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# Extended Dividend, Cash Flow and Residual Income Valuation Models - Accounting for Deviations from Ideal Conditions*

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**Abstract**

Standard equity valuation approaches (i.e., DDM, RIM, and DCF model) are derived under the assumption of ideal conditions, such as infinite payoffs and clean surplus accounting. Because these conditions are hardly ever met, we extend the standard approaches, based on the fundamental principle of financial statement articulation. The extended models are then tested empirically by employing two sets of forecasts: (1) analyst forecasts provided by Value Line and (2) forecasts generated by cross-sectional regression models. The main result is that our extended models yield considerably smaller valuation errors. Moreover, by construction, identical value estimates are obtained across the extended models. By reestablishing empirical equivalence under non-ideal conditions, our approach provides a benchmark that enables us to quantify the errors resulting from individual deviations from ideal conditions, and thus, to analyze the robustness of the standard approaches. Finally, by providing a level playing field for the different valuation approaches, our findings have implications for other empirical settings, for example, estimating the implied cost of capital.

*JEL Classification:* G12, G14, M41.
*Keywords*: Dirty Surplus, Terminal Value, Steady-State, Valuation Error.

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# 1. Introduction

This paper demonstrates the importance of accrual accounting and financial statement articulation (Penman and Yehuda 2009; Penman 2010) as anchors for standard equity valuation approaches, namely the dividend discount model (DDM), the residual income model (RIM), and the discounted cash flow (DCF) model. We extend the work of Lundholm and O'Keefe 2001a and others, by broadening the consistent financial planning approach to account for non-ideal valuation conditions, such as dirty surplus accounting and the consequences for terminal value modeling.[1] These theoretical considerations yield extended DDM, RIM, and DCF valuation formulas, which directly incorporate adjustment terms, thus capturing these non-ideal effects. We then test our comprehensive models on a large dataset of more than 1,700 firms, based on Value Line (VL) analyst forecasts and the more recent mechanical forecasting approach based on cross-sectional regression models (Fama and French 2000, 2006; Hou and Robinson 2006; Hou, van Dijk, and Zhang 2010; Lee, So, and Wang 2010).

The empirical analysis of our extended models reveals two major advantages. Firstly, the proposed models generate considerably smaller valuation errors, suggesting that market prices can be explained significantly better, if deviations from ideal conditions are taken into account. Secondly, by reestablishing equivalence for the first time in an empirical investigation, the extended models provide a benchmark valuation, because they yield identical valuation results under both ideal and non-ideal conditions. This benchmark allows us to analyze the extent to which specific deviations from ideal conditions distort the valuation results of the standard models which invariably neglect appropriate adjustments.

[1] Throughout the paper, we use the term "consistent financial planning" to refer to pro-forma financial statements, which conform to financial statement articulation and the principles of accrual accounting.

While Lundholm and O'Keefe (2001a) point out that the models should also incorporate dirty surplus and other corrections for non-ideal conditions, the present paper demonstrates how to achieve this. Specifically, we analyze how a careful implementation of the Lundholm and O'Keefe 2001a approach should look like from both theoretical and empirical perspectives. In addition, we consider whether implementation issues affect the DDM, RIM, and DCF model differently. In particular, we examine the role of payout and retention modeling in these three approaches.[2] Finally and most importantly, we examine whether it is worthwhile to consider implementation issues and whether this improves valuation accuracy.

Our main results are as follows: bias and inaccuracy decrease markedly in comparison to the standard models. For example, the average bias of the extended DCF model is 48 percentage points smaller (mechanical forecast setting) and 23 percentage points smaller (VL analyst forecast setting) than that of its standard counterpart.[3] Therefore, this answers the question of whether valuation accuracy can be increased by carefully incorporating payout/retention policies and by accounting for deviations from non-ideal conditions.

Consequently, our study makes a significant contribution to capital market research. Firstly, by using an integrated framework to quantify the magnitude of dirty surplus accounting, equity issuance and share repurchases, and the intertwined issue of terminal value calculations, our

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[2] The issue of whether dirty surplus and payout/investment modeling matters has not yet been resolved. For example, Ohlson (1999) discusses theoretical considerations supporting the argument that dirty surplus should not matter (at least in expectation). However, Hand and Landsman (2005), Chambers, Linsmeier, Shakespeare, and Sougiannis (2007) and Landsman, Miller, Peasnell, and Yeh (2011) document empirically that dirty surplus does indeed have pricing implications. Secondly, Miller and Modigliani's 1961 dividend displacement property is challenged by the recent literature (DeAngelo and DeAngelo 2006). Furthermore, Fama and French (2001), Grullon and Michaely (2002), and DeAngelo, DeAngelo, and Skinner (2004) point out that payout policies differ across firms, depending on their profitability and investment opportunities. Finally, Fairfield, Whisenant, and Yohn (2003a, b) show that growth in operating assets can be disaggregated into accruals and growth in long-term net operating assets, which has implications for future profitability and diminishing marginal returns on investment.

