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Bias, accuracy and explainability of the Ohlson (1995) valuation model *vs.* the traditional dividend, abnormal earnings and free cash flow models: evidence from the Spanish stock market [*]

Sesgo, precisión y capacidad explicativa del modelo de valoración de Ohlson (1995) frente a los modelos tradicionales de dividendos, resultados anormales y flujos libres de caja: evidencia para el mercado bursátil español

Raúl Iñiguez Sánchez [**]**.** Universidad de Alicante
Carmelo Reverte Maya. Universidad Politécnica de Cartagena

ABSTRACT In this paper we compare the bias, accuracy and explainability of the Ohlson (1995) valuation model versus the traditional dividend, abnormal earnings and free cash flow models for a sample of Spanish listed firms over the period 2000-2008. The study aims to replicate the actual behaviour of financial practitioners when they estimate the value of a firm's shares. Our results document that the most accurate model is the Ohlson (1995) specification that considers the «other information» variable and intermediate persistence for both abnormal earnings and the «other information» variable. The abnormal earnings model also has a high performance, especially for the zero-growth case, confirming that a firm cannot increase abnormal earnings indefinitely. Finally, we have also assessed the relative performance of each model by computing future abnormal returns from a strategy based on the V/P ratio (intrinsic value divided by price). Our results provide evidence that most models are able, on average, of identifying overvalued and undervalued shares.

KEYWORDS Ohlson model; Valuation; Dividends; Abnormal earnings; Free cash-flow; Analyst's earnings forecasts.

RESUMEN El presente trabajo compara el sesgo, precisión y capacidad explicativa del modelo de valoración de Ohlson (1995) frente a los tradicionales modelos de descuento de dividendos, de resultado residual y de flujos libres de caja, utilizando una muestra de empresas españolas cotizadas en el periodo 2000-2008. El estudio replica el comportamiento que, en la práctica, llevaría a cabo un analista cuando se enfrenta a la tarea de estimar el valor de las acciones de una empresa, obteniéndose que el modelo de valoración más preciso es el de Ohlson (1995) que considera la variable «otra información» y que utiliza persistencias intermedias tanto para la evolución futura de los resultados anormales

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** **Correspondence addresses:** Raúl Iñiguez Sánchez. Departamento de Economía Financiera y Contabilidad. Universidad de Alicante. Carretera de San Vicente s/n , 03690 San Vicente del Raspeig, Alicante (España). Tel. +34 965903400 Extensión: 3140, E-mail: raul.iniguez@ua.es; Carmelo Reverte Maya. Departamento de Economía Financiera y Contabilidad. Universidad Politécnica de Cartagena. Facultad de Ciencias de la Empresa, c/Real, 3, 30201 Cartagena (España). Tel. +34 968325925. E-mail: carmelo.reverte@upct.es

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como para la de dicha variable «otra información». El modelo de resultado residual también obtiene buenos resultados, especialmente cuando se realiza el supuesto de crecimiento cero de los resultados anormales futuros, lo que confirma que las empresas generalmente no pueden aumentar su rentabilidad anormal de manera indefinida en el tiempo. Por último, el análisis de las rentabilidades de mercado futuras que se obtendrían en una estrategia basada en la ratio V/P (valor intrínseco dividido por precio de mercado) muestra que la mayoría de modelos son capaces, en promedio, de identificar acciones infra y sobrevaloradas.

PALABRAS CLAVE Modelo de Ohlson; Valoración; Dividendos; Resultado anormal; Flujo libre de caja; Predicciones de beneficios de los analistas

1. INTRODUCTION

The valuation of equity assets is an area of finance that has received a considerable amount of attention from both the academic and professional worlds (e.g., Copeland *et al.* 1994). Valuation models are used by a multitude of money managers, investment bankers and securities analysts on a daily basis to accurately value equity assets. Valuations are required in many contexts, such as investment analysis, capital budgeting, merger and acquisitions (M&A), initial public offerings (IPO), takeover bids, privatizations, etc. Thus, the accuracy of the alternative valuation methods in determining the value of an equity asset is an issue of the utmost importance.

The calculation of equity value is typically presented as a matter of estimating the expected future cash flows generated from owning an asset and discounting those cash flows, based on their assessed risk, to their present value. As pointed out by Penman and Sougiannis (1998), extensive research on asset pricing models has focused on specifying risk to discount payoffs, but little attention has been given to the specification of the payoffs to be discounted. The *dividend discounting model* (DDM) targets the actual distributions to shareholders but its application in practice (over finite horizons) is viewed as problematic. The formula requires the prediction of dividends to perpetuity for going concerns, but the Miller and Modigliani (1961) dividend irrelevance proposition states that price is unrelated to the timing of expected payout prior to or after any finite horizon. Thus, forecasted dividends to a finite horizon are uninformative about price. This calls for forecasting something more fundamental than dividends. To solve this so-called "*dividend conundrum*", alternative valuation approaches forecast attributes within the firm, which are said to capture value-creating activities, rather than the value-irrelevant payout activities. Among these approaches, it can be highlighted the *free cash flow model* (FCF) and the *abnormal earnings model* or *residual income valuation model* (AEM). However, all the previous valuation approaches require the projection of future flows. Future expectations cannot be observed and the model proposed by Ohlson (1995) solves this problem by specifying a linear model for the time-series behaviour of residual income. This produces a closed valuation formula, in which value depends solely on known accounting variables plus the 'other information' variable.

It is a little surprising that, given the many prescriptions in valuation books and their common use in practice, there is little empirical evaluation of the comparative accuracy of these alternative valuation models, and no evidence at all has been provided so far for the Spanish setting. To our knowledge, prior research on the US market has focused on comparing the DDM, AEM and FCF models (Francis *et al.,* 2000; Penman and Sougiannis, 1998; Courteau *et al.,* 2001), ignoring whether the Ohlson (1995) valuation model could potentially lead to more accurate intrinsic value estimates. This paper attempts to fill the gap in the academic literature by providing a contrast of the accuracy of the value estimates derived from the Ohlson (1995) model as compared to those obtained from the traditional valuation models (i.e., dividend discounting model, free cash flow model and abnormal earnings model). In doing so, this study aims to replicate the situation faced by investors (or financial analysts) when using a valuation model to calculate an estimate of the intrinsic value of a firm's shares. In this context, our empirical study tries to ascertain which series of forecasts investors seem to use to value equity securities.

Our results document that the most accurate model for our sample of Spanish listed firms is the Ohlson (1995) model, which clearly dominates the traditional dividend and free cash flow models. As the Ohlson (1995) model considers book value of equity and earnings as relevant valuation attributes, our paper also contributes to prior accounting research in Spain by providing evidence on the usefulness of accrual accounting. Prior evidence for Spain shows that accrual accounting contributes to facilitate the forecasting of future earnings and cash flows (see, for example, Gabás and Apellániz, 1994; Sancho and Giner, 1996; Reverte, 2002), and that it is useful for financial analysis (see, for example, Iñíguez and Poveda, 2008). Our study also complements prior evidence on the usefulness of the Ohlson (1995) model using Spanish samples (Giner and Iñíguez, 2006a, 2006b).

The rest of the paper is organized as follows. Section 2 outlines the valuation models analyzed in our paper. Section 3 reviews previous research comparing estimates derived from valuation models. Section 4 describes the data and the methodology. Section 5 reports the results. Finally, Section 6 summarizes the main findings of our study.

2. VALUATION MODELS

Discounted cash flow models (i.e., DDM, AEM and FCF) attempt to estimate value by estimating the expected future payoffs generated from owning an asset and discounting those cash flows to their present value. The discount rate used in the model is related to the risk associated with those future payoffs. Although the previous three models differ with respect to the payoff attribute considered, it can be shown that, under certain conditions, they yield theoretically equivalent measures of intrinsic value. In practice, however, they will differ if the forecasted attributes, growth rates, or discount rates employed are inconsistent. Next, we briefly outline each of the valuation models considered in our study.

2.1. DESCRIPTION OF VALUATION MODELS

2.1.1. *Dividend discounting model (DDM)*

According to the DDM, the value of a stock can be expressed as the sum of the discounted future dividends payments to shareholders over the life of the firm, with the terminal value equal to the liquidating dividend (Williams, 1938). Analytically:

$$V_t = \sum_{j=1}^{\infty} \frac{E_t\left[DIV_{t+j}\right]}{\left(1+k_e\right)^j} \tag{1}$$

where:

V_t: value of the firm's equity at time t.

DIV_{t+j}: dividends at time $t+j$.

k_e: cost of equity capital.

2.1.2. *Abnormal earnings model (AEM)*

The DDM can be easily transformed into the abnormal earnings or residual income valuation model (AEM) by introducing two conditions: *i)* the accounting system follows the *clean surplus relation,* i.e., all changes in book value are reported as either income or dividends (net of capital contributions), and *ii)* the abnormal earnings (x_t^a) are defined as the excess of accounting earnings over the normal earnings that could be obtained by opening equity ($x_t^a = x_t - k_e \cdot bv_{t-1}$). In the AE model, the value of the firm's equity equals the book value of equity plus the present value of expected abnormal earnings:

$$V_t = bv_t + \sum_{j=1}^{\infty} \frac{E_t\left[x_{t+j}^a\right]}{\left(1+k_e\right)^j} \tag{2}$$

where:

V_t : value of the firm's equity at time t.

bv_t: book value of equity at time t.

x_{t+j}^a: abnormal earnings of year $t+j$ (j>1).

This model appears in previous studies, such as Dechow *et al.* (1999) and Ohlson (1995). However, its origin goes back, at least, to the seminal works of Preinreich (1938), Edwards and Bell (1961) and Peasnell (1982).

2.1.3. *The Ohlson (1995) model (OHL)*

Future expectations cannot be observed and the Ohlson (1995) model solves this problem by specifying a linear Markovian structure for the time-series behaviour of residual income. This produces a closed valuation formula, in which value depends solely on known accounting variables plus the “other information” variable.

In particular, the Ohlson (1995) linear valuation function is:

$$V_t = bv_t + a_1 x_t^a + a_2 v_t \quad (3)$$

where:

$$a_1 = \frac{\omega}{1 + k_e - \omega}; \qquad a_2 = \frac{1 + k_e}{(1 + k_e - \omega)(1 + k_e - \gamma)}$$

v_t: 'other information' variable at time t.

ω: persistence of abnormal earnings ($0 \leq \omega \leq 1$).

