

1) The estimation of ω is based on 29,828 firm-year observations from 1969 to 1998. The total observations available for AR(1) regression, however, are 25,187 from 1971 to 1998 because 2-year lagged book value is required for construction of lagged RI.
2) All regression variables on the per-share basis are scaled by stock price at the end of year t.
3) Figures in parentheses are t-statistics.
4) The most extreme 1% of regression variables are deleted.
5) The discount rate r, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
6) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
7) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings, and x_t^a denotes residual income for period t.

Table 6.2: Effects of abnormal items – scaled by stock price

$$X3^a_{t+1} = \omega_0 + \omega_1 X3^a_t + \omega_2 EXC_t + \omega_3 EXT_t + \varepsilon_{t+1} \text{ (Column X3}_a\text{)}$$

$$X3^a_{t+1} = \omega_0 + \omega_1 X3^a_t + \omega_4 AEX_t + \varepsilon_{t+1} \text{ (Column X3}_b\text{)}$$

$$X4^a_{t+1} = \omega_0 + \omega_1 X4^a_t + \omega_2 EXC_t + \varepsilon_{t+1} \text{ (Column X4)}$$

	$X3_a$	$X3_b$	X4
ω_0	-0.022***	-0.023***	-0.016***
	(-18.66)	(-18.81)	(-16.60)
ω_1	0.671***	0.663***	0.636***
	(123.44)	(123.90)	(142.30)
ω_2	-0.596***	-	-0.616***
	(-18.82)	-	(-23.60)
ω_3	-0.684***	-	-
	(-36.24)	-	-
ω_4	-	-0.682***	-
	-	(-46.34)	-
Adj. R^2	0.387	0.386	0.451
N	24514	24675	24651

Note:

1) The estimation of ω is based on 29,828 firm-year observations from 1969 to 1998. The total observations available for AR(1) regression, however, are 25,187 from 1971 to 1998 because 2-year lagged book value is required for construction of lagged RI.
2) All regression variables on the per-share basis are scaled by stock price at the end of year t.
3) Figures in parentheses are t-statistics.
4) The most extreme 1% of regression variables are deleted.
5) The discount rate r, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
6) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
7) X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings and x^a_t denotes residual income for period t.
8) *EXC* is exceptional items, *EXT* is extraordinary items, and *AEX* is all abnormal items (i.e., *EXC* + *EXT*)
9) The results in column $X3_a$ are from equation $X3^a_{t+1} = \omega_0 + \omega_1 X3^a_t + \omega_2 EXC_t + \omega_3 EXT_t + \varepsilon_{t+1}$, while the results in column $X3_b$ are from $X3^a_{t+1} = \omega_0 + \omega_1 X3^a_t + \omega_4 AEX_t + \varepsilon_{t+1}$

Table 6.3: Pooled unconditional ω with four lags – scaled by stock price

$$x_{t+1}^{a} = \omega_0 + \omega_1 x_t^a + \omega_2 x_{t-1}^a + \omega_3 x_{t-2}^a + \omega_4 x_{t-3}^a + \varepsilon_{t+1}$$

	X1	X2	X3	X4
ω_0	-0.018***	-0.021***	-0.030***	-0.021***
	(-15.76)	(-19.46)	(-19.49)	(-16.91)
ω_1	0.680***	0.695***	0.480***	0.615***
	(101.50)	(104.84)	(70.83)	(90.69)
ω_2	-0.045***	-0.019**	0.047***	-0.015*
	(-5.55)	(-2.33)	(5.97)	(-1.87)
ω_3	-0.017**	0.004	-0.006	-0.019**
	(-2.07)	(0.47)	(-0.65)	(-2.18)
ω_4	0.084***	0.055***	0.074***	0.081***
	(11.24)	(7.60)	(9.28)	(10.53)
Adj. R^2	0.493	0.556	0.318	0.432
N	19215	19232	19133	19189

Note:

1) The estimation of ω is based on 29,828 firm-year observations from 1969 to 1998. The total observations available for AR(4) regression, however, are 19,753 from 1974 to 1998 because 5-year lagged book value is required for construction of 4-year lagged RI.
2) All regression variables on the per-share basis are scaled by stock price at the end of year t.
3) Figures in parentheses are t-statistics.
4) The most extreme 1% of regression variables are deleted.
5) The discount rate r, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
6) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
7) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings and x_t^a denotes residual income for period t.

Table 6.4: Pooled unconditional ω with book value – scaled by stock price

Panel A: $x_{t+1}^a = \omega_0 + \omega_1 x_t^a + \omega_2 b_{t-1} + \varepsilon_{t+1}$

	X1	X2	X3	X4
ω_0	0.021***	0.018***	0.026***	0.022***
	(16.12)	(15.29)	(15.66)	(15.90)
ω_1	0.448***	0.459***	0.317***	0.410***
	(75.57)	(79.16)	(53.61)	(69.30)
ω_2	-0.048***	-0.053***	-0.067***	-0.052***
	(-42.69)	(-47.88)	(-49.85)	(-44.19)
Adj. R^2	0.501	0.568	0.358	0.453
N	24727	24738	24664	24709

Panel B: $x_{t+1}^a = \omega_0 + \omega_1 x_t^a + \omega_2 b_t + \varepsilon_{t+1}$

	X1	X2	X3	X4
ω_0	0.033***	0.032***	0.032***	0.032***
	(27.68)	(28.96)	(19.49)	(24.68)
ω_1	0.455***	0.460***	0.363***	0.429***
	(92.42)	(98.60)	(69.85)	(85.25)
ω_2	-0.057***	-0.063***	-0.065***	-0.057***
	(-60.65)	(-70.23)	(-55.42)	(-57.58)
Adj. R^2	0.539	0.609	0.377	0.484
N	24706	24717	24641	24687

Panel C: $x_{t+1}^a = \omega_0 + \omega_1 x_t + \omega_2 b_{t-1} + \varepsilon_{t+1}$

	X1	X2	X3	X4
ω_0	0.030***	0.027***	0.030***	0.029***
	(23.10)	(22.79)	(18.15)	(20.99)
ω_1	0.391***	0.393***	0.305***	0.370***
	(63.60)	(63.65)	(50.49)	(60.61)
ω_2	-0.125***	-0.132***	-0.122***	-0.122***
	(-153.78)	(-174.10)	(-113.90)	(-138.42)
Adj. R^2	0.501	0.560	0.366	0.451
N	24709	24710	24656	24689

Note:

1) The estimation of ω is based on 29,828 firm-year observations from 1969 to 1998. The total observations available for each regression, however, are 25,187 from 1971 to 1998 because 2-year lagged book value is required for one of the explanatory variables.
2) All regression variables on the per-share basis are scaled by stock price at the end of year t.
3) Figures in parentheses are t-statistics.
4) The most extreme 1% of regression variables are deleted.
5) The discount rate r, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
6) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
7) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings and x_t^a denotes residual income for period t.

Table 6.5: Firm-specific conditional ω (ω^f) – scaled by stock price

Panel A: Determinants of ω^f

$$x_t^a = \omega_0 + \omega_1 x_{t-1}^a + \omega_2(x_{t-1}^a q1_{t-1}) + \omega_3(x_{t-1}^a q2_{t-1}) + \omega_4(x_{t-1}^a q3_{t-1}) + \omega_5(x_{t-1}^a q4_{t-1}) + \omega_6(x_{t-1}^a q5_{t-1}) + \omega_7(x_{t-1}^a div_{t-1}) + \omega_8(x_{t-1}^a ind_{t-1}) + \varepsilon_t$$

	X1	X2	X3$_a$	X3$_b$	X4
ω_0	-0.011***	-0.012***	-0.018***	-0.019***	-0.012***
	(-12.02)	(-13.90)	(-15.30)	(-15.53)	(-12.57)
ω_1	0.680***	0.697***	0.719***	0.704***	0.707***
	(37.47)	(42.43)	(44.56)	(45.49)	(38.63)
ω_2	-0.600***	-0.728***	-0.332***	-0.248***	-0.526***
	(-15.99)	(-20.67)	(-7.84)	(-6.43)	(-13.32)
ω_3	-	-	-0.424***	-	-0.374**
	-	-	(-2.60)	-	(-2.53)
ω_4	-	-	-1.336***	-	-
	-	-	(-18.38)	-	-
ω_5	-	-	-	-1.186***	-
	-	-	-	(-10.17)	-
ω_6	-1.005***	-0.940***	-0.794***	-0.838***	-0.966***
	(-13.98)	(-14.38)	(-9.33)	(-10.17)	(-12.50)
ω_7	0.270***	0.265***	0.282***	0.292***	0.299***
	(14.87)	(18.87)	(12.00)	(12.58)	(14.75)
ω_8	0.182***	0.231***	0.115***	0.104***	0.125***
	(9.31)	(13.24)	(6.38)	(5.83)	(6.16)
Adj. R^2	0.476	0.561	0.360	0.356	0.438
N	24446	24476	24228	24344	24325

Note:

1) The estimation of ω is based on 29,828 firm-year observations from 1969 to 1998. The total observations available for regression, however, are 25,187 from 1971 to 1998 because 2-year lagged book value is required for explanatory variables.
2) All regression variables on the per-share basis are scaled by stock price at the end of year *t*-1.
3) Figures in parentheses are t-statistics.
4) The most extreme 1% of regression variables are deleted.
5) The discount rate *r*, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
6) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
7) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings and x_t^a denotes residual income for period *t*.
8) The regression equations of X3$_a$ and X3$_b$ are the same except that the regression equation of X3$_a$ includes exceptional and extraordinary items separately, while the regression equation of X3$_b$ includes those items (i.e., all abnormal items) in an explanatory variable.

Table 6.5 (continued)

Panel B: Distribution of conditional ω (ω^f)

$$\omega_t^f = \omega_1 + \omega_2 q1_t + \omega_3 q2_t + \omega_4 q3_t + \omega_5 q4_t + \omega_6 q5_t + \omega_7 div_t + \omega_8 ind_t$$

	ω^f (X1)	ω^f (X2)	ω^f (X3$_a$)	ω^f (X3$_b$)	ω^f (X4)
N	8346	8346	8346	8346	8346
Mean	0.744	0.788	0.713	0.703	0.747
Std	0.518	0.624	0.556	0.491	0.488
1%	-0.049	-0.127	-0.493	-0.416	-0.058
5%	0.426	0.429	0.325	0.312	0.414
10%	0.553	0.581	0.515	0.506	0.543
Q1	0.699	0.742	0.691	0.679	0.698
Median	0.797	0.851	0.793	0.779	0.800
Q3	0.867	0.925	0.856	0.841	0.868
90%	0.922	0.981	0.911	0.897	0.929
95%	0.952	1.011	0.944	0.930	0.963
99%	1.003	1.068	0.998	0.984	1.019
$0 < \omega^f < 1$	98%	92%	97%	97%	97%
$0.5 < \omega^f < 1$	91%	86%	90%	90%	90%

Note:

9) $q1_t$ is defined as $|x_t^a / b_{t-1}|$;

$q2_t$ is defined as $|EXC_t / b_{t-1}|$ where *EXC* is exceptional items;

$q3_t$ is defined as $|EXT_t / b_{t-1}|$ where *EXT* is extraordinary items;

$q4_t$ is defined as $|AEX_t / b_{t-1}|$ where *AEX* is all exceptional and extraordinary items;

$q5_t$ is defined as $|OA_t / TA_{t-1}|$ where *OA* is the operating accruals and *TA* is the total assets

OA_t is calculated as follows;

$OA_t = (\Delta CA_t - \Delta CASH_t) - (\Delta CL_t - \Delta STD_t - \Delta TP_t) - DEP_t$

where ΔCA is the change of current assets, $\Delta CASH$ is the change of cash/cash equivalent, ΔCL is the change of current liabilities, ΔSTD is the change of debt included in current liabilities, ΔTP is the change of income taxes payable, *DEP* is depreciation and amortization expense

div_t is dividend payout ratio, i.e., d_t / x_t, where d_t is the net ordinary dividends;

ind_t is defined as the first order autoregressive coefficient from residual income autoregression for all firms in the same industry.

10) The total firm-year observations used for the distribution of firm-specific ω (i.e., ω^f) are 8,346 from 1989 to 1998.

Table 6.6: Unconditional γ - scaled by stock price

$$v_{t+1} = \gamma_0 + \gamma_1 v_t + \varepsilon_{t+1}$$

Panel A: Pooled γ

	X1	X2	X3	X4
γ_0	0.009^{***}	0.009^{***}	0.014^{***}	0.011^{***}
	(13.68)	(14.75)	(15.40)	(15.39)
γ_1	0.354^{***}	0.366^{***}	0.323^{***}	0.337^{***}
	(36.67)	(37.85)	(32.63)	(33.68)
Adj. R^2	0.166	0.174	0.136	0.143
N	6779	6775	6768	6773

Panel B: Year-specific γ

	X1		X2		X3		X4	
	γ_0	γ_1	γ_0	γ_1	γ_0	γ_1	γ_0	γ_1
91	0.001	0.421	0.002	0.454	0.006	0.405	0.004	0.382
92	0.003	0.383	0.004	0.396	0.009	0.379	0.006	0.381
93	0.006	0.351	0.007	0.359	0.009	0.364	0.008	0.342
94	0.007	0.333	0.008	0.348	0.010	0.333	0.009	0.321
95	0.007	0.337	0.008	0.350	0.010	0.324	0.009	0.330
96	0.007	0.338	0.009	0.347	0.011	0.317	0.010	0.317
97	0.008	0.341	0.009	0.354	0.012	0.316	0.010	0.324
98	0.009	0.354	0.009	0.366	0.014	0.323	0.011	0.337

Note:
1) The estimation of γ is based on 8,346 firm-year observations from 1989 to 1998. The total observations available for AR(1) regression, however, are 6,875 from 1990 to 1998 because a lagged OI is used as the explanatory variable. I/B/E/S earnings forecasts for U.K. firms are available only after 1990.
2) All regression variables on the per-share basis are scaled by stock price at the end of year *t*.
3) Figures in parentheses are t-statistics.
4) The most extreme 1% of regression variables are deleted.
5) The discount rate *r*, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
6) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
7) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings and x_t^a denotes residual income for period *t*.
8) v_t is defined as $f_{t+1}^a - \omega_{1,t} x_t^a$. f_{t+1}^a is one-year ahead residual income forecasts, and is defined as $f_{t+1} - rb_t$, where f_{t+1} is the first one-year ahead I/B/E/S median earnings forecasts (FY1) measured after the earnings announcement for year *t*.
9) For the case of LID7 (i.e., $\omega_1 = 0$ and OI is incorporated), γ_1 should be estimated from the regression of scaled f_{t+1}^a on lagged scaled f_{t+1}^a, because $v_t = f_{t+1}^a$ in this case. γ_1 in this case is in the range of 0.735 to 0.835.

Table 6.7: Residual income forecasting ability – scaled by stock price

$$AFE_{ri} = \left| E_t\left[x_{t+1}^a\right] - x_{t+1}^a \right| / P_t$$

	X1	X2	X3	X4
LID1	0.035	0.035	0.038	0.036
	(0.067)	(0.067)	(0.090)	(0.074)
LID2	0.020	0.020	0.028	0.022
	(0.061)	(0.060)	(0.107)	(0.074)
LID3	0.022	0.021	0.029	0.024
	(0.052)	(0.052)	(0.084)	(0.062)
LID4	0.022	0.022	0.029	0.024
	(0.053)	(0.054)	(0.113)	(0.064)
LID5-LID9	0.016†‡	0.016†‡	0.020†‡	0.017†‡
	(0.043)	(0.043)	(0.069)	(0.051)

Note:

1) Residual income forecasting ability is defined as the absolute difference between the forecasted residual income and the realized residual income for year t+1, scaled by stock price at the end of year t. The figures shown in the table are median values. The mean values are shown in parentheses.
2) Firm-year observations used for the absolute forecast errors are 6,875 from 1990 to 1998.
3) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings and x_t^a denotes residual income for period t.
4) Firm-specific persistence parameters used in 4th column (i.e., X3) for LID4 come from the result related to $X3_a$ in Table 6.5. However, the median and mean absolute forecast errors are very similar to those calculated when firm-specific persistence parameters from the result related to $X3_b$ are used.
5) † (‡) indicates that the median (mean) absolute forecast errors of LID5-LID9 are significantly different from those of other four models at 1% level. The sign test or Wilcoxon signed rank test (T test) is used for the test of median (mean) differences.

Table 6.8: Reliability test – scaled by stock price

Panel A: Bias ($FE_{sp} = (V_t - P_t^{c,3}) / P_t^{c,3}$)

	X1	X2	X3	X4
LID1	-0.476 (-0.282)	-0.476 (-0.282)	-0.476 (-0.282)	-0.476 (-0.282)
LID2	-0.512 (-0.677)	-0.517 (-0.684)	-0.529 (-0.953)	-0.521 (-0.789)
LID3	-0.487 (-0.352)	-0.489 (-0.365)	-0.496 (-0.361)	-0.492 (-0.360)
LID4	-0.500 (-0.378)	-0.511 (-0.310)	-0.510 (-0.382)	-0.513 (-0.393)
LID5	-0.461 (-0.294)	-0.461 (-0.294)	-0.461 (-0.294)	-0.461 (-0.294)
LID6	-0.431 (-0.371)	-0.431 (-0.371)	-0.431 (-0.371)	-0.431 (-0.371)
LID7	-0.440 (-0.322)	-0.440 (-0.322)	-0.440 (-0.322)	-0.440 (-0.322)
LID8	-0.445 (-0.310)	-0.445 (-0.312)	-0.449 (-0.305)	-0.447 (-0.308)
LID9	-0.434 (-0.290)	-0.428 (-0.287)	-0.434 (-0.280)	-0.433 (-0.285)

Panel B: Test for differences of median and mean bias

The sign test (superscripted by S) and the Wilcoxon signed rank test (superscripted by W) are used for the test of median differences, while the student's t test is used for the test of mean differences. Note that each two samples for the test are paired. The median (mean) bias of value estimates based on LID6 and LID9 is significantly different from the median (mean) bias of almost all other model-based value estimates at the 1% level. **This panel only includes the results of the test for median (mean) differences whose *p*-value is larger than 1%.** Figures in parentheses are *p*-values of test statistics.

X1		X2		X3		X4	
LID6	LID9	LID6	LID9	LID6	LID9	LID6	LID9
Test for differences of median bias							
-	-	vs. LID9^{W} (0.025)	vs. LID6^{W} (0.025)	-	-	-	vs. LID7^{S} (0.981)
Test for differences of mean bias							
vs. LID3 (0.099) vs. LID4 (0.564)	vs. LID1 (0.104) vs. LID5 (0.217)	vs. LID3 (0.553) vs. LID4 (0.540)	vs. LID1 (0.415) vs. LID4 (0.817) vs. LID5 (0.049)	vs. LID3 (0.378) vs. LID4 (0.328)	vs. LID1 (0.535)	vs. LID3 (0.338) vs. LID4 (0.051)	vs. LID1 (0.581)

Table 6.8 (continued)

Panel C: Accuracy ($AFE_{sp} = \left|V_t - P_t^{c,3}\right| / P_t^{c,3}$)

	X1	X2	X3	X4
LID1	0.537 (0.581)	0.537 (0.581)	0.537 (0.581)	0.537 (0.581)
LID2	0.521 (0.763)	0.526 (0.768)	0.542 (1.061)	0.530 (0.870)
LID3	0.522 (0.559)	0.524 (0.560)	0.537 (0.579)	0.529 (0.568)
LID4	0.526 (0.547)	0.531 (0.665)	0.535 (0.555)	0.536 (0.556)
LID5	0.512 (0.546)	0.512 (0.546)	0.512 (0.546)	0.512 (0.546)
LID6	0.447 (0.482)	0.447 (0.482)	0.447 (0.482)	0.447 (0.482)
LID7	0.471 (0.491)	0.471 (0.491)	0.471 (0.491)	0.471 (0.491)
LID8	0.485 (0.510)	0.483 (0.505)	0.494 (0.521)	0.489 (0.514)
LID9	0.477 (0.502)	0.473 (0.498)	0.484 (0.517)	0.479 (0.508)

Panel D: Test for differences of median and mean accuracy

The sign test (superscripted by S) and the Wilcoxon signed rank test (superscripted by W) are used for the test of median differences, while the student's t test is used for the test of mean differences. Note that each two samples for the test are paired. The median (mean) accuracy of value estimates based on LID6 and LID9 is significantly different from the median (mean) accuracy of almost all other model-based value estimates at the 1% level. **This panel only includes the results of the test for median (mean) differences whose *p*-value is larger than 1%.** Figures in parentheses are *p*-values of test statistics.

X1		X2		X3		X4	
LID6	LID9	LID6	LID9	LID6	LID9	LID6	LID9
Test for differences of median bias							
-	vs. LID2^{S} (0.029)	-	-	-	-	-	-
Test for differences of mean bias							
vs. LID7 (0.213)	-	vs. LID4 (0.068) vs. LID7 (0.213) vs. LID9 (0.020)	vs. LID4 (0.095) vs. LID6 (0.020)	vs. LID7 (0.213)	vs. LID8 (0.014)	vs. LID7 (0.213)	-

Table 6.8 (continued)

Panel E: Explainability (R^2 of $P_t^{c,3} = \lambda_0 + \lambda_1 V_t + u_t$)

	X1	X2	X3	X4
LID1	0.338	0.338	0.338	0.338
LID2	0.500	0.502	0.366	0.439
LID3	0.408	0.409	0.381	0.388
LID4	0.446	0.449	0.427	0.418
LID5	0.395	0.395	0.395	0.395
LID6	0.618	0.618	0.618	0.618
LID7	0.507	0.507	0.507	0.507
LID8	0.464	0.472	0.440	0.457
LID9	0.478	0.487	0.450	0.461

Note:

1) Bias (Accuracy) is defined as the signed (absolute) difference between the value estimates and the current stock price, scaled by the current stock price. The figures shown in Panel A and C are median values. The mean values are shown in parentheses.
2) Explainability (Panel E) is defined as the ability of value estimates to explain cross-sectional variation in current stock prices (i.e., OLS R^2).
3) Firm-year observations used for bias (accuracy) tests are 6,835 from 1991 to 1998. While, firm-year observations used for explainability tests are 6,717 to 6,728 from 1991 to 1998 because the most extreme 1% of regression variables are deleted.
4) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, and X4 is post-exceptional and pre-extraordinary earnings.
5) Firm-specific persistence parameters used in 4th column (i.e., X3) of each panel for LID4 come from the result related to $X3_a$ in Table 6.5. However, the signed (absolute) forecast error and R^2 are very similar to those calculated when firm-specific persistence parameters from the result related to $X3_b$ are used.
6) $P_t^{c,3}$ is the observed stock price at 3 months after the fiscal year end, and V_t is the estimated intrinsic value.

Table 6.9: Unconditional ω – scaled by book value

$$x_{t+1}^a = \omega_0 + \omega_1 x_t^a + \varepsilon_{t+1}$$

Panel A: Pooled ω

	X1	X2	X3	X4
ω_0	-0.0002	-0.005***	-0.009***	-0.002**
	(-0.22)	(-7.46)	(-8.89)	(-2.12)
ω_1	0.608***	0.615***	0.437***	0.559***
	(126.92)	(131.57)	(84.01)	(112.85)
Adj. R^2	0.394	0.411	0.222	0.340
N	24788	24788	24768	24773

Panel B: Year-specific ω

	X1		X2		X3		X4	
	ω_0	ω_1	ω_0	ω_1	ω_0	ω_1	ω_0	ω_1
89	-0.002	0.628	-0.009	0.635	-0.006	0.483	-0.0002	0.608
90	-0.003	0.631	-0.010	0.638	-0.008	0.479	-0.002	0.608
91	-0.005	0.624	-0.012	0.629	-0.011	0.470	-0.004	0.598
92	-0.006	0.616	-0.012	0.620	-0.013	0.469	-0.005	0.588
93	-0.005	0.608	-0.012	0.612	-0.013	0.457	-0.006	0.572
94	-0.004	0.599	-0.011	0.603	-0.012	0.442	-0.005	0.563
95	-0.003	0.599	-0.009	0.604	-0.012	0.437	-0.004	0.561
96	-0.002	0.603	-0.008	0.607	-0.011	0.437	-0.003	0.561
97	-0.001	0.603	-0.007	0.608	-0.010	0.433	-0.002	0.555
98	-0.0002	0.608	-0.005	0.615	-0.009	0.437	-0.002	0.559

Note:

1) The estimation of ω is based on 29,828 firm-year observations from 1969 to 1998. The total observations available for AR(1) regression, however, are 25,187 from 1971 to 1998 because 2-year lagged book value is required for construction of lagged RI.
2) All regression variables on the per-share basis are scaled by book value at the end of year t.
3) Figures in parentheses are t-statistics.
4) The most extreme 1% of regression variables are deleted.
5) The discount rate r, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
6) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
7) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings, and x_t^a denotes residual income for period t.

Table 6.10: Firm-specific conditional ω (ω^f) – scaled by book value

Panel A: Determinants of ω^f

$$x_t^a = \omega_0 + \omega_1 x_{t-1}^a + \omega_2(x_{t-1}^a q1_{t-1}) + \omega_3(x_{t-1}^a q2_{t-1}) + \omega_4(x_{t-1}^a q3_{t-1}) + \omega_5(x_{t-1}^a q4_{t-1}) + \omega_6(x_{t-1}^a q5_{t-1}) + \omega_7(x_{t-1}^a div_{t-1}) + \omega_8(x_{t-1}^a ind_{t-1}) + \varepsilon_t$$

	X1	X2	X3$_a$	X3$_b$	X4
ω_0	0.011*	-0.001**	-0.006***	-0.006***	-0.001
	(1.90)	(-2.00)	(-5.91)	(-5.65)	(-0.66)
ω_1	0.108***	0.138***	0.487***	0.393***	0.342***
	(2.63)	(3.46)	(12.01)	(10.09)	(7.85)
ω_2	-0.004	-0.053*	0.062**	0.083***	0.041
	(-0.16)	(-1.94)	(2.32)	(3.25)	(1.47)
ω_3	-	-	-1.358***	-	-1.742**
	-	-	(-10.54)	-	(-14.70)
ω_4	-	-	-1.556***	-	-
	-	-	(-28.26)	-	-
ω_5	-	-	-	-1.297***	-
	-	-	-	(-31.18)	-
ω_6	-0.600***	-0.591***	-0.437***	-0.397***	-0.520***
	(-9.61)	(-9.75)	(-6.40)	(-6.02)	(-7.86)
ω_7	0.547***	0.520***	0.356***	0.403***	0.487***
	(26.19)	(28.59)	(13.55)	(15.40)	(21.44)
ω_8	0.794***	0.778***	0.396***	0.485***	0.491***
	(12.61)	(12.63)	(5.14)	(6.53)	(7.04)
Adj. R^2	0.436	0.461	0.323	0.315	0.403
N	24522	24520	24354	24455	24410

Note:
1) The estimation of ω is based on 29,828 firm-year observations from 1969 to 1998. The total observations available for regression, however, are 25,187 from 1971 to 1998 because 2-year lagged book value is required for explanatory variables.
2) All regression variables on the per-share basis are scaled by book value at the end of year t-1.
3) Figures in parentheses are t-statistics.
4) The most extreme 1% of regression variables are deleted.
5) The discount rate r, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
6) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
7) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings and x_t^a denotes residual income for period t.
8) The regression equations of X3$_a$ and X3$_b$ are the same except that the regression equation of X3$_a$ includes exceptional and extraordinary items separately, while the regression equation of X3$_b$ includes those items (i.e., all abnormal items) in an explanatory variable.

Table 6.10 (continued)

Panel B: Distribution of conditional ω (ω^f)

$$\omega_t^f = \omega_1 + \omega_2 q1_t + \omega_3 q2_t + \omega_4 q3_t + \omega_5 q4_t + \omega_6 q5_t + \omega_7 div_t + \omega_8 ind_t$$

	ω^f (X1)	ω^f (X2)	ω^f (X3$_a$)	ω^f (X3$_b$)	ω^f (X4)
N	8346	8346	8346	8346	8346
Mean	0.793	0.803	0.714	0.705	0.780
Std	0.157	0.173	0.443	0.356	0.194
1%	0.425	0.425	-0.389	-0.182	0.219
5%	0.545	0.554	0.390	0.412	0.529
10%	0.605	0.618	0.558	0.541	0.606
Q1	0.707	0.720	0.694	0.668	0.717
Median	0.788	0.803	0.769	0.742	0.793
Q3	0.880	0.889	0.825	0.808	0.868
90%	1.006	1.005	0.899	0.892	0.972
95%	1.057	1.059	0.952	0.951	1.027
99%	1.133	1.161	1.011	1.033	1.089
$0 < \omega^f < 1$	89%	89%	97%	96%	92%
$0.5 < \omega^f < 1$	87%	87%	91%	90%	88%

Note:

9) $q1_t$ is defined as $\left|x_t^a / b_{t-1}\right|$;

$q2_t$ is defined as $\left|EXC_t / b_{t-1}\right|$ where *EXC* is exceptional items;

$q3_t$ is defined as $\left|EXT_t / b_{t-1}\right|$ where *EXT* is extraordinary items;

$q4_t$ is defined as $\left|AEX_t / b_{t-1}\right|$ where *AEX* is all exceptional and extraordinary items;

$q5_t$ is defined as $\left|OA_t / TA_{t-1}\right|$ where *OA* is the operating accruals and *TA* is the total assets

OA_t is calculated as follows;

$OA_t = (\Delta CA_t - \Delta CASH_t) - (\Delta CL_t - \Delta STD_t - \Delta TP_t) - DEP_t$

where ΔCA is the change of current assets, $\Delta CASH$ is the change of cash/cash equivalent, ΔCL is the change of current liabilities, ΔSTD is the change of debt included in current liabilities, ΔTP is the change of income taxes payable, *DEP* is depreciation and amortization expense

div_t is dividend payout ratio, i.e., d_t / x_t, where d_t is the net ordinary dividends;

ind_t is defined as the first order autoregressive coefficient from a residual income autoregression for all firms in the same industry.

10) The total firm-year observations used for the distribution of firm-specific ω (i.e., ω^f) are 8,346 from 1989 to 1998.