[3] See Table 5.

findings contribute to previous literature analyzing the different model specifications separately (e.g., Penman and Sougiannis 1998; Francis, Olsson, and Oswald 2000; Courteau, Kao, and Richardson 2001). Secondly, in capital market research, there is a need to deal with data which is affected by non-ideal conditions and the question arises as to how these can be incorporated into a consistent financial forecast setting. Thus, our study complements the mechanical forecasting line of research (Hou et al. 2010; Lee et al. 2010), by showing how to forecast a full set of consistent financial statements, which is in turn used to derive the forecasts necessary for the DDM, RIM, and DCF model. In the same vein, we show how to exploit essential information contained in VL forecast data, so as to obtain consistent value estimates. However, as in the existing literature, implementing intrinsic value models is fraught with additional simplifications besides the ones we address here. In particular, we cannot rule out that our approach violates non-arbitrage considerations. Moreover, estimating discount rates exogenously by the CAPM is potentially inconsistent with the intrinsic value models (Morel 2003). In addition, while recent literature has demonstrated that discount rates are time varying (e.g., Ang and Liu 2004; Callen and Lyle 2010), we employ constant cost of equity. However, while the latter assumption could be relaxed, it should not drive our results, since improving cost of capital estimates would benefit all three models in the same manner. Overall, the obtained identical value estimates and increased valuation accuracy indicate that it is worth adjusting the models, based on the consistent financial planning approach.

In sum, adjusting the models to given data yields important insights. In particular, if dirty surplus and share repurchases influence payout ratios and thus growth rates and finally shareholder value, it is important to develop models that are capable of capturing these components. Finally, our results might also have practical implications for the standard setters, because the derivation of fair value estimates is encountered in many different circumstances under IFRS and US-GAAP accounting. Deviations from ideal conditions should certainly be taken into account in projecting pro-forma firm accounts (i.e., balance sheets and income statements).

The remainder of this study is organized as follows: Section 2 discusses the related literature and Section 3 introduces the extended DDM, RIM and DCF model and reviews the standard models. Section 4 describes the implementation of the models, based on mechanical projections as opposed to analyst forecast data, while Section 5 contains the empirical results. Finally, Section 6 concludes.

## 2. Related literature

Firm valuation models and non-ideal valuation conditions, such as dirty surplus accounting, are not virgin territory. However, to the best of our knowledge, this is the first study that combines these two branches of the literature, by directly incorporating adjustment terms into the three valuation models. Technically, we follow the basic principles of accrual accounting and financial statement articulation to account explicitly for non-ideal valuation conditions.

Several studies demonstrate the *theoretical* equivalence of valuation models such as the DDM, RIM, and DCF model. However, this equivalence depends primarily on the assumption of ideal conditions.

Feltham and Ohlson (1995) point out that the DDM, RIM, and DCF model are equivalent, if payoff data for an infinite horizon are available, and Penman (1998) demonstrates that appropriate terminal value calculations are also important. More recently, Levin and Olsson (2000) and Lundholm and O'Keefe (2001a) analyze the consequences of pro-forma financial statement planning. However, they show that the same growth rate can be used when calculating the terminal values for all three models, if this growth rate is used to derive future balance sheets and income statements. Growth is then exogenous and the corresponding payout ratio endogenous. By contrast, Penman (2005) demonstrates that model-specific growth rates need to be used if one forecasts the different payoffs (dividends, cash flows, or abnormal earnings) of the models directly. Consequently, growth is endogenous and the corresponding payout ratio exogenous.

While the different growth rates are theoretically appealing, any direct empirical measurement must rely on some ad-hoc assumptions, yielding different value estimates. In order to overcome this problem, our approach corresponds to that of Lundholm and O'Keefe 2001a, but broadens their approach to the full-set of pro-forma financial statements applicable in real world empirical applications.

Moreover, our paper is related to *empirical* studies investigating the accuracy of valuation models (e.g., Bernard 1995; Kaplan and Ruback 1995; Frankel and Lee 1998; Penman and Sougiannis 1998; Francis et al. 2000; Courteau et al. 2001; Sougiannis and Yaekura 2001). For example, Penman and Sougiannis (1998) are concerned with the important issue of how the three intrinsic value methods perform, if applied to a truncated forecast horizon arising naturally in practice. Based on an ex-post-portfolio approach with realized payoff data, they find that RIM yields the lowest valuation errors, followed by the DDM and DCF model. Employing an ex-ante approach based on analyst forecasts, Francis et al. (2000) confirm that the RIM outperforms the other models. In addition, Courteau et al. (2001) compare the RIM to the DCF approach. Also using VL data, they find that the DCF model and RIM perform significantly differently, if price- or non-price-based terminal values are employed. Finally, Lundholm and O'Keefe (2001a) point out that the empirical findings in the abovementioned studies are driven by the particular mode of implementation.[4] Apart from a cost of capital argument, they attribute these mixed findings to two factors in particular. Firstly, different steady-state assumptions, and thus, independent growth modeling, payout decisions, and assumptions on future investment opportunities lead to different value estimates for the three models. Secondly, dirty surplus accounting impairs valuation equivalence.

Consequently, we built on the theoretical framework of Lundholm and O'Keefe 2001a. Specifically, we follow the well-established principle of accrual accounting and financial statement articulation for financial planning (e.g., Palepu, Healy, and Bernard 2003; Penman 2010) and extend this approach by incorporating adjustments for non-ideal conditions, such as dirty surplus accounting and the consequences of terminal value modeling.[5]

Previous empirical literature has focused mainly on two aspects, the measurement issue and the value relevance of dirty surplus. Regarding the first aspect, for example, O'Hanlon and Pope (1999), Dhaliwal, Subramanyam, and Trezevant (1999), Lo and Lys (2000), and Chambers et al. (2007) establish that earnings are heavily distorted by dirty surplus. The second strand of research analyzes the value relevance of dirty surplus accounting flows, yielding mixed results. Dhaliwal et al. (1999) find no evidence that comprehensive income in the U.S. is more strongly associated with returns/market values or more accurately predicts future cash flows/income than net income. By contrast, Kanagaretnam, Mathieu, and Shehata (2009) find a stronger association between dirty surplus and share returns, when using more recent data. Biddle and Choi (2006) report that comprehensive income, as defined in SFAS 130, outweighs net income in explaining equity returns. In a related research design, Isidro, O'Hanlon, and Young (2006) explore the