γ: persistence of the «other information» ($0 \leq \gamma \leq 1$).

2.1.4. *Discounted Free Cash Flow Model (FCF)*

The discounted free cash flow model considers free cash flows in place of dividends, based on the assumption that free cash flows provide a better representation of value added over a short horizon. Free cash flows are the cash flows available to be distributed to both equityholders and debtholders, after deducting all required investments. Analytically (Copeland *et al.,* 1994):

$$V_t = \sum_{j=1}^{\infty} \frac{FCF_{t+j}}{\left(1 + k_0\right)^j} - D_t \quad (4)$$

where:

FCF_t: free cash flow available to both equityholders and debtholders at time t.

D_t: net interest-bearing debt at time t.

k_o: weighted average cost of capital, computed as

$$k_0 = k_e \cdot \frac{bv_t}{bv_t + D_t} + k_d \cdot (1 - t) \cdot \frac{D_t}{bv_t + D_t} \quad (5)$$

being k_d the cost of debt, and t the effective tax rate.

Next, we present the specifications that we implement of the valuation models.

2.2. Implementation of the models

2.2.1. *Dividend discounting model*

In line with previous research, we consider the Gordon (1959) model, and assume that next-year forecasted dividends grow in perpetuity at a constant rate g:

$$\text{DDM1:} \quad V_t = \frac{E_t\,[DIV_{t+1}]}{k_e - g}$$

Next, we expand the previous dividend discounting formula by using all the dividend forecasts made by analysts (from *t+1* to *t+4*) and adding then a terminal value based on expected growth rate. Therefore:

$$\text{DDM2:} \quad V_t = \frac{E_t\,[DIV_{t+1}]}{(1+k_e)} + \frac{E_t\,[DIV_{t+2}]}{(1+k_e)^2} + \frac{E_t\,[DIV_{t+3}]}{(1+k_e)^3} + \frac{E_t\,[DIV_{t+4}]}{(1+k_e)^4} + \frac{E_t\,[DIV_{t+4}]\,(1+g)}{(k_e - g)(1+k_e)^4}$$

We consider different specifications for the growth rate (g), between 0% and 4%. k_e is computed as explained below for the abnormal earnings model(1).

2.2.2. *Abnormal earnings model (AEM)*

A key aspect when implementing this model is the calculation of abnormal earnings, which are defined as the excess of accounting earnings over the normal earnings that could be obtained by investing opening book value of equity at the cost of equity capital ($x_t^a = x_t - k_e \cdot bv_{t-1}$). In order to measure the cost of equity capital, as it is usual in the literature, we employ the CAPM model, i.e:

$$k_e = r_f + \beta \cdot (r_m - r_f)$$

where r_f is the risk-free interest rate, β is the beta or systematic risk, and $(r_m - r_f)$ the market risk premium.

Once we have computed abnormal earnings, we can consider several specifications of the AEM model (expression *[2]*). Similar to the DDM, we expand the AEM using all the earnings forecasts made by analysts (from *t+1* to *t+4*) and adding then a terminal value based on expected growth rate. Therefore:

$$\text{AEM:} \quad V_t = bv_t + \frac{E_t\,[x^a_{t+1}]}{(1+k_e)} + \frac{E_t\,[x^a_{t+2}]}{(1+k_e)^2} + \frac{E_t\,[x^a_{t+3}]}{(1+k_e)^3} + \frac{E_t\,[x^a_{t+4}]}{(1+k_e)^4} + \frac{E_t\,[x^a_{t+4}]\,(1+g)}{(k_e - g)(1+k_e)^4}$$

In this expression, future abnormal earnings are computed as:

$$E_t\,[x^a_{t+1}] = E_t\,[x_{t+1}] - k_e \cdot bv_t$$
$$E_t\,[x^a_{t+2}] = E_t\,[x_{t+2}] - k_e \cdot E\,[bv_{t+1}]$$
$$\ldots$$

where all necessary forecasts have been obtained directly from consensus analysts forecasts of earnings and book values.

As an alternative, we use earnings and dividends forecasts and then apply the clean surplus relation for estimating future book values, i.e:

$$E_t\,[bv_{t+1}] = bv_t + E_t\,[x_{t+1}] - E_t\,[DIV_{t+1}]$$
$$E_t\,[bv_{t+2}] = E_t\,[bv_{t+1}] + E_t\,[x_{t+2}] - E_t\,[DIV_{t+2}]$$
$$\ldots$$

(1) We have considered other assumptions for the DDM, as the Gordon model using contemporaneous dividends, or computing an implicit growth rate or a long-term growth rate. Results are similar to those presented here.

Therefore, we compute the value of a firm's shares based on the AEM considering the following four alternatives [2]:

AEM1: Estimating abnormal earnings forecasts directly from consensus analysts' predictions of earnings and book values.

AEM2: Estimating abnormal earnings forecasts from *clean surplus* book value predictions.

Finally, we use an AE model following similar assumptions to the Gordon model in the case of the DDM. Therefore, we use only the nearest predictions to compute value (models AEM3 and AEM4):

AEM3: $V_t = bv_t + \frac{E_t[x^a_{t+1}]}{(k_e - g)}$

AEM4: $V_t = bv_t + \frac{E_t[x^a_{t+1}]}{(1 + k_e)} + \frac{E_t[x^a_{t+2}]}{(k_e - g)(1 + k_e)}$

AEM3 and AEM4 models are based on the conclusions of Frankel and Lee (1998). This study finds evidence that increasing the forecast horizon from 1 to 3 years does not produce better value estimates, maybe due to the loss in accuracy inherent in long-term forecasts. So, one or two year ahead forecasts of AE seem to be enough to estimate firm value. We again consider several values for the growth rate (*g*), between 0% and 4%, for the implementation of the AEM models.

2.2.3. *Ohlson (1995) model*

We consider several specifications of the Ohlson (1995) valuation model, depending on the consideration or not of the 'other information' variable and the value adopted by the persistence parameters (ω and γ).

a) Models ignoring the "other information" variable (v_t=0)

When we ignore the "other information" variable in the Ohlson (1995) model, value is derived throughout the following expression:

OHL1: $V_t = bv_t + \frac{\hat{w}}{(1 + k_e - \hat{w})} x^a_t$

As a particular case, if ω = 0, then:

OHL2: $V_t = bv_t$

And, if ω = 1, then:

OHL3: $V_t = bv_t + \frac{x^a_t}{k_e}$

(2) For all abnormal earnings models, we have computed an implicit growth rate or we have used the long term growth rate instead of using a fixed growth rate between 0 and 4%, and the results are similar to those presented here.

b) Models considering the "other information" variable:

In this case, value is derived from expression *[3]*:

$$V_t = bv_t + \frac{\omega}{1 + k_e - \omega} x_t^a + \frac{(1 + k_e)}{(1 + k_e - \omega)(1 + k_e - \gamma)} v_t$$

As a particular case, if $\omega = \gamma = 0$, then:

$$V_t = bv_t + \frac{v_t}{(1 + k_e)}$$

And, if $\omega = 1$ and $\gamma = 0$; or if $\omega = 0$ and $\gamma = 1$, then:

$$V_t = bv_t + \frac{\omega}{k_e} x_t^a + \frac{1}{k_e} v_t$$

Several points need to be addressed. The "other information" variable has been measured following the suggestion of Ohlson (2001), which assumes that analysts use all available information to make their predictions about future earnings and thus are the best available estimation of one year-ahead accounting earnings. Therefore, considering the linear information dynamics, it can be proved that the 'other information' variable is the difference between analysts' forecasts of abnormal earnings and the expectations based on the historical series of abnormal earnings. Analytically:

$$v_t = f_t^{a,t+1} - \omega\, x_t^a = f_t^{t+1} - k_e \cdot bv_t - \omega\, x_t^a$$

where $f_t^{a,t+1}$ is the prediction of next-year abnormal earnings made at time *t,* and f_t^{t+1} is the consensus analysts' forecast of next-year earnings made at time *t*.

Substituting the previous expression of v_t in expression [3] gives rise to the following specification:

OHL4: $$V_t = bv_t - \frac{\hat{\omega}\hat{\gamma}\, x_t^a}{(1 + k_e - \hat{\omega})(1 + k_e - \hat{\gamma})} + \frac{(1 + k_e) f_t^{a,t+1}}{(1 + k_e - \hat{\omega})(1 + k_e - \hat{\gamma})}$$

As a particular case, if $\omega = \gamma = 0$, then:

OHL5: $$V_t = bv_t + \frac{f_t^{a,t+1}}{1 + k_e}$$

And, if $\omega = 1$ and $\gamma = 0$; or if $\omega = 0$ and $\gamma = 1$, then:

OHL6: $$V_t = bv_t + \frac{f_t^{a,t+1}}{k_e}$$

Note that these specifications appear in the application of the Ohlson (1995) model made by Dechow *et al.* (1999).

To estimate the persistence of both abnormal earnings (ω) and that of the «other information» variable (γ), we run an AR (1) model with the data from the previous years before the valuation date. Analytically:

$$RTDO_t^a = \beta + \omega \cdot RTDO_{t-1}^a + e_t$$

$$v_t = a_0 + \gamma v_{t-1} + e_t$$

Data from year 2000 to the year in which we estimate firm value are used for estimating the persistence parameters of both abnormal earnings (ω) and the «other information» variable (γ). Therefore, we use a rolling procedure and incorporate an additional year for the estimation of the persistence parameters.

2.2.4. *Free cash flow model*

We consider the following specification expanding expression *[4]*:

$$\text{FCF:} \quad V_t = \frac{E_t\,[FCF_{t+1}]}{(1 + k_0)} + \frac{E_t\,[FCF_{t+2}]}{(1 + k_0)^2} + \frac{E_t\,[FCF_{t+3}]}{(1 + k_0)^3} + \frac{E_t\,[FCF_{t+4}]}{(1 + k_0)^4} + \frac{E_t\,[FCF_{t+4}]\,(1 + g)}{(k_0 - g)(1 + k_0)^4} - D_t$$

where $E_t\,[FCF_{t+j}]$ are taken directly from the database of consensus analysts forecasts, and k_o is computed as indicated in expression [5]. Both the cost of debt (interest expense divided by debt) and effective tax rate (taxes divided by earnings before taxes) are computed using financial statement information available at each valuation date. As in the previous models, we also consider several specifications for the terminal growth rate (g), between 0% and 4%.