Table 6.11: Unconditional γ - scaled by book value

$$v_{t+1} = \gamma_0 + \gamma_1 v_t + \varepsilon_{t+1}$$

Panel A: Pooled γ when $v_t = f^a_{t+1} - \omega_{1,t} x^a_t$

	X1	X2	X3	X4
γ_0	0.015***	0.016***	0.025***	0.020***
	(12.20)	(12.92)	(15.43)	(14.94)
γ_1	0.529***	0.526***	0.501***	0.493***
	(58.19)	(58.67)	(52.49)	(53.98)
Adj. R^2	0.333	0.337	0.289	0.301
N	6783	6782	6780	6782

Panel B: Year-specific γ when $v_t = f^a_{t+1} - \omega_{1,t} x^a_t$

	X1		X2		X3		X4	
	γ_0	γ_1	γ_0	γ_1	γ_0	γ_1	γ_0	γ_1
91	0.0004	0.472	0.002	0.466	0.004	0.550	0.002	0.526
92	0.004	0.437	0.006	0.429	0.009	0.524	0.008	0.450
93	0.009	0.449	0.010	0.443	0.015	0.472	0.012	0.433
94	0.012	0.456	0.013	0.450	0.019	0.449	0.016	0.440
95	0.012	0.477	0.013	0.477	0.020	0.458	0.016	0.444
96	0.013	0.474	0.014	0.472	0.021	0.462	0.018	0.441
97	0.014	0.506	0.015	0.503	0.022	0.488	0.019	0.471
98	0.015	0.529	0.016	0.526	0.025	0.501	0.020	0.493

Panel C: Pooled γ when $v_t = f^a_{t+1} - \omega_{0,t} b_t - \omega_{1,t} x^a_t$

	X1	X2	X3	X4
γ_0	0.017***	0.021***	0.031***	0.023***
	(13.53)	(16.46)	(19.03)	(16.43)
γ_1	0.530***	0.527***	0.507***	0.494***
	(58.82)	(59.36)	(54.03)	(54.56)
Adj. R^2	0.338	0.342	0.301	0.305
N	6783	6782	6780	6782

Panel D: Year-specific γ when $v_t = f^a_{t+1} - \omega_{0,t} b_t - \omega_{1,t} x^a_t$

	X1		X2		X3		X4	
	γ_0	γ_1	γ_0	γ_1	γ_0	γ_1	γ_0	γ_1
91	0.004	0.475	0.009	0.473	0.010	0.558	0.005	0.528
92	0.007	0.438	0.012	0.437	0.016	0.530	0.011	0.451
93	0.012	0.452	0.017	0.452	0.022	0.479	0.016	0.436
94	0.015	0.459	0.019	0.459	0.026	0.457	0.019	0.443
95	0.015	0.480	0.019	0.478	0.027	0.466	0.019	0.446
96	0.016	0.476	0.020	0.474	0.028	0.470	0.020	0.444
97	0.016	0.508	0.020	0.505	0.029	0.494	0.021	0.474
98	0.017	0.530	0.021	0.527	0.031	0.507	0.023	0.494

Note:

1) The estimation of γ is based on 8,346 firm-year observations from 1989 to 1998. The total observations available for AR(1) regression, however, are 6,875 from 1990 to 1998 because lagged OI is used for explanatory variable. I/B/E/S earnings forecasts for U.K. firms are available only after 1990.
2) All regression variables on the per-share basis are scaled by book value at the end of year t.
3) Figures in parentheses are t-statistics.
4) The most extreme 1% of regression variables are deleted.
5) The discount rate r, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
6) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
7) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, X4 is post-exceptional and pre-extraordinary earnings and x_t^a denotes residual income for period t.
8) v_t is defined as $f_{t+1}^a - \omega_{1,t}x_t^a$ for Panel A and B and as $f_{t+1}^a - \omega_{0,t}b_t - \omega_{1,t}x_t^a$ for Panel C and D. f_{t+1}^a is one-year ahead residual income forecasts, and is defined as $f_{t+1} - rb_t$, where f_{t+1} is the first one-year ahead I/B/E/S median earnings forecasts (FY1) measured after the earnings announcement for year t.

Table 6.12: Parameters under the restriction of ω_1 and/or γ_1 – scaled by book value

Panel A: γ_1 when $\omega_1 = 0$ (in LID7)

91	0.805
92	0.791
93	0.794
94	0.814
95	0.842
96	0.850
97	0.849
98	0.866

Panel B: ω_0 when $\omega_1 = 0$ (in LID10, LID13 and LID14)

	X1	X2	X3	X4
89	-0.018	-0.034	-0.020	-0.014
90	-0.018	-0.033	-0.019	-0.013
91	-0.019	-0.033	-0.022	-0.015
92	-0.020	-0.034	-0.025	-0.017
93	-0.021	-0.035	-0.027	-0.019
94	-0.020	-0.033	-0.026	-0.018
95	-0.019	-0.032	-0.026	-0.018
96	-0.018	-0.030	-0.025	-0.017
97	-0.017	-0.029	-0.024	-0.016
98	-0.016	-0.027	-0.024	-0.016

Panel C: γ_0 when $\omega_1 = 0$ and $\gamma_1 = 0$ (in LID13)

	X1	X2	X3	X4
91	0.076	0.093	0.078	0.071
92	0.065	0.082	0.068	0.061
93	0.065	0.081	0.068	0.060
94	0.067	0.083	0.071	0.063
95	0.068	0.084	0.073	0.065
96	0.069	0.084	0.074	0.066
97	0.072	0.087	0.078	0.069
98	0.077	0.091	0.082	0.074

Table 6.12 (continued)

Panel D: γ_0 and γ_1 when $\omega_1 = 0$ and $\gamma_1 = \hat{\gamma}_1$ (in LID14)

	X1		X2		X3		X4	
	γ_0	γ_1	γ_0	γ_1	γ_0	γ_1	γ_0	γ_1
91	-0.022	0.806	-0.019	0.816	-0.020	0.808	-0.022	0.803
92	-0.010	0.792	-0.007	0.799	-0.008	0.793	-0.011	0.789
93	-0.000	0.805	0.002	0.808	0.001	0.808	-0.001	0.802
94	0.006	0.829	0.008	0.834	0.008	0.834	0.006	0.826
95	0.007	0.857	0.008	0.863	0.008	0.862	0.006	0.855
96	0.008	0.865	0.010	0.871	0.009	0.870	0.008	0.864
97	0.011	0.863	0.013	0.869	0.013	0.868	0.011	0.862
98	0.013	0.879	0.014	0.886	0.014	0.884	0.013	0.878

Panel E: γ_0 when $\omega_1 = \hat{\omega}_1$ and $\gamma_1 = 0$ (in LID15)

	X1	X2	X3	X4
91	0.039	0.048	0.053	0.039
92	0.037	0.045	0.054	0.039
93	0.040	0.048	0.056	0.042
94	0.042	0.050	0.059	0.045
95	0.043	0.052	0.061	0.046
96	0.044	0.053	0.062	0.048
97	0.046	0.054	0.065	0.050
98	0.048	0.056	0.068	0.053

Note:

1) The estimation of ω (Panel B) is based on 29,828 firm-year observations from 1969 to 1998, while the estimation of γ is based on 8,346 firm-year observations from 1989 to 1998.
2) All regression variables on the per-share basis are scaled by book value at the end of year t.
3) The most extreme 1% of regression variables are deleted.
4) The discount rate r, which varies over the years, is 5% plus 12-month average (up to fiscal year end month) of the U.K. Gross Redemption Yield on 20 year Gilts.
5) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, and X4 is post-exceptional and pre-extraordinary earnings.
6) In Panel A, γ_1 is the estimated slope coefficient from the regression of book value-scaled f^a_{t+1} on lagged book value-scaled f^a_{t+1}, because $v_t = f^a_{t+1}$ in this case.
7) In Panel B, ω_0 for year t is the mean of book value-scaled RI using data up to year t (i.e., $\overline{\left(x^a_t / b_{t-1}\right)}$, where bar denotes 'mean').
8) In Panel C, γ_0 for year t is $\overline{\left(f^a_{t+1} / b_{t-1}\right) - \omega_{0,t}\left(b_t / b_{t-1}\right)}$.
9) In Panel D, γ_0 and γ_1 are the estimated parameters of AR(1) OI regression where $v_t = f^a_{t+1} - \omega_{0,t} b_t$
10) In Panel E, γ_0 for year t is $\overline{\left(f^a_{t+1} / b_{t-1}\right) - \omega_{0,t}\left(b_t / b_{t-1}\right) - \omega_{1,t}\left(x^a_t / b_{t-1}\right)}$.

Table 6.13: Reliability test – scaled by book value

Panel A: Bias ($FE_{sp} = (V_t - P_t^{c,3}) / P_t^{c,3}$)

	X1	X2	X3	X4
LID1	-0.476 (-0.282)	-0.476 (-0.282)	-0.476 (-0.282)	-0.476 (-0.282)
LID2	-0.512 (-0.677)	-0.517 (-0.684)	-0.529 (-0.953)	-0.521 (-0.789)
LID3	-0.486 (-0.345)	-0.487 (-0.347)	-0.494 (-0.343)	-0.491 (-0.354)
LID4	-0.524 (-0.535)	-0.527 (-0.455)	-0.512 (-0.385)	-0.528 (-0.471)
LID5	-0.461 (-0.294)	-0.461 (-0.294)	-0.461 (-0.294)	-0.461 (-0.294)
LID6	-0.431 (-0.371)	-0.431 (-0.371)	-0.431 (-0.371)	-0.431 (-0.371)
LID7	-0.430 (-0.319)	-0.430 (-0.319)	-0.430 (-0.319)	-0.430 (-0.319)
LID8	-0.447 (-0.308)	-0.447 (-0.308)	-0.451 (-0.302)	-0.448 (-0.307)
LID9	-0.427 (-0.280)	-0.426 (-0.280)	-0.432 (-0.271)	-0.428 (-0.274)
LID10	-0.584 (-0.429)	-0.657 (-0.527)	-0.620 (-0.475)	-0.574 (-0.415)
LID11	-0.528 (-0.403)	-0.606 (-0.509)	-0.600 (-0.489)	-0.536 (-0.414)
LID12	-0.540 (-0.568)	-0.616 (-0.559)	-0.631 (-0.548)	-0.553 (-0.519)
LID13	-0.211 (0.050)	-0.197 (0.069)	-0.220 (0.037)	-0.219 (0.038)
LID14	-0.466 (-0.343)	-0.468 (-0.350)	-0.455 (-0.330)	-0.461 (-0.337)
LID15	-0.033 (0.266)	-0.005 (0.304)	-0.059 (0.241)	-0.040 (0.262)
LID16	-0.225 (-0.003)	-0.199 (0.031)	-0.176 (0.077)	-0.186 (0.060)
EBO1	-0.431 (-0.371)	-0.431 (-0.371)	-0.431 (-0.371)	-0.431 (-0.371)
EBO2	-0.393 (-0.313)	-0.392 (-0.312)	-0.393 (-0.313)	-0.393 (-0.313)
EBO3	-0.405 (-0.334)	-0.404 (-0.332)	-0.402 (-0.335)	-0.405 (-0.335)
EBO4	-0.413 (-0.402)	-0.413 (-0.402)	-0.413 (-0.402)	-0.413 (-0.402)
EBO5	-0.370 (-0.312)	-0.369 (-0.311)	-0.370 (-0.312)	-0.370 (-0.312)
EBO6	-0.372 (-0.324)	-0.371 (-0.321)	-0.371 (-0.324)	-0.373 (-0.324)

Table 6.13 (continued)

Panel B: Test for differences of median and mean bias – based on X4

For the test of median differences, the sign test is used when two samples are paired, while the Mann-Whitney U test (Wilcoxon rank sum test) is used when two samples have different observations. For the test of mean differences, the student's t test is used when two samples are paired, while the two-sample t test is used when two samples have different observations. The median (mean) bias of value estimates based on LID9, LID16, EBO2 and EBO5 is significantly different from the median (mean) bias of almost all other model-based value estimates at the 1% level. **This panel only includes the results of the test for median (mean) differences whose *p*-value is larger than 1%.** Figures in parentheses are *p*-values of test statistics. Even though this panel only reports the test results based on X4, the results based on the three other earnings measures are very similar in terms of the significance of differences.

LID9	LID16	EBO2	EBO5
Test for differences of median bias			
-	-	vs. EBO6	vs. EBO6
		(0.631)	(0.161)
Test for differences of mean bias			
vs. LID1	-	vs. LID1	vs. LID1
(0.109)		(0.038)	(0.085)
vs. EBO5		vs. LID5	vs. LID3
(0.015)		(0.172)	(0.012)
		vs. LID7	vs. LID5
		(0.566)	(0.273)
		vs. LID8	vs. LID7
		(0.643)	(0.635)
		vs. LID14	vs. LID8
		(0.032)	(0.731)
		vs. EBO3	vs. LID9
		(0.074)	(0.015)
		vs. EBO5	vs. LID14
		(0.936)	(0.089)
		vs. EBO6	vs. EBO2
		(0.457)	(0.936)
			vs. EBO3
			(0.147)
			vs. EBO6
			(0.509)

Table 6.13 (continued)

Panel C: Accuracy ($AFE_{sp} = \left|V_t - P_t^{c,3}\right| / P_t^{c,3}$)

	X1	X2	X3	X4
LID1	0.537 (0.581)	0.537 (0.581)	0.537 (0.581)	0.537 (0.581)
LID2	0.521 (0.763)	0.526 (0.768)	0.542 (1.061)	0.530 (0.870)
LID3	0.523 (0.560)	0.524 (0.560)	0.537 (0.577)	0.530 (0.567)
LID4	0.549 (0.742)	0.557 (0.735)	0.538 (0.562)	0.546 (0.635)
LID5	0.512 (0.546)	0.512 (0.546)	0.512 (0.546)	0.512 (0.546)
LID6	0.447 (0.482)	0.447 (0.482)	0.447 (0.482)	0.447 (0.482)
LID7	0.460 (0.480)	0.460 (0.480)	0.460 (0.480)	0.460 (0.480)
LID8	0.487 (0.513)	0.487 (0.513)	0.498 (0.527)	0.491 (0.517)
LID9	0.472 (0.501)	0.472 (0.500)	0.482 (0.517)	0.477 (0.509)
LID10	0.610 (0.609)	0.670 (0.646)	0.640 (0.628)	0.603 (0.606)
LID11	0.558 (0.573)	0.618 (0.614)	0.615 (0.618)	0.563 (0.582)
LID12	0.565 (0.768)	0.634 (0.915)	0.642 (0.655)	0.571 (0.665)
LID13	0.436 (0.593)	0.436 (0.599)	0.437 (0.588)	0.437 (0.589)
LID14	0.519 (0.546)	0.521 (0.552)	0.512 (0.542)	0.517 (0.543)
LID15	0.410 (0.653)	0.413 (0.674)	0.416 (0.652)	0.413 (0.654)
LID16	0.409 (0.530)	0.403 (0.540)	0.406 (0.569)	0.402 (0.557)
EBO1	0.447 (0.482)	0.447 (0.482)	0.447 (0.482)	0.447 (0.482)
EBO2	0.408 (0.433)	0.407 (0.432)	0.408 (0.433)	0.408 (0.433)
EBO3	0.417 (0.431)	0.415 (0.430)	0.415 (0.431)	0.416 (0.431)
EBO4	0.448 (0.582)	0.448 (0.582)	0.448 (0.582)	0.448 (0.582)
EBO5	0.397 (0.495)	0.397 (0.494)	0.395 (0.495)	0.397 (0.495)
EBO6	0.395 (0.471)	0.396 (0.470)	0.397 (0.471)	0.396 (0.472)

Table 6.13 (continued)

Panel D: Test for differences of median and mean accuracy – based on X4

For the test of median differences, the sign test is used when two samples are paired, while the Mann-Whitney U test (Wilcoxon rank sum test) is used when two samples have different observations. For the test of mean differences, the student's t test is used when two samples are paired, while the two-sample t test is used when two samples have different observations. The median (mean) accuracy of value estimates based on LID9, LID16, EBO2 and EBO5 is significantly different from the median (mean) accuracy of almost all other model-based value estimates at the 1% level. **This panel only includes the results of the test for median (mean) differences whose *p*-value is larger than 1%.** Figures in parentheses are *p*-values of test statistics. Even though this panel only reports the test results based on X4, the results based on the three other earnings measures are very similar in terms of the significance of differences.

LID9	LID16	EBO2	EBO5
Test for differences of median accuracy			
-	vs. EBO3	vs. EBO3	vs. EBO3
	(0.068)	(0.032)	(0.186)
	vs. EBO4	vs. EBO6	vs. EBO6
	(0.014)	(0.394)	(0.999)
	vs. EBO6		
	(0.020)		
Test for differences of mean accuracy			
vs. EBO5	vs. LID3	vs. EBO3	vs. LID6
(0.315)	(0.124)	(0.902)	(0.328)
	vs. LID5		vs. LID7
	(0.100)		(0.276)
	vs. LID14		vs. LID8
	(0.090)		(0.116)
	vs. EBO4		vs. LID9
	(0.014)		(0.315)
			vs. EBO1
			(0.328)
			vs. EBO6
			(0.154)

Table 6.13 (continued)

Panel E: Explainability (R^2 of $P_t^{c,3} = \lambda_0 + \lambda_1 V_t + u_t$)

	X1	X2	X3	X4
LID1	0.338	0.338	0.338	0.338
LID2	0.500	0.502	0.366	0.439
LID3	0.397	0.398	0.361	0.386
LID4	0.308	0.263	0.425	0.379
LID5	0.395	0.395	0.395	0.395
LID6	0.618	0.618	0.618	0.618
LID7	0.540	0.540	0.540	0.540
LID8	0.457	0.458	0.429	0.451
LID9	0.485	0.484	0.454	0.469
LID10	0.333	0.329	0.325	0.328
LID11	0.414	0.427	0.373	0.394
LID12	0.289	0.170	0.415	0.356
LID13	0.391	0.391	0.391	0.391
LID14	0.474	0.469	0.477	0.478
LID15	0.416	0.418	0.404	0.416
LID16	0.457	0.454	0.434	0.442
EBO1	0.618	0.618	0.618	0.618
EBO2	0.669	0.667	0.669	0.669
EBO3	0.671	0.668	0.670	0.671
EBO4	0.513	0.513	0.513	0.513
EBO5	0.585	0.585	0.585	0.586
EBO6	0.586	0.585	0.586	0.587

Note:

1) Bias (Accuracy) is defined as the signed (absolute) difference between the value estimates and the current stock price, scaled by the current stock price. The figures shown in Panel A and C are median values. The mean values are shown in parentheses.
2) Explainability (Panel E) is defined as the ability of value estimates to explain cross-sectional variation in current stock prices (i.e., OLS R^2)
3) Firm-year observations used for bias (accuracy) tests are 6,835 from 1991 to 1998 for all models except 2-year horizon EBO models (5,958) and 3-year horizon EBO models (3,033). While firm-year observations used for explainability tests range from 6,705 to 6,728 from 1991 to 1998 for all models except 2-year horizon EBO models (about 5,870) and 3-year horizon EBO models (about 2,988). The number of observations used for explainability tests is the figure after deleting the most extreme 1% of regression variables.
4) X1 is pre-exceptional and pre-extraordinary earnings, X2 is full-tax adjusted pre-exceptional and pre-extraordinary earnings, X3 is post-exceptional and post-extraordinary earnings, and X4 is post-exceptional and pre-extraordinary earnings.
5) Firm-specific persistence parameters used in 4th column (i.e., X3) of each panel for LID4 come from the result related to $X3_a$ in Table 6.10.
6) $P_t^{c,3}$ is the observed stock price at 3 months after the fiscal year end, and V_t is the estimated intrinsic value.

Table 6.14: Sensitivity to book value growth rate – scaled by book value, based on X4

Panel A: Bias ($FE_{sp} = (V_t - P_t^{c,3}) / P_t^{c,3}$)

	$bg = 0\%$	$bg = 2\%$	$bg = 4\%$	$bg = 6\%$	$bg = 8\%$
LID10	-0.544 (-0.374)	-0.557 (-0.391)	-0.574 (-0.415)	-0.604 (-0.452)	-0.657 (-0.522)
LID11	-0.522 (-0.396)	-0.528 (-0.403)	-0.536 (-0.414)	-0.548 (-0.430)	-0.571 (-0.459)
LID12	-0.546 (-0.505)	-0.549 (-0.511)	-0.553 (-0.519)	-0.561 (-0.532)	-0.574 (-0.555)
LID13	-0.290 (-0.061)	-0.261 (-0.020)	-0.219 (0.038)	-0.154 (0.130)	-0.035 (0.304)
LID14	-0.449 (-0.327)	-0.456 (-0.332)	-0.461 (-0.337)	-0.472 (-0.342)	-0.473 (-0.334)
LID15	-0.162 (0.088)	-0.109 (0.159)	-0.040 (0.262)	0.078 (0.426)	0.285 (0.737)
LID16	-0.257 (-0.043)	-0.227 (-0.002)	-0.186 (0.060)	-0.115 (0.159)	0.005 (0.353)

Panel B: Accuracy ($AFE_{sp} = \left|V_t - P_t^{c,3}\right| / P_t^{c,3}$)

	$bg = 0\%$	$bg = 2\%$	$bg = 4\%$	$bg = 6\%$	$bg = 8\%$
LID10	0.581 (0.595)	0.590 (0.599)	0.603 (0.606)	0.625 (0.620)	0.671 (0.653)
LID11	0.553 (0.577)	0.558 (0.579)	0.563 (0.582)	0.573 (0.587)	0.591 (0.598)
LID12	0.563 (0.656)	0.566 (0.660)	0.571 (0.665)	0.578 (0.674)	0.589 (0.689)
LID13	0.447 (0.562)	0.440 (0.571)	0.437 (0.589)	0.429 (0.624)	0.438 (0.712)
LID14	0.491 (0.507)	0.505 (0.521)	0.517 (0.543)	0.537 (0.580)	0.569 (0.659)
LID15	0.406 (0.572)	0.409 (0.602)	0.413 (0.654)	0.435 (0.752)	0.502 (0.978)
LID16	0.415 (0.521)	0.409 (0.534)	0.402 (0.557)	0.406 (0.603)	0.432 (0.721)

Panel C: Explainability (R^2 of $P_t^{c,3} = \lambda_0 + \lambda_1 V_t + u_t$)

	$bg = 0\%$	$bg = 2\%$	$bg = 4\%$	$bg = 6\%$	$bg = 8\%$
LID10	0.333	0.332	0.328	0.325	0.306
LID11	0.392	0.394	0.394	0.397	0.403
LID12	0.362	0.359	0.356	0.352	0.334
LID13	0.392	0.391	0.391	0.386	0.376
LID14	0.528	0.510	0.478	0.425	0.347
LID15	0.423	0.418	0.416	0.404	0.389
LID16	0.451	0.447	0.442	0.429	0.407

Note:

1) Bias (Accuracy) is defined as the signed (absolute) difference between the value estimates and the current stock price, scaled by the current stock price. The figures shown in Panel A and B are median values. The mean values are shown in parentheses.
2) Explainability (Panel C) is defined as the ability of value estimates to explain cross-sectional variation in current stock prices (i.e., OLS R^2)
3) Earnings before extraordinary items (i.e., X4) is used.
4) bg denotes future book value growth rate.
5) $P_t^{c,3}$ is the observed stock price at 3 months after the fiscal year end, and V_t is the estimated intrinsic value.

Table 6.15: Sensitivity to residual income growth rate – scaled by book value, based on X4

Panel A: Bias ($FE_{sp} = (V_t - P_t^{c,3}) / P_t^{c,3}$)

	$g_r = 0\%$	$g_r = 2\%$	$g_r = 4\%$	$g_r = 6\%$	$g_r = 8\%$
EBO4	-0.431	-0.432	-0.413	-0.384	-0.328
	(-0.371)	(-0.384)	(-0.402)	(-0.425)	(-0.454)
EBO5	-0.393	-0.387	-0.370	-0.331	-0.262
	(-0.313)	(-0.313)	(-0.312)	(-0.310)	(-0.300)
EBO6	-0.405	-0.392	-0.373	-0.336	-0.266
	(-0.335)	(-0.331)	(-0.324)	(-0.312)	(-0.287)

Panel B: Accuracy ($AFE_{sp} = \left|V_t - P_t^{c,3}\right| / P_t^{c,3}$)

	$g_r = 0\%$	$g_r = 2\%$	$g_r = 4\%$	$g_r = 6\%$	$g_r = 8\%$
EBO4	0.447	0.451	0.448	0.453	0.504
	(0.482)	(0.519)	(0.582)	(0.698)	(0.957)
EBO5	0.408	0.408	0.397	0.386	0.407
	(0.433)	(0.455)	(0.495)	(0.569)	(0.735)
EBO6	0.416	0.407	0.396	0.377	0.382
	(0.431)	(0.446)	(0.472)	(0.520)	(0.635)

Panel C: Explainability (R^2 of $P_t^{c,3} = \lambda_0 + \lambda_1 V_t + u_t$)

	$g_r = 0\%$	$g_r = 2\%$	$g_r = 4\%$	$g_r = 6\%$	$g_r = 8\%$
EBO4	0.618	0.557	0.513	0.420	0.295
EBO5	0.669	0.610	0.586	0.487	0.365
EBO6	0.671	0.639	0.587	0.497	0.384

Note:

1) Bias (Accuracy) is defined as the signed (absolute) difference between the value estimates and the current stock price, scaled by the current stock price. The figures shown in Panel A and B are median values. The mean values are shown in parentheses.
2) Explainability (Panel C) is defined as the ability of value estimates to explain cross-sectional variation in current stock prices (i.e., OLS R^2)
3) Earnings before extraordinary items (i.e., X4) is used.
4) g_r denotes future residual income growth rate.
5) $P_t^{c,3}$ is the observed stock price at 3 months after the fiscal year end, and V_t is the estimated intrinsic value.

Table 6.16: Sensitivity to discount rate – scaled by book value, based on X4

Panel A: Bias ($FE_{sp} = (V_t - P_t^{c,3}) / P_t^{c,3}$)

	Year-specific	r = 10%	r = 12%	r = 14%	r = 16%	r = 18%
LID1	-0.476 (-0.282)	-0.476 (-0.282)	-0.476 (-0.282)	-0.476 (-0.282)	-0.476 (-0.282)	-0.476 (-0.282)
LID2	-0.521 (-0.789)	-0.520 (-0.976)	-0.524 (-0.861)	-0.524 (-0.778)	-0.522 (-0.716)	-0.520 (-0.668)
LID3	-0.491 (-0.354)	-0.496 (-0.373)	-0.494 (-0.365)	-0.492 (-0.356)	-0.491 (-0.349)	-0.490 (-0.343)
LID4	-0.528 (-0.471)	-0.480 (0.022)	-0.497 (-0.629)	-0.514 (-0.146)	-0.527 (-0.504)	-0.517 (-0.388)
LID5	-0.461 (-0.294)	-0.444 (-0.272)	-0.454 (-0.285)	-0.463 (-0.298)	-0.473 (-0.310)	-0.482 (-0.322)
LID6	-0.431 (-0.371)	-0.241 (-0.173)	-0.368 (-0.311)	-0.458 (-0.409)	-0.526 (-0.483)	-0.579 (-0.541)
LID7	-0.430 (-0.319)	-0.352 (-0.233)	-0.403 (-0.291)	-0.444 (-0.337)	-0.478 (-0.373)	-0.505 (-0.402)
LID8	-0.448 (-0.307)	-0.411 (-0.261)	-0.434 (-0.290)	-0.455 (-0.315)	-0.473 (-0.337)	-0.490 (-0.356)
LID9	-0.428 (-0.274)	-0.364 (-0.185)	-0.406 (-0.243)	-0.441 (-0.289)	-0.472 (-0.329)	-0.499 (-0.364)
LID10	-0.574 (-0.415)	-0.098 (0.239)	-0.323 (-0.071)	-0.459 (-0.257)	-0.549 (-0.381)	-0.613 (-0.469)
LID11	-0.536 (-0.414)	-0.044 (0.253)	-0.288 (-0.080)	-0.431 (-0.269)	-0.523 (-0.392)	-0.587 (-0.475)
LID12	-0.553 (-0.519)	-0.001 (-0.916)	-0.213 (-0.422)	-0.396 (-0.057)	-0.542 (-0.533)	-0.609 (-0.519)
LID13	-0.219 (0.038)	0.259 (0.699)	-0.060 (0.264)	-0.249 (0.003)	-0.376 (-0.171)	-0.467 (-0.295)
LID14	-0.461 (-0.337)	-0.213 (-0.007)	-0.400 (-0.260)	-0.513 (-0.412)	-0.589 (-0.513)	-0.645 (-0.584)
LID15	-0.040 (0.262)	1.126 (1.844)	0.366 (0.808)	-0.064 (0.222)	-0.322 (-0.127)	-0.496 (-0.359)
LID16	-0.186 (0.060)	0.877 (1.494)	0.194 (0.562)	-0.200 (0.032)	-0.437 (-0.284)	-0.590 (-0.489)
EBO1	-0.431 (-0.371)	-0.241 (-0.173)	-0.368 (-0.311)	-0.458 (-0.409)	-0.526 (-0.483)	-0.579 (-0.541)
EBO2	-0.393 (-0.313)	-0.164 (-0.054)	-0.310 (-0.221)	-0.414 (-0.339)	-0.493 (-0.428)	-0.554 (-0.497)
EBO3	-0.405 (-0.335)	-0.171 (-0.064)	-0.322 (-0.236)	-0.430 (-0.358)	-0.511 (-0.449)	-0.573 (-0.520)
EBO4	-0.413 (-0.402)	-0.095 (-0.101)	-0.321 (-0.325)	-0.457 (-0.460)	-0.547 (-0.550)	-0.612 (-0.615)
EBO5	-0.370 (-0.312)	0.005 (0.095)	-0.252 (-0.185)	-0.406 (-0.353)	-0.509 (-0.465)	-0.583 (-0.545)
EBO6	-0.373 (-0.324)	0.010 (0.096)	-0.254 (-0.190)	-0.410 (-0.361)	-0.515 (-0.475)	-0.589 (-0.556)

Table 6.16 (continued)

Panel B: Accuracy ($AFE_{sp} = \left|V_t - P_t^{c,3}\right| / P_t^{c,3}$)

	Year-specific	$r = 10\%$	$r = 12\%$	$r = 14\%$	$r = 16\%$	$r = 18\%$
LID1	0.537 (0.581)	0.537 (0.581)	0.537 (0.581)	0.537 (0.581)	0.537 (0.581)	0.537 (0.581)
LID2	0.530 (0.870)	0.531 (1.060)	0.534 (0.938)	0.532 (0.856)	0.530 (0.797)	0.531 (0.753)
LID3	0.530 (0.567)	0.531 (0.569)	0.529 (0.568)	0.529 (0.568)	0.531 (0.567)	0.531 (0.567)
LID4	0.546 (0.635)	0.546 (1.457)	0.553 (1.557)	0.554 (1.958)	0.549 (0.804)	0.542 (0.568)
LID5	0.512 (0.546)	0.502 (0.545)	0.509 (0.546)	0.515 (0.548)	0.520 (0.550)	0.526 (0.552)
LID6	0.447 (0.482)	0.311 (0.416)	0.392 (0.449)	0.469 (0.496)	0.532 (0.542)	0.583 (0.584)
LID7	0.460 (0.480)	0.404 (0.451)	0.437 (0.467)	0.470 (0.487)	0.497 (0.505)	0.520 (0.521)
LID8	0.491 (0.517)	0.464 (0.505)	0.479 (0.511)	0.494 (0.519)	0.508 (0.527)	0.521 (0.534)
LID9	0.477 (0.509)	0.441 (0.505)	0.462 (0.507)	0.483 (0.514)	0.505 (0.522)	0.527 (0.532)
LID10	0.603 (0.606)	0.455 (0.710)	0.479 (0.602)	0.531 (0.584)	0.585 (0.598)	0.633 (0.623)
LID11	0.563 (0.582)	0.434 (0.698)	0.448 (0.575)	0.499 (0.560)	0.552 (0.578)	0.602 (0.606)
LID12	0.571 (0.665)	0.551 (3.643)	0.452 (1.504)	0.480 (1.400)	0.563 (0.821)	0.622 (0.638)
LID13	0.437 (0.589)	0.503 (0.968)	0.431 (0.691)	0.443 (0.586)	0.477 (0.554)	0.518 (0.555)
LID14	0.517 (0.543)	0.435 (0.547)	0.469 (0.502)	0.535 (0.530)	0.597 (0.574)	0.649 (0.620)
LID15	0.413 (0.654)	1.127 (1.940)	0.525 (1.025)	0.404 (0.637)	0.441 (0.526)	0.524 (0.537)
LID16	0.402 (0.557)	0.887 (1.606)	0.442 (0.827)	0.402 (0.546)	0.484 (0.513)	0.601 (0.579)
EBO1	0.447 (0.482)	0.311 (0.416)	0.392 (0.449)	0.469 (0.496)	0.532 (0.542)	0.583 (0.584)
EBO2	0.408 (0.433)	0.261 (0.368)	0.343 (0.397)	0.428 (0.449)	0.501 (0.503)	0.558 (0.552)
EBO3	0.416 (0.431)	0.244 (0.339)	0.347 (0.385)	0.438 (0.448)	0.516 (0.508)	0.576 (0.561)
EBO4	0.448 (0.582)	0.311 (0.607)	0.379 (0.560)	0.473 (0.589)	0.555 (0.631)	0.617 (0.672)
EBO5	0.397 (0.495)	0.262 (0.539)	0.320 (0.474)	0.423 (0.512)	0.518 (0.565)	0.588 (0.615)
EBO6	0.396 (0.472)	0.242 (0.486)	0.311 (0.438)	0.426 (0.492)	0.521 (0.554)	0.593 (0.609)

Table 6.16 (continued)

Panel C: Explainability (R^2 of $P_t^{c,3} = \lambda_0 + \lambda_1 V_t + u_t$)

	Year-specific	r = 10%	r = 12%	r = 14%	r = 16%	r = 18%
LID1	0.338	0.338	0.338	0.338	0.338	0.338
LID2	0.439	0.366	0.418	0.443	0.457	0.464
LID3	0.386	0.400	0.392	0.387	0.381	0.378
LID4	0.379	0.156	0.156	0.158	0.314	0.433
LID5	0.395	0.393	0.393	0.393	0.393	0.393
LID6	0.618	0.625	0.625	0.625	0.625	0.625
LID7	0.540	0.551	0.544	0.533	0.523	0.514
LID8	0.451	0.453	0.450	0.446	0.443	0.439
LID9	0.469	0.462	0.464	0.462	0.464	0.466
LID10	0.328	0.326	0.326	0.326	0.326	0.326
LID11	0.394	0.363	0.368	0.376	0.378	0.383
LID12	0.356	0.096	0.215	0.252	0.301	0.404
LID13	0.391	0.349	0.355	0.363	0.371	0.379
LID14	0.478	0.483	0.509	0.534	0.551	0.557
LID15	0.416	0.358	0.375	0.396	0.416	0.436
LID16	0.442	0.374	0.397	0.424	0.455	0.502
EBO1	0.618	0.625	0.625	0.625	0.625	0.625
EBO2	0.669	0.655	0.656	0.657	0.658	0.658
EBO3	0.671	0.667	0.671	0.672	0.672	0.673
EBO4	0.513	0.515	0.515	0.515	0.515	0.515
EBO5	0.586	0.575	0.577	0.579	0.580	0.582
EBO6	0.587	0.576	0.580	0.584	0.590	0.591

Note:
1) Bias (Accuracy) is defined as the signed (absolute) difference between the value estimates and the current stock price, scaled by the current stock price. The figures shown in Panel A and B are median values. The mean values are shown in parentheses.
2) Explainability (Panel C) is defined as the ability of value estimates to explain cross-sectional variation in current stock prices (i.e., OLS R^2)
3) Earnings before extraordinary items (i.e., X4) is used.
4) r denotes future discount rate.
5) $P_t^{c,3}$ is the observed stock price at 3 months after the fiscal year end, and V_t is the estimated intrinsic value.