4 See also the debate between Lundholm and O'Keefe (2001b) and Penman (2001) in "Contemporary Accounting Research".

5 Note that our approach differs from the usual way (presented in many textbooks) of adjusting the data on security valuation. Instead of adjusting the data, we enhance the models.

association between valuation errors from the standard RIM and violations of the clean surplus relation. They find weak evidence of the relationship between valuation errors and dirty surplus flows.[6] Finally, Chambers et al. (2007) find that other comprehensive income (OCI) is value relevant. Investors are especially likely to price two components of OCI: foreign currency translation adjustment and unrealized gains/losses based on available-for-sale securities. Interestingly, Chambers et al. (2007) find that marketable security adjustments are valued at a rate greater than dollar-for-dollar, although the theory predicts that these components should be purely transitory. In summary, Chambers et al. (2007) attribute the lack of consistent results to the differences between the research designs employed, among other factors. In line with their results, we find that dirty surplus is of particular importance to improve valuation precision. For example, for the RIM valuation, the average bias can be reduced by 22 percentage points, if the regression-based forecast approach (e.g., Hou et al. 2010; Lee et al. 2010) is used, and still by six percentage points, if VL forecast data is explored with respect to financial statement articulation.[7]

Besides correcting for dirty surplus, we also highlight the importance of a comprehensive definition of dividends. We therefore employ another important correction which considers transactions with the equity owners via capital increases and share repurchases (Fama and French 2001, 2005, 2008).

6 Although it is related, the research design of Isidro et al. 2006 is essentially quite different. For example, we explicitly incorporate dirty surplus flows into the DDM, RIM and DCF model, allowing us to analyze how dirty surplus empirically affects the individual models.

7 See Table 7.

## 3. Valuation methods

***Extended valuation methods under non-ideal conditions***

This section presents the three most common equity valuation models, incorporating our model-specific extensions. We consider the *Dividend Discount Model (DDM),* the *Residual Income Model (RIM)* and the *Discounted Cash Flow (DCF) model*.[8] These models are generally derived under ideal conditions (i.e., clean surplus accounting and full payoff information, such as share repurchases and capital contributions). Furthermore, because forecasts up to infinity are not available, we present the models in their common two-stage form, with an explicit forecast period lasting a limited number of years and a terminal period. The terminal period captures the value beyond the explicit forecast period by a terminal value, which is often calculated on the basis of (growing) perpetuities.

As a starting point, we assume ideal conditions. The following relations then hold and are used to describe the development of stock and flow items over time $t$ (Christensen and Feltham 2009):

(CSR) $$bv_t = bv_{t-1} + x_t - d_t, \tag{1}$$

(FAR) $$debt_t = debt_{t-1} + int_t \left(1-s\right) + d_t - fcf_t, \tag{2}$$

(NIR) $$int_t = r_D \cdot debt_{t-1}, \tag{3}$$

(OAR) $$fcf_t = oi_t - \left(oa_t - oa_{t-1}\right). \tag{4}$$

The first two equations, the clean surplus relation (CSR) and the financial asset relation (FAR), focus on the balance sheet, and the net interest relation (NIR) and the operating asset relation (OAR) show corresponding relations between the flow items. In this respect, the clean surplus

8 For the DDM, see Williams (1938), Gordon (1959), and Gordon and Shapiro (1956). For the RIM, see Preinreich (1938), Edwards and Bell (1961), and Peasnell (1982). For the DCF model, see Rappaport (1986) and Copeland, Koller, and Murrin (1994).

relation postulates that changes in the book value of equity $bv$ between two periods result exclusively from differences between earnings $x$ and net dividends $d$. Turning to the financial asset relation, at first glance, one would expect to see interest and principal payments with respect to the progression of debt over time. While interest payments $int$ are obviously included in the financial asset relation, it is necessary to recognize that $int_t \cdot s + d_t - fcf_t$ corresponds to principal payments, where $s$ is the corporate tax rate and $fcf$ is the free cash flow. Defining the FAR in this way is standard in the literature and offers the advantage of incorporating a definition of free cash flow.

Ideally, interest payments are given by the product of debt from the previous period, multiplied by the cost of debt $r_D$ as stated by the net interest relation. More precisely, $debt$ is the sum of interest-bearing liabilities and preferred stock.[9] Finally, noting that the book value of equity could also be expressed as $bv_t = oa_t - debt_t$, where $oa$ refers to operating assets, and using the definition of operating income $oi_t = x_t + int_t\left(1 - s\right)$, free cash flow is defined by the resolved operating asset relation in equation (4).

While these four equations are useful for planning the explicit forecast horizon $(t = 1,2,...,T)$, another planning approach is needed for the terminal period $(T + 1)$, in order to circumvent the problem of obtaining infinite payoff forecasts for the three models. This planning approach is given by the financial statement steady-state (Lundholm and O'Keefe 2001a; Levin and Olsson 2000).

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9 In our analysis, we abstract from a distinction between operating and financial assets (i.e., trade securities). See, for instance, Feltham and Ohlson (1995), where financial assets are defined as cash and marketable securities minus debt. For the treatment of preferred stock as debt, see Penman (2010).

(FSS) Financial statement steady-state: $item^{i}_{T+t+1} = \left(1+g\right) item^{i}_{T+t} \; \forall \, i,t$ .