For the purposes of valuation, the use of FCF can be problematic due to the variability of capital expenditures and the high amount necessary to renovate investments or to growth continuously. As a result, we often observe negative expected free cash flows in the short-term forecast horizon, being the value estimates irrelevant. Thus, to obtain feasible value estimates through the application of the FCF model, we would need a longer forecast horizon or a higher terminal value, which makes the model difficult to implement with our data. To solve some of these limitations in the implementation of the FCF model, we also compute value estimates directly from cash flows from operations (CF). Analytically:

$$\text{CF:} \quad V_t = \frac{E_t\,[CF_{t+1}]}{(1 + k_0)} + \frac{E_t\,[CF_{t+2}]}{(1 + k_0)^2} + \frac{E_t\,[CF_{t+3}]}{(1 + k_0)^3} + \frac{E_t\,[CF_{t+4}]}{(1 + k_0)^4} + \frac{E_t\,[CF_{t+4}]\,(1 + g)}{(k_0 - g)(1 + k_0)^4} - D_t$$

where $E_t\,[CF_{t+j}]$ are taken directly from the database of consensus analysts forecasts.

3. LITERATURE REVIEW

Several studies investigate the ability of one or more of the previously outlined valuation methods to generate reasonable estimates of market values. Kaplan and Ruback (1995) compare value estimates derived from one form of discounted cash flow, a single-stage free cash flow model, and simple multiple comparison models with the transaction values of 51 highly leveraged transactions. Their results indicate that the median cash flow value estimate is within 10 percent of the market price, and that cash flow estimates significantly outperform estimates based on comparables or multiples approaches. Frankel and Lee (1998) document that the value estimates derived from the abnormal earnings model explain a significantly larger proportion of the variation in stock prices than value estimated based on earnings, book values, or a combination of the two.

Bernard (1995) compares the ability of forecasted dividends and the intrinsic values derived from the AE model to explain variation in current stock prices. He shows that dividends explain 29% of the variation in stock prices, compared to 68% of the AE model.

Using an *ex post* approach based on realizations of the payoff attributes as proxies for expected values at the valuation date, Penman and Sougiannis (1998) estimate intrinsic values for horizons of T=1 to T=10 years. They find that, regardless of the length of the forecast horizon, AE value estimates are significantly better than those provided by the FCF model, with DDM value estimates standing in between AE and FCF models.

Taking Value Line forecasts over a 5-year horizon, Francis *et al.* (2000) revisit the issue of model comparison from an *ex ante* perspective, comparing the accuracy and explanatory power of the DDM, AEM and FCF models. These authors conclude that the value estimates derived from the AE model performed significantly better than the value estimates derived from both the FCF and DDM models. The data also support that the abnormal earnings value estimates explain a significantly higher proportion of the variation in the market prices, when compared to the other two discounted cash flow models. The authors attribute the high performance of the abnormal earnings value estimates to the ability of book value, which is part of the residual income equation, to explain a large portion of intrinsic value.

Courteau *et al.* (2001) explore whether, over a five-year valuation horizon, DDM, FCF and AE models are empirically equivalent when Penman's (1998) theoretically «ideal» terminal value expressions are employed in each model. Using Value Line terminal stock price forecasts at the horizon to proxy for such values, they find empirical support for the prediction of equivalence between these three price-based valuation models. They also demonstrate that, within each class of the FCF and AE valuation models, the model that employs Value Line forecasted price in the terminal value expression generates the lowest pricing errors, compared to models that employ non price-based terminal value under an arbitrary growth assumption. They also revisit the issue of the apparent superiority of the AE model, and find that this result does not hold in a level playing field where an approximation of ideal terminal values is employed. In fact, the price-based AE model is marginally outperformed by the price-based FCF and DDM models, in terms of pricing errors as well as its ability to explain current market price.

To summarize, there is a general evidence of the superiority of AE models in comparison to other popular valuation models (like DDM and FCF). In our study we contribute to the literature by adding the Ohlson (1995) model to the comparison of the relative performance of valuation models. The Ohlson (1995) model is expected to yield superior valuation results, as it is based on the AE model, but derives value based only on contemporaneous accounting data. This avoids the use of forecasts of future flows for the finite horizon and the forecast of the terminal value at the end of that horizon.

4. DATA AND METHODOLOGY

Our objective is to replicate the behaviour of the financial practitioners when using a valuation model to estimate the intrinsic value of a firm's shares. Given that they will not have access to the real future figures, we use analysts' forecasts as we are interested in comparing the valuation models from a purely pragmatic perspective. Under ideal conditions, all models should yield identical value estimates but, in practice, the concrete implementation of each model, including the difficulty of forecasting the relevant variables, will result in different value estimates.

Bearing that in mind, our sample is comprised of listed Spanish firms with available analysts' forecasts for the fundamental attributes of each valuation model during the 2000-2008 time period. Data on analysts' forecasts and the other inputs of the valuation models are collected from the Factset Estimates (Extel-Connect) database. This database provides forecasts (in a per-share basis) for dividends, book values, earnings and free cash flows for up to four years and also a projected long-term growth rate. For a firm to be included in the sample, we require at least two years of forecasts of the fundamental attributes. If a firm has only forecasts for *t+1* and *t+2*, we project forecasts for *t+3* and *t+4* using the long-term growth rate. The database also provides the financial statement information required to complete the study, i.e., book value of equity, earnings, total debt, cost of debt and effective tax-rate[(3)]. Intrinsic values for each firm's shares are derived from each of the valuation models. Consistent with prior literature (Francis *et al.,* 2000; Courteau *et al.,* 2001), negative overall intrinsic values are capped at zero based on the notion of limited liability constraints.

Regarding the cost of equity capital, we use the one-year Treasury bill rate as the risk-free interest rate, and the betas provided in the Factset database, which are based on historical 5-year market model regressions using the IBEX-35 as the market index. The market risk premium chosen is 5.24%, which is the historical premium for the Spanish stock market for the period 1980-2004 (AECA, 2005). Weighted average cost of capital is computed following expression [5], where both the cost of debt (interest expense divided by debt) and effective tax rate (taxes divided by earnings before taxes) are computed using financial statement information available at each valuation date.

The initial sample is formed by the 148 firms and nine years (2000 to 2008) included in the Factset database at the moment of implementing our empirical study. This gives a maximum number of observations of 1,332. However, some firms lack basic accounting information (book value and earnings) and are not quoted all years, which results in 339 missing values. Besides, to implement the Ohlson (1995) model, we need to compute current abnormal earnings and to estimate abnormal earnings persistence each year using consecutive historical accounting data. This causes another 219 missing values. Therefore, the lack of accounting data and the need for an initial estimation period for the Ohlson (1995) parameters results in 558 missing intrinsic values. Finally, we found 134 missing values due to the inexistence of analysts' forecasts of future earnings, book value and dividends. The final intrinsic values computed for the DDM, AEM and OHL model are 640. Table 1 shows the description of the sample.

(3) We winsorize all the variables, including effective tax-rate and cost of equity capital, at 5.th and 95.th percentiles to avoid pervasive effects of extreme values.

TABLE 1
SAMPLE DESCRIPTION

	Missing values	*Number of observations*	*Model*
Number of Spanish Firms with analysts forecasts in Factset database: 148; Sample Period: 9 years		1,332	
Basic accounting information: book value and earnings per share (accounting information is not available for all firms all periods as not all firms are quoted all years)	-339	993	
Estimation period for the Ohlson (1995) model. Model OHL4 requires the estimation of the abnormal earnings and the other information persistences	-219	774	
Analyst's forecasts (earnings, dividend and book value analyst's forecasts are not available for all firms all periods)	-134	640	DDM, AEM and OHL
Additional accounting variables: debt and effective tax-rates	-158	482	
Analyst's forecasts (cash flow forecasts)	-30	452	CF
Analyst's forecasts (free cash flow forecasts)	-186	266	FCF

We must clarify that we will use the same 640 observations for each model. If observations were different across models, the differences that we may find in the performance of each implemented model might be attributable to differences in the sample. Also note that the implementation of the cash flow models drastically reduces our sample. We need additional accounting variables (effective tax-rate and debt) —158 missing values—, cash-flows forecasts —30 missing values—, and free cash flow forecasts —186 additional missing values—. As including (free) cash flow models would reduce the sample substantially we drop these models from the first set of tables with the basic results and rather present their results at the end of that section [(4)].

4.1. BIAS, ACCURACY AND EXPLANATORY POWER OF COMPETING VALUATION MODELS

Once we have computed intrinsic values from each of the valuation models, the basic methodology applied here is similar to that used by previous related studies (Francis *et al.,* 2000; Penman and Sougiannis, 1998; Courteau *et al.,* 2001) in their comparison of the bias, accuracy and explanatory power of the alternative valuation models. The bias (signed prediction error) denotes the deviation of the intrinsic value estimate at time *t* from the share price at time *t*, i.e:

$$bias_t = (price_t - intrinsic\ value\ estimate_t) / price_t$$

(4) As we point out in the sensitivity analysis, we also run all the study using different samples (those that maximize sample size for each model, independent of the other ones), and the results are similar to those obtained for the common sample (640 observations).

However, we need to determine the precision of each valuation model, as a valuation model may provide unbiased values but with high negative and positive errors compensating each other. The accuracy (absolute prediction error) is measured as the absolute price scaled difference between the value estimate and the current price of the security, i.e.:

$$accuracy_t = | \, price_t - intrinsic\ value\ estimate_t \, | \, / \, price_t$$

Finally, the explanatory power of the models is measured as the ability of value estimates to explain cross-sectional variation in current security prices, i.e:

$$P_{it} = \beta V^M_{it} + e_{it} \qquad (6)$$

where V^M_{it} is the intrinsic value of firm *i*'s shares at time *t* derived from model M.