Table 6.17: Sensitivity to benchmarking stock price – scaled by book value, based on X4

Panel A: Bias ($FE_{sp} = (V_t - P_t^{c,n}) / P_t^{c,n}$)

	$P_t^{c,3}$	$P_t^{c,4}$	$P_t^{c,5}$	$P_t^{c,6}$	$P_t^{c,7}$
LID1	-0.476 (-0.282)	-0.482 (-0.291)	-0.485 (-0.292)	-0.478 (-0.277)	-0.475 (-0.259)
LID2	-0.521 (-0.789)	-0.532 (-0.798)	-0.535 (-0.794)	-0.530 (-0.793)	-0.527 (-0.795)
LID3	-0.491 (-0.354)	-0.500 (-0.363)	-0.506 (-0.363)	-0.498 (-0.349)	-0.494 (-0.334)
LID4	-0.528 (-0.471)	-0.534 (-0.478)	-0.537 (-0.480)	-0.530 (-0.469)	-0.525 (-0.461)
LID5	-0.461 (-0.294)	-0.469 (-0.303)	-0.473 (-0.305)	-0.462 (-0.289)	-0.463 (-0.272)
LID6	-0.431 (-0.371)	-0.439 (-0.381)	-0.444 (-0.383)	-0.439 (-0.371)	-0.435 (-0.359)
LID7	-0.430 (-0.319)	-0.439 (-0.329)	-0.444 (-0.330)	-0.432 (-0.316)	-0.429 (-0.301)
LID8	-0.448 (-0.307)	-0.458 (-0.316)	-0.463 (-0.317)	-0.453 (-0.302)	-0.449 (-0.286)
LID9	-0.428 (-0.274)	-0.437 (-0.284)	-0.441 (-0.286)	-0.430 (-0.270)	-0.424 (-0.253)
LID10	-0.574 (-0.415)	-0.580 (-0.422)	-0.583 (-0.423)	-0.575 (-0.410)	-0.573 (-0.395)
LID11	-0.536 (-0.414)	-0.544 (-0.422)	-0.549 (-0.422)	-0.541 (-0.410)	-0.538 (-0.396)
LID12	-0.553 (-0.519)	-0.561 (-0.525)	-0.565 (-0.527)	-0.559 (-0.518)	-0.555 (-0.510)
LID13	-0.219 (0.038)	-0.232 (0.025)	-0.234 (0.024)	-0.219 (0.047)	-0.217 (0.072)
LID14	-0.461 (-0.337)	-0.472 (-0.344)	-0.476 (-0.344)	-0.467 (-0.330)	-0.472 (-0.319)
LID15	-0.040 (0.262)	-0.049 (0.246)	-0.056 (0.245)	-0.040 (0.273)	-0.034 (0.303)
LID16	-0.186 (0.060)	-0.195 (0.047)	-0.203 (0.046)	-0.188 (0.070)	-0.184 (0.094)
EBO1	-0.431 (-0.371)	-0.439 (-0.381)	-0.444 (-0.383)	-0.439 (-0.371)	-0.435 (-0.359)
EBO2	-0.393 (-0.313)	-0.403 (-0.324)	-0.411 (-0.331)	-0.404 (-0.315)	-0.399 (-0.303)
EBO3	-0.405 (-0.335)	-0.415 (-0.348)	-0.416 (-0.353)	-0.409 (-0.343)	-0.405 (-0.335)
EBO4	-0.413 (-0.402)	-0.426 (-0.412)	-0.434 (-0.414)	-0.429 (-0.403)	-0.427 (-0.394)
EBO5	-0.370 (-0.312)	-0.381 (-0.324)	-0.388 (-0.332)	-0.382 (-0.315)	-0.377 (-0.305)
EBO6	-0.373 (-0.324)	-0.386 (-0.337)	-0.389 (-0.344)	-0.382 (-0.335)	-0.380 (-0.330)

Table 6.17 (continued)

Panel B: Accuracy ($AFE_{sp} = \left|V_t - P_t^{c,n}\right| / P_t^{c,n}$)

	$P_t^{c,3}$	$P_t^{c,4}$	$P_t^{c,5}$	$P_t^{c,6}$	$P_t^{c,7}$
LID1	0.537 (0.581)	0.542 (0.584)	0.547 (0.589)	0.544 (0.593)	0.546 (0.604)
LID2	0.530 (0.870)	0.541 (0.880)	0.544 (0.881)	0.541 (0.892)	0.541 (0.904)
LID3	0.530 (0.567)	0.537 (0.572)	0.545 (0.578)	0.541 (0.579)	0.543 (0.587)
LID4	0.546 (0.635)	0.556 (0.641)	0.562 (0.647)	0.556 (0.648)	0.558 (0.656)
LID5	0.512 (0.546)	0.518 (0.551)	0.526 (0.556)	0.522 (0.558)	0.522 (0.569)
LID6	0.447 (0.482)	0.458 (0.492)	0.464 (0.499)	0.460 (0.497)	0.460 (0.501)
LID7	0.460 (0.480)	0.469 (0.487)	0.474 (0.495)	0.467 (0.494)	0.467 (0.501)
LID8	0.491 (0.517)	0.498 (0.522)	0.505 (0.528)	0.500 (0.529)	0.500 (0.539)
LID9	0.477 (0.509)	0.484 (0.514)	0.491 (0.520)	0.483 (0.522)	0.484 (0.532)
LID10	0.603 (0.606)	0.609 (0.611)	0.613 (0.615)	0.609 (0.616)	0.609 (0.623)
LID11	0.563 (0.582)	0.570 (0.587)	0.575 (0.592)	0.571 (0.593)	0.572 (0.598)
LID12	0.571 (0.665)	0.579 (0.671)	0.584 (0.676)	0.581 (0.677)	0.579 (0.686)
LID13	0.437 (0.589)	0.440 (0.588)	0.443 (0.594)	0.444 (0.607)	0.450 (0.630)
LID14	0.517 (0.543)	0.525 (0.549)	0.528 (0.555)	0.528 (0.559)	0.535 (0.568)
LID15	0.413 (0.654)	0.416 (0.650)	0.422 (0.657)	0.426 (0.677)	0.432 (0.706)
LID16	0.402 (0.557)	0.411 (0.558)	0.413 (0.564)	0.418 (0.578)	0.421 (0.600)
EBO1	0.447 (0.482)	0.458 (0.492)	0.464 (0.499)	0.460 (0.497)	0.460 (0.501)
EBO2	0.408 (0.433)	0.417 (0.441)	0.427 (0.447)	0.421 (0.450)	0.421 (0.451)
EBO3	0.416 (0.431)	0.425 (0.440)	0.425 (0.440)	0.418 (0.434)	0.416 (0.432)
EBO4	0.448 (0.582)	0.458 (0.592)	0.466 (0.599)	0.465 (0.600)	0.468 (0.608)
EBO5	0.397 (0.495)	0.405 (0.501)	0.413 (0.507)	0.415 (0.513)	0.414 (0.516)
EBO6	0.396 (0.472)	0.404 (0.478)	0.408 (0.477)	0.403 (0.473)	0.406 (0.474)

Table 6.17 (continued)

Panel C: Explainability (R^2 of $P_t^{c,n} = \lambda_0 + \lambda_1 V_t + u_t$)

	$P_t^{c,3}$	$P_t^{c,4}$	$P_t^{c,5}$	$P_t^{c,6}$	$P_t^{c,7}$
LID1	0.338	0.330	0.338	0.325	0.326
LID2	0.439	0.431	0.438	0.432	0.421
LID3	0.386	0.382	0.391	0.377	0.378
LID4	0.379	0.368	0.374	0.361	0.359
LID5	0.395	0.386	0.395	0.381	0.381
LID6	0.618	0.609	0.616	0.607	0.597
LID7	0.540	0.530	0.539	0.527	0.523
LID8	0.451	0.442	0.451	0.439	0.438
LID9	0.469	0.461	0.470	0.459	0.456
LID10	0.328	0.321	0.329	0.316	0.316
LID11	0.394	0.390	0.398	0.384	0.385
LID12	0.356	0.346	0.348	0.336	0.332
LID13	0.391	0.383	0.390	0.375	0.375
LID14	0.478	0.467	0.467	0.460	0.457
LID15	0.416	0.406	0.413	0.399	0.397
LID16	0.442	0.434	0.441	0.431	0.427
EBO1	0.618	0.609	0.616	0.607	0.597
EBO2	0.669	0.664	0.671	0.663	0.651
EBO3	0.671	0.668	0.678	0.677	0.680
EBO4	0.513	0.506	0.517	0.506	0.492
EBO5	0.586	0.582	0.590	0.585	0.559
EBO6	0.587	0.585	0.596	0.597	0.601

Note:

1) Bias (Accuracy) is defined as the signed (absolute) difference between the value estimates and the current stock price, scaled by the current stock price. The figures shown in Panel A and B are median values. The mean values are shown in parentheses.
2) Explainability (Panel C) is defined as the ability of value estimates to explain cross-sectional variation in current stock prices (i.e., OLS R^2)
3) Earnings before extraordinary items (i.e., X4) is used.
4) $P_t^{c,n}$ is the observed stock price at n months after the fiscal year end, and V_t is the estimated intrinsic value.

Table 6.18: Sensitivity to consensus earnings forecasts – scaled by book value, based on X4

	Bias		Accuracy		Explainability	
	Median	Mean	Median	Mean	Median	Mean
LID1	-0.476 (-0.282)	-0.476 (-0.282)	0.537 (0.581)	0.537 (0.581)	0.338	0.338
LID2	-0.521 (-0.789)	-0.521 (-0.789)	0.530 (0.870)	0.530 (0.870)	0.439	0.439
LID3	-0.491 (-0.354)	-0.491 (-0.354)	0.530 (0.567)	0.530 (0.567)	0.386	0.386
LID4	-0.528 (-0.471)	-0.528 (-0.471)	0.546 (0.635)	0.546 (0.635)	0.379	0.379
LID5	-0.461 (-0.294)	-0.461 (-0.294)	0.512 (0.546)	0.511 (0.546)	0.395	0.395
LID6	-0.431 (-0.371)	-0.430 (-0.371)	0.447 (0.482)	0.445 (0.482)	0.618	0.620
LID7	-0.430 (-0.319)	-0.429 (-0.318)	0.460 (0.480)	0.461 (0.481)	0.540	0.536
LID8	-0.448 (-0.307)	-0.448 (-0.307)	0.491 (0.517)	0.491 (0.517)	0.451	0.451
LID9	-0.428 (-0.274)	-0.429 (-0.275)	0.477 (0.509)	0.477 (0.508)	0.469	0.471
LID10	-0.574 (-0.415)	-0.574 (-0.415)	0.603 (0.606)	0.603 (0.606)	0.328	0.328
LID11	-0.536 (-0.414)	-0.536 (-0.414)	0.563 (0.582)	0.563 (0.582)	0.394	0.394
LID12	-0.553 (-0.519)	-0.553 (-0.519)	0.571 (0.665)	0.571 (0.665)	0.356	0.356
LID13	-0.219 (0.038)	-0.218 (0.040)	0.437 (0.589)	0.437 (0.589)	0.391	0.391
LID14	-0.461 (-0.337)	-0.464 (-0.339)	0.517 (0.543)	0.517 (0.543)	0.478	0.479
LID15	-0.040 (0.262)	-0.036 (0.266)	0.413 (0.654)	0.413 (0.656)	0.416	0.415
LID16	-0.186 (0.060)	-0.183 (0.064)	0.402 (0.557)	0.401 (0.558)	0.442	0.440
EBO1	-0.431 (-0.371)	-0.430 (-0.371)	0.447 (0.482)	0.445 (0.482)	0.618	0.620
EBO2	-0.393 (-0.313)	-0.392 (-0.312)	0.408 (0.433)	0.408 (0.432)	0.669	0.672
EBO3	-0.405 (-0.335)	-0.405 (-0.334)	0.416 (0.431)	0.416 (0.431)	0.671	0.672
EBO4	-0.413 (-0.402)	-0.410 (-0.400)	0.448 (0.582)	0.445 (0.582)	0.513	0.517
EBO5	-0.370 (-0.312)	-0.368 (-0.311)	0.397 (0.495)	0.394 (0.494)	0.586	0.588
EBO6	-0.373 (-0.324)	-0.373 (-0.324)	0.396 (0.472)	0.397 (0.472)	0.587	0.589

Note:

1) Bias (Accuracy) is defined as the signed (absolute) difference between the value estimates and the current stock price, scaled by the current stock price. The figures shown in column 'bias' and 'accuracy' are median values. The mean values are shown in parentheses.
2) Explainability is defined as the ability of value estimates to explain cross-sectional variation in current stock prices (i.e., OLS R^2)
3) Earnings before extraordinary items (i.e., X4) is used.
4) Median and mean in the second row denote respectively median and mean analysts earnings forecasts provided by I/B/E/S.

Appendix 6.1: The practical issue of estimating RI parameters when OI is dealt with

When we incorporate OI in the linear information dynamics by using analysts' earnings forecasts, a practical issue about the estimation of RI parameters could arise. This is because the parameters are estimated using Eq. 1 practically, despite the real equation including the OI variable. Since we want to estimate ω_0 and ω_1 in Eq. 1 using historical data, a corresponding estimating equation should be the following form theoretically.

$$x_t^a = \omega_0 + \omega_1 x_{t-1}^a + v_{t-1} + u_{1t} \qquad \text{(Eq. A6.1.1)}$$

However, OI (v) is unobservable in this equation. Even though analysts' earnings forecasts can be used to estimate OI, we first need to estimate ω_0 and ω_1 in Eq. 1 because v_t is defined as $f_{t+1}^a - \omega_0 - \omega_1 x_t^a$. Consequently, we have to use another equation for estimating ω_0 and ω_1 empirically. The alternative estimating equation for Eq. A6.1.1 is as follows:

$$x_t^a = \omega_0' + \omega_1' x_{t-1}^a + u_{2t} \qquad \text{(Eq. A6.1.2)}$$

Here, ω_0' and ω_1' are apparently different from ω_0 and ω_1, respectively, because ω_0' and ω_1' comprise the effect of omitting variable, v. Turning first to the issue of estimating ω_1, one thing we could reasonably assume is the independence between RI and OI. Since OI is defined as information about future residual income not captured by historical accounting numbers, this assumption seems to be rational. Thus, under the assumption that there is no correlation between RI and OI variables in the right-hand side of Eq. A6.1.1, ω_1' estimated from Eq. A6.1.2 appears to be a reasonable estimate for the real coefficient ω_1.

Let's consider the next issue about estimating ω_0. Even in the above assumption, ω_0' is not equal to ω_0. Since all effects of omitting OI variable are absorbed into the intercept term, ω_0' will be ω_0 plus mean OI (*MOI*). Thus, the real intercept term ω_0 can be estimated, as long as *MOI* is available. However, 'other information' cannot be measured without ω_0, because it is defined as $f_{t+1}^a - \omega_0 - \omega_1 x_t^a$. Thus, it is difficult to estimate ω_0 in practice. In this study, ω_0' estimated Eq. A6.1.2 is used as a proxy of the real intercept term ω_0, despite the possibility of some noise.

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CHAPTER 7

APPLICABILITY OF COMPETING VALUATION MODELS: U.K. EVIDENCE

7.1. Introduction and Motivation

Even though all 'linear information dynamics (LID)' approaches and 'Edwards-Bell-Ohlson (EBO)' approaches are rooted in the well-known residual income valuation (RIV) relationship, the implementation procedures and the underlying assumptions are different under each approach, so the resulting value estimates can vary. The LID valuation approach is based on the idea that historical accounting information plays a major role in predicting future residual incomes, so that the estimated LID parameters and current accounting and 'other information' are sufficient for the estimation of a firm's intrinsic value. On the other hand, the EBO valuation approach uses analysts' earnings forecasts directly to arrive at forecasts of future residual incomes within a forecast horizon. These are used together with assumptions about residual income growth in the post-horizon period to arrive at value estimates.[95] There could be various LID-type and EBO-type valuation models according to the assumptions of LID in the first case, and various sets of forecast horizon and terminal value (TV) assumptions in the second case.

[95] Strictly speaking, an EBO valuation approach could use any kind of residual income forecasts. For example, a mechanical time-series equation using historical accounting data can be used to forecast future earnings (or residual incomes). Most empirical studies show that EBO approaches using analysts' earnings forecasts are superior to those using mechanical earnings forecasts (see Francis, Olsson and Oswald, 1999; Frankel and Lee, 1998) in EBO approach. I shall only consider EBO valuation approaches that use analysts' earnings forecasts.

Following the seminal theoretical works of Ohlson (1995) and Feltham and Ohlson (1995, 1996), many researchers have tried to investigate the LID model's validity empirically. However, the unobservable nature of 'other information (OI)' in LID has led many researchers to ignore OI in the empirical implementation of Ohlson (1995) and Feltham and Ohlson (1995, 1996). Some effort to seek a good proxy of OI has been made more recently in order to incorporate OI in the empirical examination of LID models. These include Dechow, Hutton and Sloan (1999), Myers (1999b), Ohlson (2001), Liu and Ohlson (2000), and Begley and Feltham (2000).[96] Besides, many researchers have also tried to modify the original LID of Ohlson (1995) and Feltham and Ohlson (1995, 1996) (Biddle, Chen and Zhang, 2000; Ota, 2000; Pope and Wang, 1999; Choi, O'Hanlon and Pope, 2002). Despite the efforts devoted to the LID approaches, the EBO approaches are also still booming in the equity valuation area. Frankel and Lee (1998) and Lee, Myers and Swaminathan (1999) compare various EBO valuation models with traditional or time-series valuation models. And Francis, Olsson and Oswald (2000), Penman and Sougiannis (1998), and Courteau, Kao and Richardson (2000) compare the EBO approach-based residual income (RI) valuation models with the theoretically identical 'present value of expected dividend (PVED)' model and 'discounted cash flow (DCF)' model.[97]

[96] Myers (1999b) uses order backlog as a proxy of 'OI', while the other papers use analysts' earnings forecasts for the calculation of 'OI'.

[97] Lundholm and O'Keefe (2001a) argue that the claim of the RIV model's superiority over the theoretically equivalent 'present value of expected dividend (PVED)' model and 'discounted cash flow (DCF)' model is flawed as a consequence of 3 commonly occurring implementation errors – labeled as 'the inconsistent forecasts error', 'the incorrect discount rate error' and 'the missing cash flow error'. Their critique does not address the comparison of two alternative approaches to RI-based valuation (LID and EBO). These two approaches contain obviously different procedures and assumptions when predicting the future residual incomes, so that the examination of the relative superiority of models is still an empirical issue.

However, in spite of a large amount of work on the LID and EBO approaches to equity valuation, most researchers just concentrate on the average reliability of the competing valuation models. For example, Dechow, Hutton and Sloan (1999) compare 8 LID models using the pooled data in terms of bias and accuracy, and conclude that Ohlson's (1995) OI-inclusive LID approach is, on average, outperformed by a simple valuation model that capitalises just one-year ahead earnings forecasts.

The issue of the conditions under which one model dominates the other models remains unanswered, and I intend to address it here. A company's accounting methods/systems and economic properties could make one class of valuation model more applicable than other classes in the case of that company. Therefore, it is likely that a particular model will dominate other models in some, but not all circumstances. This issue is quite important especially for practitioners, because equity valuation is a task that must be carried out on a firm-by-firm basis ultimately.

A recent study that deals with the different applicability under different conditions of different accounting-based valuation models is Sougiannis and Yaekura (2000). They compare the accuracy of 5 models – the EBO model with the assumed TV (COMBO), the earnings capitalisation model (CM), the EBO model without TV (RIM), the book value model (BVM) and the earnings model (ERM) – and show that COMBO dominates the other four models, on average. However, only in 48% of firm-years is the value estimate given by COMBO the most accurate of the value estimates given by the various models. CM, RIM, BVM and ERM give the highest accuracy for 18%, 13%, 11% and 10% of the sample firm-years. They show that the different ex-ante properties of each firm can result in different applicability of those models. Thus, even though a model performs best on average, we cannot conclude that the model gives the most reliable value estimates in all cases.

My research is in line with Sougiannis and Yaekura (2000) in the context of the examination of various models' reliability in certain circumstances. However, Sougiannis and Yaekura (2000) only focus on the comparison of the EBO approach-based models and the earnings capitalization model. Although the LID and the EBO approaches are particular objects of interest to researchers in equity valuation, there is no explicit research that compares the LID and the EBO approaches, to my knowledge.[98] Together with the limited amount of previous work on the applicability of various valuation models, the lack of research on the comparison of the LID and the EBO valuation models motivates me to investigate under what conditions EBO models are more appropriate than LID models, and vice versa. Also, it is of interest whether the modification of the Ohlson (1995) LID through the incorporation of intercept terms would give more reliable value estimates in many circumstances. Thus, in this chapter, I compare the applicability of three approaches to valuation - the 'other information'-inclusive Ohlson (1995) LID model (henceforth, the Ohlson LID or LID9 unless otherwise stated), the 'other information' and 'intercept'-inclusive LID model with the assumption of 4% book value growth (henceforth, the 'intercept-inclusive' LID or

[98] In Dechow, Hutton and Sloan (1999), the model which capitalises the one-year ahead analysts' earnings forecasts is the same as the one-year horizon EBO model with no growth in the post-horizon period. However, they consider this model as a special case of Ohlson (1995) model and do not include any more EBO approach-based models in their research.

LID16 unless otherwise stated), and the 2-year horizon EBO model with the assumption of 4% residual income growth (henceforth, the EBO or EBO5 unless otherwise stated).[99]

The choice of three general models for the applicability test is firstly based on the previous chapter that examines the overall bias and accuracy of various valuation models in the U.K. The results show that these three models seem to give relatively accurate and unbiased value estimates compared to their variants. Moreover, since the objective of the models' applicability test in this chapter is to compare three different approaches to RI-based equity valuation, it could be more appropriate to use the most comprehensive model for each approach. Table 7.1, Panel A summarises 'central tendency' and 'extreme tendency' of value estimates arising from the adoption of three general models as well as their overall median and mean accuracy figures. 'Central tendency' is defined as the percentage of firm-years where the value estimate is within 15% of the observed stock price, while 'extreme tendency' is defined as the percentage of firm-years where the value estimate is outside the range from -100% to +100% of the observed stock price. Thus, for a specific valuation model, a firm-year whose value estimate is categorised as 'central tendency' ('extreme tendency') can be thought as a good (bad) performer. Book value model (LID1), earnings model (LID2) and one-year ahead earnings capitalisation model (EBO1) are used just as 'naïve' benchmarks.[100]

[99] See Chapter 3 for details of the development of the 'intercept-inclusive' LID model. Chapter 4 and Chapter 6 show US and UK evidence that the 'intercept-inclusive' LID approach gives the most unbiased value estimates on average compared to the Ohlson LID and the EBO approaches.

[100] Median and mean figures relating to the first 5 models in Table 7.1, Panel A are a bit different from those in Chapter 6. This is because firm-years whose 2-year ahead earnings forecasts are missing are deleted in order to compare more precisely models' relative applicability through the same firm-years. Consequently, total observations for the first 5 models are 5,958 as those for EBO5 rather than 6,835.

In Table 7.1, Panel A, it is interesting that none of the three general models dominates the other two in all aspects. The 'intercept-inclusive' LID model (LID16) dominates in terms of median accuracy, central tendency and the number of negative value estimates. However, LID16 is dominated in terms of mean accuracy and extreme tendency. Similarly, the EBO model (EBO5) dominates in terms of both median and mean accuracy and the number of the most accurate value estimates, but is dominated in terms of the number of negative value estimates and the number of the least accurate value estimates.[101] On the other hand, the Ohlson LID model (LID9) gives much fewer extreme value estimates, although it seems to be inferior to the other two models in terms of median accuracy, central tendency and the number of the most accurate value estimates. One more interesting point to note here is that, as in Sougiannis and Yaekura's (2000) study, even simpler models such as LID1, LID2 and EBO1 give the most accurate value estimates in some firm-years. This result indicates that even simple models can be most appropriate in some cases. Thus examining the conditions under which these simple models are the best is also a worthwhile objective for further research.

Table 7.1, Panel B contains some noteworthy preliminary results about whether firm-specific characteristics determine central tendency and extreme tendency of value estimates. Here, eight firm-specific variables are used: earnings-to-price (E/P) ratio,

[101] The percentage shown in the columns 'most accurate' and 'least accurate' in Table 7.1, Panel A is the relative percentage of 6 models. If we focus on just three general models, LID9, LID16 and EBO5 respectively give the most (least) accurate value estimates for 18.6% (54.1%), 37.8% (17.0%) and 43.6% (29.0%).

market-to-book (P/B) ratio, R&D-to-book (RD/B) ratio, book value growth (BG), firm size (LMV, logarithm of market value), analyst-based 1-year ahead RI-to-book (FRI/B) ratio, stock price (P) and current residual income (RI). It is interesting that good performers (firm-years whose value estimate is categorised as 'central tendency') and bad performers (firm-years whose value estimate is categorised as 'extreme tendency') occur in almost all portfolios formed by firm-specific ex-ante variables, indicating that none of the eight variables solely and completely determines central tendency and extreme tendency of value estimates. However, the frequency of good performers and bad performers seems to be different according to the level of some firm-specific variables such as E/P, P/B, FRI/B and RI. In particular, many bad performers occur in the extreme level of variables (i.e., first and/or tenth decile portfolios) regardless of models and firm-specific variables. Altogether, these results support the possibility of the different applicability of valuation models and the combined impact of some firm-specific variables, rather than a sole variable, on the models' applicability.

In the next section 7.2, I develop predictions about the applicability of 3 general models (the Ohlson LID, the 'intercept-inclusive' LID and the EBO) across various conditions. Section 7.3 describes the construction of portfolios according to those conditions, and Section 7.4 presents the empirical results. Section 7.5 concludes with some discussion of limitations of the study.

7.2. Predictions about the Applicability of Models

7.2.1. Differences in competing models

RI-based valuation models present a value estimate as a function of current book value and the present value of expected future residual income. However, there are a number of different approaches to the implementation of the RI valuation relationship. The approaches that I intend to explore here are the Ohlson LID approach (LID9), the 'intercept-inclusive' LID approach with the assumed future book value growth rate of 4% (LID16), and the EBO approach with the assumed future residual income growth rate of 4% (EBO5). Before developing predictions about the models' applicability, it is worthwhile to compare the differences between these 3 approaches. Figure 7.1 illustrates how much value estimates based on different approaches can differ, even though models in each panel use or predict the same (or very similar) RI forecasts for the next 2 years. Although the present value of future residual incomes presented in Figure 7.1 depends on some parameter estimates and assumptions, this rough example shows that the patterns of future RI streams can be very different from each other. This implies that the different model specification itself can give rise to significantly different value estimates. Thus, analysing and forecasting which pattern a firm's future RI will follow could be an important issue in equity valuation. Ex-ante firm characteristics may be able to explain which model fits a firm best. Before developing predictions about the issue of 'firm characteristic-model fit', the characteristics of three models that can derive different value estimates are discussed below.

'Historical' vs. 'Forecast'

First, we can divide these approaches into two types – 'historical' type and 'forecast' type. The two LID approaches referred to above use historical accounting numbers to estimate RI and OI persistence (and intercept) parameters, and adopt those parameters in the pricing model to estimate an intrinsic value. Although these two LID approaches use one-year ahead earnings forecasts for the calculation of 'other information', which is an important component in the linear information dynamics, I term these LID approaches as 'historical' because historical accounting numbers are more important components of the valuation model. On the other hand, the EBO approach is based on forecasted RIs and terminal values, so I term the EBO approach as 'forecast' type.[102] These 'historical' type and 'forecast' type approaches can produce different value estimates empirically, because historical earnings and forecasted earnings convey different information to market participants.