According to the FSS, each *item i* on the balance sheet (operating assets, debt, and shareholders' equity) and on the income statement (earnings, operating income, and interest expenses) grows beyond the explicit forecast period up to infinity at the rate *g*. This framework ensures that the forecasted balance sheets and income statements are internally consistent with one another. Consequently, this planning approach provides a benchmark for forecasting financial performance. Most importantly, payoff forecasts derived from this approach are coherent with each other, and the three models yield the same valuation result (Lundholm and O'Keefe 2001a; Levin and Olsson 2000). In particular, a consistent financial statement model is required in which income statements and balance sheets are linked through retained earnings (e.g., Palepu et al. 2003).[10]

However, while Lundholm and O'Keefe (2001a) note that it is probably important to consider the effects of non-ideal valuation conditions, such as dirty surplus accounting, formulas incorporating these extensions are not provided. The following section fills this gap by relying on the principle of financial statement articulation and allowing for non-ideal valuation conditions.

*Dividend Discount Model*

The dividend $d=div^{total}$ in the DDM must include all cash transfers between the equity owners and the firm. If, for simplicity, only cash dividends $div^{cash}$ are used (e.g., Francis et al. 2000), a

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[10] Starting in period *T,* the corresponding payoffs (i.e., dividend, residual income, cash flow or all items i on the balance sheet and income statement) are assumed to grow indefinitely towards infinity at the rate *g*.

substantial part of cash transfers is neglected.[11] To highlight the importance of capital increases and share repurchases (e.g., Fama and French 2001, 2005, 2008; Grullon and Michaely 2002), we separate total dividends $div^{total}$ into cash dividends $div^{cash}$ and net capital contributions $netcap$. Thus, dividends are given as $div^{total} = div^{cash} + netcap$, where $netcap$ represents the difference between share repurchases and capital increases.[12] Furthermore, Lundholm and O'Keefe (2001a) show that dividends in the terminal value phase must conform to financial statement articulation $d_{T+1} = \left(1+g\right) x_T - \left(1+g\right) bv_T + bv_T = \left(1+g\right) x_T - g \cdot bv_T$. However, this expression assumes clean surplus earnings $x_T$ to determine the terminal value of the DDM.

Because the clean surplus relation is usually violated under US-GAAP accounting, it is necessary to incorporate a dirty surplus correction in the DDM.[13] By the definition of the DDM, dividends are given exogenously during the explicit forecast period. Thus, the correction is required only for the terminal period, in which net dividends are determined endogenously by the prescribed consistent pro-forma financial planning technique. Since the applied forecasting approach described in the next section produces (1) clean earnings time series and (2) dirty earnings time series, the standard recursive equation $bv_t = bv_{t-1} + x_t - d_t$ will be affected twice. In other words, differences arise between clean earnings and dirty earnings, and between the clean book value and the dirty book value. Correcting for differences between clean and dirty earnings and capturing other clean surplus violations attributable, for example, to the accounting for employee

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11 However, note that the objective of Francis et al. 2000 was to provide evidence of how the models perform under common practice.

12 Note that $netcap$ can easily be obtained, if one forecasts total dividends as well as cash dividends, as outlined in the next section ($netcap = div^{total} - div^{cash}$).

13 Clean surplus violations include, for example, unrealized gains and losses on securities available-for-sale, on foreign currency translations or on derivative instruments. For the individual components to be included in other comprehensive income see SFAS 130.39 and Penman (2010).

stock options and related share transactions ensures "super clean surplus" accounting (Feltham 1996; Christensen and Feltham 2003). Under super clean surplus accounting, share issuance is recorded at fair market value. Thus, this concept entails the advantage that the valuation models measure the value of current shares outstanding, rather than the market value of current shares outstanding *plus* the market value of all other equity claimants (Landsman, Peasnell, Pope, and Yeh 2006; Landsman, Miller, Peasnell, and Yeh 2011).

Specifically, clean earnings consist of the 'dirty' earnings $x^{dirt}$ and the dirty surplus correction $x\_dirt_T^{cor}$ (i.e., $x_T^{clean} = x_T^{dirt} + x\_dirt_T^{cor}$).[14] The same logic leads to the corresponding book value equation: $bv_T^{clean} = bv_T^{dirt} + bv\_dirt_T^{cor}$. Put differently, a super clean surplus accounting equation is given by $bv_T^{clean} = bv_{T-1}^{dirt} + bv\_dirt_{T-1}^{cor} + x_T^{dirt} + x\_dirt_T^{cor} - d_T$. However, note that Landsman et al. (2011) rely on realized data and even then, they have to estimate share repurchases and issues at market value, since these transactions are not generally reported at (fair) market value in the accounting system. Similarly, our dirty surplus corrections are attributable to forecasting a 'super clean' and a 'dirty' series of book values and income figures.[15] Incorporating these insights into the standard dividend equation $d_{T+1} = \left(1+g\right) x_T - g \cdot bv_T$ yields:

$$d_{T+1} = \left(1+g\right) x_T^{dirt} + \left(1+g\right)\left(x_T^{clean} - x_T^{dirt}\right) - g \cdot bv_T^{dirt} - g \cdot \left(bv_T^{clean} - bv_T^{dirt}\right) \tag{5}$$

14 Alternative specifications of dirty surplus income $x^{dirt}$ can be earnings measures such as comprehensive income according to SFAS No. 130, net income or net income before extraordinary items and special items. In our study, we use net income before extraordinary items as the $x^{dirt}$ measure, because SFAS 130 “Reporting of Comprehensive Income” only became effective in 1997, and is thus not available in entirety for our sample period.