4.2. Future abnormal returns

Another way of assessing the relative performance of each model is to compute future market returns from a strategy based on the V/P ratio (intrinsic value divided by price). Therefore, each year we form 4 portfolios according to the V/P ratio of each model. Low V/P stocks (i.e., stocks overpriced relative to their intrinsic value) appear in portfolio 1, while high V/P stocks (i.e., stocks underpriced relative to their intrinsic value) appear in portfolio 4. We expect negative future returns for portfolio 1 (intrinsic value lower than price, expected decrease in price), and positive future returns for portfolio 4 (intrinsic value higher than price, expected increase in price). Once the portfolios are formed each year, we compute market returns based on the difference between next-year observed price and current price, adjusted by dividends and other operations. Then, we adjust returns by risk applying the CAPM model:

*Abnormal return = Return – (risk free rate + beta * premium risk)*

5. RESULTS

Tables 2 and 3 report the descriptive statistics of our sample. It can be seen that the mean (median) cost of equity capital is 6,72% (6,80%), the mean (median) weighted average cost of equity capital is 5,54% (5,22%), and the mean (median) beta is 0,68 (0.71). Results not tabulated about persistence parameters in the Ohlson (1995) model show that the mean (median) abnormal earnings persistence (ω) is 0.7395 (0.7483). Regarding the «other information» variable, the mean (median) persistence (γ) is 0.3852 (0.3833). Persistence estimations out of the range 0-1 have been modified to 0 (if negative) or 1 (if more than 1).

TABLE 2
DESCRIPTIVE STATISTICS (CONTEMPORANEOUS VARIABLES)

P_t: price share at time t; Bv_t: book value per share at time t; X_t: earnings per share at time t; DIV_t: dividend per share at time t; FCF_t: free cash flow per share at time t; CF_t: cash flow per share at time t; k_e: cost of equity capital at time t; k_d: cost of debt at time t; ko: weighted average cost of capital at time t; rf_t: risk-free interest rate at time t; $beta_t$: beta at time t; x_t^a: abnormal earnings at time t; Mean: Mean value of each variable; p 25: percentile 25% of each variable; Median: Median value of each variable; p 75: percentile 75% of each variable. Number of observations = 640.

Variable	*Mean*	*p25*	*Median*	*p75*
P_t	13.25	3.37	7.87	14.84
Bv_t	7.99	2.00	3.93	6.82
X_t	1.47	0.15	0.47	1.02
DIV_t	0.39	0.00	0.15	0.39
FCF_t	0.33	-0.12	0.39	1.16
CF_t	1.63	0.42	0.91	1.89
k_e	6.72%	4.75%	6.80%	8.34%
K_d	4.45%	3.15%	3.83%	5.61%
K_o	5.54%	3.90%	5.22%	6.76%
rf	3.10%	2.35%	2.85%	3.77%
$beta_t$	0.68	0.34	0.71	1.00
x_t^a	0.85	-0.01	0.24	0.66

TABLE 3
DESCRIPTIVE STATISTICS (ANALYSTS' FORECASTS)

$E_t\,[DIV_{t+j}]$: forecasted dividend per share j years-ahead; $E_t\,[x_{t+j}]$: forecasted earnings per share j years-ahead; $E_t\,[bv_{t+j}]$: forecasted book value per share j years-ahead; $E_t\,[fcf_{t+j}]$: forecasted free cash flow per share j years-ahead; $E_t\,[cf_{t+j}]$: forecasted cash-flow per share j years-ahead; *ltg*: forecasted long-term growth at time t; Mean: Mean value of each variable; p25: percentile 25% of each variable; Median: Median value of each variable; p75: percentile 75% of each variable. Number of observations = 640.

Variable	*Mean*	*p25*	*Median*	*p75*
$E_t\,[DIV_{t+1}]$	0.35	0.04	0.18	0.42
$E_t\,[DIV_{t+2}]$	0.38	0.05	0.20	0.45
$E_t\,[DIV_{t+3}]$	0.41	0.05	0.21	0.50
$E_t\,[DIV_{t+4}]$	0.45	0.06	0.23	0.55
$E_t\,[x_{t+1}]$	0.96	0.25	0.55	1.14
$E_t\,[x_{t+2}]$	1.06	0.29	0.64	1.28
$E_t\,[x_{t+3}]$	1.19	0.32	0.76	1.43
$E_t\,[x_{t+4}]$	1.35	0.37	0.87	1.67
$E_t\,[bv_{t+1}]$	7.50	2.38	4.55	7.74
$E_t\,[bv_{t+2}]$	8.13	2.59	4.88	8.56
$E_t\,[bv_{t+3}]$	9.05	2.88	5.31	9.80
$E_t\,[bv_{t+4}]$	10.01	3.22	5.96	11.30

(Continue in next page)

TABLE 3 (CONT.)
DESCRIPTIVE STATISTICS (ANALYSTS' FORECASTS)

$E_t\,[fcf_{t+1}]$	0.82	0.02	0.49	1.31
$E_t\,[fcf_{t+2}]$	1.05	0.12	0.60	1.51
$E_t\,[fcf_{t+3}]$	1.30	0.13	0.77	1.69
$E_t\,[fcf_{t+4}]$	1.55	0.13	0.83	1.89
$E_t\,[cf_{t+1}]$	1.74	0.50	1.08	2.17
$E_t\,[cf_{t+2}]$	1.91	0.57	1.19	2.36
$E_t\,[cf_{t+3}]$	2.13	0.60	1.30	2.70
$E_t\,[cf_{t+4}]$	2.38	0.68	1.44	2.95
ltg	14.54%	7.50%	11.00%	15.82%

Table 4 shows the median signed error of the estimates derived from the valuation models taken into consideration. It can be seen that the Ohlson (1995) valuation models perform relatively well, especially OHL3 and OHL6, with a median signed error of -0.03. The rest of models are quite sensitive to the growth rate (*g*) chosen. For instance, the DDM2 works well for high growth rates (4%) (bias=-0.04). On the contrary, the AE model performs better for low *g* (bias= -0.01 and 0.07 for g=0% for the AEM3 and AEM4 models, respectively). This could be in line with the hypothesis sustained by Ohlson (1995) that abnormal earnings cannot increase indefinitely [Ohlson (1995) does not allow $\omega > 1$, which is equivalent to g>0]. Moreover, Ohlson (1995) establishes that the persistence of abnormal earnings should lie between 0 and 1 (a competitive economy would force abnormal earnings to be zero in the long-term), which implies that growth (*g*) is 0 or negative.

TABLE 4
BIAS OF EACH MODEL

This table shows the median signed error of the estimates derived from each valuation model, computed as: $bias_t$ =($price_t$- intrinsic value $estimate_t$)/ $price_t$; g = growth rate used to compute intrinsic value. N: Number of observations. Models used to compute intrinsic value are summarized in the Appendix.

Model	-	*g=0%*	*g=1%*	*g=2%*	*g=3%*	*g=4%*	*N*
DDM1	–	-0.63	-0.56	-0.47	-0.35	-0.18	640
DDM2	–	-0.53	-0.46	-0.36	-0.23	-0.04	640
AEM1	–	0.29	0.41	0.59	0.86	1.20	640
AEM2	–	0.30	0.43	0.62	0.91	1.25	640
AEM3	–	-0.01	0.09	0.20	0.42	0.70	640
AEM4	–	0.07	0.15	0.29	0.48	0.81	640
OHL1	-0.14	–	–	–	–	–	640
OHL2	-0.51	–	–	–	–	–	640
OHL3	-0.03	–	–	–	–	–	640
OHL4	-0.12	–	–	–	–	–	640
OHL5	-0.47	–	–	–	–	–	640
OHL6	-0.03	–	–	–	–	–	640

Given that valuation models may provide unbiased values but with high negative and positive errors compensating each other, we also compute the accuracy of each model, measured as the absolute prediction error. It can be seen in table 5 that the lowest valuation errors pertain to the Ohlson (1995) models (between 0.42 and 0.54). The most accurate model is the OHL4 model (0.42), which considers the «other information» variable and intermediate persistence for both abnormal earnings and the «other information» variable (between 0 and 1). Low valuation errors are also attained by the AE model, especially for the zero-growth case (g=0%), confirming that abnormal earnings cannot increase indefinitely.

Table 5
Absolute prediction errors of each model

This table shows the median absolute prediction error of the estimates derived from each valuation model, computed as: $accuracy_t = |price_t – intrinsic\ value\ estimate_t| / price_t$; g = growth rate used to compute intrinsic value. *N*: Number of observations. Models used to compute intrinsic value are summarized in the Appendix.

Model	_	*g=0%*	*g=1%*	*g=2%*	*g=3%*	*g=4%*	*N*
DDM1	–	0.63***	0.59***	0.60***	0.67***	0.76***	640
DDM2	–	0.56***	0.55***	0.58***	0.68***	0.80***	640
AEM1	–	0.52***	0.64***	0.81***	1.00***	1.20***	640
AEM2	–	0.52***	0.63***	0.81***	1.00***	1.25***	640
AEM3	–	0.46**	0.52***	0.69***	0.96***	1.00***	640
AEM4	–	0.44***	0.52***	0.66***	0.91***	1.00***	640
OHL1	0.46**	-	-	-	-	-	640
OHL2	0.54***	-	-	-	-	-	640
OHL3	0.51***	-	-	-	-	-	640
OHL4	**0.42**	-	-	-	-	-	640
OHL5	0.51***	-	-	-	-	-	640
OHL6	0.51***	-	-	-	-	-	640

The lowest valuation error appears in bold letter.
* With a significance of 10%, the valuation error significantly differs from the lowest valuation error.** Idem at 5% *** Idem at 1%.

To see whether the differences in absolute prediction errors are statistically significant, we perform tests of equality of means and medians. The null hypothesis is that the difference in the forecast errors between two competing models has a zero median/mean. We choose as base model for the comparison the one with the lowest forecast error (OHL4), thus the tests indicate which models behave significantly worse than OHL4. The results of the Wilcoxon signed-rank test for the equality of medians are shown in Table V. The median absolute forecast errors from all models are significantly higher than those from the OHL4 model at a 1% level, with the exception of OHL1 (*p*-value= 1,34%) and AEM3 g=0% (*p*-value= 4,93%), where the differences are statistically significant at a 5% level. The results of the T-test for the equality of means —not tabulated— are quite similar. All the models perform significantly worse than OHL4 with the only exceptions of OHL2 and OHL5.

For the sake of brevity, we have not tabulated the results from the equality tests between all pairs of valuation models. In particular, OHL1, OHL2 and OHL5 perform better than all DDM and AEM models at a 5% level, except for AEM3 (g=0%) and AEM4 (g=0%). OHL3 and OHL6 perform better than all DDM and AEM models at a 5% level, except for AEM3 (g=0%), DDM2 (g=0%) and DDM3 (g=0%). AEM3 (g=0%) and AEM4 (g=0%) perform better than all DDM models at a 5% level, and also perform better than AEM1 and AEM2 models. Finally, AEM1 and AEM2 do not always reach at least a 5% significant difference in comparison with DDM models.