It is generally said that analysts who act as financial experts and information intermediaries provide more value-relevant information than the historical financial statements do. The superiority of analysts' forecasts over historical accounting numbers in terms of information content are supported by many previous studies (Fried and Givoly, 1982; Brown *et al.*, 1987a; Brown *et al.*, 1987b). In this context, 'forecast'-type valuation approaches may work better than 'historical'-type valuation approaches, on average. However, it is also possible that historical accounting numbers give quite

[102] Obviously, forecasts could be inferred by analysis of past accounting numbers. However, the EBO approach does not explicitly use inputs derived from historical accounting numbers.

sufficient information for some firms' equity value. The possible superiority of 'historical'-type approaches over 'forecast'-type approaches can be explained by doubts on the quality of analysts' earnings forecasts. Prior research documented that 1) the analysts' forecasts are optimistically biased and inaccurate (Fried and Givoly, 1982, O'Brien, 1988; Richardson *et al*, 1999; Easterwood and Nutt, 1999), 2) the analysts' forecasts sometimes reflect the politics rather than the true profitability of firms in order to get firms' inside information easily (Das *et al.*, 1998), and 3) the analysts' forecasts do not reflect all of the expected payoffs over firms' life (Sougiannis and Yaekura, 2000).

In short, the LID (EBO) approaches primarily focus on historical earnings (analysts' forecasts) in the valuation model. Thus, if historical earnings (analysts' forecasts) provide quite sufficient value-relevant information, the LID (EBO) approaches may work better than the EBO (LID) approaches. Because both historical earnings and analysts' forecasts may be complementary information sources for equity valuation, a potentially superior valuation model could be developed if the model can capture and summarize both sets of information. A feature of the 'intercept-inclusive' LID approach developed here is that it does capture both sets of information to some extent, and especially the OI intercept (γ_0) brings in the history of forecasts.[103]

[103] Utilisation of analysts' earnings forecasts for the calculation of 'other information' in LID approach (Dechow *et al.*, 1999; Ohlson, 2001; Liu and Ohlson, 2000; Begley and Feltham, 2002) makes a large contribution in the context of summarizing both historical earnings and analysts' forecasts. Thus, the future development of superior model could be the modification of those models. The 'intercept-inclusive' LID approach developed in this thesis could be one of those efforts.

'Unbiased' vs. 'Biased' (Accounting Conservatism)

The second difference between the 3 general models is related to model specification. Let's compare the two LID approaches first. The Ohlson LID approach and the 'intercept-inclusive' LID approach are based on different assumptions about the firms' accounting systems. The Ohlson LID approach assumes that the accounting system is unbiased (i.e., zero intercept in AR(1) RI and OI generating equations) so that residual incomes revert to zero eventually. In this context, the Ohlson LID approach could work relatively well in the circumstance where the firms' accounting system is relatively unbiased. On the other hand, the 'intercept-inclusive' LID approach allows for a biased accounting system (i.e., non-zero intercept in AR(1) RI and OI generating equations), so that residual income is expected to converge to a non-zero mean RI, which is included in the pricing model to capture the bias of the accounting system. Since conservative accounting is more common, the value estimates based on the 'intercept-inclusive' LID approach could be more reliable than those based on the Ohlson LID approach, on average, as shown in Chapter 6.

However, it is worth noting that the additional term in the 'intercept-inclusive' LID model is quite sensitive to both the discount rate and the growth rate (of the scaling variable) practically. For this reason, it could be possible that the 'intercept-inclusive' LID approach gives more biased and less accurate value estimates than the Ohlson LID approach in the unbiased accounting environment, if the additional term fails to capture the unbiasedness precisely.[104] These cases can happen more severely when we adopt

[104] Theoretically, the additional term must be zero if accounting system is completely unbiased.

pooled persistence/intercept parameters and constant discount/growth rate rather than firm-specific parameters and rates.

In the case of the EBO approaches, the terminal value is considered as an adjuster of accounting conservatism as well as a reflector of residual income growth. Thus, the estimation of terminal value is the most important task when one employs the EBO approach in equity valuation. However, the large downward bias as shown in previous studies seems to indicate that the terminal value estimators in most studies are not well specified. Sougiannis and Yaekura (2000) documented that the valuation bias will be invariant to the level of conservatism if the terminal value captures the conservatism effect well, but their terminal value estimators also failed to adjust the effect totally.

In short, the Ohlson LID model is specified under the assumption of unbiased accounting, while the 'intercept-inclusive' LID model and the EBO model with terminal value are specified in order to capture the effect of biased accounting (i.e., mainly conservatism). Because the practice of conservative accounting is prevalent, the 'intercept-inclusive' LID approach and the EBO approach could provide more reliable value estimates than the Ohlson LID approach, on average. The relative conservatism-adjusting ability of the additional term in the 'intercept-inclusive' LID model and the terminal value in the EBO model depends on how one specifies those terms in each model.

'Growth'

Finally, the assumptions of each model regarding firms' growth are different. This issue is quite related to the conservatism issue discussed in the above. Note that the additional intercept-related term in the 'intercept-inclusive' LID model and the terminal value in the EBO model are each a reflector of firms' growth as well as an adjustment for firms' conservatism. On the other hand, the Ohlson LID approach does not explicitly deal with firms' growth. Again, the relative growth-reflecting ability of both reflectors depends on how one forecasts and extrapolates firms' potential future growth (specifically, growth of the scaling variable in the case of the 'intercept-inclusive' LID approach and growth of residual income in the case of the EBO approach). The misestimate of firms' growth could create large measurement error because both reflectors (or adjusters) capture a considerable portion of firms' value.

Diagram 7.1: Characteristics of three models

	Ohlson (1995) LID Approach	Intercept-inclusive LID Approach	EBO Approach
Information	Historical*	Historical*	Forecast
Accounting System	Unbiased	Biased / Unbiased**	Biased / Unbiased**
Growth	No	Yes / No**	Yes / No**

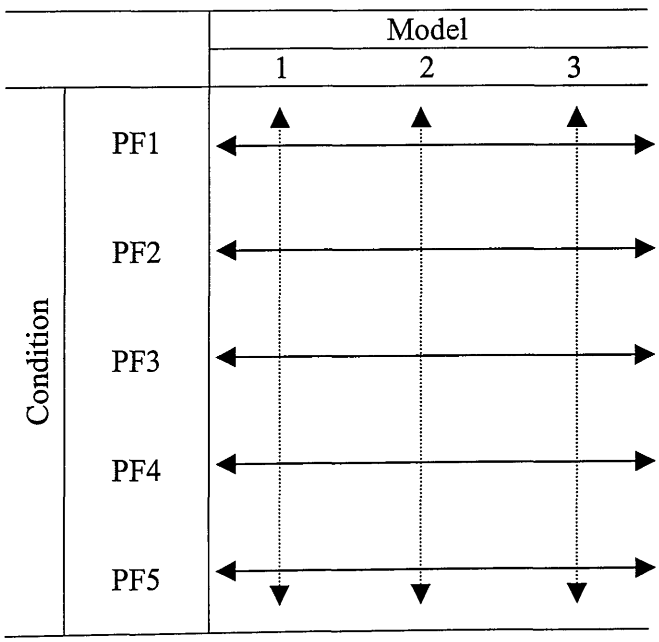
* Note that the OI-inclusive LID approach does capture earnings forecasts as well as historic patterns, and is therefore not entirely 'historical'.

** The additional term in the 'intercept-inclusive' LID model from the incorporation of RI and OI intercepts and the terminal value in the EBO model allow for biased accounting system and future growth. In theory, these terms will be zero for unbiased accounting system and zero future growth.

7.2.2. Predictions

A model's applicability can be considered in two ways. In the case where a model provides more (or less) reliable value estimates than the other models in the same condition, it is the model's relative applicability against the other models - labeled as 'applicability across models'. On the other hand, in the case where a model offers more (or less) reliable value estimates for a certain condition (e.g. high conservatism) than for the other conditions (e.g. low conservatism), it is the models' relative applicability across the condition (e.g. conservatism) – labeled as 'applicability across conditions'. In this section, I develop predictions about the models' applicability in both aspects. The models' applicability test is mainly conducted by comparing median bias and accuracy measures rather than mean measures, because median measures are less affected by extreme outliers.

Diagram 7.2: 'Applicability across models' and 'applicability across conditions'



Note: ←→ indicates 'applicability across models' (i.e. comparison of bias or accuracy between models, under a specific condition). ←⋯→ indicates 'applicability across conditions' (i.e. comparison of bias or accuracy between conditions, under a specific model). PF1 to PF5 indicates portfolios partitioned according to firm-specific ex-ante characteristics such as earnings-to-price ratio, market-to-book ratio.

Model and Earnings Attributes Fit

In equity valuation, one of the most common perspectives is that stock prices are determined by the market's expectations of a firm's future performance. Investors can rely on both historical and forecasted information to predict a firm's future payoffs and make a decision for their investment, and this is quite reasonable assuming that investors recognise the relative importance of historical and forecasted information for a certain firm. If historical earnings are poor indicators of a firm's future performance, investors are likely to focus more on analysts' earnings forecasts than on historical earnings (Tse and Yaansah, 1999). In contrast, if historical earnings offer sufficient information for a firm's future performance, investors seem to have little incentive to use analysts' earnings forecasts. Note that, on average, analysts' earnings forecasts are also biased and inaccurate as a number of previous studies show, even though they are the most comprehensive sources providing information about a firm's future payoffs (Sougiannis and Yaekura, 2000). As mentioned before, the LID approaches are mainly based on historical accounting information (current and past earnings and book values), while the EBO approaches are largely based on analysts' earnings forecasts.

Tse and Yaahsah (1999) use the earnings-to-price (E/P) ratio as a proxy for earnings attributes. An extreme (high and low) E/P ratio means that earnings contain a large portion of abnormal items (exceptional and extraordinary items) which are likely to be transitory, while a moderate E/P ratio means that earnings are likely to be relatively permanent. It might be more difficult in practice that one can project high volatile and transitory earnings into future prospects regardless of valuation approaches. Note also that much of the information in analysts' forecasts could be inferred from the analysis of past earnings in most cases. Thus, if all other conditions are the same, the performance of the EBO approach relative to the LID approaches might be expected to be weaker for moderate E/P firms. It is because historical earnings could be good indicators of a firm's future performance so both approaches can be largely based on historical earnings. Even though analysts can use other value-relevant information for moderate E/P firms, their relative contribution is expected to be small. It is even possible that, in some cases, the LID approaches might give less measurement error than the EBO approach for moderate E/P firms.

On the other hand, the performance of the EBO approach relative to the LID approaches might be expected to be stronger for extreme E/P firms because here historical earnings are not very informative for a firm's future payoffs, and analysts could offer significant other value-relevant information. So far, I have not developed any prediction about the relative applicability between two LID approaches. However, if other conditions are not controlled at all, the 'intercept-inclusive' LID approach is expected to be more suitable than the Ohlson LID approach in all cases of E/P ratios because accounting conservatism is almost universally observed. The details about the relationship between conservatism and models' applicability are discussed next.

Model and Conservatism Fit

Accounting conservatism is one of the most important topics in accounting research. However, there is no generally accepted practical definition of conservatism. A descriptive definition of accounting conservatism is that revenue and gains are recognised slowly, but expense and losses quickly. That is, accounting conservatism causes earnings to reflect bad news in a more timely manner than good news. Another definition of conservatism relates to how accounting reflects investment. Thus, one could also define conservatism in terms of undervaluation of investments at the outset. From the above definitions of conservatism, several measures can be used empirically to gauge the degree of accounting conservatism.[105]

Some recent studies show that the value relevance of accounting earnings has declined over time (Brown, Lo and Lys, 1999; Francis and Schipper, 1999; Collins, Maydew and Weiss, 1997; Lev and Zarowin, 1999), and the degree of earnings conservatism has increased in recent years (Givoly and Hayn, 2000). Because of the properties of earnings conservatism, it is quite possible that conservatism works to lessen the information content of accounting earnings. Besides, the large negative abnormal items that are recently more common in firms' accounting systems could make the quality of earnings worse in terms of valuation.

In the context of valuation, conservatism makes historical earnings less important. If investors recognise that conservatism is prevalent in their target firm, they may concentrate on analysts' forecasted information rather than historical information. Thus, in general, the EBO approach is likely to be more appropriate than the Ohlson LID approach for high conservatism firms. As noted above, the EBO approach allows for a

[105] Givoly and Hayn (2000) uses four kinds of measures to estimate accounting conservatism: 1) the level and rate of accumulation over time of negative nonoperating accruals, 2) measures based on the earnings-return association during periods of good news and bad news, 3) the skewness and the variability of earnings relative to cash flows, and 4) the market-to-book ratio.

conservatism effect through terminal value that could adjust firms' conservatism. In this context, the 'intercept-inclusive' LID approach could also be more appropriate than the Ohlson LID approach for high conservatism firms, even though both approaches mainly use historical information. Note that intercept terms included in LID capture omitted information in RI and OI auto-regressive equations, and the additional term comprising intercept (and persistence) parameters and discount/growth rates in the pricing model could work as an adjuster of firms' conservatism. However, it is difficult to predict the relative conservatism-adjusting ability between the 'intercept-inclusive' LID model and the EBO model. Probably, the relative conservatism-adjusting ability depends on the specification of the terminal value term in the EBO model and of the additional intercept term in the 'intercept-inclusive' LID model. On the other hand, since the Ohlson LID approach is specified under the assumption that the accounting system is unbiased (i.e., no conservatism), it may be relatively more appropriate than the other two approaches for non- or low-conservatism firms. In the extreme case of a firm whose accounting system is completely unbiased, historical earnings totally represent the firm's past performance in a timely manner so that they could be good indicators of the firm's future performance.

In terms of each model's relative applicability across conservatism, the Ohlson LID approach is predicted to be more appropriate for non- or low-conservatism firms than for high conservatism firms. However, in the case of the 'intercept-inclusive' and the EBO approaches, this is again a matter of model specification. Theoretically, the relative reliability must not vary according to the level of conservatism if the terminal value in the EBO model and the additional term in the 'intercept-inclusive' model can capture the effect of conservatism totally. But practically, the consistent valuation errors shown in prior studies may indicate that those two adjusters do not completely capture the conservatism effect. If the pooled sub-sample is used in practice as in this study, the sensitivity of those two adjusters could be larger (i.e., more biased and inaccurate) for non- or low-conservatism firms than for high conservatism firms. Thus, the 'intercept-inclusive' LID and the EBO approaches are predicted to be more appropriate for high-conservatism firms.

For the measurement of conservatism, several proxies are devised empirically. Among them, I use 2 ratios - the market-to-book (P/B) ratio and the R&D-to-book (RD/B) ratio. To the extent that equity valuation by investors is based on the present value of future residual incomes, the P/B ratio would tend to be higher when accounting measurement is more conservative (Givoly and Hayn, 2000). And it is expected that higher levels of conservatism occur for high RD/B firms as more R&D capital will be missing from the book values of those firms relative to low RD/B firms (Sougiannis and Yaekura, 2000; Amir, Lev and Sougiannis, 1999).

Model and Growth Fit

Sougiannis and Yaekura (2000) documented that higher RD/B ratio (i.e., higher conservatism) is consistent with higher growth. The summary statistics in their paper show that the median values of the present value of expected residual income over the four-year forecast horizon (PVRI), the analysts' expected EPS growth rate (GR) and the one-year growth in expected residual income (Ks) of the high RD/B portfolio are significantly larger than the corresponding values of the low RD/B and zero RD/B portfolios. That is, the RD/B ratio is likely to capture growth as well as conservatism effects. Hayn (1995) also stated that earnings reported by growing companies may not be indicative of their future prospects, because current earnings of these firms not only fail to capture the future growth potential but also tend to be distorted by the expensing of large intangible investments. A good example is some internet firms. The current earnings of those firms are very small or even negative but until recently the market's expectations (i.e., stock price) for many of those firms was very high.

As mentioned above, the additional term of the 'intercept-inclusive' LID approach and the terminal value of the EBO approach also operate as a reflector of firms' future growth. On the other hand, the Ohlson LID approach does not consider firms' future growth in the pricing model. Thus, the 'intercept-inclusive' LID approach and the EBO approach are expected to be relatively more suitable than the Ohlson LID approach for high growth firms, and vice versa for low growth firms. In this study, I use historical book value growth rate, calculated as current book value per share over previous book value per share, as a proxy for firms' future growth potential.

Model and Size Fit

Even though firm size itself is not an economic fundamental, it seems to be highly correlated with other firm specific properties. In particular, the information content of accounting earnings can vary according to firm size. Earnings reported by large firms may be sufficient for those firms' future prospects, because of the relatively low volatility (i.e, high persistence) of earnings series. Amir, Lev and Sougiannis (1999) also state that analysts' relative contribution to investors is smaller (larger) for large (small) firms. In this context, the LID approaches are expected to be more appropriate than the EBO approach for large firms, and vice versa for small firms.

In terms of the models' applicability across firm size, the Ohlson LID and the 'intercept-inclusive' LID approaches may produce more reliable value estimates for large firms than for small firms, because earnings of small firms are likely to be less indicative of those firms' future performance. Hayn's (1995) study, which examined the information content of losses, indirectly mentioned the relationship between firm size and the information content. “Losses are less informative about firms' future prospects, and the presence of losses is more pronounced for small firms”. The EBO approach is also predicted to give more reliable value estimates for large firms than for small firms. Although the analysts' relative contribution over financial statement information may be larger for small firms, the absolute contribution would be larger for large firms because large firms have a richer information environment and offer greater benefits from acquiring information. This means that the private-search activities for non-earnings information are more concentrated on large firms, so that analysts' earnings forecasts are more accurate for large firms (Freeman, 1987). Consequently, investors rely more on analysts' earnings forecasts of large firms than of small firms (Francis, Olsson and Oswald, 1999).

Model and Forecasted Profitability Fit

Even though the LID approaches use one-year ahead RI forecasts for the calculation of

OI, the main components of LID models are historical information. Thus, forecasted profitability may be an important ex-ante determinant to distinguish the models' applicability. Future profitability could be related to firms' accounting conservatism and future growth potential. If a firm's accounting system is highly conservative so that the recognition of a large portion of revenue and gains are delayed to the future, its future profitability will be large. Thus, it makes sense that the accounting conservatism and the forecasted profitability are positively and largely correlated (see the correlation coefficient between P/B and FRI/B in Table 7.3). Moreover, it is reasonable assuming that a firm's future growth potential and future profitability are also positively correlated. In this sense, the predictions about model and forecasted profitability fit could be similar to the predictions about model and conservatism fit and model and growth fit. For forecasted profitability, analyst-based one-year ahead RI forecast-to-book value (FRI/B) ratio will be used in this study. Thus, the 'intercept-inclusive' LID approach and the EBO approach are expected to be relatively more appropriate than the Ohlson LID approach for high FRI/B firms, and vice versa for low FRI/B firms.

Model and Industry Fit

Even though Sougiannis and Yaekura (2000) documented that industry membership is not a factor affecting the models' applicability, I still suspect that industry characteristics could be related to a particular model's superiority. The level of conservatism of the pharmaceutical industry seems to be different from that of food & drug retailers. And the growth opportunities of software & computer service industry are likely to be larger than those of gas distributors. Thus, I predict that the models' relative validity is different across industries.

In order to examine the model-industry fit, I first categorise industry groups according to technology evolution – low-tech industry and high-tech industry. This kind of grouping seems to be highly related to firms' growth and conservatism. Secondly, FTSE global classification is used to examine models' applicability for each industry group - nine industry groups excluding 'financials'. Among 9 industry groups, 'utilities' (regulated industry) and 'information technology' (high-tech industry) will be specially examined because of their different industry characteristics. In general, the regulated firms and the low-tech firms are stable and less conservative, but high-tech firms have growth opportunities and high conservatism. Therefore, historical accounting information seems to play a larger role in regulated and low-tech industry than in high-tech industry, and analysts' contribution seems to be larger in high-tech industry than in low-tech and regulated industry (Amir, Lev and Sougiannis, 1999). Thus, as with the relationship between models and conservatism (or growth, forecasted profitability), the Ohlson LID approach is predicted to be relatively more suitable for regulated and low-tech industry, and the 'intercept-inclusive' LID and the EBO approaches are likely to be relatively more suitable for high-tech industry. If the models' applicability consistently depends on industry-specific attributes, industry characteristics will be important determinants of firm valuation.

7.3. Constructing Portfolios and Descriptive Statistics

In order to investigate the effect of firm specific properties on the bias and the accuracy of competing value estimates, various ex-ante variables are considered. These include earnings-to-price (E/P) ratio, market-to-book (P/B) ratio, R&D-to-book (RD/B) ratio, book value growth (BG), firm size (LMV), analyst-based RI forecast-to-book (FRI/B) ratio, technology innovation and industry groups. E/P ratio is used as a proxy measure for earnings persistence and P/B ratio and RD/B ratio are used as a proxy for accounting conservatism.

Earnings-to-Price (E/P) ratio

Table 7.2, Panel A shows descriptive statistics of quintile portfolios formed by earnings-to-price (E/P) ratio. Each portfolio has 1,191 or 1,192 firm-years. The lowest E/P portfolio has a median E/P ratio of -0.8% and mean E/P ratio of -11.6%, while the highest E/P portfolio has median E/P ratio of 11.0% and mean E/P ratio of 13.3%. Without the extreme E/P portfolios (PF1 and PF5), the distribution of E/P ratios (PF2 - PF4) seems to be close to the normal distribution, because median and mean values are quite similar. The association between E/P and other variables is not likely to be clear. In other words, the level of other variables doesn't seem to be monotonic from low E/P portfolio to high E/P portfolio. This relation is confirmed by low correlation between E/P and other variables shown in Table 7.3.

Market-to-Book (P/B) ratio

Similar to E/P portfolios, quintile portfolios are constructed according to the level of the market-to-book (P/B) ratio. Median (mean) value changes quite dramatically portfolio by portfolio - 0.79 (0.75) in PF1, 1.90 (1.91) in PF3, 4.90 (7.74) in PF5. Note that median and mean P/B in PF1 to PF4 are similar, but mean value is much larger than median value in the case of PF5. The statistics also confirm that the accounting conservatism is a pervasive phenomenon in U.K. companies recently. The median and mean P/B ratio in the highest P/B portfolio are 4.90 and 7.74, indicating that the stock price for companies in this portfolio is determined largely by the market's expectations on future potential payoffs. Unlike in Panel A, the portfolios constructed using the level of P/B ratio show a monotonic pattern in RD/B, LMV, FRI/B, P and RI, indicating that these variables seem to be positively correlated with P/B ratio. In other words, more conservative firms tend to have higher R&D investment, market value (price) and current and future residual income. Spearman rank correlation coefficients with other variables except E/P ratio are all significant and highly positive (Table 7.3).

R&D-to-Book (RD/B) ratio

Because there are many firms with zero R&D, it is difficult to construct equal size portfolios. Another problem related to RD/B portfolios is that R&D used here (Datastream item 119) consists of regular write-offs of the capitalised R&D as well as amounts expensed in the year that are not capitalised. Thus, some amounts in this figure stem from the capitalised R&D investment, so that RD/B ratio cannot precisely capture the expensed R&D investment missing from the book value in the year. However, as a proxy of accounting conservatism, RD/B ratio seems to be in line with P/B ratio, another proxy of accounting conservatism. That is, the median P/B ratio is 1.76 for the low RD/B portfolio compared to 2.86 for the high RD/B portfolio. The median (mean) R&D investment in the low RD/B portfolio is 1.1% (1.3%) of book value, while in the high RD/B portfolio it is 8.5% (15.7%).

Book value growth (BG)

Even though the average book value growth rate in the sample period (1991-1998) is about 4%, many firm-years have a negative growth rate (PF1 and PF2) or very high growth rate (PF5). Thus, BG calculated by current book value per share over previous book value per share might not be a good proxy for future potential growth. Despite this limitation, BG will be used as one of the ex-ante variables for the models' applicability test.

Other variables

The logarithm of the market value (LMV) is used as a proxy for firm size, and the analyst-based RI forecast-to-book (FRI/B) ratio is used as a firm's future profitability. Compared with the historical average RI (median -0.002, mean -0.066), the median (mean) FRI/B of the pooled data is positive, suggesting that analysts are optimistic. Note, however, that there are also many negative FRI/B firms. The fact that the correlation between FRI/B and P/B is very high (see Table 7.3) makes sense because highly conservative firms will achieve high profitability in the future (i.e., high unrecorded goodwill). Table 7.2, Panel G summarises portfolios constructed according to technology innovation. As shown in Appendix 7.2, 15 industries are categorised as high-tech industry (836 firm-years) and 14 industries as low-tech industry (849 firm-years). This categorisation is similar to Francis and Schipper (1999), but industry classification is based on FTSE level 5 classification. High-tech firms tend to be more conservative (higher P/B and RD/B), fast growing (higher BG), smaller (smaller LMV), and profitable (higher FRI/B and RI). Also, Table 7.2, Panel H shows portfolios formed by FTSE level 3 industry classification. Among 9 industry groups, UTL (utilities) and IMT (information technology) seem to have different industry characteristics compared with other industry groups. In the case of UTL, E/P, P/B, LMV, P and RI are quite different from other industry groups, while in the case of IMT, P/B, RD/B, BG, FRI/B and P are very odd compared with other industry groups.

7.4. Empirical Results

7.4.1. Applicability of alternative valuation models

In order to examine the applicability of alternative valuation models, I present statistical testing and graphical illustration. First, as shown in Table 7.4, I partition firm-years according to firm-specific ex-ante characteristics into portfolios (usually quintile portfolios), then compare bias and accuracy of value estimates across models and conditions. In Table 7.4, bold numbers indicate the most unbiased and the most accurate median and mean value estimates across models given a specified condition. Wilcoxon signed rank test and paired t test are used for the equality test of medians and means, respectively, and more than two bold numbers in one portfolio indicates that these numbers are not significantly different from each other.[106] On the other hand, # indicates the most unbiased and the most accurate median and mean value estimates across conditions given a specified model. Wilcoxon rank sum test and t test (Cochran t test for two samples with unequal variances and pooled t test for two samples with equal variances) are used for the equality test of medians and means, respectively.[107] Here, more than two #s in one model indicates that these numbers are not significantly different from each other. Second, as shown in Figure 7.2, I partition firm-years according to firm-specific ex-ante characteristics into 100 percentile portfolios, and the median value of signed valuation errors and absolute valuation errors of each portfolio are depicted graphically. This graphical illustration helps us understand conditions under which models give rise to the different level of applicability.

Across E/P (Table 7.4, Panel A; Figure 7.2, Panel A.1 & A.2)

Table 7.4, Panel A shows that for portfolios PF2 to PF4, value estimates based on the 'intercept-inclusive' LID model seem to be less biased than those based on the Ohlson model and the EBO model, but statistically similar to the EBO model-based value estimates in terms of accuracy (see bold numbers). Moreover, most #s in this model (mean bias -0.102, median accuracy 0.332 and mean accuracy 0.373) are found in PF4, indicating that value estimates in PF4 seem to be less biased and more accurate compared to those in other E/P portfolios. Thus, the 'intercept-inclusive' LID model seems to give reliable value estimates for moderate E/P firms (PF2 - PF4) across models

[106] Note that each two samples in a specified condition (e.g., LID9- and LID16-based value estimates in the lowest E/P ratio portfolio) for the equality test are paired (i.e., dependent).
[107] Note that each two samples in a specified model (e.g., value estimates in PF1 and PF2 that are derived from applying LID9 model) for the equality test are independent.

and conditions in terms of bias and accuracy as predicted, indicating that this model captures well high residual income (or earnings) persistence from historical accounting data. However, the 'intercept-inclusive' LID model is very unreliable for extreme E/P firms (PF1 and PF5). Note that this model causes quite large positive bias (overestimation of 27.9% in PF1 and 32.5% in PF5, on average) and inaccuracy (75.6% in PF1 and 58.9% in PF5, on average) for extreme E/P firms.

On the other hand, the EBO model seems to perform best for high E/P firms (PF5) across models (see bold numbers in PF5) and conditions (see #s in EBO5). This may be explained by the analysts' larger contribution in this portfolio than in other portfolios over the information in the financial statements. Alternatively or supplementarily, this might be explained by high E/P ratios encouraging analysts to forecast earnings more optimistically. The optimistic earnings forecasts shifts the EBO value estimates, that are commonly undervalued as previous empirical studies show, to the positive direction (i.e., to be more close to stock price). However, the EBO model is not likely to be more appropriate than the LID models for low E/P firms (PF1), to be inconsistent with my expectation. If current earnings are negative or very low,[108] the short-term earnings is more likely to be forecasted as negative or very low by analysts, even though the long-term earnings can more precisely reflect the market's expectations. Thus, the short-term horizon EBO model could fail to capture the market's expectations. Another possible explanation about the weak fit between low E/P and the EBO model is the existence of negative value estimates. The fact that 67.7% (unreported) of total negative value

[108] Median E/P ratio is negative up to the 11th percentile portfolios, and 54% of firm-years in the first quintile portfolio has negative earnings.

estimates derived from the adaptation of the EBO model belong to the first quintile portfolio formed by E/P ratio may, at least partially, affect the weak fit.

The Ohlson LID model, on the other hand, seems to give relatively good value estimates for extreme E/P firms, although the evidence is not very strong. Compared to the other two models, the Ohlson LID model gives relatively high accuracy for low E/P firms (median accuracy 0.492, mean accuracy 0.616), and compared to different E/P levels, it performs well for high E/P firms (median accuracy 0.325, mean accuracy 0.437). This result is not consistent with my expectation. This implies that capturing high persistence from historical data is not enough to value a firm using the Ohlson LID approach. As shown in Table 7.2, Panel A, the average P/B ratio in the highest E/P portfolio (PF5) is 1.581, which is quite small compared to that in other E/P portfolios. Thus, the superiority of the Ohlson LID model in the highest E/P portfolio over moderate E/P portfolios may be because the effect of conservatism dilutes quite largely the effect of earnings persistence on the applicability of the Ohlson LID model. Notwithstanding, it is surprising that the Ohlson LID model performs relatively better for extreme E/P firms rather than for moderate E/P firms.

Panel A in both Table 7.4 and Figure 7.2 also show that all three models perform well for relatively high E/P firms. However, the terms 'moderate' and 'extreme' are ambiguous and subjective. If we accept extreme E/P ratios to be bottom and top 1-2%, all models are likely to be more appropriate for moderate E/P firms than for extreme E/P firms.[109] Altogether, my several expectations about the model-earnings attributes fit are partially supported. The performance of the EBO approach relative to the 'intercept-inclusive' LID approach seems to be weak for moderate E/P firms than for high extreme E/P firms. However, this is not the case for its relative performance over the Ohlson LID approach and for low extreme E/P firms. The 'intercept-inclusive' LID dominates the Ohlson LID just for moderate E/P firms, but not for extreme E/P firms. If we ignore very extreme E/P cases, the 'intercept-inclusive' LID approach seems to be more reliable than the other two models in most cases.[110]

Across P/B (Table 7.4, Panel B; Figure 7.2, Panel B.1 & B.2)

The results shown in Table 7.4, Panel B and Figure 7.2, Panel B are relatively consistent with my expectations about the model-conservatism fit. First, the Ohlson LID model dominates the 'intercept-inclusive' LID and the EBO models for low P/B (i.e., non-conservatism or low conservatism) firms and vice versa for moderate and high P/B (i.e., high conservatism) firms (compare numbers horizontally). Especially, between the 11th percentile (median P/B of 0.8) and the 26th percentile (median P/B of 1.2) portfolios, the superiority of the Ohlson LID model looks stronger (see Figure 7.2, Panel B.1 & B.2). Note that median and mean P/B ratio is greater than 1.3 for portfolios PF2 - PF5 as shown in Table 7.2, Panel B, indicating that accounting conservatism is pervasive in the U.K. during the sample period, 1991-1998. Second, the Ohlson LID model seems to be more appropriate for low P/B firms than for moderate and high P/B firms, and the

[109] In fact, median (mean) E/P ratio of bottom and top 1-2% is extremely small or large compared to that of the rest.