15 Note that in our setting and in conformity with the Abnormal Earnings Growth (AEG) model of Ohlson and Juettner-Nauroth 2005, earnings and dividends exert a significant impact and we therefore obtain the book values as residuals. Thus, the two series of book values $bv_t^{dirt}$ ($bv_t^{clean}$) are indirectly implied by dirty (clean) earnings forecasts $x_t^{dirt}$ ($x_t^{clean}$) and cash (total) dividend forecasts $div_t^{cash}$ ($div_t^{total}$) due to the dirty (clean) surplus relation. In our empirical approach, we therefore use only realized book values to initialize the dirty (clean) surplus relation, maintaining the principle of consistent financial planning.

Re-arranging yields:

$$d_{T+1} = \underbrace{\left(1+g\right) x_T^{dirt} - g \cdot bv_T^{dirt}}_{d_{T+1}^{dirt}} + \underbrace{\left(1+g\right)\left(x_T^{clean} - x_T^{dirt}\right) - g \cdot \left(bv_T^{clean} - bv_T^{dirt}\right)}_{dirt_{T+1}^{cor}} \tag{6}$$

Hence, using $d_t = div_t^{cash} + netcap_t$ for all $t = 1,2,...,T$ and the newly defined dividend for the terminal period, leads to our extended DDM valuation equation:

(DDM^extended) $$V_0 = \sum_{t=1}^{T} \frac{div_t^{cash} + netcap_t}{\left(1+r_E\right)^t} + \frac{d_{T+1}^{dirt} + dirt_{T+1}^{cor}}{\left(1+r_E\right)^T \left(r_E - g\right)}, \text{ with} \tag{7}$$

$$\begin{aligned}
&div_t^{cash} = cash\ dividends,\\
&netcap_t = div_t^{total} - div_t^{cash} = share\ repurchases\ in\ t - capital\ increases\ in\ t,\\
&dirt_{T+1}^{cor} = \left(1+g\right)\left(x_T^{clean} - x_T^{dirt}\right) - g \cdot \left(bv_T^{clean} - bv_T^{dirt}\right),\\
&d_{T+1}^{dirt} = \left(1+g\right) x_T^{dirt} - g \cdot bv_T^{dirt},\\
&r_E = cost\ of\ equity,\ and\\
&V_0 = intrinsic\ value\ estimate\ at\ time\ t = 0.
\end{aligned}$$

For ease of exposition, we assume that the valuation date is *t=0*. Note that the $dirt_{T+1}^{cor}$ term is only necessary, because we need (dirty) income and book value measures to calculate the numerator in the terminal period. Furthermore, since we extend the three valuation models by directly incorporating the adjustment terms, the $dirt_{T+1}^{cor}$ term in our extended DDM consists of both a correction for earnings and an adjustment for book values. Finally, since the terminal value expression is based on consistent financial planning, the book value correction in the terminal period also accounts for transactions between equity owners and the firm (share repurchases and capital increases) using the clean surplus relation. However, in the empirical estimates (Section 5), we explicitly show the impact of net capital contributions in the terminal period, so as to enhance transparency.

*Residual Income Model*

Because the clean surplus relation is usually violated under US-GAAP accounting, equation (8) shows that a dirty surplus correction should also be incorporated into the RIM:

$$\begin{aligned} x_t^a &= x_t - r_E \cdot bv_{t-1} = \left(x_t^{dirt} + x\_dirt_t^{cor}\right) - r_E\left(bv_{t-1}^{dirt} + bv\_dirt_{t-1}^{cor}\right) \\ &= \left(x_t^{dirt} - r_E \cdot bv_{t-1}^{dirt}\right) + x\_dirt_t^{cor} - r_E \cdot bv\_dirt_{t-1}^{cor} \\ &= x_t^{a,dirt} + \left(x_t^{clean} - x_t^{dirt}\right) - r_E\left(bv_{t-1}^{clean} - bv_{t-1}^{dirt}\right) \\ &= x_t^{a,dirt} + dirt_t^{cor}. \end{aligned} \tag{8}$$

Note that, in contrast to the DDM, clean surplus violations must be incorporated during the explicit forecast period, as well as during the terminal period.

The extended RIM, which is based on the consistent financial planning approach, includes the dirty surplus correction, which consequently results in the following expression:

$$(\text{RIM}^{\text{extended}}) \quad V_0 = bv_0 + \sum_{t=1}^{T} \frac{x_t^{a,dirt} + dirt_t^{cor}}{\left(1+r_E\right)^t} + \frac{x_{T+1}^{a,dirt} + dirt_{T+1}^{cor}}{\left(1+r_E\right)^T\left(r_E - g\right)}, \text{ with} \tag{9}$$

$$\begin{aligned} x_t^{a,dirt} &= x_t^{dirt} - r_E \cdot bv_{t-1}^{dirt}, \\ dirt_t^{cor} &= \left(x_t^{clean} - x_t^{dirt}\right) - r_E\left(bv_{t-1}^{clean} - bv_{t-1}^{dirt}\right), \\ x_{T+1}^{a,dirt} &= \left(1+g\right) x_T^{dirt} - r_E \cdot bv_T^{dirt}, \text{ and} \\ dirt_{T+1}^{cor} &= \left(1+g\right)\left(x_T^{clean} - x_T^{dirt}\right) - r_E\left(bv_T^{clean} - bv_T^{dirt}\right). \end{aligned}$$

*Discounted Cash Flow Model*

In line with the DDM and RIM, dirty surplus accounting necessitates the inclusion of an appropriate correction term in the DCF approach:[16]