To summarize our findings, we find evidence of a significant superiority of the Ohlson (1995) models. Our results also corroborate those obtained by Frankel and Lee (1998), as models based on abnormal earnings for one and two-years ahead (AEM3 and AEM4) perform better than those based on longer horizons. Our results are also consistent with the evidence in previous studies for the US market that show the superiority of the AEM over the DDM (Francis *et al.,* 2000; Penman and Sougiannis, 1998; Courteau *et al.,* 2001), although only for short-term abnormal earnings forecasts models.

Next, we provide evidence on the explanatory power of each model by regressing prices on the intrinsic values derived from each model. Table 6 shows the results from the P/V regressions (using Ordinary Least Squares) as well as the results from the Wald test for testing the hypothesis that $\beta = 1$ and the Akaike Information Criterion (AIC). AIC is a measure of the goodness of fit of a statistical model, and it is considered a tool for model selection, being the best model the one with the minimum AIC. It can be observed that the β coefficients are statistically significant in all cases, although the Wald test does not allow to accept in any case (except OHL2 with $\beta = 1.05$) that the estimated coefficient is equal to one. Nevertheless, DDM and OHL models yield coefficients around 1, depending on the specific assumptions underlying each case. However, the estimated beta from the AEM is in all cases less than 0.7. This result may be showing that there are other value relevant attributes not included in the models [5], or that stock prices are not reflecting immediately all the intrinsic value of the firm. In the latter case, if market prices revert slowly to intrinsic values, it would be possible to obtain abnormal returns (Frankel and Lee, 1998; Lee *et al.,* 1999). We explore this issue later in the return analysis.

(5) We run equation [6] without an intercept because we are interested in comparing models only with the relevant variables that incorporate each one. Nevertheless, we would like to mention that we have run equation [6] with an intercept and all estimated intercepts are significant at 1% in all models and cases. This would confirm that there are omitted value-relevant variables in each model.

Table 6

Price-Intrinsic value regressions

This table shows the results from estimating the following regression: $P_{it} = \beta V_{it} + e_{it}$; where P_{it}: market price at time *t*; V_{it}: intrinsic value computed using each model; g= growth rate used to compute intrinsic value; *p-v* Wald: *P-value* of the Wald test: $\beta = 1$; R^2: adjusted R^2 of the regression; AIC: Akaike information criterion; N: number of observations. Models used to compute intrinsic value are summarized in the Appendix.

Model	β	*p-v Wald*	R^2	*AIC*	*N*
DDM1 g=0%	1.48***	0.00	0.59	1.95	640
DDM1 g=1%	1.14***	0.00	0.56	2.01	640
DDM1 g=2%	0.76***	0.00	0.51	2.13	640
DDM1 g=3%	0.51***	0.00	0.48	2.19	640
DDM1 g=4%	0.46***	0.00	0.52	2.11	640
DDM2 g=0%	1.10***	0.01	0.57	1.98	640
DDM2 g=1%	0.86***	0.00	0.55	2.05	640
DDM2 g=2%	0.58***	0.00	0.48	2.18	640
DDM2 g=3%	0.40***	0.00	0.45	2.24	640
DDM2 g=4%	0.36***	0.00	0.49	2.17	640
AEM1 g=0%	0.37***	0.00	0.57	2.00	640
AEM1 g=1%	0.30***	0.00	0.53	2.08	640
AEM1 g=2%	0.22***	0.00	0.48	2.19	640
AEM1 g=3%	0.15***	0.00	0.41	2.31	640
AEM1 g=4%	0.13***	0.00	0.41	2.32	640
AEM2 g=0%	0.37***	0.00	0.58	1.98	640
AEM2 g=1%	0.30***	0.00	0.54	2.07	640
AEM2 g=2%	0.22***	0.00	0.48	2.18	640
AEM2 g=3%	0.15***	0.00	0.41	2.31	640
AEM2 g=4%	0.12***	0.00	0.41	2.32	640
AEM3 g=0%	0.61***	0.00	0.69	1.68	640
AEM3 g=1%	0.50***	0.00	0.65	1.80	640
AEM3 g=2%	0.36***	0.00	0.58	1.98	640
AEM3 g=3%	0.25***	0.00	0.52	2.10	640
AEM3 g=4%	0.23***	0.00	0.54	2.06	640
AEM4 g=0%	0.56***	0.00	0.69	1.67	640
AEM4 g=1%	0.46***	0.00	0.65	1.78	640
AEM4 g=2%	0.34***	0.00	0.59	1.96	640
AEM4 g=3%	0.23***	0.00	0.53	2.09	640
AEM4 g=4%	0.21***	0.00	0.54	2.06	640
OHL1	0.52***	0.00	0.55	2.04	640
OHL2	1.05***	0.12	0.62	1.86	640
OHL3	0.44***	0.00	0.49	2.16	640
OHL4	0.66***	0.00	0.68	1.69	640
OHL5	1.09***	0.01	0.67	1.74	640
OHL6	0.44***	0.00	0.49	2.16	640

* Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Comparing directly the explanatory power of the competing models, we can appreciate that AEM3 and AEM4, both with g=0%, and the Ohlson models considering the 'other information' variable (OHL4 and OHL5) are the models with higher adjusted R^2. Regarding AIC, the lower values are also obtained by these models. AEM3 and AEM4 perform better than AEM1 and AEM2 but there is not a clear superiority of AEM1 and AEM2 over the DDM. Note again that models with a low growth rate obtain better results than models with a high growth rate.

To summarize, results are similar to those obtained in the bias and accuracy analysis, although slightly less favourable to the Ohlson (1995) model. Nevertheless, the Ohlson (1995) model does not require an estimation of the growth rate, while the results for the DDM and AEM are quite sensitive to the selected growth rate. At the best, AE models perform in a similar way than the genuine Ohlson (1995) model.

To provide evidence on the influence of growth choice in the computation of intrinsic values, Table 7 shows the results, not for a fixed growth rate *g*, but assuming the firm-specific expected growth rate forecasted by analysts (N=635 observations, as there are five missing values). We find again evidence of the superiority of the Ohlson (1995) model, as the other models yield higher errors and lower explanatory power [(6)].

TABLE 7
ABSOLUTE PREDICTION ERROR AND PRICE-INTRINSIC VALUE REGRESSIONS FOR FIRM SPECIFIC GROWTH RATE

This table shows the absolute prediction error of the estimates derived from each valuation model. The accuracy is computed as: $accuracy_t = |price_t - intrinsic\ value\ estimate_t| / price_t$; g= growth rate used to compute intrinsic value. Also this table shows the estimated coefficient (β), the significance of this coefficient (* Significant at 10%, ** Significant at 5%, *** Significant at 1%), and the adjusted R^2 of the following regression: $P_{it} = \beta V_{it} + e_{it}$; where P_{it}: market price at time *t*; V_{it}: intrinsic value computed using each model; AIC: Akaike information criterion; N: number of observations. Models used to compute intrinsic value are summarized in the Appendix.

Panel A: Growth rate equal to the one expected by analysts.

Model	*Absolute prediction error*	β	R^2	*AIC*	*N*
DDM1	0.79***	0.45***	0.54	2.06	635
DDM2	0.89***	0.35***	0.52	2.12	635
AEM1	1.25***	0.13***	0.41	2.32	635
AEM2	1.34***	0.13***	0.40	2.32	635
AEM3	1.00***	0.23***	0.56	2.02	635
AEM4	1.00***	0.21***	0.55	2.05	635

Panel B: Ohlson (1995) models (independent of growth rate).

Model	*Absolute prediction error*	β	R^2	*AIC*	*N*
OHL1	0.46**	0.52***	0.55	2.04	635
OHL2	0.54***	1.05***	0.62	1.87	635
OHL3	0.51***	0.43***	0.49	2.16	635
OHL4	**0.42**	0.66***	0.68	1.69	635
OHL5	0.50***	1.09***	0.67	1.75	635
OHL6	0.51***	0.43***	0.49	2.16	635

The lowest absolute error appears in bold letter.
* With a significance of 10%, the valuation error significantly differs from the lowest valuation error; ** Idem at 5%;*** Idem at 1%.

(6) We have also computed an implicit growth (observed growth between 2 years). Results are similar to those presented here.

Regarding the return analysis, Table 8 shows the mean one-year-ahead market abnormal returns for the V/P strategy [7]. Abnormal returns are adjusted by risk (through the CAPM model). Results are consistent with previous literature (Frankel and Lee, 1998; Lee *et al.,* 1999), in that abnormal returns are negative for portfolio 1 and positive for portfolio 4 in most cases. This shows that most models are able, on average, of identifying overvalued and undervalued shares. The highest differential between abnormal returns of portfolios 1 and 4 is obtained by models AEM1 and AEM2 (between 19-22%), followed by OHL1-3-4-6 with values ranging from 18 to 20%. The rest of the models yield differential abnormal returns between portfolios 1 and 4 above 10% in all cases, showing that market prices tend to revert to the intrinsic values computed by the models.

TABLE 8

ABNORMAL RETURNS (IN %)

This table shows the mean one-year-ahead abnormal returns in percentage (AbRet) of a V/P strategy. Each year we form 4 portfolios according to the 640 computed V/P ratios of each model. Low V/P ratios appear in portfolio 1, while high V/P ratios appear in portfolio 4. Returns are computed based on the difference between next-year observed price and contemporaneous price, adjusted by dividends and other operations. Abnormal returns are computed taking into account the CAPM model. Models used to compute intrinsic value are summarized in the Appendix.