[110] All three models are largely unreliable for very extreme E/P firms, indicating that none of models cannot capture the effect of extremely abnormal E/P ratios to the valuation formula.

'intercept-inclusive' LID and the EBO models are likely to be more appropriate for moderate P/B firms than for extreme P/B firms (compare numbers vertically).

Additionally, for moderate conservatism firms (PF2 and PF3), the 'intercept-inclusive' LID model dominates the other two models, while for high conservatism firms (PF4 and PF5), the EBO model dominates the other two models. This result implies that the EBO model (the 'intercept-inclusive' LID model) adjusts high (moderate) conservatism better than the 'intercept-inclusive' LID model (the EBO model). Another interesting point is that, as shown in Figure 7.2, Panel B, the bias and accuracy patterns based on the LID approach and the EBO approach are quite different from each other. The bias based on the LID approach monotonically changes from overestimation to underestimation as the P/B ratio increases, while the EBO approach consistently gives underestimated value estimates regardless of the level of P/B ratio. Related to these bias patterns, the accuracy pattern based on the LID model seems to be quadratic, not linear, while that based on the EBO model seems to be linear (moderately decreasing).[111] Especially, when P/B ratio is between 1.3 and 2.0 (between 30th percentile and 54th percentile portfolios), median absolute valuation errors of each portfolio from the application of the 'intercept-inclusive' LID model are around 18% of stock price (unreported), which is quite reliable.[112] Note also that even though the overall change in bias and accuracy is quite large in response to change of P/B ratio, the volatility from one portfolio to the next portfolio is not so large for all three models. This means that P/B ratio could be one of

[111] The accuracy pattern based on the Ohlson model is also quadratic if we consider the whole portfolios (Figure 7.2, Panel B.2), but if we ignore some extremely low P/B portfolios, it is close to linear (increasing) rather than quadratic.

[112] Recall that median absolute forecast error of the 'intercept-inclusive' LID model using the pooled data is 39.5% of stock price.

the most important determinants on the applicability of the valuation model.

Across RD/B (Table 7.4, Panel C; Figure 7.2, Panel C.1 & C.2)

For another proxy of accounting conservatism, RD/B ratio is used in this study. However, the relationship between RD/B ratio and models' applicability is not clear. Notwithstanding, all models seem to perform better for low RD/B firms than for high RD/B firms (see #s in each model). For zero or low RD/B firms, the 'intercept-inclusive' LID model is likely to dominate the other two models in terms of median bias (-0.159 and -0.169) and accuracy (0.391 and 0.340), while for high RD/B firms, the EBO model seems to dominate the LID models (see median bias of -0.372 and median accuracy of 0.403). Regardless of the level of RD/B ratio, the 'intercept-inclusive' LID and the EBO models seem to dominate the Ohlson model. Datastream item (DS 119) used for R&D investment, as mentioned in Section 7.3, may cause weak or inconsistent evidence against my expectations. DS 119 consists of both regular write-offs and amounts expended in the year, so that R&D investment doesn't exactly represent the missing amounts from the book value in the year. Dividing capitalised R&D and expended R&D may help to examine the models' applicability more clearly.

Across BG (Table 7.4, Panel D; Figure 7.2, Panel D.1 & D.2)

The relationship between BG and models' applicability is not clear. First, from the median accuracy numbers in Table 7.4, Panel D, the 'intercept-inclusive' LID and the EBO approaches are likely to be more accurate than the Ohlson LID approach regardless of the level of book value growth rate. However the mean accuracy numbers show a different story. Compared with the EBO model, the 'intercept-inclusive' LID model gives less biased value estimates in most percentile and quintile portfolios. However, in terms of accuracy, the 'intercept-inclusive' LID model seems to be only dominant in the 3rd quintile portfolio (PF3, median accuracy 0.340 versus 0.410). Second, both LID models perform relatively better for the 2nd and 3rd quintile portfolios, while the EBO model performs better for the 4th quintile portfolio (see #s in each model). An additional interesting point is that the accuracy pattern of the 'intercept-inclusive' LID and the Ohlson LID models seems to be quadratic to the level of BG, but not in the case of the EBO model. The utilisation of BG as a proxy of firms' future growth could be a source of the inconsistency of the results with regard to my expectations, because historical book value growth cannot fully capture a firm's future potential growth. The utilisation of another growth proxy (e.g., long-term earnings growth forecast) might be able to improve the applicability test.

Across firm size (Table 7.4, Panel E; Figure 7.2, Panel E.1 & E.2)

Consistent with my expectations about the model-firm size fit, the 'intercept-inclusive' LID model gives rise to smaller absolute valuation errors for large firms (PF5) relative to other models (see bold numbers in PF5). This model also performs relatively well in most size portfolios except PF1 in terms of bias. However, for small firms (PF1), it gives large positive bias (mean bias of 0.489) and low accuracy (mean accuracy of 0.746). On the other hand, the Ohlson model performs well for small firms across models (see bold numbers in PF1 and PF2) and conditions (see #s in LID9). This result is not consistent with my expectations. Why is the Ohlson model more appropriate for small firms rather than for large firms? Probably, this is because stock price of these small firms is quite similar to their book value in many cases, except some growing high-tech firms. Note that the Ohlson model gives quite similar value estimate to the book value, because unrecorded goodwill captured by the Ohlson model is negligible in most cases.

If we compare the EBO model with only the 'intercept-inclusive' LID model, my expectations seem to be supported partly. The EBO model gives more accurate value estimates than the 'intercept-inclusive' LID model for small and moderate firms (PF1 - PF3). However, inconsistent with my expectations, it seems to be better for small firms than for large firms. Probably, this is because analysts' absolute as well as relative contribution over historical information is larger for small firms than for large firms. It may be true in the sense that information about small firms is much more private than that about large firms so that analysts' relatively small efforts to reflect small firms' private information into their earnings forecasts could add a significant amount to historical information.

Across FRI/B (Table 7.4, Panel F; Figure 7.2, Panel F.1 & F.2)

There is a relatively clear relationship between FRI/B ratio and models' applicability. Consistent with my expectations about the model-future profitability fit, the 'intercept-inclusive' LID and the EBO models seem to dominate the Ohlson model for high FRI/B firms, and vice versa for low FRI/B firms (compare numbers horizontally). The Ohlson model is likely to be better for low FRI/B firms than for high FRI/B firms, and vice versa for the EBO model (compare numbers vertically). However, the 'intercept-inclusive' LID model seems to perform better for moderate FRI/B firms rather than for high FRI/B firms. In fact, the pattern of bias and accuracy in FRI/B portfolios is very similar to that in P/B portfolios. As shown in Figure 7.2, Panel F.2, the accuracy pattern based on the 'intercept-inclusive' and the Ohlson LID models seems to be quadratic to the level of FRI/B ratio, while the absolute valuation errors based on the EBO model seem to decrease in the level of FRI/B ratio. This is not surprising because FRI/B and P/B have a very high positive correlation coefficient (see Table 7.3: Pearson coefficient of 0.821 and Spearman coefficient of 0.742). Consequently, FRI/B ratio can also be used as an important determinant of the applicability of the valuation model.

Across technology innovation and industry sectors (Table 7.4, Panel G & H)

As shown in Table 7.4, Panel G, value estimates based on the Ohlson model seem to be less biased and more accurate for low-tech industry than for high-tech industry (see #s in LID9) so that my expectations about the model-industry fit is supported. However, to be inconsistent with my expectations, the 'intercept-inclusive' LID and the EBO models also perform better for low-tech industry than for high-tech industry. The results shown in Panel G are consistent with those in Panel H. All three models seem to give most accurate value estimates for the 'utilities' industry and least (or not good) value estimates for 'information technology' industry. Why do all three models not fit well for high-tech industry? Among some possible explanations, the mis-specification of the model could be most plausible. That is, all three models fail to capture markets' expectations regarding potential growth and profitability for high-tech firms.

The evidence for the applicability across models seems to be mixed and unclear. The 'intercept-inclusive' LID approach gives less biased value estimates than other models for most industry groups except 'utilities' and 'information technology' industry groups. For 'utilities' and 'information technology' industry groups, it respectively gives quite large upward bias and downward bias, so the EBO model outperforms it. The superiority of models across the industry sectors is more mixed in terms of accuracy. The EBO model seems to give more accurate value estimates for the 'utilities' industry compared to other models.

7.4.2. Determinants of valuation errors

Table 7.5, Panel A shows regression of value-to-price (V/P) ratio on various firm-specific ex-ante variables and industry dummy variables. The coefficients of all ex-ante variables are significantly different from zero, indicating that these variables are the determinants of (signed) valuation errors regardless of valuation models. Specifically, P/B and firm size (LMV) seems to be the most important determinants of valuation errors derived from the application of the Ohlson LID and the 'intercept-inclusive' LID models. On the other hand, FRI/B and P/B are the most influential variables for the applicability of the EBO model in terms of bias. V/P ratio decreases as P/B and LMV (FRI/B) increases (decreases). Interestingly, V/P ratio increases in the level of E/P and RD/B ratio in the case of the EBO model, while it decreases in the case of the LID models.

Another interesting result in Table 7.5, Panel A is that industry membership is generally unlikely to affect to V/P ratio for all models, indicating that valuation bias is not determined by which industry a firm belongs to. However, the 'utilities' industry sector shows different characteristics. The coefficient on this industry dummy is significantly positive for all models.

As mentioned in the above section, valuation errors could be non-linear with respect to some ex-ante variables. Therefore, it may be useful to include quadratic terms of variables into the regression equation. Table 7.5, Panel B shows that disregarding industry dummies, but regarding quadratic terms of other variables increases R^2 considerably for the Ohlson LID and the 'intercept-inclusive' LID models (in the case of the EBO model, moderate decrease). Almost all variables including quadratic terms seem to be significant. In particular, the P/B ratio and its quadratic term are very significant for the case of the Ohlson LID and the 'intercept-inclusive' LID models, and FRI/B ratio and its quadratic term for the case of the EBO model. This means that accounting conservatism and future profitability are quite related to the applicability of the LID models and the EBO models, respectively.

Consistent with Sougiannis and Yaekura (2000), the coefficient on P/B is negative, while the coefficient on $(P/B)^2$ is positive (Sougiannis and Yaekura (2000) use valuation error (i.e., 1 - V/P) as the dependent variable and book-to-market ratio and its quadratic terms as independent variables). This implies that V/P decreases as P/B increases and after reaching a minimum, V/P increases again. Thus, V/P is a convex function of P/B for all models. On the other hand, V/P is a concave function of FRI/B for all models. As to E/P, V/P is convex for the LID models, but concave for the EBO model.

The regression model in Table 7.6, Panel A is the same as that in Table 7.5, Panel A except that absolute valuation error rather than V/P is used as the dependent variable. Similar to the previous regression analysis, industry membership is unlikely to be an important determinant of the accuracy of the valuation model, even though the coefficients of some industry dummies are significantly different from zero in the case of the EBO model. The most important variables to determine the absolute valuation errors are P/B and E/P for the Ohlson LID model, LMV and E/P for the 'intercept-inclusive' LID model, and FRI/B and E/P for the EBO model. It is worth noting that E/P is universally an important determinant in the accuracy of value estimates. Again, the regression results after disregarding industry dummies and introducing quadratic terms are shown in Table 7.6, Panel B. Here, we can see that $(E/P)^2$, P/B, $(P/B)^2$ and FRI/B are largely associated with the accuracy of value estimates derived from applying the Ohlson LID model, while FRI/B and $(FRI/B)^2$ are the most important determinants of the accuracy of the EBO-based value estimates. As to the 'intercept-inclusive' LID model, $(E/P)^2$ and $(P/B)^2$ are the most influential variables on the accuracy of value estimates. Taken together with previous graphical and portfolio analysis, E/P, P/B and FRI/B seem to be the most influential ex-ante variables on the applicability of valuation models. Thus, considering these firm-specific variables when adopting a model to value a firm could be helpful in practice.

One interesting point to note here is that R^2 is substantially smaller than R^2 in Table 7.5, indicating that firm-specific ex-ante variables used in this study explain bias of value estimates very well, but not accuracy of value estimates. Omitted variables are one possible explanation, but the mis-specification of regression models seems to be more related to the quite different R^2 between two regression models. While bias figures seem to be a linear or a quadratic non-linear function of firm-specific variables, accuracy figures may be a more complex non-linear function of those firm-specific variables. Thus, identifying determinants of accuracy (of value estimates) and better relations between determinants and accuracy needs to be further studied

7.5. Conclusions

This study is motivated by concern about the issue of the conditions under which a valuation model dominates other models. In this study, three general valuation models are considered; the 'other information'-inclusive Ohlson (1995) LID model (the Ohlson LID), the 'other information' and 'intercept'-inclusive LID model with the assumption of 4% book value growth rate (the 'intercept-inclusive' LID) and 2-year horizon EBO model with the assumption of a 4% residual income growth rate (the EBO). It is interesting that none of the three general models dominates the other two in all aspects such as median accuracy, mean accuracy, central tendency, and extreme tendency. The Ohlson LID, the 'intercept-inclusive' LID and the EBO approaches respectively give the most accurate value estimates for 18.6%, 37.8% and 43.6% of 5,958 firm-years. Thus, the objective of this study is to examine which firm characteristic can explain these comparable figures - 18.6%, 37.8% and 43.6%. Because these three valuation approaches contain apparently different procedures and assumptions, the models' relative applicability across conditions can vary.

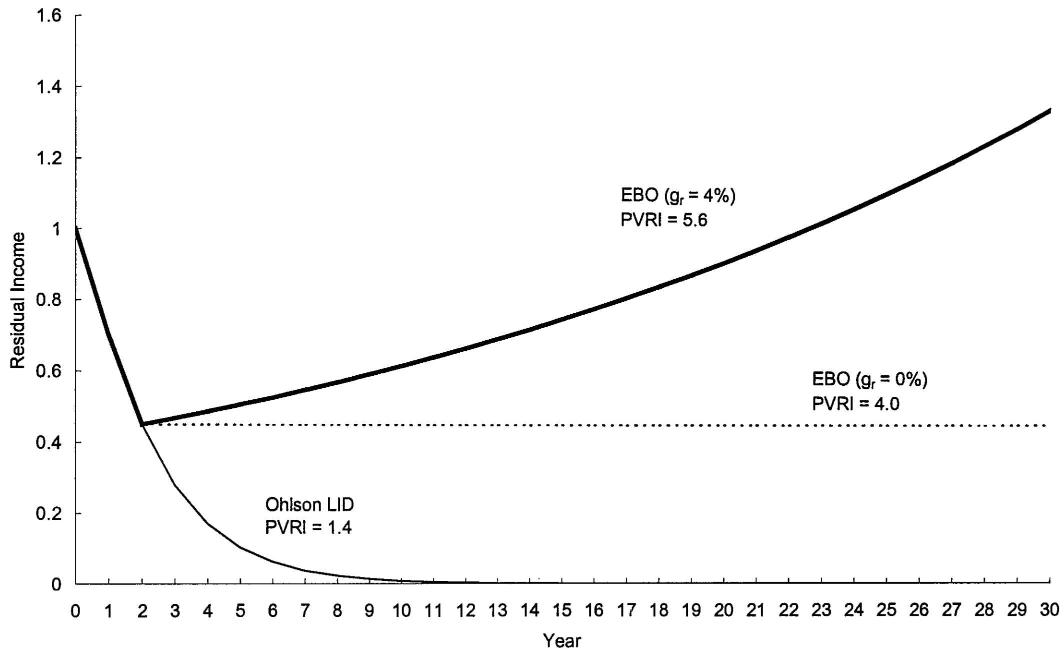
The firm-specific ex-ante variables to examine the models' relative applicability are earnings-to-price (E/P) ratio, market-to-book (P/B) ratio, R&D-to-book (RD/B) ratio, book value growth (BG), firm size (logarithm of market value; LMV), analyst-based RI forecast-to-book (FRI/B) ratio, technology innovation and industry groups. Among these ex-ante variables, E/P, P/B and FRI/B seem to be the most influential variables on the applicability of models. Compared to other models, the 'intercept-inclusive' LID model performs relatively well for moderate E/P, P/B and FRI/B firms, while the Ohlson LID model performs relatively well for low E/P, P/B and FRI/B firms. On the other hand, the EBO model seems to give relatively reliable value estimates for high E/P, P/B and FRI/B firms.

The relationship between models' relative applicability and other ex-ante variables such as RD/B, BG, firm size and industry membership is not that clear, even though there are some differences in bias and accuracy according to the model and the condition. More disappointingly, some results based on the graphical and portfolio analysis are inconsistent with my predictions. The unclear relationship and/or the inconsistency of results with my expectations might be due to i) wrong prediction development, ii) wrong variable construction or iii) mis-specification of models. First, some predictions developed in this study could be controversial, so more sophisticated predictions need to be developed in future research. Second, as to the wrong variable construction, RD/B, BG and technology innovation could give rise to problems. Thus, it may improve the applicability test if we carefully select R&D investment figures as a proxy for accounting conservatism, future growth proxy rather than BG, and industries that correctly represent high or low technology innovation. Finally, there could be model mis-specification problems. Because the pooled persistence and intercept LID parameters, year-specific discount rate and constant book value and residual income growth rate are used in this study, value estimates derived from applying the LID and the EBO models could have 'noise'. Thus, firm-year specific LID parameters, discount rate and future growth rate might eliminate some of the noise included in the value estimates. As to the model specification problem, it might also improve models' reliability if we modify the additional term in the 'intercept-inclusive' LID model and the terminal value in the EBO model to adjust better accounting conservatism, future growth potential and future profitability. Thus, how some ex-ante variables can be used to modify the models could be an important theoretical and practical issue.

Figure 7.1: Example of possible differences between value estimates arising from the adoption of different RIV models

Panel A: Ohlson LID versus 2-year horizon EBO

$$x_t^a = 1, f_{t+1}^a = 0.7, f_{t+2}^a = 0.45, b_t = 5, \omega_1 = 0.6, \gamma_1 = 0.3, r = 12\%$$



Panel B: 'Intercept-inclusive' LID versus 2-year horizon EBO

$$x_t^a = 1, f_{t+1}^a = 0.7, f_{t+2}^a = 0.501, b_t = 5, \omega_0 = -0.02, \omega_1 = 0.6, \gamma_0 = 0.025, \gamma_1 = 0.3, r = 12\%$$

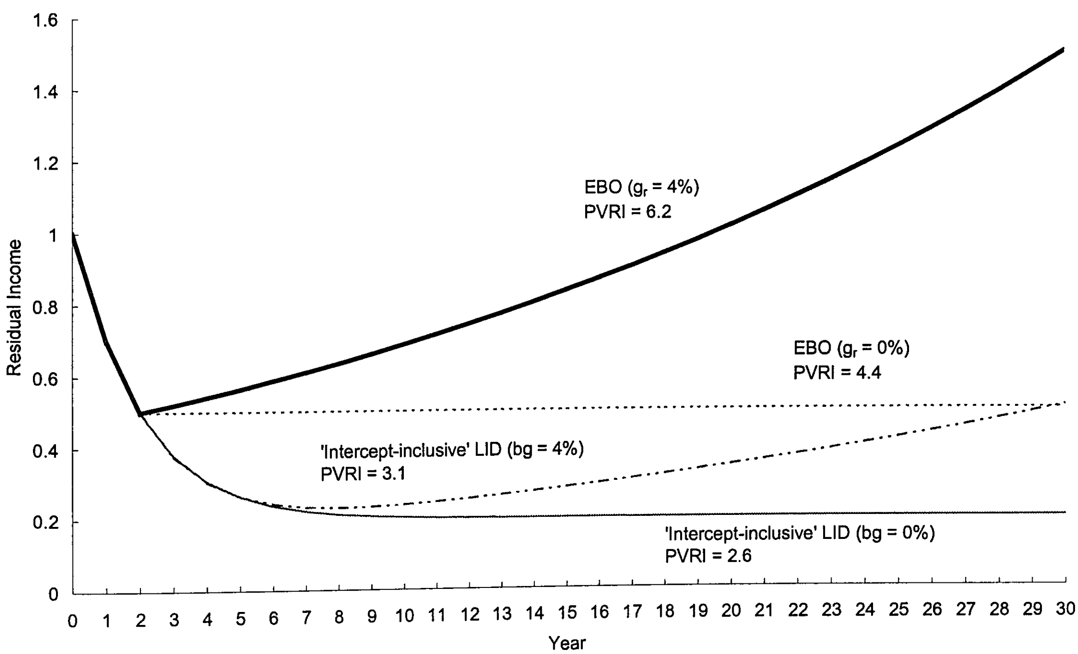
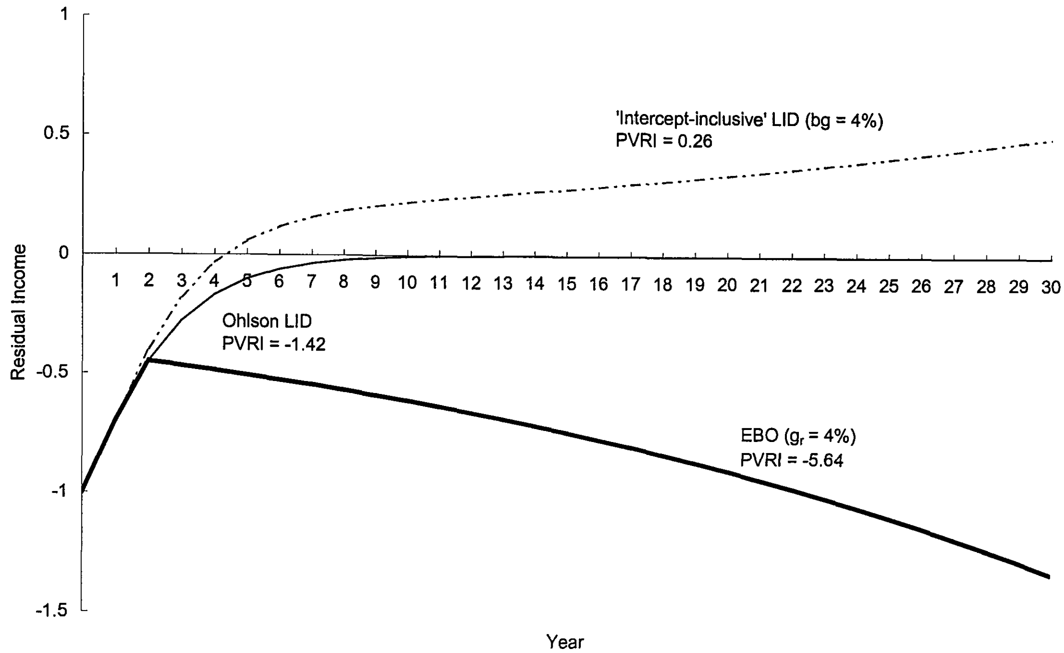


Figure 7.1 (continued)

Panel C: 3 models with negative RI forecasts

$$x_t^a = -1, f_{t+1}^a = -0.7, f_{t+2}^a = -0.45, b_t = 5, \omega_0 = -0.02, \omega_1 = 0.6, \gamma_0 = 0.025, \gamma_1 = 0.3, r = 12\%$$

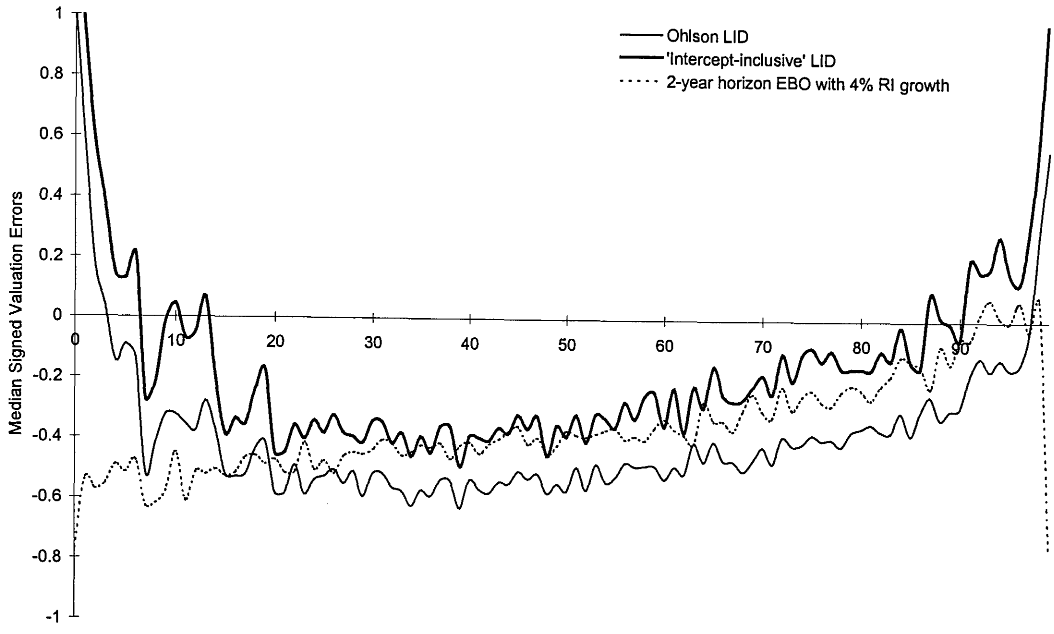


Note:

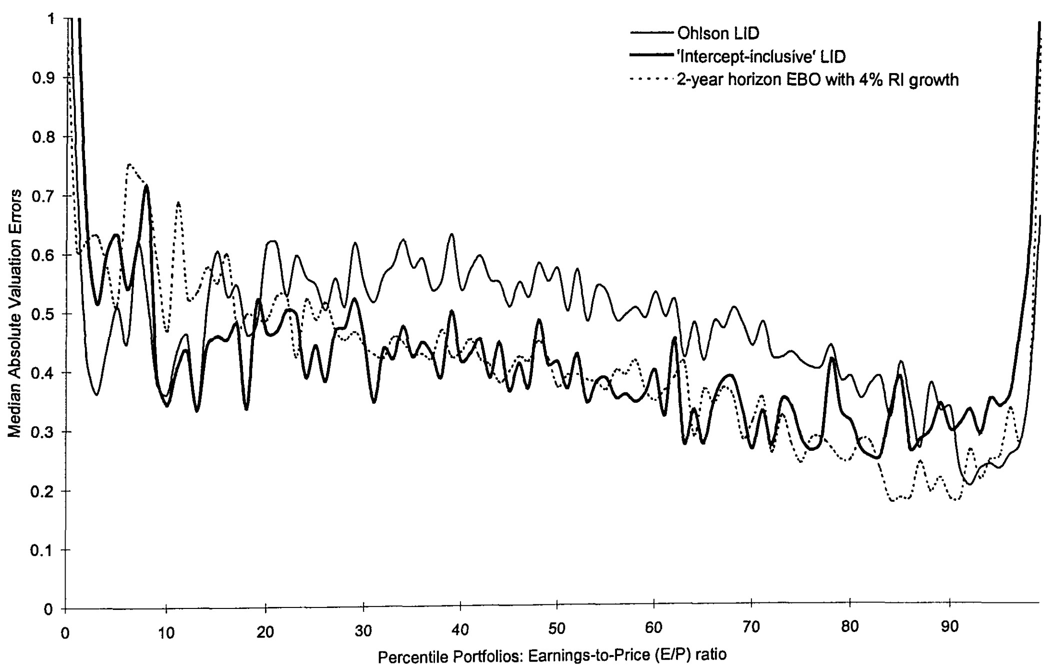
1) In each panel, I assume that alternative models can forecast the same (or very similar) 2-year ahead RI. Note that 1-year ahead RI forecasts used for alternative models are always the same by the model specification. Thus, the models in each panel use exactly the same (or very similar) RI forecasts for the next 2 years.
2) The purpose of these rough examples is to show how much value estimates based on different RI-based valuation approaches can differ, even though models use or predict the same (or very similar) RI for the next 2 years.
3) I present Panel A and Panel B separately, because 2-year ahead residual incomes predicted by using the 'intercept-inclusive' LID and the Ohlson LID approaches can not be the same as long as the term added by incorporating the RI and OI intercepts (i.e., $\omega_0'(1+bg)+\gamma_0'-\omega_0'\gamma_1$, see Chapter 3 for details) into the residual income generating equation of the 'intercept-inclusive' LID approach is not zero. If this term is zero, the intrinsic values estimated by both LID approaches will be the same.
4) Panel C shows the case where one and two-year ahead analysts' forecasts are negative.
5) These graphs are based on the numerical examples provided in Appendix 7.1. I use the reasonable LID intercept and persistence parameters (see Dechow *et al.*, 1999 and Chapter 6), the discount rate of 12%, the future RI growth rate (denoted as 'g_r') of 4% and zero and the future book value growth rate (denoted as '*bg*') of 4% and zero.