[16] This cash flow definition, assuming ideal conditions (i.e., CSR holds), is derived by Penman 1998 and applied by Courteau et al. 2001. It entails the advantage that it resembles a flow-to-equity-type cash flow model and thus can be discounted at the cost of equity, instead of the weighted average cost of capital (*wacc*), when a pure free cash flow definition is employed. Overall, all three intrinsic values models, the DDM, the RIM and this DCF model can be discounted at the cost of equity and are therefore directly comparable.

$$
\begin{aligned}
cf_t &= fcf_t^{dirt} - r_D\left(1-s\right) debt_{t-1} + r_E \cdot debt_{t-1} + x\_dirt_t^{cor}, with \\
fcf_t^{dirt} &= oi_t^{dirt} - (oa_t - oa_{t-1}).
\end{aligned} \tag{10}
$$

Equation (10) omits, however, the relation $bv_t^{clean} = bv_t^{dirt} + bv\_dirt_t^{cor}$, which is hidden in the debt term, recalling that $bv_t = oa_t - debt_t$. In addition, the developed representation includes the counterintuitive term $r_E \cdot debt_{t-1}$, which simply derives from to the fact that the entity DCF model was deliberately rendered comparable to the equity perspective of the RIM and DDM. Thus, to capture dirty book values and provide a more intuitive, but parsimonious form, we note that $bv_t = oa_t - debt_t$ can be expressed as $debt_{t-1} = oa_{t-1} - bv_{t-1}^{dirt} - (bv_{t-1}^{clean} - bv_{t-1}^{dirt})$. Inserting this term into equation (10) after some basic simplifications and recalling that $oi_t^{dirt} = x_t^{dirt} + int_t\left(1-s\right)$ yields:[17]

$$
cf_t = \underbrace{x_t^{dirt} - oa_t + (1+r_E)\, oa_{t-1} - r_E \cdot bv_{t-1}^{dirt}}_{cf_t^{dirt}} + \underbrace{x\_dirt_t^{cor} - r_E\,(bv_{t-1}^{clean} - bv_{t-1}^{dirt})}_{dirt_t^{cor}}. \tag{11}
$$

This equation states that the cash flow available $cf_t$ consists of the dirty surplus cash flow $cf_t^{dirt}$, which is calculated indirectly starting from dirty earnings, and the dirt correction $dirt^{cor}$. Further, in contrast to equation (10), it provides an economically intuitive interpretation of $cf_t^{dirt}$, because it is now closely reformulated as a residual earnings approach. Loosely speaking, a 'dirty' cash flow is positive, if the cost of equity is earned on the previously employed book value $x_t^{dirt} - r_E \cdot bv_{t-1}^{dirt}$, and current investments $oa_t$ are less than the cost of equity-adjusted previous-period assets $(1+r_E)\, oa_{t-1}$. Accounting for $dirt^{cor}$ leads to the following extended DCF

[17] Since Bowman (1979) and Sweeney, Warga, and Winters (1997) provide strong empirical evidence that book values are a good proxy for market values of debt, we do not incorporate an additional adjustment term to capture this effect in our models.

model:

$$(\text{DCF}^{\text{extended}}) \quad V_0 = \sum_{t=1}^{T} \frac{cf_t^{dirt} + dirt_t^{cor}}{\left(1+r_E\right)^t} + \frac{cf_{T+1}^{dirt} + dirt_{T+1}^{cor}}{\left(1+r_E\right)^T \left(r_E - g\right)} - debt_0, \text{ with} \tag{12}$$

$$\begin{aligned}
cf_t^{dirt} &= x_t^{dirt} - oa_t + (1+r_E)\, oa_{t-1} - r_E \cdot bv_{t-1}^{dirt}, \\
dirt_t^{cor} &= (x_t^{clean} - x_t^{dirt}) - r_E\,(bv_{t-1}^{clean} - bv_{t-1}^{dirt}), \\
cf_{T+1}^{dirt} &= (1+g)\left(x_T^{dirt} - oa_T\right) + (1+r_E)\, oa_T - r_E \cdot bv_T^{dirt}, \text{ and} \\
dirt_{T+1}^{cor} &= \left(1+g\right)\left(x_T^{clean} - x_T^{dirt}\right) - r_E\,(bv_T^{clean} - bv_T^{dirt}).
\end{aligned}$$

If the extended versions of the DDM, RIM and DCF model are applied, where the corrections are captured in the numerator of the terminal value, the same growth rate *g* can be used for all three models.

***The standard models as special cases of the extended valuation methods***

Empirical studies testing the accuracy of valuation techniques do not account for deviations from ideal conditions in their models (e.g., Penman and Sougiannis 1998; Francis et al. 2000). In addition, these studies simply extrapolate the last payoff of the explicit forecast period ad infinitum, assuming the same ad hoc growth rate (typically 0 percent, 2 percent, or 4 percent for all three models). As we demonstrate in the empirical part of our study, this model implementation leads to substantial distortions, especially for the DDM and DCF model.