Model	*AbRet*		*AbRet (g=0%)*		*AbRet (g=1%)*		*AbRet (g=2%)*		*AbRet (g=3%)*		*AbRet (g=4%)*	
	P1	*P4*	*P1*	*P4*	*P1*	*P4*	*P1*	*P4*	*P1*	*P4*	*P1*	*P4*
DDM1	-	-	-9.34	3.90	-8.68	4.83	-8.73	5.74	-9.71	5.21	-9.52	4.45
DDM2	-	-	-8.20	5.42	-8.08	4.26	-8.07	3.52	-8.13	5.81	-8.13	3.46
AEM1	-	-	-14.11	7.35	-14.49	8.35	-13.97	5.64	-16.02	5.18	-16.70	5.42
AEM2	-	-	-13.45	5.87	-13.73	6.05	-14.86	4.46	-14.64	4.70	-16.19	5.49
AEM3	-	-	-9.29	3.78	-9.78	3.89	-9.38	3.09	-9.30	3.13	-9.87	4.73
AEM4	-	-	-10.53	8.61	-10.73	8.42	-9.04	6.95	-9.09	5.48	-10.90	4.71
OHL1	-13.43	3.70	-	-	-	-	-	-	-	-	-	-
OHL2	-9.31	3.97	-	-	-	-	-	-	-	-	-	-
OHL3	-13.39	6.67	-	-	-	-	-	-	-	-	-	-
OHL4	-12.76	4.36	-	-	-	-	-	-	-	-	-	-
OHL5	-9.96	1.96	-	-	-	-	-	-	-	-	-	-
OHL6	-13.39	6.67	-	-	-	-	-	-	-	-	-	-

To conclude this section, we provide the results from the (free) cash flow models for the reduced sample in Table 9. It can be observed that CF and FCF models perform poorly. Using equal samples (same number of observations for all models), evidence shows that CF and FCF perform significantly worse than the rest of the models, being the differences quite remarkable. Therefore, the practical implementation of the (free) cash flow model seems to be problematic. Although it may be argued that the different performance of the CF and FCF valuation models may be biased due to the low number

(7) Results remain unchanged if we compute median returns.

of intrinsic values computed, the large valuation errors and the low explanatory power seem to rule out this hypothesis [(8)].

Table 9
Results for the (free) cash flow models

This table shows the median absolute prediction error of the estimates derived from each valuation model, computed as: *accuracy*$_t$ = $|price_t – intrinsic\ value\ estimate_t|\ /\ price_t$; g= growth rate used to compute intrinsic value. It also shows the results from estimating the following regression: $P_{it} = \beta V_{it} + e_{it}$; where P_{it}: market price at time *t*; V_{it}: intrinsic value computed using each model; *p-v* Wald: *P-value* of the Wald test: $\beta = 1$; R^2: adjusted R^2 of the regression; AIC: Akaike information criterion; N: Number of observations.

Panel A: Absolute prediction errors.

Model	-	*g=0%*	*g=1%*	*g=2%*	*g=3%*	*g=4%*	*N*
DDM1	-	0.68***	0.63***	0.67***	0.69***	0.74***	266
DDM2	-	0.61***	0.58***	0.59***	0.65***	0.76***	266
AEM1	-	0.42***	0.51***	0.66***	0.84***	1.00***	266
AEM2	-	0.41***	0.49***	0.61***	0.82***	1.00***	266
AEM3	-	0.41	0.46***	0.55***	0.71***	0.99***	266
AEM4	-	0.38	0.44***	0.53***	0.69***	0.98***	266
OHL1	0.45***	-	-	-	-	-	266
OHL2	0.58***	-	-	-	-	-	266
OHL3	0.42***	-	-	-	-	-	266
OHL4	**0.38**	-	-	-	-	-	266
OHL5	0.55***	-	-	-	-	-	266
OHL6	0.42***	-	-	-	-	-	266
FCF	-	0.85***	1.00***	1.00***	1.00***	1.20***	266
CF	-	1.09***	1.69***	2.68***	4.45***	5.97***	266

The lowest valuation error appears in bold letter. * With a significance of 10%, the valuation error significantly differs from the lowest valuation error.** Idem at 5% ***Idem at 1%.

Panel B: Price-Intrinsic value regressions (N=266)

Model	β	p-v Wald	R^2	Model	β	p-v Wald	R^2
DDM1 g=0%	1.61***	0.00	0.56	AEM3 g=3%	0.30***	0.00	0.51
DDM1 g=1%	1.26***	0.00	0.54	AEM3 g=4%	0.27***	0.00	0.54
DDM1 g=2%	0.86***	0.00	0.49	AEM4 g=0%	0.63***	0.00	0.69
DDM1 g=3%	0.57***	0.00	0.45	AEM4 g=1%	0.53***	0.00	0.65
DDM1 g=4%	0.50***	0.00	0.49	AEM4 g=2%	0.39***	0.00	0.57
DDM2 g=0%	1.17***	0.00	0.55	AEM4 g=3%	0.27***	0.00	0.50
DDM2 g=1%	0.92***	0.06	0.52	AEM4 g=4%	0.24***	0.00	0.52
DDM2 g=2%	0.62***	0.00	0.45	OHL1	0.72***	0.00	0.66
DDM2 g=3%	0.42***	0.00	0.42	OHL2	1.03**	0.47	0.57
DDM2 g=4%	0.38***	0.00	0.46	OHL3	0.64***	0.00	0.61

(Continue in next page)

(8) Table 9 is tabulated with 266 common observations for the free cash flow model (FCF). If we consider the 452 common observations for the cash flow model (CF) we obtain the same evidence.

TABLE 9 (CONT.)

RESULTS FOR THE (FREE) CASH FLOW MODELS

AEM1 g=0%	0.36***	0.00	0.51	OHL4	0.79***	0.00	0.71
AEM1 g=1%	0.29***	0.00	0.47	OHL5	1.09***	0.03	0.62
AEM1 g=2%	0.21***	0.00	0.41	OHL6	0.64***	0.00	0.61
AEM1 g=3%	0.14***	0.00	0.34	FCF g=0%	0.23***	0.00	0.25
AEM1 g=4%	0.12***	0.00	0.34	FCF g=1%	0.19***	0.00	0.27
AEM2 g=0%	0.37***	0.00	0.51	FCF g=2%	0.13***	0.00	0.29
AEM2 g=1%	0.30***	0.00	0.47	FCF g=3%	0.09***	0.00	0.28
AEM2 g=2%	0.21***	0.00	0.41	FCF g=4%	0.07***	0.00	0.29
AEM2 g=3%	0.14***	0.00	0.34	CF g=0%	0.10***	0.00	0.26
AEM2 g=4%	0.12***	0.00	0.34	CF g=1%	0.07***	0.00	0.23
AEM3 g=0%	0.71***	0.00	0.70	CF g=2%	0.03***	0.00	0.18
AEM3 g=1%	0.59***	0.00	0.66	CF g=3%	0.03***	0.00	0.22
AEM3 g=2%	0.43***	0.00	0.58	CF g=4%	0.03***	0.00	0.27

* Significant at 10%, ** Significant at 5%, *** Significant at 1%.

6. SENSITIVITY ANALYSIS

Our intrinsic values depend on a series of decisions about key variables. To assess the sensitivity of our results to those decisions, we have repeated our analysis with different definitions of these key variables and the results remain unchanged.

First, we repeat the analyses, but without the winsorization of extreme values. Results, reported in Table 10, show the same evidence found before. The only noticeable difference is that absolute valuation errors of OHL4 are significantly lower than AEM3 g=0% only at 10% (*p-value* = 5.2%).

Second, it could be argued that, for short time series, the estimations of the persistence parameters in the Ohlson (1995) model may be inadequate. Therefore, we replace time series-based persistences for the Ohlson (1995) model with cross-sectional-based ones (i.e., the same persistence for all firms in a given year). The estimation procedure only affects OHL1 and OHL4, as the rest of the Ohlson models consider extreme persistences (0 or 1). Results (not tabulated) are similar, although a little worse for the cross sectional estimations (a worsening of 0.09 in terms of median absolute valuation errors; and lower R^2 although beta nearest to 1). The evidence shows than the time series estimations achieve better results than the cross sectional ones, confirming that Ohlson (1995) is a firm-specific valuation model.

Third, we repeat the analysis by using market risk premiums of 4%, 5%, 6% and 7%. Results for the 4% and 7% cases are shown in Table 11. We find evidence that the performance is too sensible to the risk premium chosen in most models, especially for the AEM ones, although the tenor of the results are quite similar. Note that short-term abnormal earnings models improve considerably their accuracy with high risk premiums as AEM3-AEM4 with g=0% and risk premium=7%, OHL1 and OHL4 obtain similar errors (there are no statistically significant differences in their absolute valuation errors). Nevertheless, once again the evidence is favourable to the Ohlson (1995) models, as they perform consistently in all situations, independently of the growth rate and the risk premium chosen.

Fourth, we present in table 12 mean errors instead of median errors. Evidence is even more robust in favour of the Ohlson (1995) models, as they estimate prices better than the rest of the models (errors between 0.47 and 0.56). The median absolute forecast errors from all models are significantly higher than those from the OHL4 model at a 1% level. Only the short term AE models with g=0% draw similar results, although AE models perform poorly with high growth rates (high valuation errors). Nevertheless, note that mean valuation errors may be affected by extreme values, so we rely on conclusions obtained in the main analysis based on median valuation errors.

TABLE 10
ABSOLUTE PREDICTION ERRORS OF EACH MODEL (WITHOUT WINSORIZATION)

This table shows the median absolute prediction error of the estimates derived from each valuation model, computed as: *accuracy*$_t$ = |*price*$_t$–*intrinsic value estimate*$_t$| / *price*$_t$; g= growth rate used to compute intrinsic value. *N*: Number of observations. Models used to compute intrinsic value are summarized in the Appendix.

Model	-	*g=0%*	*g=1%*	*g=2%*	*g=3%*	*g=4%*	*N*
DDM1	-	0.63***	0.60***	0.60***	0.67***	0.76***	640
DDM2	-	0.56***	0.56***	0.58***	0.68***	0.82***	640
AEM1	-	0.53***	0.66***	0.83***	1.00***	1.22***	640
AEM2	-	0.53***	0.68***	0.85***	1.00***	1.28***	640
AEM3	-	0.46*	0.52***	0.69***	0.96***	1.00***	640
AEM4	-	0.44***	0.52***	0.66***	0.91***	1.00***	640
OHL1	0.46**	-	-	-	-	-	640
OHL2	0.54***	-	-	-	-	-	640
OHL3	0.51***	-	-	-	-	-	640
OHL4	**0.42**	-	-	-	-	-	640
OHL5	0.51***	-	-	-	-	-	640
OHL6	0.51***	-	-	-	-	-	640

The lowest valuation error appears in bold letter.
* With a significance of 10%, the valuation error significantly differs from the lowest valuation error. ** Idem at 5%. *** Idem at 1%.