Figure 7.2: Applicability of valuation models across firm-specific ex-ante variables

Panel A.1: Median bias (= $(V_t - P_t) / P_t$) across earnings-to-price (E/P) ratios



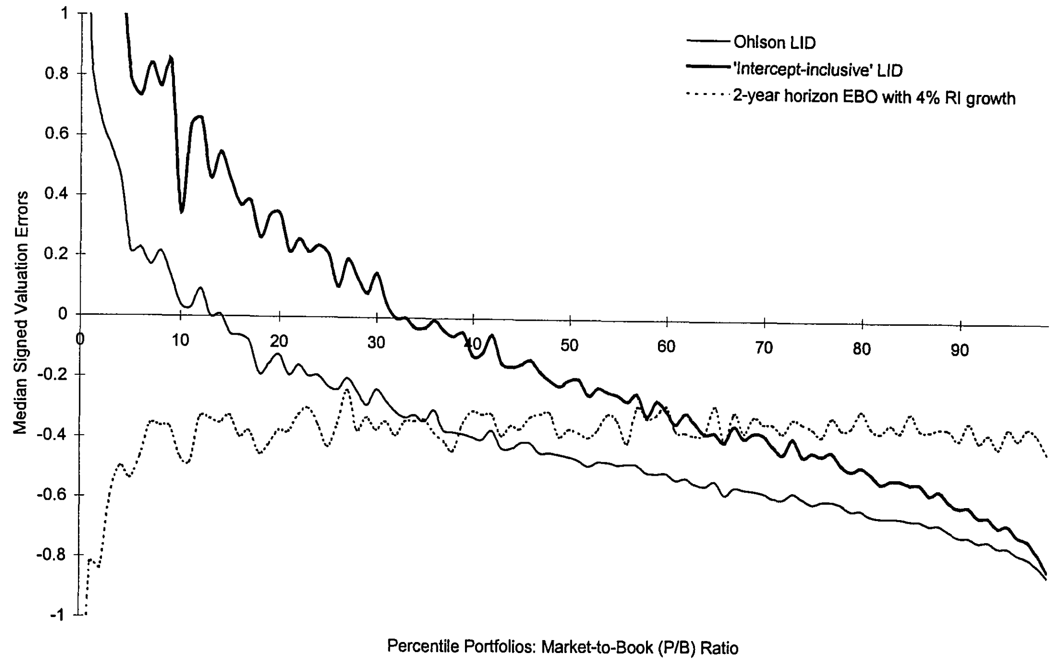
Panel A.2: Median accuracy (= $| V_t - P_t | / P_t$) across earnings-to-price (E/P) ratios



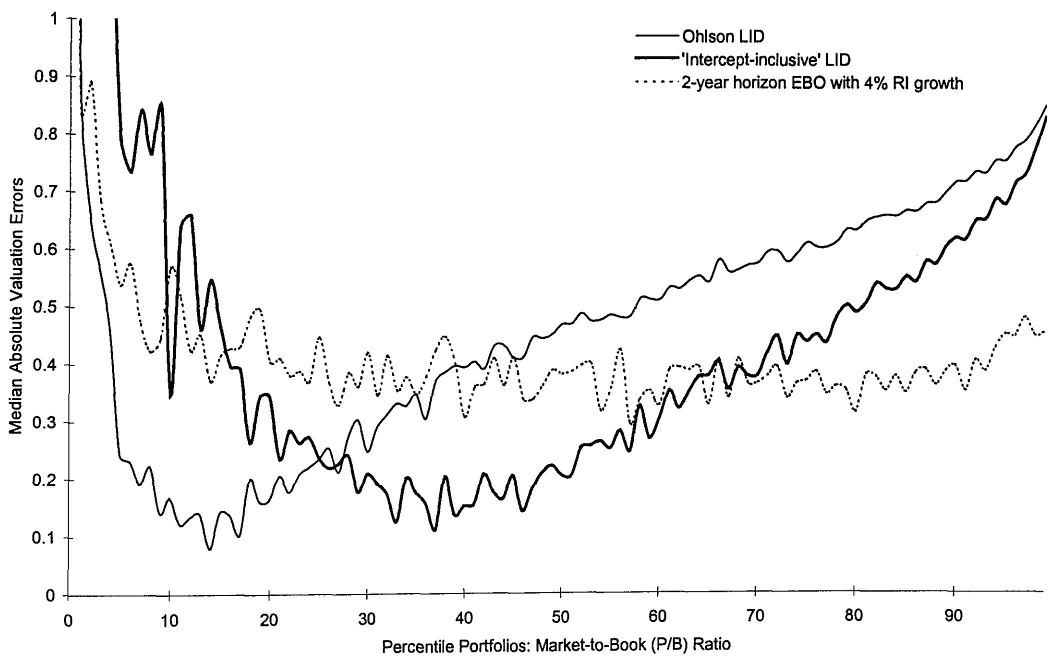
Note: Total observations (5,958) are ranked by E/P ratio and grouped into 100 portfolios, and the median value of signed valuation errors (Panel A.1) and absolute valuation errors (Panel A.2) of each portfolio is depicted. Y axis is adjusted to range from -1 to 1 for Panel A.1 and from 0 to 1 for Panel A.2 to make patterns look clear. So some of extreme forecast errors are cut (In Panel A.1, 1st percentile portfolio (1.041) for the Ohlson LID and 1st (1.429) and 100th (1.095) for the 'intercept-inclusive' LID. In Panel A.2, 1st percentile portfolio (1.160) for the Ohlson LID, 1st (1.439), 2nd (1.045) and 100th (1.095) for the 'intercept-inclusive' LID).

Figure 7.2 (continued)

Panel B.1: Median bias (= $(V_t - P_t) / P_t$) across market-to-book (P/B) ratios



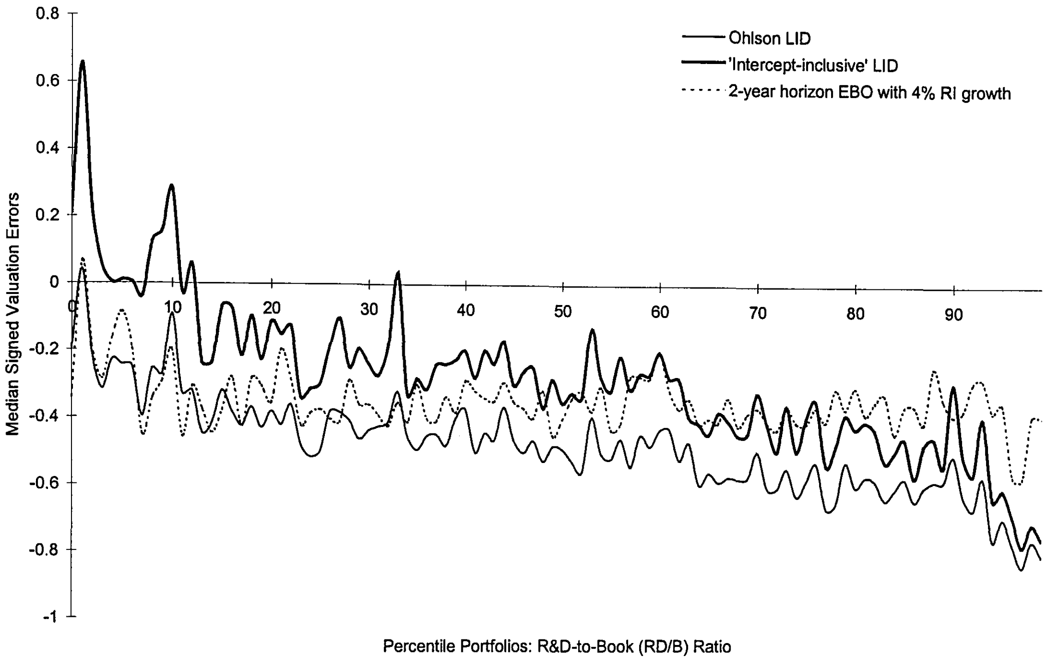
Panel B.2: Median accuracy (= $| V_t - P_t | / P_t$) across market-to-book (P/B) ratios



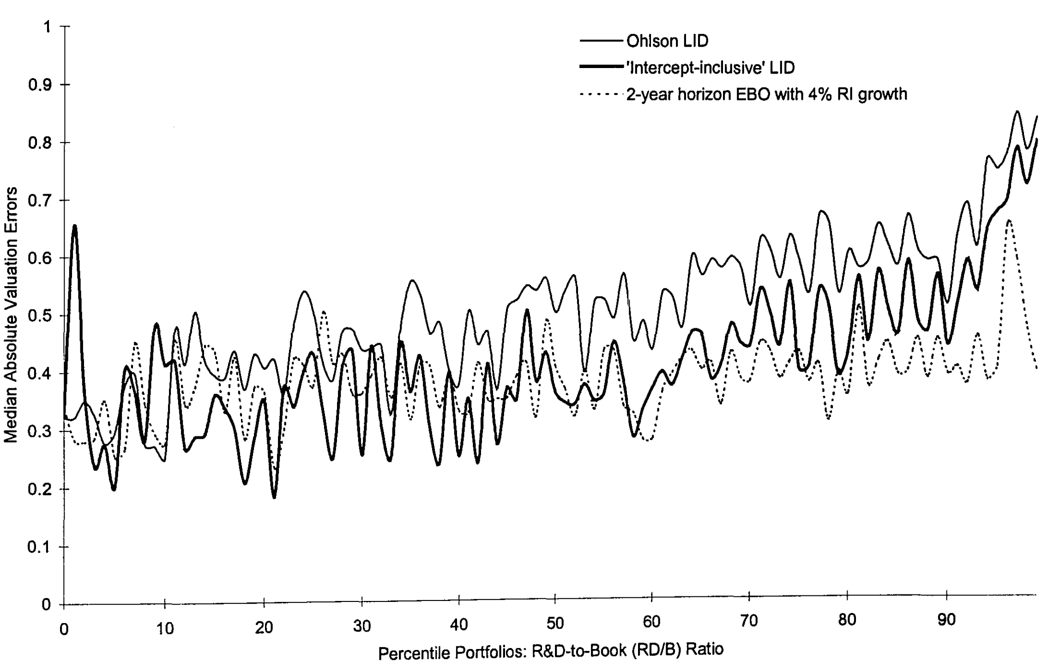
Note: Total observations (5,958) are ranked by P/B ratio and grouped into 100 portfolios, and the median value of signed valuation errors (Panel B.1) and absolute valuation errors (Panel B.2) of each portfolio is depicted. Y axis is adjusted to range from -1 to 1 for Panel B.1 and from 0 to 1 for Panel B.2 to make patterns look clear. So some of extreme forecast errors are cut (In Panel B.1 and B.2, 1st (2.653) percentile portfolio for the Ohlson LID, 1st (4.274), 2nd (1.654), 3rd (1.505), 4th (1.119) and 5th (1.125) for the 'intercept-inclusive' LID, and 1st (-1.994 singed forecast error, 1.994 absolute forecast error) for the EBO).

Figure 7.2 (continued)

Panel C.1: Median bias (= $(V_t - P_t) / P_t$) across R&D-to-book (RD/B) ratios



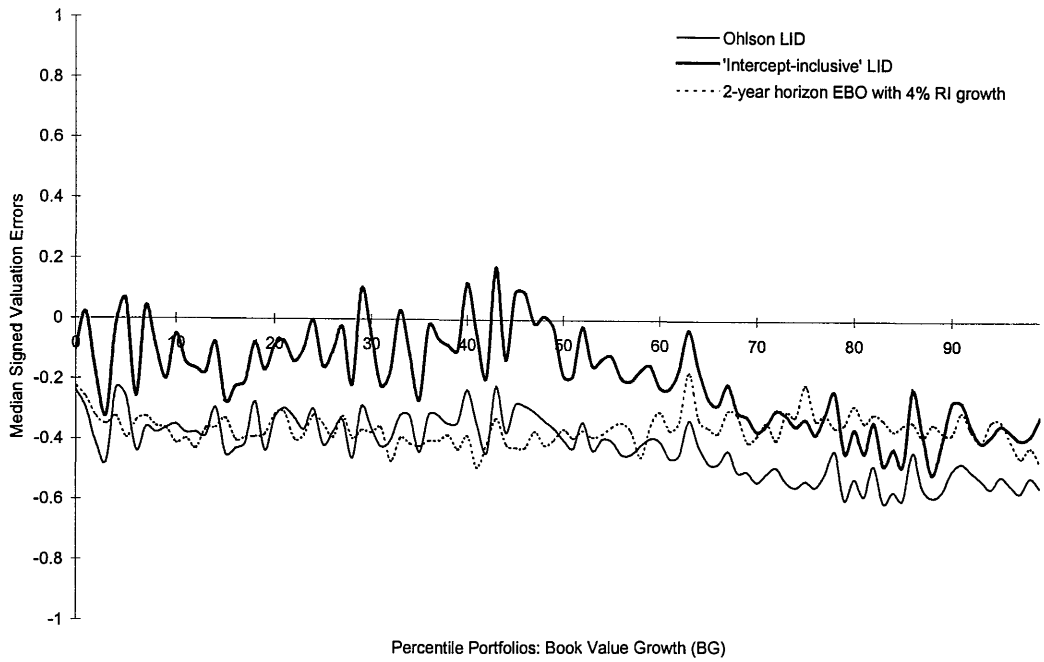
Panel C.2: Median accuracy (= $| V_t - P_t | / P_t$) across R&D-to-book (RD/B) ratios



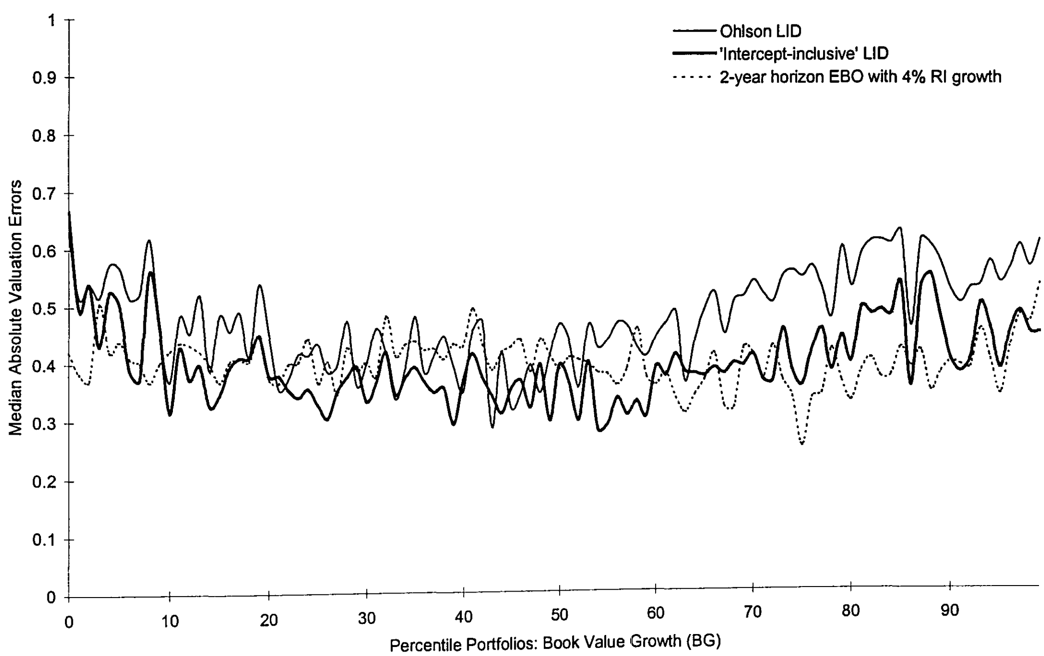
Note: Among total observations (5,958), 3,947 observations that have zero R&D are excluded here. The rest of observations (2,011) are ranked by RD/B ratio and grouped into 100 portfolios, and the median value of signed valuation errors (Panel C.1) and absolute valuation errors (Panel C.2) of each portfolio is depicted.

Figure 7.2 (continued)

Panel D.1: Median bias (= $(V_t - P_t) / P_t$) across book value growth (BG)



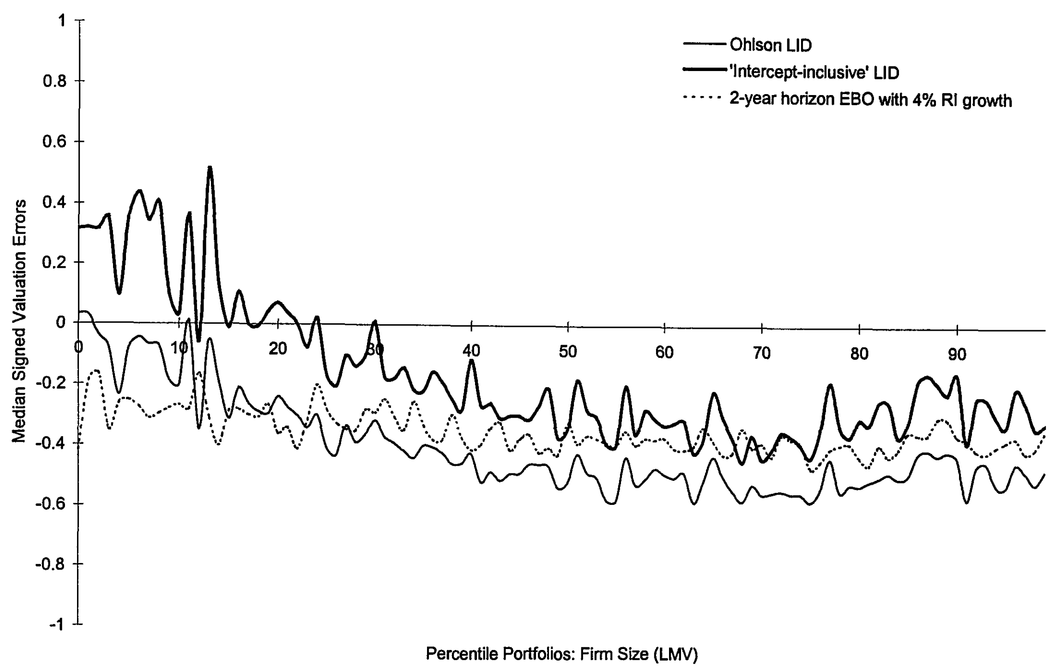
Panel D.2: Median accuracy (= $| V_t - P_t | / P_t$) across book value growth (BG)



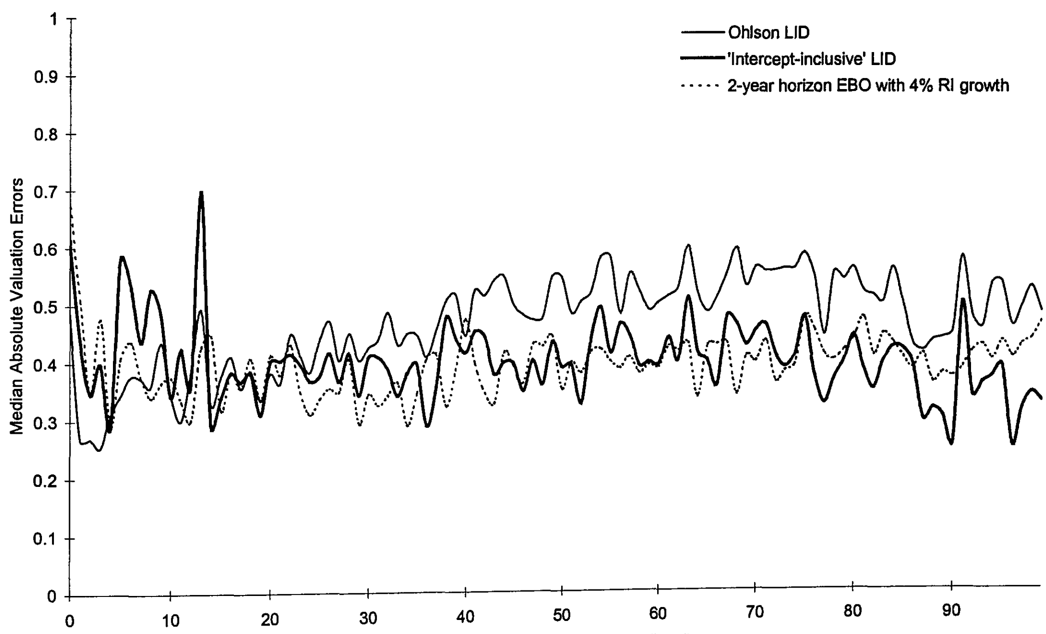
Note: Total observations (5,958) are ranked by BG and grouped into 100 portfolios, and the median value of signed valuation errors (Panel D.1) and absolute valuation errors (Panel D.2) of each portfolio is depicted.

Figure 7.2 (continued)

Panel E.1: Median bias (= $(V_t - P_t) / P_t$) across firm size (LMV)



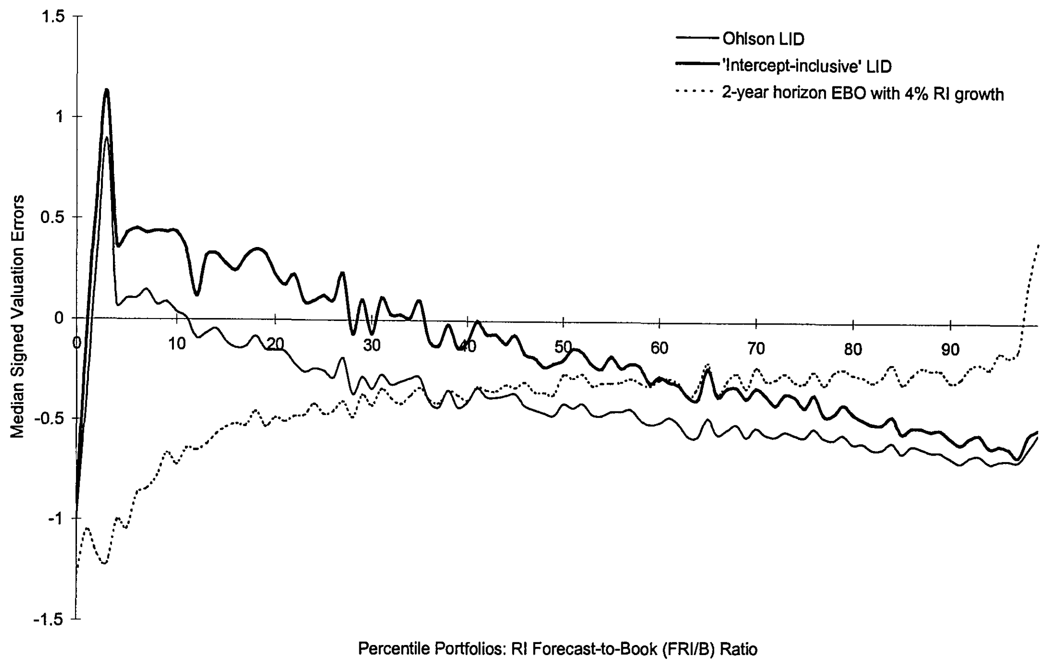
Panel E.2: Median accuracy (= $| V_t - P_t | / P_t$) across firm size (LMV)



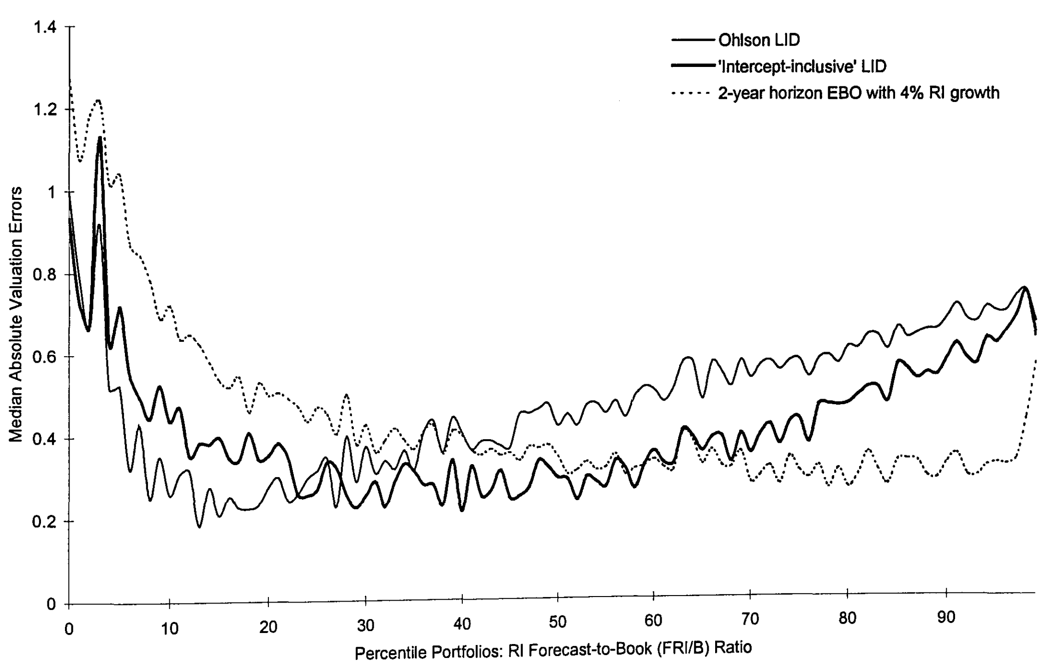
Note: Total observations (5,958) are ranked by LMV (logarithm of market value) and grouped into 100 portfolios, and the median value of signed valuation errors (Panel E.1) and absolute valuation errors (Panel E.2) of each portfolio is depicted.

Figure 7.2 (continued)

Panel F.1: Median bias (= $(V_t - P_t) / P_t$) across RI forecast-to-book (FRI/B) ratios



Panel F.2: Median accuracy (= | $V_t - P_t$ | / P_t) across RI forecast-to-book (FRI/B) ratios



Note: Total observations (5,958) are ranked by FRI/B and grouped into 100 portfolios, and the median value of signed valuation errors (Panel F.1) and absolute valuation errors (Panel F.2) of each portfolio is depicted. Analyst-based one-year ahead RI is used as FRI.

Table 7.1: Absolute valuation errors based on the pooled sample

$$V_t = b_t \tag{LID1}$$

$$V_t = \frac{R_t}{r_t} x_t - d_t \tag{LID2}$$

$$V_t = \frac{1}{r_t} f_{t+1} \tag{EBO1}$$

$$V_t = b_t + \frac{-\omega_{1t}\gamma'_{1t}}{(R_t - \omega_{1t})(R_t - \gamma'_{1t})} x_t^a + \frac{R_t}{(R_t - \omega_{1t})(R_t - \gamma'_{1t})} f_{t+1}^a \tag{LID9}$$

$$V_t = b_t + \frac{-\omega_{1t}\gamma_{1t}}{(R_t - \omega_{1t})(R_t - \gamma_{1t})} x_t^a + \frac{R_t}{(R_t - \omega_{1t})(R_t - \gamma_{1t})} f_{t+1}^a + \frac{R_t(\omega_{0t}BG - \omega_{0t}\gamma_{1t} + \gamma_{0t})}{(R_t - BG)(R_t - \omega_{1t})(R_t - \gamma_{1t})} b_t \tag{LID16}$$

$$V_t = b_t + \frac{f_{t+1} - r_t b_t}{R_t} + \frac{f_{t+2} - r_t \bar{b}_{t+1}}{(r_t - g_r)R_t} \tag{EBO5}$$

Panel A: Absolute valuation errors of value estimates

	Median	Mean	Std	Central Tendency		Extreme Tendency		Negative Estimate		Most Accurate	Least Accurate
LID1	0.531	0.576	0.841	668	11.2%	197	3.3%	0	0.0%	10.0%	41.1%
LID2	0.533	0.850	1.899	416	7.0%	812	13.6%	775	13.0%	6.0%	31.9%
EBO1	0.453	0.481	0.422	607	10.2%	220	3.7%	147	2.5%	8.5%	3.6%
LID9	0.478	0.505	0.566	768	12.9%	182	3.1%	27	0.5%	8.6%	1.3%
LID16	0.395	0.519	0.824	1038	17.4%	441	7.4%	16	0.3%	30.4%	9.9%
EBO5	0.397	0.495	0.912	845	14.2%	398	6.7%	288	4.8%	36.6%	12.2%

Note:

1) This table is based on earnings measure X4 (i.e., earnings before extraordinary items).
2) Total observation is 5,958 from 1991 to 1997.
3) LID1 is book value model, LID2 is earnings model and EBO1 is 1-year horizon EBO model with the assumption of zero RI growth in the post horizon. LID9 is OI-inclusive Ohlson (1995) LID model, LID16 is OI and intercept-inclusive LID model with the assumption of 4% book value growth, and EBO5 is 2-year horizon EBO model with the assumption of 4% RI growth in the post horizon.
4) RI and OI intercept and persistence parameters (ω_0, ω_1, γ_0, γ_1) and discount rate ($r_t = R_t$ - 1) are year-specific, while RI growth rate (g_r) and book value growth rate ($bg = BG$ - 1) are constant (4%). Note that OI persistence parameters in LID9 and LID16 are practically different.
5) Central tendency is defined as the percent of observations where the value estimate is within 15% of the observed stock price (i.e., $|V_t - P_t| / P_t \leq 0.15$). Extreme tendency is defined as the percent of observations where the value estimate is outside 100% of the observed stock price (i.e., $|V_t - P_t| / P_t \geq 1$).
6) The percentage in the columns 'most accurate' and 'least accurate' is the relative percentage of 6 models (e.g., Compared to 5 other models, LID1 gives rise to the most accurate value estimates of 10% of total observations).

Table 7.1 (continued)

Panel B: Characteristics of firm-years in central tendency and extreme tendency

Good (Bad) performers are defined as firm-years whose value estimate is categorised as 'central tendency' ('extreme tendency'). Good (bad) performers when LID9 is adopted are 768 (182) firm-years, good (bad) performers when LID16 is adopted are 1,038 (441) firm-years, and good (bad) performers when EBO5 is adopted are 845 (398) firm-years. Each figure in the table is a ratio of good (bad) performers who belong to each portfolio formed by a firm-specific ex-ante variable (e.g., E/P ratio) using total observations of 5,958 to total good (bad) performers. For example, 14.2% of 768 good performers arising from the adoption of LID9 belongs to the first decile portfolio formed by E/P ratio (i.e., the lowest E/P portfolio).

Distribution of E/P ratios of good performers and bad performers

	Decile portfolios formed by earnings-to-price (E/P) ratio										Total
	1	2	3	4	5	6	7	8	9	10	
Good performers											
LID9	14.2	10.8	7.3	3.1	4.9	5.3	8.7	11.5	12.2	21.9	100%
LID16	6.5	11.2	7.5	8.8	8.2	9.5	9.4	13.7	13.5	11.8	100%
EBO5	6.0	6.4	4.1	4.0	3.6	6.2	9.3	14.3	23.9	22.1	100%
Bad performers											
LID9	64.3	3.8	2.7	2.2	0.5	2.2	2.7	1.6	1.1	18.7	100%
LID16	37.9	9.3	4.8	4.3	2.9	3.9	3.6	4.8	6.1	22.4	100%
EBO5	43.2	15.3	6.3	4.0	4.0	3.5	2.5	3.3	4.0	13.8	100%

Distribution of P/B ratios of good performers and bad performers

	Decile portfolios formed by market-to-book (P/B) ratio										Total
	1	2	3	4	5	6	7	8	9	10	
Good performers											
LID9	17.6	41.5	24.6	8.2	2.6	1.7	1.3	0.3	0.9	1.3	100%
LID16	3.2	10.6	17.2	25.7	23.3	12.0	4.2	1.5	0.8	1.3	100%
EBO5	8.0	11.2	12.9	11.4	11.0	10.8	8.6	9.5	9.9	6.6	100%
Bad performers											
LID9	62.6	8.2	3.8	2.2	1.1	3.8	3.3	2.2	3.8	8.8	100%
LID16	70.3	15.2	2.9	2.3	1.1	1.6	1.4	1.4	1.4	2.5	100%
EBO5	40.2	7.5	6.0	4.5	5.3	5.3	7.8	3.5	6.8	13.1	100%

Distribution of RD/B ratios of good performers and bad performers

	Zero vs. Non-zero RD/B		Total	Portfolios formed by R&D-to-book (RD/B) ratio					Total
	Zero RD/B	Non-zero RD/B		1	2	3	4	5	
Good performers									
LID9	76.4	23.6	100%	9.4	4.7	5.2	2.9	1.4	23.6%
LID16	69.7	30.3	100%	8.8	7.5	6.1	4.7	3.2	30.3%
EBO5	66.9	33.1	100%	11.1	5.0	6.9	4.3	5.9	33.1%
Bad performers									
LID9	71.4	28.6	100%	3.8	3.8	5.5	2.2	13.2	28.6%
LID16	79.8	20.2	100%	5.4	5.4	3.4	2.3	3.6	20.2%
EBO5	68.8	31.2	100%	2.0	2.8	6.0	4.5	15.8	31.2%

Note: Portfolios 1 to 5 are partitions of non-zero RD/B observations. Total observations of zero (non-zero) RD/B firm-years are 3,947 (2,011). Total observations of each portfolio (1 to 5) are 402 or 403.