In order to obtain the standard versions of the models, as implemented in previous empirical studies, one simply has to set $netcap_t = 0$ and $dirt_t^{cor} = 0 \; \forall t$ and extrapolate the last explicit payoff ad infinitum, assuming that growth rates across all three models are equal (i.e., $g^{DDM} = g^{RIM} = g^{DCF} = g$):

(DDM$^{\text{standard}}$) $V_0^{DDM} = \sum_{t=1}^{T} \frac{div_t^{cash}}{\left(1+r_E\right)^t} + \frac{\left(1+g\right) div_T^{cash}}{\left(1+r_E\right)^T \left(r_E - g\right)}$, (13)

(RIM$^{\text{standard}}$) $V_0^{RIM} = bv_0 + \sum_{t=1}^{T} \frac{x_t^{a,dirt}}{\left(1+r_E\right)^t} + \frac{\left(1+g\right) x_T^{a,dirt}}{\left(1+r_E\right)^T \left(r_E - g\right)}$, (14)

(DCF$^{\text{standard}}$) $V_0^{DCF} = \sum_{t=1}^{T} \frac{cf_t^{dirt}}{\left(1+r_E\right)^t} + \frac{\left(1+g\right) cf_T^{dirt}}{\left(1+r_E\right)^T \left(r_E - g\right)} - debt_0$. (15)

These standard models serve as a familiar framework for an empirical evaluation of the extended models.

***The impact of deviations from ideal conditions***

Because, by construction, the extended models yield identical valuations, they can be used as a benchmark for quantifying the impact of individual deviations from ideal conditions. The overall value impact is obtained simply by comparing the extended and standard models. For example, for the DDM, the difference between the extended model from equation (7) and the simple model from equation (13) is as follows:

$$\begin{aligned}
\Delta^{DDM} &= \sum_{t=1}^{T} \frac{div_t^{cash} + netcap_t}{\left(1+r_E\right)^t} + \frac{d_{T+1}^{dirt} + dirt_{T+1}^{cor}}{\left(1+r_E\right)^T \left(r_E - g\right)} - \sum_{t=1}^{T} \frac{div_t^{cash}}{\left(1+r_E\right)^t} - \frac{\left(1+g\right) div_T^{cash}}{\left(1+r_E\right)^T \left(r_E - g\right)} \\
&= \sum_{t=1}^{T} \frac{netcap_t}{\left(1+r_E\right)^t} + \frac{\left(1+g\right) netcap_T}{\left(1+r_E\right)^T \left(r_E - g\right)} + \frac{dirt_{T+1}^{cor}}{\left(1+r_E\right)^T \left(r_E - g\right)} + \frac{\Delta tv^{DDM}}{\left(1+r_E\right)^T \left(r_E - g\right)}.
\end{aligned}$$

This overall value impact can be separated into its single present value components: (1) the net capital contributions during the explicit forecast period and the terminal period, (2) the dirty surplus correction, and (3) the model-specific terminal value adjustment $\Delta tv^{DDM}$. For the DDM, for example, the latter correction term is simply given by:

$$\Delta tv^{DDM} = d_{T+1}^{dirt} - \left(1+g\right)\left(div_T^{cash} + netcap_T\right) = d_{T+1}^{dirt} - \left(1+g\right) div_T^{total}. \tag{16}$$

Equation (16) captures deviations that cannot be attributed to $netcap$ and $dirt^{cor}$. Thus, adding $netcap,\ dirt^{cor}$, and $\Delta tv^{DDM}$ to the standard DDM yields the same value estimate as the extended DDM.

In the RIM, the difference between the terminal value calculations in (9) and (14), which is not induced by $dirt^{cor}$, is given by:[18]

$$\Delta tv^{RIM} \quad = -r_E\left(bv_T^{dirt} - \left(1+g\right)bv_{T-1}^{dirt}\right). \tag{17}$$

Finally, in the DCF model, the difference between the extended and standard versions of the model emerges from the $dirt^{cor}$ and $\Delta tv^{DCF}$ components. $\Delta tv^{DCF}$ is defined as:

$$\Delta tv^{DCF} = \left(1+r_E\right)\left(oa_T - \left(1+g\right)oa_{T-1}\right) - r_E\left(bv_T^{dirt} - \left(1+g\right)bv_{T-1}^{dirt}\right). \tag{18}$$

Table 1 summarizes the corrections accounted for in the extended versions, compared to their standard counterparts.

[Insert TABLE 1 about here]

## 4. Implementing the models based on mechanical projections versus analyst forecasts

***Mechanical projections***

Our tests of the extended models require forecasts of several items, which can either be forecasted mechanically via regressions or obtained directly from analyst forecasts (e.g., VL). Turning to the first method and using mechanical forecasting, we build on Fama and French

[18] An alternative derivation of this term is given in Lundholm and O'Keefe 2001a.

2000, 2006 and more recently Hou and Robinson 2006, Hou et al. 2010, and Lee et al. 2010. These studies establish that the cross-sectional models perform extraordinarily well in explaining variation across firms in terms of profitability and investment. Furthermore, these cross-sectional models provide the key advantage that analyst coverage is not required and a large sample of individual firms with only minimal time series data is required, thus minimizing survivorship bias. Furthermore, the forecasts are free from well-documented biases in analysts' forecasts (e.g., Chan, Karceski, and Lakonishok 2003).

Based on this approach, we estimate cross-sectional regression models for our variables of interest, such as earnings, dividends, capital expenditures (among others) on a rolling sample and generate mechanical out-of-sample forecasts. Following Hou et al. (2010), we estimate the following annual pooled cross-section regressions for $y_{i,t+\tau} = \left\{ x_{i,t+\tau}^{clean}, div_{i,t+\tau}^{total} \right\}$ on a rolling sample window for different lag lengths $\tau = 1,2,...,5$ :

$$y_{i,t+\tau} = \beta_0 + \beta_1 ev_{i,t} + \beta_2 ta_{i,t} + \beta_3 div_{i,t}^{total} + \beta_4 dd_{i,t}^{total} + \beta_5 x_{i,t}^{clean} + \beta_6 neg\_x_{i,t}^{clean} + \beta_7 acc_{i,t} + \varepsilon_{i,t+\tau} \qquad (19)$$

We then predict one to five-year-ahead forecasts $(\tau = 1,2,...,5)$ for our clean earnings and total dividend variables.