Fifth, we assess the relative performance of the Ohlson and Juettner-Nauroth (2005) model (OJM). This model could be considered a derivation not only from the Ohlson (1995) model, but also from the dividend and the abnormal earnings model, as it considers in the valuation formula both earnings and dividends. We take in consideration two derivations of the OJM [(9)]:

OJM1: the two-period Ohlson-Juettner model:

$$V_t = \frac{E_t[x_{t+1}]}{k_e} + \frac{E_t[x_{t+2} + k_e \cdot d_{t+1} - (1+k_e) \cdot x_{t+1}]}{k_e \cdot (k_e - g)}$$

(9) See Ohlson and Juettner-Nauroth (2005) and Brief (2007) for detailed derivation of the Ohlson-Juettner model.

OJM2: The PEG model:

$$V_t = \frac{E_t\,[x_{t+2} - x_{t+1}]}{k_e^2}$$

where $E_t\,[x_{t+j}]$ is the expected earnings per share for period $t+j$.

Table 11
Absolute prediction error of each model (premium risk= 4% and 7%)

This table shows the median absolute prediction error of the estimates derived from each valuation model, computed as: $accuracy_t = |price_t - intrinsic\ value\ estimate_t| / price_t$; g= growth rate used to compute intrinsic value. Models used to compute intrinsic value are summarized in the Appendix. *N*: Number of observations = 640

Model	*-*	*g=0%*	*g=2%*	*g=4%*	*-*	*g=0%*	*g=2%*	*g=4%*
Premium	4%	4%	4%	4%	7%	7%	7%	7%
DDM1	-	0.58***	0.60***	0.85***	-	0.68***	0.64***	0.68***
DDM2	-	0.51**	0.64***	0.99***	-	0.62***	0.60***	0.71***
AEM1	-	0.65***	1.00***	2.04***	-	0.43***	0.57***	0.88***
AEM2	-	0.66***	1.00***	2.08***	-	0.44***	0.56***	0.86***
AEM3	-	0.49***	0.89***	1.33***	-	0.46	0.55***	0.86***
AEM4	-	0.47***	0.88***	1.48***	-	**0.42**	0.52***	0.80***
OHL1	0.46*	-	-	-	0.44	-	-	-
OHL2	0.54***	-	-	-	0.54***	-	-	-
OHL3	0.59***	-	-	-	0.47**	-	-	-
OHL4	**0.43**	-	-	-	0.43	-	-	-
OHL5	0.50	-	-	-	0.51**	-	-	-
OHL6	0.59***	-	-	-	0.47**	-	-	-

The lowest valuation error appears in bold letter.
* With a significance of 10%, the valuation error significantly differs from the lowest valuation error. ** Idem at 5%. *** Idem at 1%.

Table 12
Absolute prediction error of each model (mean valuation error)

This table shows the median absolute prediction error of the estimates derived from each valuation model, computed as: $accuracy_t = |price_t - intrinsic\ value\ estimate_t| / price_t$; g= growth rate used to compute intrinsic value. *N*: Number of observations. Models used to compute intrinsic value are summarized in the Appendix.

Model		*g=0%*	*g=1%*	*g=2%*	*g=3%*	*g=4%*	*N*
DDM1	-	0.63***	0.59***	0.59***	0.67***	0.76***	640
DDM2	-	0.57***	0.57***	0.59***	0.75***	0.89***	640
AEM1	-	0.67***	0.85***	1.19***	1.72***	2.09***	640
AEM2	-	0.67***	0.85***	1.19***	1.72***	2.09***	640
AEM3	-	0.52***	0.65***	0.90***	1.32***	1.60***	640
AEM4	-	0.53***	0.67***	0.97***	1.42***	1.71***	640
OHL1	0.50***	-	-	-	-	-	640
OHL2	0.52***	-	-	-	-	-	640
OHL3	0.56***	-	-	-	-	-	640
OHL4	**0.47**	-	-	-	-	-	640
OHL5	0.49***	-	-	-	-	-	640
OHL6	0.56***	-	-	-	-	-	640

The lowest valuation error appears in bold letter.
* With a significance of 10%, the valuation error significantly differs from the lowest valuation error. ** Idem at 5%. *** Idem at 1%.

TABLE 13
RESULTS OF THE OHLSON- JUETTNER MODELS

Panel A. Absolute prediction errors of each model

This table shows the median absolute prediction error of the estimates derived from each valuation model, computed as: $accuracy_t = |price_t - intrinsic\ value\ estimate_t| / price_t$; g= growth rate used to compute intrinsic value. *N*: Number of observations.

Model	-	g=0%	g=1%	g=2%	g=3%	g=4%	N
OJ1		1.21	1.40	1.71	2.14	2.84	640
OJ2	1.00						640

Panel B. Price-Intrinsic value regressions

This table shows the results from estimating the following regression: $P_{it} = \beta V_{it} + e_{it}$; where P_{it}: market price at time *t*; V_{it}: intrinsic value computed using each model; g= growth rate; *p-v* Wald: p-value of the test: $\beta = 1$; R^2: adjusted R^2 of the regression; AIC: Akaike information criterion; N: number of observations.

Model	β	p-v Wald	R^2	AIC	N
OJ1 g=0%	0.04***	0.00	0.19	2.62	640
OJ1 g=1%	0.03***	0.00	0.18	2.64	640
OJ1 g=2%	0.02***	0.00	0.15	2.67	640
OJ1 g=3%	0.02***	0.00	0.15	2.68	640
OJ1 g=4%	0.01***	0.00	0.15	2.68	640
OJ2	0.04***	0.00	0.17	2.65	640

* Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Panel C. Abnormal returns (in %)

This table shows the mean one-year-ahead abnormal returns in percentage (AbRet) of a V/P strategy. Each year we form 4 portfolios according to the V/P ratio of each model. Low V/P ratios appear in portfolio 1, while high V/P ratios appear in portfolio 4. Returns are computed based on the difference between next year observed price and contemporaneous price, adjusted by dividends and other operations. Abnormal returns are computed taking into account the CAPM model. Models used to compute intrinsic value are summarized in Appendix.

Model	AbRet		AbRet (g=0%)		AbRet (g=1%)		AbRet (g=2%)		AbRet (g=3%)		AbRet (g=4%)	
	P1	*P4*	*P1*	*P4*	*P1*	*P4*	*P1*	*P4*	*P1*	*P4*	*P1*	*P4*
OJ1	-	-	-10.14	5.50	-10.00	4.88	-10.00	4.44	-10.00	5.29	-10.18	5.60
OJ2	-11.04	4.32										

Previous evidence regarding these models points out that OJM performs worse than AEM. Penman (2005) suggests that OJM increases the complexity of the model and could induce more forecast errors, as it requires both expected earnings, dividends and a growth rate. Also, unlike the AEM that includes book value in the model as a value relevant variable, the missing book value in the OJM may result in a loss of information embedded in the balance sheet. Penman (2005) provides some descriptive statistics that show that AEM estimates are generally more accurate than OJM estimates. Similarly, Brief (2007) finds that the variability of the distribution of OJM estimates is greater than that of AEM estimates. Results in Table 13 confirm the findings of previous studies by showing that OJM is not as accurate as OHL, AEM and DDM models. OJM results in higher valuation errors and lower explanatory power, although it is able to detect undervalued and overvalued shares.

Sixth, we analyse whether our results are consistent across years. We compute the valuation errors on a yearly basis and include year dummies in the price-value regressions. Results (not tabulated) are very similar, and even better for the Ohlson (1995) model. For example, the best model, OHL4, obtains median absolute errors between 0.38 and 0.42 each year, with the only exception of two years where the errors are 0.45 and 0.51. The performance of the OHL models is generally quite consistent year to year. However, the best AE models (AEM3 g=0% and AEM4 g=0%) obtain very different results depending of the specific year analysed. AEM3 g=0% has errors between 0.35 and 0.72 (in four years the errors are above 0.54); and AEM4 g=0% has errors between 0.30 and 0.83 (in three years the errors are above 0.71). Regarding the best DDM models (DDM2 g=0% and g=1%) results are also are inconsistent across years, although not as variable as AEM (between 0.46 and 0.69 with g=0%; and 0.47 and 0.65 with g=1%).

Seventh, one may argue that investors usually consider risk-free rates which take into account a longer horizon, as the 10 year T-bill rate. This often results in a higher discount rate that could improve the performance of (free) cash flow models. However, results (not tabulated) are quite similar to those presented here.

Finally, we have repeated our study allowing different samples for each model, that is, maximizing the number of observations for each model. Observations range from 816 for DDM, 795 for AEM and between 651-944 for the OHL. Results (not tabulated) remain unchanged despite the different sample composition in each model.

7. CONCLUSIONS

In this paper we compare the bias, accuracy and explainability of the Ohlson (1995) valuation model *versus* the traditional dividend, abnormal earnings and free cash flow models for a sample of Spanish listed firms over the period 2000-2008. It is a little surprising that, given the many prescriptions in valuation books and their common use in practice, there is little empirical evaluation of the comparative accuracy of these alternative valuation models, and no evidence at all has been provided so far for the Spanish setting. To our knowledge, prior research on the US market has focused on comparing the DDM, AE and FCF models (Francis *et al.,* 2000; Penman and Sougiannis, 1998; Courteau *et al.,* 2001), ignoring whether the Ohlson (1995) valuation model could potentially lead to more accurate intrinsic value estimates. This paper attempts to fill this gap in the academic literature comparing the accuracy of the value estimates derived from the Ohlson (1995) model with those obtained from the traditional valuation models (i.e., dividend discounting model, free cash flow model and abnormal earnings model). Our objective is to replicate the behaviour of the financial practitioners when using a valuation model to estimate the intrinsic value of a firm's shares. Given that they will not have access to the real future figures, we use analysts' forecasts as we are interested in comparing the valuation models from a purely pragmatic perspective.

In this context, our empirical study tries to ascertain which series of forecasts investors seem to use to value equity securities.