Table 7.1 (continued)

Panel B (continued)

Distribution of BG of good performers and bad performers

	Decile portfolios formed by book value growth (BG)										Total
	1	2	3	4	5	6	7	8	9	10	
Good performers											
LID9	10.5	11.2	11.6	13.2	13.9	10.4	11.3	6.5	5.9	5.5	100%
LID16	6.8	9.7	11.7	12.4	11.8	12.1	9.4	9.0	7.7	9.3	100%
EBO5	11.2	9.6	11.0	8.9	8.3	9.0	13.6	10.9	10.1	7.5	100%
Bad performers											
LID9	41.8	18.1	5.5	7.1	7.7	3.8	2.2	1.6	5.5	6.6	100%
LID16	23.4	13.2	10.4	12.7	12.9	7.3	4.5	3.6	5.2	6.8	100%
EBO5	25.4	12.3	12.8	7.0	7.8	4.0	4.3	3.8	7.0	15.6	100%

Distribution of LMV ratios of good performers and bad performers

	Decile portfolios formed by firm size (LMV: logarithm of market value)										Total
	1	2	3	4	5	6	7	8	9	10	
Good performers											
LID9	18.6	14.5	13.5	12.5	10.7	6.9	5.9	5.7	6.8	4.9	100%
LID16	8.1	11.8	11.1	10.0	9.9	8.7	9.3	7.5	11.3	12.2	100%
EBO5	13.4	14.4	10.8	14.6	7.9	9.1	7.6	6.9	8.4	7.0	100%
Bad performers											
LID9	35.7	18.1	9.3	8.8	7.7	7.1	7.7	0.5	4.4	0.5	100%
LID16	30.8	20.2	13.8	8.6	7.9	6.1	5.4	1.4	3.9	1.8	100%
EBO5	23.6	15.1	9.8	9.5	6.8	6.8	8.8	5.0	8.5	6.0	100%

Distribution of FRI/B ratios of good performers and bad performers

	Decile portfolios formed by analyst-based 1-year ahead RI-to-book (FRI/B) ratio										Total
	1	2	3	4	5	6	7	8	9	10	
Good performers											
LID9	13.7	24.0	18.6	13.9	10.4	8.1	4.7	2.5	1.4	2.7	100%
LID16	7.0	11.5	15.0	15.4	14.5	13.6	8.1	6.3	5.1	3.6	100%
EBO5	1.9	3.7	6.7	8.5	11.6	13.5	11.2	14.8	15.5	12.5	100%
Bad performers											
LID9	71.4	11.0	4.4	1.6	0.5	0.0	0.5	1.1	1.1	8.2	100%
LID16	44.0	24.9	12.5	5.7	3.9	2.0	1.4	0.7	0.7	4.3	100%
EBO5	69.3	4.0	1.5	1.3	0.5	2.5	1.0	1.8	1.5	16.6	100%

Table 7.1 (continued)

Panel B (continued)

Distribution of P of good performers and bad performers

	Decile portfolios formed by stock price (P)										Total
	1	2	3	4	5	6	7	8	9	10	
Good performers											
LID9	17.7	14.8	15.2	12.2	9.8	7.6	4.9	6.0	4.9	6.8	100%
LID16	9.1	9.6	11.6	12.1	10.9	12.0	10.1	6.7	9.2	8.7	100%
EBO5	12.3	14.4	13.7	11.6	12.1	10.7	7.1	6.7	4.9	6.5	100%
Bad performers											
LID9	33.5	17.0	12.1	5.5	7.1	4.4	4.9	3.3	4.9	7.1	100%
LID16	31.5	20.0	11.3	7.5	7.3	5.2	4.5	2.7	3.9	6.1	100%
EBO5	21.9	16.6	11.3	9.0	6.3	6.0	5.3	4.5	7.0	12.1	100%

Distribution of RI of good performers and bad performers

	Decile portfolios formed by current residual income (RI)										Total
	1	2	3	4	5	6	7	8	9	10	
Good performers											
LID9	18.9	16.4	16.7	18.8	11.6	7.0	4.6	2.0	1.8	2.3	100%
LID16	9.6	12.2	13.4	14.0	12.8	11.8	8.5	6.6	5.4	5.7	100%
EBO5	3.7	7.8	7.0	8.9	11.0	13.1	13.3	12.5	10.8	12.0	100%
Bad performers											
LID9	60.4	15.9	10.4	3.8	1.6	3.8	0.0	1.1	1.1	1.6	100%
LID16	42.0	18.6	13.2	12.7	6.1	2.9	1.1	0.9	1.4	1.1	100%
EBO5	41.5	16.3	10.3	7.8	5.0	7.3	3.5	2.8	2.3	3.3	100%

Table 7.2: Descriptive statistics of portfolios

Panel A: Quintile portfolios formed by earnings-to-price (E/P) ratio

	N	E/P	P/B	RD/B	BG	LMV	FRI/B	P	RI
PF1 (low E/P)	1191	-0.008 (-0.116)	1.573 (3.653)	0.000 (0.065)	0.929 (1.094)	10.737 (10.944)	-0.057 (-0.018)	0.935 (1.780)	-0.104 (-0.305)
PF2	1192	0.049 (0.048)	2.573 (4.219)	0.000 (0.028)	1.058 (1.197)	11.849 (12.076)	0.029 (0.151)	2.145 (2.808)	0.004 (-0.017)
PF3	1192	0.063 (0.063)	2.293 (2.788)	0.000 (0.022)	1.058 (1.136)	11.727 (11.953)	0.037 (0.083)	2.263 (2.792)	0.015 (0.008)
PF4	1192	0.078 (0.078)	1.884 (2.197)	0.000 (0.016)	1.052 (1.129)	11.211 (11.462)	0.028 (0.072)	1.657 (2.163)	0.013 (0.004)
PF5 (high E/P)	1191	0.110 (0.133)	1.300 (1.581)	0.000 (0.012)	1.065 (1.089)	10.453 (10.922)	0.021 (0.062)	1.256 (1.726)	0.011 (-0.023)
Pooled	5958	0.063 (0.041)	1.895 (2.888)	0.000 (0.029)	1.042 (1.129)	11.277 (11.471)	0.015 (0.070)	1.613 (2.254)	-0.002 (-0.066)

Panel B: Quintile portfolios formed by market-to-book (P/B) ratio

	N	E/P	P/B	RD/B	BG	LMV	FRI/B	P	RI
PF1 (low P/B)	1191	0.069 (0.003)	0.788 (0.745)	0.000 (0.006)	1.005 (1.005)	10.031 (10.404)	-0.066 (-0.063)	0.845 (1.506)	-0.099 (-0.322)
PF2	1192	0.071 (0.053)	1.313 (1.321)	0.000 (0.010)	1.035 (1.117)	11.024 (11.342)	-0.021 (-0.012)	1.319 (2.069)	-0.034 (-0.075)
PF3	1192	0.067 (0.058)	1.895 (1.905)	0.000 (0.017)	1.055 (1.156)	11.470 (11.739)	0.015 (0.024)	1.781 (2.343)	0.001 (-0.018)
PF4	1192	0.064 (0.053)	2.690 (2.731)	0.000 (0.029)	1.077 (1.143)	11.679 (11.878)	0.064 (0.073)	1.973 (2.464)	0.031 (0.027)
PF5 (high P/B)	1191	0.053 (0.039)	4.900 (7.740)	0.000 (0.081)	1.095 (1.223)	11.837 (11.994)	0.180 (0.328)	2.352 (2.890)	0.056 (0.055)
Pooled	5958	0.063 (0.041)	1.895 (2.888)	0.000 (0.029)	1.042 (1.129)	11.277 (11.471)	0.015 (0.070)	1.613 (2.254)	-0.002 (-0.066)

Table 7.2 (continued)

Panel C: Portfolios formed by R&D-to-book (RD/B) ratio

	N	E/P	P/B	RD/B	BG	LMV	FRI/B	P	RI
PF1 (zero RD/B)	3947	0.064 (0.038)	1.742 (2.609)	0.000 (0.000)	1.041 (1.143)	10.919 (11.077)	0.008 (0.060)	1.365 (2.025)	-0.005 (-0.077)
PF2 (low RD/B)	1005	0.067 (0.063)	1.758 (2.054)	0.011 (0.013)	1.044 (1.073)	12.500 (12.560)	0.011 (0.042)	2.548 (2.934)	-0.003 (-0.090)
PF3 (high RD/B)	1006	0.057 (0.030)	2.864 (4.816)	0.085 (0.157)	1.048 (1.129)	11.756 (11.930)	0.061 (0.139)	1.771 (2.477)	0.014 (0.000)
Pooled	5958	0.063 (0.041)	1.895 (2.888)	0.000 (0.029)	1.042 (1.129)	11.277 (11.471)	0.015 (0.070)	1.613 (2.254)	-0.002 (-0.066)

Panel D: Quintile portfolios formed by book value growth (BG)

	N	E/P	P/B	RD/B	BG	LMV	FRI/B	P	RI
PF1 (low BG)	1191	0.044 (-0.065)	1.900 (4.436)	0.000 (0.061)	0.766 (0.698)	10.812 (11.074)	-0.003 (0.110)	1.084 (1.710)	-0.066 (-0.263)
PF2	1192	0.060 (0.055)	1.566 (2.079)	0.000 (0.019)	0.973 (0.969)	11.245 (11.459)	-0.006 (0.025)	1.489 (2.138)	-0.033 (-0.084)
PF3	1192	0.070 (0.075)	1.551 (1.860)	0.000 (0.016)	1.042 (1.042)	11.230 (11.405)	-0.006 (0.016)	1.657 (2.266)	-0.015 (-0.051)
PF4	1192	0.071 (0.081)	2.130 (2.482)	0.000 (0.018)	1.111 (1.114)	11.561 (11.752)	0.044 (0.069)	1.963 (2.585)	0.025 (0.024)
PF5 (high BG)	1191	0.060 (0.060)	2.573 (3.584)	0.000 (0.029)	1.333 (1.822)	11.468 (11.666)	0.052 (0.129)	1.900 (2.573)	0.042 (0.041)
Pooled	5958	0.063 (0.041)	1.895 (2.888)	0.000 (0.029)	1.042 (1.129)	11.277 (11.471)	0.015 (0.070)	1.613 (2.254)	-0.002 (-0.066)

Table 7.2 (continued)

Panel E: Quintile portfolios formed by firm size (LMV)

	N	E/P	P/B	RD/B	BG	LMV	FRI/B	P	RI
PF1 (small LMV)	1191	0.069 (-0.005)	1.173 (1.745)	0.000 (0.024)	1.011 (1.072)	9.231 (9.129)	-0.027 (0.000)	0.635 (0.871)	-0.030 (-0.167)
PF2	1192	0.068 (0.045)	1.695 (2.877)	0.000 (0.022)	1.038 (1.169)	10.352 (10.355)	0.008 (0.076)	1.155 (1.557)	-0.004 (-0.090)
PF3	1192	0.064 (0.056)	2.208 (3.051)	0.000 (0.034)	1.060 (1.174)	11.277 (11.282)	0.028 (0.078)	1.784 (2.311)	0.007 (-0.043)
PF4	1192	0.060 (0.052)	2.417 (3.500)	0.000 (0.032)	1.054 (1.123)	12.270 (12.306)	0.034 (0.085)	2.281 (2.793)	0.013 (-0.015)
PF5 (large LMV)	1191	0.061 (0.057)	2.117 (3.266)	0.003 (0.033)	1.054 (1.106)	14.070 (14.285)	0.030 (0.110)	3.347 (3.739)	0.013 (-0.018)
Pooled	5958	0.063 (0.041)	1.895 (2.888)	0.000 (0.029)	1.042 (1.129)	11.277 (11.471)	0.015 (0.070)	1.613 (2.254)	-0.002 (-0.066)

Panel F: Quintile portfolios formed by analyst-based RI forecast-to-book (FRI/B) ratio

	N	E/P	P/B	RD/B	BG	Log(MV)	FRI/B	P	RI
PF1 (low FRI/B)	1191	0.034 (-0.038)	0.899 (1.752)	0.000 (0.035)	0.988 (1.111)	10.402 (10.644)	-0.090 (-0.133)	0.968 (1.886)	-0.131 (-0.352)
PF2	1192	0.065 (0.048)	1.323 (1.432)	0.000 (0.012)	1.035 (1.141)	11.231 (11.451)	-0.028 (-0.029)	1.561 (2.183)	-0.045 (-0.094)
PF3	1192	0.068 (0.069)	1.824 (1.924)	0.000 (0.016)	1.055 (1.117)	11.482 (11.695)	0.015 (0.016)	1.792 (2.307)	0.002 (-0.005)
PF4	1192	0.068 (0.067)	2.567 (2.715)	0.000 (0.024)	1.083 (1.077)	11.479 (11.622)	0.074 (0.076)	1.837 (2.319)	0.037 (0.040)
PF5 (high FRI/B)	1191	0.063 (0.060)	4.285 (6.619)	0.000 (0.057)	1.094 (1.198)	11.723 (11.944)	0.214 (0.420)	1.928 (2.576)	0.065 (0.079)
Pooled	5958	0.063 (0.041)	1.895 (2.888)	0.000 (0.029)	1.042 (1.129)	11.277 (11.471)	0.015 (0.070)	1.613 (2.254)	-0.002 (-0.066)

Panel G: Portfolios formed by technology innovation

	N	E/P	P/B	RD/B	BG	LMV	FRI/B	P	RI
Low-tech	849	0.066 (0.028)	1.600 (1.917)	0.000 (0.007)	1.041 (1.076)	11.306 (11.493)	-0.003 (0.010)	1.461 (2.085)	-0.015 (-0.083)
High-tech	836	0.056 (0.027)	2.723 (4.541)	0.057 (0.136)	1.061 (1.123)	11.034 (11.232)	0.044 (0.126)	1.472 (2.015)	0.007 (-0.026)
Pooled	5958	0.063 (0.041)	1.895 (2.888)	0.000 (0.029)	1.042 (1.129)	11.277 (11.471)	0.015 (0.070)	1.613 (2.254)	-0.002 (-0.066)

Table 7.2 (continued)

Panel H: Portfolios formed by industry groups

	N	E/P	P/B	RD/B	BG	LMV	FRI/B	P	RI
RSR	149	0.047 (0.011)	1.514 (2.057)	0.000 (0.004)	1.041 (1.099)	12.256 (12.546)	-0.035 (-0.005)	1.460 (2.369)	-0.032 (-0.090)
BIN	922	0.062 (0.025)	1.545 (1.806)	0.000 (0.010)	1.024 (1.046)	11.564 (11.620)	-0.009 (0.000)	1.493 (2.081)	-0.020 (-0.098)
GIN	1009	0.064 (0.044)	2.090 (2.543)	0.019 (0.049)	1.035 (1.092)	11.336 (11.352)	0.027 (0.061)	1.500 (2.078)	0.006 (-0.024)
CGD	524	0.069 (0.052)	1.606 (1.882)	0.000 (0.012)	1.030 (1.056)	10.363 (10.486)	0.009 (0.017)	1.143 (1.558)	-0.008 (-0.041)
NCG	747	0.066 (0.050)	2.151 (3.437)	0.000 (0.053)	1.047 (1.112)	11.468 (11.718)	0.020 (0.040)	1.957 (2.370)	0.003 (-0.018)
CSV	2053	0.060 (0.039)	2.000 (3.469)	0.000 (0.006)	1.045 (1.217)	11.163 (11.388)	0.019 (0.105)	1.720 (2.475)	-0.002 (-0.118)
NSV	145	0.069 (0.053)	2.128 (2.580)	0.000 (0.003)	1.078 (1.094)	12.362 (12.857)	0.030 (0.130)	1.583 (2.364)	0.010 (0.022)
UTL	152	0.120 (0.129)	1.125 (1.309)	0.002 (0.003)	1.084 (1.084)	13.876 (13.614)	0.022 (0.055)	3.731 (4.253)	0.033 (0.038)
IMT	257	0.051 (0.020)	3.516 (5.523)	0.094 (0.206)	1.095 (1.132)	10.688 (10.692)	0.110 (0.293)	1.009 (1.579)	0.015 (-0.002)
Pooled	5958	0.063 (0.041)	1.895 (2.888)	0.000 (0.029)	1.042 (1.129)	11.277 (11.471)	0.015 (0.070)	1.613 (2.254)	-0.002 (-0.066)

Note:

1) This table is based on earnings measure X4 (i.e., earnings before extraordinary items).
2) N is the number of firm-years, E/P is earnings-to-price ratio, P/B is market-to-book ratio, RD/B is R&D-to-book ratio, BG is book value growth rate, LMV is logarithm of market value, FRI/B is analyst-based one-year ahead RI forecast-to-book ratio, P is stock price, and RI is residual income.
3) The figures are median values. The mean values are shown in parentheses.
4) For details of low-tech and high-tech industries in Panel G, see Appendix 7.2.
5) Industry groups in Panel H are based on FTSE classification (level 3). RSR is resources, BIN is basic industries, GIN is general industries, CGD is cyclical consumer goods, NCG is non-cyclical consumer goods, CSV is cyclical services, NSV is non-cyclical services, UTL is utilities, and IMT is information technology.

Table 7.3: Correlation between firm-specific ex-ante variables

		Pearson correlation coefficients							
		E/P	P/B	RD/B	BG	LMV	FRI/B	P	RI
Spearman correlation coefficients	E/P		-0.007	-0.059	0.040	0.097	0.053	0.056	**0.308**
			(0.582)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
	P/B	**-0.179**		**0.289**	-0.004	0.059	**0.821**	0.054	0.037
		(0.000)		(0.000)	(0.775)	(0.000)	(0.000)	(0.000)	(0.004)
	RD/B	-0.070	**0.227**		-0.018	0.031	0.050	0.003	0.007
		(0.000)	(0.000)		(0.169)	(0.016)	(0.000)	(0.794)	(0.588)
	BG	**0.199**	**0.188**	-0.002		0.005	-0.002	0.021	0.037
		(0.000)	(0.000)	(0.876)		(0.719)	(0.887)	(0.102)	(0.004)
	LMV	-0.057	**0.323**	**0.251**	**0.129**		0.063	**0.410**	0.069
		(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
	FRI/B	**0.215**	**0.742**	**0.145**	**0.200**	**0.226**		0.009	0.058
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.466)	(0.000)
	P	0.020	**0.318**	**0.168**	**0.200**	**0.612**	**0.191**		**-0.191**
		(0.121)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)
	RI	**0.367**	**0.628**	**0.109**	**0.472**	**0.228**	**0.747**	**0.278**	
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Note:

1) This table is based on earnings measure X4 (i.e., earnings before extraordinary items).
2) E/P is earnings-to-price ratio, P/B is market-to-book ratio, RD/B is R&D-to-book ratio, BG is book value growth rate, LMV is logarithm of market value, FRI/B is analyst-based one-year ahead RI forecast-to-book ratio, P is stock price, and RI is residual income.
3) The figures in parentheses are p-values.
4) Bold numbers indicate the correlation coefficients whose absolute magnitude is greater than 0.1 and p-value is less than 1%.

Table 7.4: Applicability of valuation models across firm-specific ex-ante variables

Bold numbers indicate the most unbiased (the smallest deviation from zero) and the most accurate median and mean value estimates across models given a specified condition (i.e., horizontal comparison). For the equality test of medians and means across models, Wilcoxon signed rank test and paired t test are used respectively. On the other hand, # indicates the most unbiased and the most accurate median and mean value estimates across conditions given a specified model (i.e., vertical comparison). Wilcoxon rank sum test is used for the equality test of medians across conditions, while Cochran t test (unequal variances) or pooled t test (equal variances) is used for the equality test of means across conditions. 10% significance level is used for all kinds of hypothesis test. LID9 is OI-inclusive Ohlson (1995) LID model, LID16 is OI and intercept-inclusive LID model with the assumption of 4% book value growth and EBO5 is 2-year horizon EBO model with the assumption of 4% RI growth (see Table 7.1 for valuation formula).

< Bias and accuracy using pooled data >

	Bias			Accuracy		
	LID9	LID16	EBO5	LID9	LID16	EBO5
Median	-0.437	**-0.211**	-0.370	0.478	**0.395**	0.397
Mean	-0.289	**0.002**	-0.312	**0.505**	0.519	**0.495**

Panel A: Across earnings-to-price (E/P) ratio

	Bias			Accuracy		
	LID9	LID16	EBO5	LID9	LID16	EBO5
Median						
PF1 (low)	-0.284	**0.007#**	-0.531	**0.492**	0.518	0.579
PF2	-0.563	**-0.388**	-0.453	0.573	**0.452**	**0.464**
PF3	-0.535	**-0.353**	-0.393	0.541	**0.395**	**0.402**
PF4	-0.444	**-0.208**	-0.299	0.451	0.332#	**0.319**
PF5 (high)	-0.237#	**0.083**	-0.112#	0.325#	0.343	**0.240#**
Mean						
PF1 (low)	**-0.076#**	0.279	-0.483	**0.616**	0.756	0.775
PF2	-0.478	**-0.262**	-0.374	0.543	**0.465**	0.497
PF3	-0.459	**-0.231**	-0.345	0.504	**0.413**	**0.428**
PF4	-0.368	**-0.102#**	-0.238	0.426#	**0.373#**	**0.379#**
PF5 (high)	**-0.064#**	0.325	**-0.122#**	0.437#	0.589	**0.396#**

Table 7.4 (continued)

Panel B: Across market-to-book (P/B) ratio

	Bias			Accuracy		
	LID9	LID16	EBO5	LID9	LID16	EBO5
Median						
PF1 (low)	**0.123**#	0.657	-0.481	**0.211**#	0.658	0.531
PF2	-0.274	**0.080**#	-0.359#	0.287	**0.201**#	0.386
PF3	-0.450	**-0.206**	-0.345#	0.452	**0.223**	0.373#
PF4	-0.576	-0.402	**-0.352**#	0.577	0.407	**0.369**#
PF5 (high)	-0.704	-0.612	**-0.371**	0.705	0.615	**0.395**
Mean						
PF1 (low)	**0.417**	1.017	-0.465	**0.521**	1.039	0.697
PF2	-0.225#	**0.118**#	-0.295#	0.292#	**0.270**#	0.415#
PF3	-0.423	**-0.179**	-0.294#	0.447	**0.264**#	0.414#
PF4	-0.542	-0.371	**-0.285**#	0.567	**0.410**	**0.416**#
PF5 (high)	-0.672	-0.577	**-0.223**#	0.700	0.613	**0.532**

Panel C: Across R&D-to-book (RD/B) ratio

	Bias			Accuracy		
	LID9	LID16	EBO5	LID9	LID16	EBO5
Median						
PF1 (zero)	-0.402#	**-0.159**#	-0.376	0.458	**0.391**	0.404
PF2 (low)	-0.406#	**-0.169**#	-0.345#	0.438#	**0.340**#	**0.367**#
PF3 (high)	-0.585	-0.428	**-0.372**	0.594	0.472	**0.403**
Mean						
PF1 (zero)	-0.240#	**0.074**	-0.324#	**0.496**	0.539	**0.502**
PF2 (low)	-0.282	**0.014**#	-0.295#	0.450#	0.442#	**0.404**#
PF3 (high)	-0.490	**-0.296**	**-0.284**#	0.595	**0.517**	**0.557**

Panel D: Across book value growth (BG)

	Bias			Accuracy		
	LID9	LID16	EBO5	LID9	LID16	EBO5
Median						
PF1 (low)	-0.376#	**-0.154**	-0.366	0.495	0.441	**0.410**
PF2	-0.360#	**-0.110**#	-0.384	0.413#	**0.355**#	**0.404**
PF3	-0.369#	**-0.096**#	-0.394	0.418#	**0.340**#	0.410
PF4	-0.494	**-0.296**	-0.335#	0.507	0.390	**0.364**#
PF5 (high)	-0.550	**-0.381**	**-0.373**	0.569	0.468	**0.400**
Mean						
PF1 (low)	**-0.145**#	0.149	-0.328#	**0.589**	0.661	**0.621**
PF2	-0.214	**0.109**#	-0.364	**0.462**#	0.513	**0.482**
PF3	-0.254	**0.099**#	-0.348	**0.436**#	0.476#	0.463
PF4	-0.395	**-0.145**	-0.250#	0.482	0.432#	**0.396**#
PF5 (high)	-0.437	**-0.204**	-0.270#	0.558	**0.514**	**0.512**

Table 7.4 (continued)

Panel E: Across firm size (i.e., across logarithm of market value (LMV))

	Bias			Accuracy		
	LID9	LID16	EBO5	LID9	LID16	EBO5
Median						
PF1 (small)	**-0.151**$^{\#}$	0.183	-0.279$^{\#}$	**0.354**$^{\#}$	0.404	0.380
PF2	-0.372	**-0.139**$^{\#}$	-0.328	0.437	0.383	**0.359**$^{\#}$
PF3	-0.499	**-0.305**	-0.382	0.520	0.405	**0.400**
PF4	-0.541	**-0.361**	-0.406	0.550	**0.423**	**0.414**
PF5 (large)	-0.488	**-0.281**	-0.398	0.493	**0.352**$^{\#}$	0.420
Mean						
PF1 (small)	**0.062**$^{\#}$	0.489	-0.221$^{\#}$	**0.513**$^{\#}$	0.746	0.604
PF2	-0.247	**0.068**$^{\#}$	-0.291$^{\#}$	**0.470**$^{\#}$	0.516	**0.458**$^{\#}$
PF3	-0.361	**-0.101**	-0.352	0.528	**0.495**	**0.473**$^{\#}$
PF4	-0.459	**-0.235**	-0.367	0.532	**0.456**	**0.478**$^{\#}$
PF5 (large)	-0.441	**-0.213**	-0.329	0.483$^{\#}$	**0.383**$^{\#}$	0.461$^{\#}$

Panel F: Across analyst-based one-year ahead RI forecast-to-book (FRI/B) ratio

	Bias			Accuracy		
	LID9	LID16	EBO5	LID9	LID16	EBO5
Median						
PF1 (low)	**-0.043**$^{\#}$	0.329	-0.692	**0.342**	0.520	0.700
PF2	-0.298	**0.055**$^{\#}$	-0.419	**0.327**$^{\#}$	**0.291**$^{\#}$	0.429
PF3	-0.432	**-0.177**	-0.321	0.439	**0.294**$^{\#}$	0.347
PF4	-0.557	-0.370	**-0.294**	0.558	0.387	**0.325**$^{\#}$
PF5 (high)	-0.659	-0.554	**-0.225**$^{\#}$	0.666	0.568	**0.329**
Mean						
PF1 (low)	**0.199**$^{\#}$	0.688	-0.812	**0.620**	0.943	0.865
PF2	-0.216	**0.148**	-0.359	**0.337**$^{\#}$	0.386	0.412
PF3	-0.372	**-0.085**$^{\#}$	-0.248	0.413	**0.332**$^{\#}$	**0.345**$^{\#}$
PF4	-0.500	-0.302	**-0.172**	0.521	**0.387**	**0.368**$^{\#}$
PF5 (high)	-0.556	-0.440	**0.031**$^{\#}$	0.635	0.547	**0.485**

Table 7.4 (continued)

Panel G: Across technology innovation

	Bias			Accuracy		
	LID9	LID16	EBO5	LID9	LID16	EBO5
Median						
low-tech	-0.372$^{\#}$	**-0.132$^{\#}$**	-0.365$^{\#}$	0.439$^{\#}$	**0.369$^{\#}$**	**0.386$^{\#}$**
high-tech	-0.565	**-0.404**	**-0.383$^{\#}$**	0.583	**0.485**	**0.422**
Mean						
low-tech	-0.216$^{\#}$	**0.124$^{\#}$**	-0.365	**0.464$^{\#}$**	0.521$^{\#}$	**0.464$^{\#}$**
high-tech	-0.463	**-0.257**	**-0.278$^{\#}$**	0.567	**0.518$^{\#}$**	0.624

Note: For details of low-tech and high-tech industries, see Appendix 7.2.

Panel H: Across industry sectors

	Bias			Accuracy		
	LID9	LID16	EBO5	LID9	LID16	EBO5
Median						
RSR	-0.335	**-0.080$^{\#}$**	-0.527	**0.458**	**0.375**	0.541
BIN	-0.352	**-0.076$^{\#}$**	-0.399	0.409	**0.352$^{\#}$**	0.411
GIN	-0.480	**-0.275**	-0.348	0.509	0.390$^{\#}$	**0.364**
CGD	-0.360	**-0.094$^{\#}$**	-0.300	0.421	0.369$^{\#}$	**0.346**
NCG	-0.470	**-0.292**	-0.369	0.481	**0.394**	**0.398**
CSV	-0.463	**-0.245**	-0.402	0.511	**0.422**	0.423
NSV	-0.472	**-0.232**	-0.372	0.473	**0.345$^{\#}$**	**0.392**
UTL	-0.059$^{\#}$	0.283	**0.003$^{\#}$**	0.244$^{\#}$	0.309$^{\#}$	**0.166$^{\#}$**
IMT	-0.608	-0.487	**-0.330**	0.639	0.570	**0.401**
Mean						
RSR	**-0.162**	0.175	**-0.290**	**0.529**	0.592	0.768
BIN	-0.221	**0.111**	-0.362	**0.424**	0.465	0.461
GIN	-0.324	**-0.062**	-0.309	0.511	0.486	**0.420**
CGD	**-0.171**	0.195	**-0.176$^{\#}$**	**0.481**	0.580	**0.503**
NCG	-0.422	**-0.176**	-0.368	0.490	**0.445**	0.474
CSV	-0.283	**0.009$^{\#}$**	-0.377	0.557	0.576	**0.518**
NSV	-0.414	**-0.190**	**-0.278**	0.448	**0.359$^{\#}$**	0.490
UTL	**-0.024$^{\#}$**	0.371	0.079$^{\#}$	**0.273$^{\#}$**	0.451	**0.307$^{\#}$**
IMT	-0.460	-0.290	**-0.002$^{\#}$**	0.605	**0.566**	0.727

Note: Industry groups are based on FTSE classification (level 3). RSR is resources, BIN is basic industries, GIN is general industries, CGD is cyclical consumer goods, NCG is non-cyclical consumer goods, CSV is cyclical services, NSV is non-cyclical services, UTL is utilities, and IMT is information technology.

Table 7.5: Regression of value-to-price ratio on firm-specific ex-ante variables

Panel A: Linear terms and industry dummies

$$V/P^{c,3} = \alpha_0 + \alpha_1(E/P) + \alpha_2(P/B) + \alpha_3(RD/B) + \alpha_4(BG) + \alpha_5(LMV) + \alpha_6(FRI/B) + \beta_1 IND_1 + \beta_2 IND_2 + \beta_3 IND_3 + \beta_4 IND_4 + \beta_5 IND_5 + \beta_6 IND_6 + \beta_7 IND_7 + \beta_8 IND_8$$

	LID9	LID16	EBO5
α_0	1.625 (46.83)***	2.207 (42.08)***	1.041 (25.24)***
α_1 (*E/P*)	-0.924 (-17.02)***	-1.094 (-13.34)***	0.186 (3.01)***
α_2 (*P/B*)	-0.126 (-44.76)***	-0.177 (-42.00)***	-0.075 (-22.13)***
α_3 (*RD/B*)	-0.293 (-3.25)***	-0.400 (-2.94)***	0.231 (2.14)**
α_4 (*BG*)	-0.072 (-5.30)***	-0.061 (-2.96)***	-0.019 (-1.18)
α_5 (*LMV*)	-0.047 (-19.79)***	-0.065 (-17.99)***	-0.027 (-9.61)***
α_6 (*FRI/B*)	0.362 (11.02)***	0.297 (6.03)***	1.870 (45.94)***
β_1 (IND_1)	0.047 (1.36)	0.110 (2.10)**	-0.035 (-0.84)
β_2 (IND_2)	-0.000 (-0.01)	0.037 (1.00)	0.041 (1.40)
β_3 (IND_3)	-0.030 (-1.31)	-0.032 (-0.93)	0.036 (1.29)
β_4 (IND_4)	-0.019 (-0.75)	0.003 (0.08)	0.102 (3.34)***
β_5 (IND_5)	-0.026 (-1.06)	-0.010 (-0.27)	0.048 (1.65)
β_6 (IND_6)	-0.011 (-0.50)	0.013 (0.37)	0.007 (0.23)
β_7 (IND_7)	-0.057 (-1.66)*	-0.071 (-1.36)	0.031 (0.76)
β_8 (IND_8)	0.322 (9.44)***	0.415 (8.04)***	0.383 (9.41)***
Adj. R^2	0.441	0.421	0.331
N	5611	5613	5620

Table 7.5 (continued)

Panel B: Linear and quadratic terms

$$V/P^{c,3} = \alpha_0 + \alpha_1(E/P) + \alpha_2(E/P)^2 + \alpha_3(P/B) + \alpha_4(P/B)^2 + \alpha_5(RD/B) + \alpha_6(RD/B)^2 + \alpha_7(BG) + \alpha_8(BG)^2 + \alpha_9(LMV) + \alpha_{10}(LMV)^2 + \alpha_{11}(FRI/B) + \alpha_{12}(FRI/B)^2$$

	LID9	LID16	EBO5
α_0	2.225 (18.09)***	2.913 (15.43)***	1.905 (11.03)***
α_1 (*E/P*)	-0.651 (-12.95)***	-0.873 (-10.87)***	0.108 (1.62)
α_2 $(E/P)^2$	2.179 (14.12)***	1.786 (6.88)***	-0.748 (-3.75)***
α_3 (*P/B*)	-0.332 (-62.63)***	-0.489 (-59.89)***	-0.094 (-12.50)***
α_4 $(P/B)^2$	0.020 (44.32)***	0.029 (43.14)***	0.001 (2.31)**
α_5 (*RD/B*)	-0.028 (-0.18)	-0.291 (-1.25)	0.475 (2.21)**
α_6 $(RD/B)^2$	-0.298 (-0.54)	0.489 (0.58)	-0.793 (-1.02)
α_7 (*BG*)	-0.172 (-4.43)***	-0.152 (-2.56)**	-0.058 (-1.05)
α_8 $(BG)^2$	0.055 (4.04)***	0.059 (2.80)***	0.012 (0.62)
α_9 (*LMV*)	-0.125 (-5.97)***	-0.141 (-4.39)***	-0.161 (-5.45)***
α_{10} $(LMV)^2$	0.004 (5.00)***	0.005 (3.52)***	0.006 (4.69)***
α_{11} (*FRI/B*)	0.635 (17.94)***	0.717 (13.18)***	2.155 (42.65)***
α_{12} $(FRI/B)^2$	-0.133 (-3.13)***	-0.210 (-3.22)***	-0.613 (-9.82)***
Adj. R^2	0.607	0.577	0.326
N	5611	5613	5620

Note:
1) This table is based on earnings measure X4 (i.e., earnings before extraordinary items).
2) LID9 is OI-inclusive Ohlson (1995) LID model, LID16 is OI and intercept-inclusive LID model with the assumption of 4% book value growth and EBO5 is 2-year horizon EBO model with the assumption of 4% RI growth (see Table 7.1 for valuation formula).
3) V is value estimate, $P^{c,3}$ is observed stock price at 3 months after the fiscal year end, *E/P* is earnings-to-price ratio, *P/B* is market-to-book ratio, *RD/B* is R&D-to-book ratio, *BG* is book value growth rate, *LMV* is logarithmic market value, *FRI/B* is analyst-based one-year ahead RI forecast-to-book ratio, and IND_t is dummy variable representing industry group to which a firm belongs.
   IND_1 = 1 if industry group is RSR, 0 otherwise; IND_2 = 1 if industry group is BIN, 0 otherwise
   IND_3 = 1 if industry group is GIN, 0 otherwise; IND_4 = 1 if industry group is CGD, 0 otherwise
   IND_5 = 1 if industry group is NCG, 0 otherwise; IND_6 = 1 if industry group is CSV, 0 otherwise
   IND_7 = 1 if industry group is NSV, 0 otherwise; IND_8 = 1 if industry group is UTL, 0 otherwise
4) The figures in parentheses are *t* statistics.
5) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
6) Industry groups are based on FTSE classification (level 3). RSR is resources, BIN is basic industries, GIN is general industries, CGD is cyclical consumer goods, NCG is non-cyclical consumer goods, CSV is cyclical services, NSV is non-cyclical services, UTL is utilities, and IMT is information technology.

Table 7.6: Regression of absolute valuation error on firm-specific ex-ante variables

Panel A: Linear terms and industry dummies

$$AFE = \alpha_0 + \alpha_1(E/P) + \alpha_2(P/B) + \alpha_3(RD/B) + \alpha_4(BG) + \alpha_5(LMV) + \alpha_6(FRI/B)$$
$$+ \beta_1 IND_1 + \beta_2 IND_2 + \beta_3 IND_3 + \beta_4 IND_4 + \beta_5 IND_5 + \beta_6 IND_6 + \beta_7 IND_7 + \beta_8 IND_8$$

	LID9	LID16	EBO5
α_0	0.143 (5.90)***	0.798 (18.79)***	0.425 (12.06)***
α_1 (*E/P*)	-0.325 (-8.60)***	-0.706 (-10.62)***	-0.627 (-11.71)***
α_2 (*P/B*)	0.070 (35.87)***	0.031 (9.05)***	0.004 (1.29)
α_3 (*RD/B*)	0.201 (3.19)***	0.034 (0.31)	0.453 (4.93)***
α_4 (*BG*)	0.042 (4.42)***	0.011 (0.69)	0.040 (2.88)***
α_5 (*LMV*)	0.011 (6.38)***	-0.036 (-12.39)***	0.002 (0.76)
α_6 (*FRI/B*)	-0.152 (-6.62)***	-0.122 (-3.04)***	-0.495 (-14.38)***
β_1 (IND_1)	-0.023 (-0.96)	0.080 (1.89)*	0.101 (2.87)***
β_2 (IND_2)	-0.032 (-1.90)*	0.001 (0.03)	-0.028 (-1.11)
β_3 (IND_3)	0.016 (1.01)	0.003 (0.12)	-0.060 (-2.53)**
β_4 (IND_4)	0.010 (0.57)	0.022 (0.72)	-0.095 (-3.65)***
β_5 (IND_5)	-0.008 (-0.46)	-0.006 (-0.19)	-0.023 (-0.95)
β_6 (IND_6)	0.010 (0.65)	0.031 (1.11)	0.017 (0.73)
β_7 (IND_7)	0.003 (0.11)	-0.013 (-0.30)	-0.033 (-0.94)
β_8 (IND_8)	-0.119 (-5.01)***	0.133 (3.18)***	-0.149 (-4.31)***
Adj. R^2	0.323	0.069	0.117
N	5612	5613	5616

Table 7.6 (continued)

Panel B: Linear and quadratic terms

$$AFE = \alpha_0 + \alpha_1(E/P) + \alpha_2(E/P)^2 + \alpha_3(P/B) + \alpha_4(P/B)^2 + \alpha_5(RD/B) + \alpha_6(RD/B)^2 + \alpha_7(BG) + \alpha_8(BG)^2 + \alpha_9(LMV) + \alpha_{10}(LMV)^2 + \alpha_{11}(FRI/B) + \alpha_{12}(FRI/B)^2$$

	LID9	LID16	EBO5
α_0	-0.006 (-0.06)	1.147 (6.54)***	0.443 (3.15)***
α_1 (*E/P*)	-0.107 (-2.73)***	-0.331 (-4.44)***	-0.352 (-6.40)***
α_2 $(E/P)^2$	1.736 (14.40)***	2.572 (10.65)***	0.571 (3.43)***
α_3 (*P/B*)	0.169 (40.75)***	-0.011 (-1.44)	0.005 (0.82)
α_4 $(P/B)^2$	-0.009 (-25.30)***	0.005 (7.19)***	0.000 (0.31)
α_5 (*RD/B*)	0.111 (0.94)	-0.052 (-0.24)	0.169 (0.97)
α_6 $(RD/B)^2$	-0.011 (-0.03)	0.138 (0.18)	0.263 (0.42)
α_7 (*BG*)	0.134 (4.43)***	0.123 (2.23)**	0.002 (0.04)
α_8 $(BG)^2$	-0.038 (-3.55)***	-0.034 (-1.74)*	0.020 (1.29)
α_9 (*LMV*)	0.005 (0.29)	-0.114 (-3.79)***	-0.012 (-0.48)
α_{10} $(LMV)^2$	-0.000 (-0.17)	0.004 (2.92)***	0.001 (0.74)
α_{11} (*FRI/B*)	-0.355 (-12.83)***	-0.193 (-3.81)***	-1.023 (-25.03)***
α_{12} $(FRI/B)^2$	0.182 (5.47)***	0.188 (3.10)***	1.193 (23.58)***
Adj. R^2	0.401	0.104	0.197
N	5612	5613	5616

Note:
1) This table is based on earnings measure X4 (i.e., earnings before extraordinary items).
2) LID9 is OI-inclusive Ohlson (1995) LID model, LID16 is OI and intercept-inclusive LID model with the assumption of 4% book value growth and EBO5 is 2-year horizon EBO model with the assumption of 4% RI growth (see Table 7.1 for valuation formula).
3) *AFE* is absolute valuation error, defined as ABS(V - $P^{c,3}$) / $P^{c,3}$ where V is value estimate and $P^{c,3}$ is observed stock price at 3 months after the fiscal year end. *E/P* is earnings-to-price ratio, *P/B* is market-to-book ratio, *RD/B* is R&D-to-book ratio, *BG* is book value growth rate, *LMV* is logarithmic market value, *FRI/B* is analyst-based one-year ahead RI forecast-to-book ratio, and IND_t is dummy variable representing industry group to which a firm belongs.
   IND_1 = 1 if industry group is RSR, 0 otherwise; IND_2 = 1 if industry group is BIN, 0 otherwise
   IND_3 = 1 if industry group is GIN, 0 otherwise; IND_4 = 1 if industry group is CGD, 0 otherwise
   IND_5 = 1 if industry group is NCG, 0 otherwise; IND_6 = 1 if industry group is CSV, 0 otherwise
   IND_7 = 1 if industry group is NSV, 0 otherwise; IND_8 = 1 if industry group is UTL, 0 otherwise
4) The figures in parentheses are *t* statistics.
5) ***, **, * show that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.
6) Industry groups are based on FTSE classification (level 3). RSR is resources, BIN is basic industries, GIN is general industries, CGD is cyclical consumer goods, NCG is non-cyclical consumer goods, CSV is cyclical services, NSV is non-cyclical services, UTL is utilities, and IMT is information technology.

Appendix 7.1: Examples for differences between alternative RIV models

Panel A: Ohlson LID versus 2-year horizon EBO

$$x_t^a = 1, f_{t+1}^a = 0.7, f_{t+2}^a = 0.45, b_t = 5, \omega_1 = 0.6, \gamma_1 = 0.3, r = 12\%$$

Year ahead	Ohlson LID		EBO5 (g_r = 4%)		EBO2 (g_r = 0%)	
	future RI	PV	future RI	PV	future RI	PV
1	0.700	0.625	0.700	0.625	0.700	0.625
2	0.450	0.359	0.450	0.359	0.450	0.359
3	0.279	0.199	0.468	0.333	0.450	0.320
4	0.170	0.108	0.487	0.309	0.450	0.286
5	0.103	0.058	0.506	0.287	0.450	0.255
6	0.062	0.031	0.526	0.267	0.450	0.228
7	0.037	0.017	0.547	0.248	0.450	0.204
8	0.022	0.009	0.569	0.230	0.450	0.182
9	0.013	0.005	0.592	0.214	0.450	0.162
10	0.008	0.003	0.616	0.198	0.450	0.145
11	0.005	0.001	0.640	0.184	0.450	0.129
12	0.003	0.001	0.666	0.171	0.450	0.116
13	0.002	0.000	0.693	0.159	0.450	0.103
14	0.001	0.000	0.720	0.147	0.450	0.092
15	0.001	0.000	0.749	0.137	0.450	0.082
16	0.000	0.000	0.779	0.127	0.450	0.073
17	0.000	0.000	0.810	0.118	0.450	0.066
18	0.000	0.000	0.843	0.110	0.450	0.059
19	0.000	0.000	0.877	0.102	0.450	0.052
20	0.000	0.000	0.912	0.095	0.450	0.047
21	0.000	0.000	0.948	0.088	0.450	0.042
22	0.000	0.000	0.986	0.081	0.450	0.037
23	0.000	0.000	1.025	0.076	0.450	0.033
24	0.000	0.000	1.066	0.070	0.450	0.030
25	0.000	0.000	1.109	0.065	0.450	0.026
26	0.000	0.000	1.153	0.061	0.450	0.024
27	0.000	0.000	1.200	0.056	0.450	0.021
28	0.000	0.000	1.248	0.052	0.450	0.019
29	0.000	0.000	1.298	0.049	0.450	0.017
30	0.000	0.000	1.349	0.045	0.450	0.015
PVRI		1.417		5.644		3.973

Appendix 7.1 (continued)

Panel B: 'Intercept-inclusive' LID versus 2-year horizon EBO

$x_t^a = 1, f_{t+1}^a = 0.7, f_{t+2}^a = 0.501, b_t = 5, \omega_0 = -0.02, \omega_1 = 0.6, \gamma_0 = 0.025, \gamma_1 = 0.3, r = 12\%$

Year ahead	'Intercept-inclusive' LID (bg = 4%)		'Intercept-inclusive' LID (bg = 0%)		EBO5 (g_r = 4%)		EBO2 (g_r = 0%)	
	future RI	PV	future RI	PV	future RI	PV	future RI	PV
1	0.700	0.625	0.700	0.625	0.700	0.625	0.700	0.625
2	0.501	0.399	0.501	0.399	0.501	0.399	0.501	0.399
3	0.378	0.269	0.379	0.270	0.521	0.371	0.501	0.357
4	0.305	0.194	0.306	0.195	0.542	0.344	0.501	0.318
5	0.264	0.150	0.262	0.149	0.564	0.320	0.501	0.284
6	0.242	0.123	0.236	0.120	0.586	0.297	0.501	0.254
7	0.233	0.105	0.220	0.100	0.610	0.276	0.501	0.227
8	0.230	0.093	0.211	0.085	0.634	0.256	0.501	0.202
9	0.232	0.084	0.205	0.074	0.659	0.238	0.501	0.181
10	0.238	0.076	0.202	0.065	0.686	0.221	0.501	0.161
11	0.245	0.070	0.200	0.057	0.713	0.205	0.501	0.144
12	0.253	0.065	0.198	0.051	0.742	0.190	0.501	0.129
13	0.262	0.060	0.198	0.045	0.771	0.177	0.501	0.115
14	0.272	0.056	0.197	0.040	0.802	0.164	0.501	0.103
15	0.283	0.052	0.197	0.036	0.834	0.152	0.501	0.092
16	0.294	0.048	0.197	0.032	0.868	0.142	0.501	0.082
17	0.305	0.044	0.197	0.029	0.902	0.131	0.501	0.073
18	0.317	0.041	0.197	0.026	0.938	0.122	0.501	0.065
19	0.330	0.038	0.196	0.023	0.976	0.113	0.501	0.058
20	0.343	0.036	0.196	0.020	1.015	0.105	0.501	0.052
21	0.357	0.033	0.196	0.018	1.056	0.098	0.501	0.046
22	0.371	0.031	0.196	0.016	1.098	0.091	0.501	0.041
23	0.386	0.028	0.196	0.014	1.142	0.084	0.501	0.037
24	0.402	0.026	0.196	0.013	1.187	0.078	0.501	0.033
25	0.418	0.025	0.196	0.012	1.235	0.073	0.501	0.029
26	0.434	0.023	0.196	0.010	1.284	0.067	0.501	0.026
27	0.452	0.021	0.196	0.009	1.336	0.063	0.501	0.023
28	0.470	0.020	0.196	0.008	1.389	0.058	0.501	0.021
29	0.488	0.018	0.196	0.007	1.445	0.054	0.501	0.019
30	0.508	0.017	0.196	0.007	1.502	0.050	0.501	0.017
PVRI		3.090		2.610		6.213		4.353

Appendix 7.1 (continued)

Panel C: 3 models with negative RI forecasts

$x_t^a = -1, f_{t+1}^a = -0.7, f_{t+2}^a = -0.45, b_t = 5, \omega_0 = -0.02, \omega_1 = 0.6, \gamma_0 = 0.025, \gamma_1 = 0.3, r = 12\%$

Year ahead	Ohlson LID		'Intercept-inclusive' LID ($bg = 4\%$)		EBO5 ($g_r = 4\%$)	
	future RI	PV	future RI	PV	future RI	PV
1	-0.700	-0.625	-0.700	-0.625	-0.700	-0.625
2	-0.450	-0.359	-0.399	-0.318	-0.450	-0.359
3	-0.279	-0.199	-0.180	-0.128	-0.468	-0.333
4	-0.170	-0.108	-0.035	-0.022	-0.487	-0.309
5	-0.103	-0.058	0.058	0.033	-0.506	-0.287
6	-0.062	-0.031	0.118	0.060	-0.526	-0.267
7	-0.037	-0.017	0.158	0.072	-0.547	-0.248
8	-0.022	-0.009	0.186	0.075	-0.569	-0.230
9	-0.013	-0.005	0.206	0.074	-0.592	-0.214
10	-0.008	-0.003	0.221	0.071	-0.616	-0.198
11	-0.005	-0.001	0.235	0.068	-0.640	-0.184
12	-0.003	-0.001	0.247	0.063	-0.666	-0.171
13	-0.002	0.000	0.259	0.059	-0.693	-0.159
14	-0.001	0.000	0.270	0.055	-0.720	-0.147
15	-0.001	0.000	0.281	0.051	-0.749	-0.137
16	0.000	0.000	0.293	0.048	-0.779	-0.127
17	0.000	0.000	0.305	0.044	-0.810	-0.118
18	0.000	0.000	0.317	0.041	-0.843	-0.110
19	0.000	0.000	0.330	0.038	-0.877	-0.102
20	0.000	0.000	0.343	0.036	-0.912	-0.095
21	0.000	0.000	0.357	0.033	-0.948	-0.088
22	0.000	0.000	0.371	0.031	-0.986	-0.081
23	0.000	0.000	0.386	0.028	-1.025	-0.076
24	0.000	0.000	0.401	0.026	-1.066	-0.070
25	0.000	0.000	0.418	0.025	-1.109	-0.065
26	0.000	0.000	0.434	0.023	-1.153	-0.061
27	0.000	0.000	0.452	0.021	-1.200	-0.056
28	0.000	0.000	0.470	0.020	-1.248	-0.052
29	0.000	0.000	0.488	0.018	-1.298	-0.049
30	0.000	0.000	0.508	0.017	-1.349	-0.045
PVRI		-1.417		0.257		-5.644

Note: PVRI denotes present value of all future residual income. EBO5 (EBO2) is 2-year horizon EBO model with the assumption of non-zero (zero) RI growth. x_t^a is current RI, f_{t+1}^a (f_{t+2}^a) is one-year (two-year) ahead RI forecasts, b_t is current book value and r is the discount rate. ω and γ are linear information dynamics parameters.

Appendix 7.2: Industries included in high-tech and low-tech samples

FTSE code	Name	Firm-years
High-tech industries		
252	Electrical Equipment	79
253	Electronic Equipment	220
345	Household Appliances & Housewares	39
446	Medical Equipment & Supplies	119
480	Pharmaceuticals	90
543	Cable & Satellite	4
546	Photography	1
673	Fixed-Line Telecommunications Services	18
678	Wireless Telecommunications Services	9
932	Computer Hardware	16
936	Semiconductors	2
938	Telecommunications Equipment	13
972	Computer Services	109
974	Internet	4
977	Software	113
		836
Low-tech industries		
137	Other Construction	194
156	Paper	25
188	Steel	25
311	Automobiles	5
313	Auto Parts	83
349	Other Textiles & Leather Goods	128
418	Soft Drinks	13
475	Household Products	31
524	Discount, Super Stores & Warehouses	6
536	Hotels	45
591	Airlines & Airports	33
596	Rail, Road & Freight	93
597	Shipping & Ports	50
630	Food & Drug Retailers	118
		849

Note: Industries used for partitioning into high-tech and low-tech industries are based on FTSE level 5 classification.

CHAPTER 8. CONCLUSIONS AND IMPLICATIONS

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CHAPTER 8

CONCLUSIONS AND IMPLICATIONS

8.1. Introduction

Even though the Ohlson (1995) model is accepted as a theoretically well-grounded equity valuation model, its value from a practical standpoint is still at issue. Lundholm (1995) addresses some frequently asked questions – (i) how does the Ohlson model really work? (ii) what about non-accounting information? (iii) how can you claim dividend-irrelevancy when we know that dividend increases are good-news signals? (iv) how restrictive is the linear information dynamic? (v) whether unbiased accounting is better or worse than conservative accounting? (vi) what are the criteria by which we should judge the model? Recent empirical studies including Dechow *et al.* (1999) (DHS) try to answer the above questions, especially questions (i), (ii), (v) and (vi), and give some contributions to the empirical implementation of the Ohlson's linear information dynamics (LID) model.[113]

However, the large negative bias in value estimates based on the Ohlson model, reported in previous empirical studies, seems to be evidence of the poor informativeness of the Ohlson LID with respect to future residual income. I suspect that this large negative bias may be caused by the assumption of unbiased accounting implied in the

[113] Studies by Hand and Landsman (1998, 1999) are related to the question (iii), and their results contrast with the value irrelevancy of dividends implied in the Ohlson model. They try to explain their results through the profitability-signaling role of dividends.

Ohlson model. Another seminal work by Feltham and Ohlson (1995), therefore, attempts to allow for conservative accounting within the linear information dynamics, but its empirical performance is also proved to be poor by some empirical studies including Myers (1999b).[114] In the presence of conservative accounting, future expected RI tends to deviate from zero, and the mean of future expected RI seems to be different from the mean of realised past RI. This means that both RI and OI intercepts in the Ohlson LID are not necessarily zero in practice. The augmentation of the Ohlson model, which is central to my thesis, is straightforward by incorporating RI and OI intercepts into the linear information dynamics. I term the augmented model as the 'intercept-inclusive' LID model.

The main objective of the thesis is to examine whether this 'intercept-inclusive' LID model captures accounting conservatism better than the extant RI-based valuation models. Specifically, the U.S. study in Chapter 4 compares the relative reliability between the 'intercept-inclusive' LID model, the Ohlson model and a special case of the Ohlson model that simply capitalises one-year ahead analysts' earnings forecasts as a flat perpetuity, in terms of bias and accuracy of value estimates. The objective of the U.K. study in Chapter 6 is to provide evidence for U.K. using a larger set of competing models based on three approaches - the Ohlson LID, the 'intercept-inclusive' LID and the EBO approaches. Finally, the U.K. study in Chapter 7 addresses a potentially important issue of the different applicability under different conditions of different RI-based valuation models. The next section summarises the empirical results of these

[114] Given the negative mean of realised past RI (i.e., negative RI intercept), as in DHS, the theoretical Feltham and Ohlson (1995) model induces larger negative bias than the theoretical Ohlson (1995) model (compare two models in Feltham and Ohlson (1995, p. 705) and Ohlson (1995, p669)).

three empirical chapters, and the final section discusses implications and limitations of the thesis.

8.2. Summary of the Empirical Results

Reliability of the 'intercept-inclusive' LID model: U.S. evidence

In Chapter 4, the reliability of the 'intercept-inclusive' LID model is compared to that of the Ohlson LID model and the one-year ahead earnings forecasts capitalisation model. In order to facilitate comparison with the study by DHS, I use U.S. data from 1950 to 1995, which are very similar to those used in DHS. For the estimation of RI and OI parameters, I also follow the procedure used in DHS, but use book value rather than stock price as a scaling variable in order to avoid a circularity problem in the implementation of the 'intercept-inclusive' LID model.

Similar to the results reported in DHS, the substantial negative biases are evident in the extant two models. However, in the 'intercept-inclusive' LID model, the negative biases are largely eliminated. In particular, at the intersection of more plausible discount rates (14% and year-specific) and assumed growth rates of the scaling variable (0%, 2%, 4%), the absolute values of the biases become much smaller. Thus, the incorporation of non-zero RI and OI intercepts into the linear information dynamics seems to capture the effects of conservative accounting well. However, value estimates based on the 'intercept-inclusive' LID model are very sensitive both to the assumed discount rate and to the assumed growth rate of the scaling variable.

Moreover, although value estimates based on the 'intercept-inclusive' LID model are substantially less biased than those based on the extant two models, there is little evidence of improvement in the accuracy of such estimates. The lack of improvement in overall valuation accuracy of the 'intercept-inclusive' LID model seems to arise from i) the increased dispersion in valuation errors due to high sensitivity to both discount rate and growth rate, and ii) the poor applicability for low stock price firms. Together with some complementary tests, it seems to be possible to improve accuracy if we carefully apply the 'intercept-inclusive' LID model by means of the reflection of firm-specific characteristics and properties into the model.

Reliability of competing valuation models: U.K. evidence

Chapter 6 provides results from the replication of DHS and some extensions using U.K. industrial data. First of all, the RI and OI parameters and the relative bias and accuracy of the Ohlson model and its variants are very consistent with U.S. results. Ohlson's AR(1) information dynamics seem to be sufficient to forecast future residual income, but it might be clear that the inclusion of book value in the information dynamics has an additional informational role for predicting future residual income. Second, the results of the relative reliability of various valuation models are robust regardless of the choice of earnings measures, but the abnormal items seem to have decremental effect on the RI persistence because those abnormal items have transitory attributes.

The main results using book value as a scaling variable show that some EBO models and the 'intercept-inclusive' LID model generally seem to perform well in terms of bias and accuracy metrics. More importantly, the development of the 'intercept-inclusive'

LID model significantly reduces the downward bias of value estimates based on the Ohlson LID model. The 'intercept-inclusive' LID model also gives quite good median accuracy, but fails to improve mean accuracy. These results are consistent with U.S. study in Chapter 4.

Finally, the relative ranking of various valuation models in terms of bias, accuracy and explainability is unlikely to be sensitive to the assumption of discount rate and growth rate and the use of different benchmarking stock prices and consensus earnings forecasts. However, the sensitivity of the 'intercept-inclusive' LID model to the assumption of discount rate and growth rate seems to be larger than that of the Ohlson LID model.

Applicability of competing valuation models: U.K. evidence

This study is based on the idea that the models' relative applicability can differ across various firm-specific characteristics and properties, because the implementation procedures and underlying assumptions of competing models are apparently different. This idea is encouraged by the preliminary results showing that none of models dominates other models in all aspects such as median accuracy, mean accuracy, central and extreme tendency.

The study provides evidence that some firm-specific ex-ante variables cause the different applicability of models. In particular, earnings-to-price (E/P) ratio, market-to-book (P/B) ratio and analyst-based one-year ahead RI forecast-to-book (FRI/B) ratio seem to be influential with regard to the applicability of models. Specifically, the 'intercept-inclusive' LID model gives rise to reliable value estimates for moderate E/P, P/B and FRI/B firms, while the Ohlson LID (the EBO) model is likely to perform well for low (high) E/P, P/B, and FRI/B firms. However, R&D-to-book (RD/B) ratio, book value growth (BG), firm size and industry membership are unlikely to be determinants of models' relative applicability. These results using a test of equality of portfolio means and medians, together with graphical illustration, are confirmed by regression analysis.

8.3. Implications and limitations

The Ohlson model must be useful in the context that it provides a unifying framework for a number of 'ad hoc' valuation models using book value, earnings, and short-term forecasts of earnings. However, most recent studies show that the Ohlson model largely understates the market's expectations. If these empirical results are reliably true, some adjustments might be needed to the Ohlson model in order to reflect practical aspects.

This thesis has an important implication to the empirical and theoretical research on the reliability of the LID model. In fact, when the Ohlson model is criticized in terms of its validity, it is not the RIV relationship itself, but the assumed linear information dynamics that is still controversial. There is of course much room to modify the Ohlson's linear information dynamics in order better to estimate intrinsic value. This thesis is one of those efforts to capture market's expectations better than the Ohlson model by allowing for conservative accounting. Even if the results of the study show that the 'intercept-inclusive' LID model does not work in all circumstances and in terms of all performance metrics, the development of the 'intercept-inclusive' LID model rectifies quite well the downward bias of the value estimates arising from the implementation of the Ohlson model.

Moreover, the 'intercept-inclusive' LID model adds an intercept parameter to the OI generating process, which is a crucial difference compared to the Feltham and Ohlson (1995) model, so that it allows the mean of expected future RI to differ from that of past realised RI. Value estimates based on the 'intercept-inclusive' LID model seem to reflect more fully the effect of conservative accounting than the Feltham and Ohlson model (unreported, but through indirect comparison). Consequently, value estimates based on the 'intercept-inclusive' LID model are likely to be superior to those from the implementation of the Ohlson unbiased-accounting LID model and the Feltham and Ohlson conservative-accounting LID model.

The study also gives some important contributions to accounting-based equity valuation in the empirical perspective. One is the comparison between the LID-type approach and the EBO-type approach, and the other is the applicability test of models. Even though both LID-type and EBO-type approaches are the main concern in RI-based valuation research, there is no explicit study on the comparison between the two approaches so far. The two approaches are based on apparently different implementation procedures and underlying assumptions, so that it is of interest to examine which approach dominates the other approach and why. In the study, the LID approaches based on the Ohlson model and the 'intercept-inclusive' model are compared with the EBO approach.

The applicability test of models across various firm-specific characteristics and properties is also an important empirical issue. In fact, it is very difficult for a specific valuation model to work best under all conditions in the complicated real world. Thus, it is likely that a particular model dominates other models in some, but not all circumstances. Related to this issue, I explore firm-specific characteristics and properties that might be potential determinants to the different applicability of valuation models. This issue could be quite important especially for practitioners, because equity valuation is a task that must be carried out on a firm-by-firm basis ultimately.

Despite some contributions of this study, there are also several limitations that need to be explored in further research. First, as shown in Chapter 4 and 6, value estimates based on the 'intercept-inclusive' LID approach are very sensitive to the assumed discount rate and growth rate. This means that estimation errors or unreasonable assumptions of discount rate and growth rate can lead to serious errors in value estimates. Thus, how to estimate those components is an important issue in further research.

Second, Chapter 4 and 6 also provide evidence that the 'intercept-inclusive' LID model does not appear to improve the overall accuracy of value estimates. This may be related to high sensitivity of value estimates to discount rates and growth rates discussed above. Another possible explanation of the lack of improvement is that this model works very poorly for some firms. For instance, the 'intercept-inclusive' LID model seems to give rise to very high positive bias for low stock price firms. Thus, firm-specific properties that lead to the poor applicability of the model need to be identified first (as in the study in Chapter 7) and then the 'intercept-inclusive' LID model needs to be further modified in order to capture the effect of those properties.

Third, some results as to the applicability test in Chapter 7 are not consistent with my predictions. The unclear or inconsistent results might be due to i) wrong prediction development, ii) wrong variable construction and/or iii) mis-specification of models. The possibility of model mis-specification is already mentioned above. It could be an important theoretical issue to modify the 'intercept-inclusive' LID model that adjusts better firm-specific properties such as accounting conservatism, future growth potential, future profitability. Predictions and variables could also be further developed in future research through the careful examination of models' characteristic and the information content of various ex-ante firm-specific properties.

In addition, the estimation of firm-specific RI and OI parameters could be developed following the idea in DHS. As mentioned above, equity valuation is ultimately for a specific stock, so how to estimate firm-specific RI and OI parameters might be an important issue for practitioners. Finally, it may be worth searching for earnings measures that are more relevant to firms' performance. As I suggested in Chapter 5, IIMR headline earnings and I/B/E/S actuals rather than the four earnings measures used in this study might be more related to stock prices because analysts and investors increasingly depend on these earnings definitions.

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