Our results document that the lowest valuation errors pertain to the Ohlson (1995) models (between 0.42 and 0.54). The most accurate model is the OHL4 model (0.42), which considers the «other information» variable and intermediate persistence for both abnormal earnings and the «other information» variable (between 0 and 1). Low valuation errors are also attained by the AE model, especially for the zero-growth case (g=0%), confirming that abnormal earnings cannot increase indefinitely. In terms of explanatory power of stock prices, the best models are those based on abnormal earnings with zero-growth, together with the Ohlson (1995) models considering «the other information» variable. Finally, we have also assessed the relative performance of each model by computing future abnormal returns from a strategy based on the V/P ratio (intrinsic value divided by price). Therefore, each year we form 4 portfolios according to the V/P ratio of each model. Low V/P ratios appear in portfolio 1, while high V/P ratios appear in portfolio 4. Our results provide evidence that abnormal returns are negative for portfolio 1 and positive for portfolio 4 in most cases, which reveals that most models are able, on average, of identifying overvalued and undervalued shares and that market prices tend to revert to the intrinsic values computed by the models. The highest differential between abnormal returns of portfolios 1 and 4 is obtained by abnormal earnings models and Ohlson models. Our results are consistent to different sensitivity analyses, such as winsorization, market premiums used, alternative ways of estimating persistence parameters in the Ohlson (1995) models, year-by-year analysis, and, finally, the number of observations available in the implementation of each valuation model. Under all dimensions considered, the Ohlson (1995) model performs in a consistent way, with stable errors independent of the number of decisions taken.

As the Ohlson (1995) model considers book value of equity and earnings as relevant valuation attributes, our paper also contributes to prior accounting research in Spain by providing evidence on the usefulness of accrual accounting (Gabás and Apellániz, 1994; Sancho and Giner, 1996; Reverte, 2002; Iñíguez and Poveda, 2008). It also complements prior evidence on the usefulness of the Ohlson (1995) model using Spanish samples (Giner and Iñíguez, 2006a, 2006b). The main implication of our study is that, even in Spain, a country with relatively poorer enforcement mechanisms than in other developed countries, accrual accounting provides useful information beyond that provided by dividends and cash flows.

REFERENCES

AECA. 2005. *Valoración de Pymes*. Documentos AECA. Serie Valoración de Empresas. Documento 7. Madrid.

Bernard, V. L. 1995. The Feltham-Ohlson Framework: Implications for Empiricists. *Contemporary Accounting Research* 11 (2): 733-747.

Brief, R. P. 2007. Accounting Valuation Models: A Short Primer. *Abacus* 43: 429-437.

Copeland, T.; Koller, T., and Murrin, J. 1994. *Measuring and Managing the Value of Companies.* 2.nd edition. New York: Wiley.

Courteau, L., Kao, J., and Richardson, G. D. 2001. Equity Valuation employing the Ideal versus Ad Hoc Terminal Value Expressions. *Contemporary Accounting Research* 18: 625-661.

Dechow, P. M.; Hutton, A. P., and Sloan, R. G. 1999. An Empirical Assessment of the Residual Income Valuation Model. *Journal of Accounting and Economics* 26: 1-34.

Edwards, E. O., and Bell, P. W., 1961. *The Theory of Measurement of Business Income*. Berkeley, California: University of California Press.

Francis, J.; Olsson, P., and Oswald, D. R. 2000. Comparing the Accuracy and Explainability of Dividend, Free Cash Flow, and Abnormal Earnings Equity Value Estimates. *Journal of Accounting Research* 38 (1): 45-70.

Frankel, R., and Lee, C. M. C. 1998. Accounting Valuation, Market Expectation, and Cross-Sectional Returns. *Journal of Accounting and Economics* 25: 283-319.

Gabás, F., and Apellániz, P. 1994. Capacidad predictiva de los componentes del beneficio: Flujos de tesorería y ajustes corto-largo plazo. *Revista Española de Financiación y Contabilidad* XXIV (78): 107-142.

Giner, B., and Iñiguez, R. 2006a. An empirical assessment of the Feltham-Ohlson models considering the sign of abnormal earnings. *Accounting and Business Research* 36 (3): 169-190.

— 2006b. La capacidad de los modelos Feltham-Olhson para predecir el resultado anormal: una aplicación empírica. *Revista Española de Financiación y Contabilidad* XXXV (132): 729-760.

Gordon, M. J. 1959. Dividends, Earnings and Stock Prices. *Review of Economics and Statistics* 41: 99-105.

Íñiguez, R., and Poveda, F. 2008. Persistencia del resultado contable y sus componentes: implicaciones de la medida de ajustes por devengo. *Revista Española de Financiación y Contabilidad* XXXVII (137): 33-61.

Kaplan, S. N., and Ruback, R. S. 1995. The Valuation of Cash Flow Forecasts: An Empirical Analysis. *The Journal of Finance* 50 (4): 1.059-1.093.

Lee, C. M. C.; Myers, J. N., and Swaminathan, B. 1999. What is the Intrinsic Value of the Dow? *The Journal of Finance* 44 (5): 1.693-1.741.

Ohlson, J. A. 1995. Earnings, Book Values, and Dividends in Equity Valuation. *Contemporary Accounting Research* 11 (2): 661-687.

— 2001. Earnings, Book Values, and Dividends in Equity Valuation: An empirical perspective. *Contemporary Accounting Research* 18 (1): 107-120.

Ohlson, J. A., and Juettner-Nauroth, B. 2005. Expected EPS and EPS growth as determinants of value. *Review of Accounting Studies* 10: 349-365.

Peasnell, K. V. 1982. Some Formal Connections Between Economic Values and Yields and Accounting Numbers. *Journal of Business Finance and Accounting* 9: 361-381.

Penman, S. 2005. Discussion of On accounting-based valuation formulae and Expected EPS and EPS growth as determinants of value. *Review of Accounting Studies* 10: 367-378.

Penman, S., and Sougiannis, T. 1998. A comparison of dividend, cash flow, and earnings approaches to equity valuation. *Contemporary Accounting Research* 15: 343-383.

Preinreich, G. A. D. 1938. Annual Survey of Economic Theory: the Theory of Depreciation. *Econometrica* 6: 219-231.

Reverte, C. 2002. Evidencia empírica sobre la utilidad de la información financiera para la predicción de los resultados futuros. *Revista Española de Financiación y Contabilidad* XXXI (111): 189-224.

Sancho, A., and Giner, B. 1996. Análisis dinámico de la capacidad de los flujos de fondos para determinar los futuros flujos de caja. *Revista Española de Financiación y Contabilidad* XXVI (86): 9-34.

Williams, J. 1938. *The Theory of Investment Value*. Harvard University Press, Cambrigde, MA.

APPENDIX

SUMMARY OF VALUATION MODELS

DIV_{t+j} : dividends at time t+j; k_e: cost of equity capital; g: growth rate; bv_t is book value of equity at time t; x^a_{t+j} are abnormal earnings of year $t+j$; ω: persistence of abnormal earnings ($0 \leq \omega \leq 1$).; $f_t^{a,t+1}$ is the prediction of next-year abnormal earnings made at time t; γ: persistence of the «other information» ($0 \leq \gamma \leq 1$); FCF_{t+j} : Consensus free cash flows' analysts forecasts for $t+j$.; k_o: weighted average cost of capital, CF_{t+j} are consensus cash flow from operations' analysts forecasts.

Dividend discounting model:

DDM1: $$V_t = \frac{E_t\,[DIV_{t+1}]}{k_e - g}$$

DDM2: $$V_t = \frac{E_t\,[DIV_{t+1}]}{(1+k_e)} + \frac{E_t\,[DIV_{t+2}]}{(1+k_e)^2} + \frac{E_t\,[DIV_{t+3}]}{(1+k_e)^3} + \frac{E_t\,[DIV_{t+4}]}{(1+k_e)^4} + \frac{E_t\,[DIV_{t+4}]\,(1+g)}{(k_e - g)(1+k_e)^4}$$

Abnormal earnings model (AEM):

AEM1 and AEM2: $$V_t = bv_t + \frac{E_t\,[x^a_{t+1}]}{(1+k_e)} + \frac{E_t\,[x^a_{t+2}]}{(1+k_e)^2} + \frac{E_t\,[x^a_{t+3}]}{(1+k_e)^3} + \frac{E_t\,[x^a_{t+4}]}{(1+k_e)^4} + \frac{E_t\,[x^a_{t+4}]\,(1+g)}{(k_e - g)(1+k_e)^4}$$

(in AEM1 future abnormal earnings and future book values have been obtained directly from consensus analysts forecasts)

(in AEM2 forecasts are estimated from *clean surplus* book value predictions)

AEM3: $$V_t = bv_t + \frac{E_t\,[x^a_{t+1}]}{(k_e - g)}$$

AEM4: $$V_t = bv_t + \frac{E_t\,[x^a_{t+1}]}{(1+k_e)} + \frac{E_t\,[x^a_{t+2}]}{(k_e - g)\,(1+k_e)}$$

Ohlson (1995) model

a) Models ignoring the 'other information' variable (vt=0)

OHL1: $$V_t = bv_t + \frac{\hat{w}}{(1 + k_e - \hat{w})}\, x^a_t$$

OHL2: $$V_t = bv_t$$

OHL3: $$V_t = bv_t + \frac{x^a_t}{k_e}$$

b) Models considering the 'other information' variable (vt≠0)

OHL4: $$V_t = bv_t - \frac{\hat{\omega}\hat{\gamma}\, x^a_t}{(1 + k_e - \hat{\omega})\,(1 + k_e - \hat{\gamma})} + \frac{(1+k_e)\, f_t^{a,t+1}}{(1 + k_e - \hat{\omega})\,(1 + k_e - \hat{\gamma})}$$

OHL5: $$V_t = bv_t + \frac{f_t^{a,t+1}}{1 + k_e}$$

OHL6: $$V_t = bv_t + \frac{f_t^{a,t+1}}{k_e}$$

Cash flow- based models:

FCF: $$V_t = \frac{E_t[FCF_{t+1}]}{(1 + k_0)} + \frac{E_t[FCF_{t+2}]}{(1 + k_0)^2} + \frac{E_t[FCF_{t+3}]}{(1 + k_0)^3} + \frac{E_t[FCF_{t+4}]}{(1 + k_0)^4} + \frac{E_t[FCF_{t+4}](1 + g)}{(k_0 - g)(1 + k_0)^4} - D_t$$

CF: $$V_t = \frac{E_t[CF_{t+1}]}{(1 + k_0)} + \frac{E_t[CF_{t+2}]}{(1 + k_0)^2} + \frac{E_t[CF_{t+3}]}{(1 + k_0)^3} + \frac{E_t[CF_{t+4}]}{(1 + k_0)^4} + \frac{E_t[CF_{t+4}](1 + g)}{(k_0 - g)(1 + k_0)^4} - D_t$$