In addition, we employ the same technique to obtain forecasts for the remaining variables (i.e., 'dirty' earnings ($x^{dirt}$), cash dividends ($div^{cash}$), capital expenditures (*capex*), depreciation and amortization (*dep*), and working capital (*wc*)): $z_{i,t+\tau} = \left\{ x_{i,t+\tau}^{dirt}, div_{i,t+\tau}^{cash}, capex_{i,t+\tau}, dep_{i,t+\tau}, wc_{i,t+\tau} \right\}$,

$$z_{i,t+\tau} = \beta_0 + \beta_1 ev_{i,t} + \beta_2 ta_{i,t} + \beta_3 div_{i,t}^{cash} + \beta_4 dd_{i,t}^{cash} + \beta_5 x_{i,t}^{dirt} + \beta_6 neg\_x_{i,t}^{dirt} + \beta_7 acc_{i,t} + \varepsilon_{i,t+\tau}. \qquad (20)$$

Note that we adopt four dependent variables in equation (20), so as to achieve consistency with equation (19). Specifically, enterprise value (*ev*), total assets (*ta*), and accruals (*acc*) are identical across both specifications. However, dividends (*div*), earnings (*x*), and their corresponding dummy variables *dd* and *neg_x*[19] are measured as total dividends and clean earnings in equation (19), while their standard counterparts, that is, cash dividends and dirty earnings, are used in equation (20). Recall that the extended DCF model in equation (12) uses forecasted changes in operating assets $\Delta oa_t = capex_t - dep_t + \Delta wc_t$. While VL forecasts are available for all three items (*capex, dep*, and *wc*), we employ equation (20) to obtain them through the mechanical forecasting approach. Finally, to obtain forecasts for book values of equity, we use observable book values at the beginning of each year and employ the clean (or dirty) surplus relation, using forecasted total dividends and clean earnings (or forecasted cash dividends and dirty earnings).

***Analyst forecast data from Value Line***

Analyst forecasts constitute an alternative to the mechanical forecasting approach. We obtain this data from VL, because, in contrast to IBES projections, VL reports more items, which are necessary for our research design.[20] VL reports forecasts for only three horizons: the current fiscal year (year one), the following fiscal year (year two), and long-run forecasts (year three to year five). We follow Bushee (2001) and assume that VL's long-range forecast labeled "three-to-five years" is a five-year-ahead forecast. Similarly to Courteau et al. (2001), we interpolate financial statement items for the third and fourth period, using straight-line growth, because valuation approaches require projected items for each explicit forecast period. Thus, our

[19] *dd* is a dummy variable that equals 0 for dividend payers and 1 for non-dividend payers, *neg_x* is a dummy variable that equals 1 for firms with positive and 0 for firms with negative earnings.

[20] Employing VL's analyst forecast data might contain potential limitations, because market expectations regarding earnings, book values, capital expenditures, etc. can be measured only with a degree of error. Empirical evidence from Abarbanell 1991, Abarbanell and Bernard 1992, and Abarbanell and Bernard 2000 shows that VL forecasts might be inefficient and biased. However, keeping this caveat in mind, we invoke the same assumption as in Courteau et al. 2001, that bias/measurement error are treated as a constant factor in our analysis. Since we also employ the mechanical forecast approach, it would be interesting to analyze whether VL forecast data provides more accurate intrinsic value estimates than the mechanical forecasting approach.

empirical implementation comprises an explicit forecast period of five fiscal year ends, with a follow-on terminal period as a (growing) perpetuity.

Employing VL data in order to be comparable to the mechanical projection approach of the previous section, requires further careful considerations. Firstly, we employ forecasts of (1) cash dividends ($div^{cash}$; available per share), (2) capital expenditures (*capex*; available per share), (3) depreciation and amortization (*dep*; available in levels), and (4) working capital (*wc*; available in levels).[21] Since the mechanical forecast approach employs levels, we multiply the per share figures by common shares outstanding, forecasted by VL data. In addition, we are left with two remaining specifications. Firstly and unfortunately, VL does not provide forecasts for share repurchases and stock issuance, that is, net capital contributions which are especially required for a thorough implementation of the DDM. Secondly, VL reports some form of 'clean' earnings, where extraordinary effects are excluded. If they also correct for the impact of dirty surplus accounting, their forecasts should be more in line with our mechanical clean earnings forecasts than the classic 'dirty' alternative.

To circumvent the first problem of non-available total dividends, we simply estimate a historical payout ratio with COMPUSTAT Data and multiply this percentage with the VL earnings forecast for each firm at each point in time (rolling estimates). Considering the potential uncertainty surrounding the impact of dirty surplus poses no problems for our extended models, since we capture any inconsistencies between clean and dirty figures with our correction terms. More specifically, while the netcap correction in the DDM and the terminal value adjustments will obviously be important, the dirty surplus correction, based on the VL implementation, reduces to differences between the series of forecasted clean and dirty book values, due to the

[21] For a more detailed variable description, see Appendices 1 and 2.

clean or dirty surplus relation. These differences only arise through employing a comprehensive dividend definition $div^{total}$ in the CSR, compared to a standard cash dividend, as in the previous literature.

***Research design and data description***

Three main data sources are used in our study. We employ annual accounting data from the COMPUSTAT North America active and research files, market data from CRSP and analyst forecasts from VL.[22] Our study spans the time period from 1988 to 2006, because sufficient VL data is not available prior to this time span. The sample ends in 2006, in order to omit any confounding effects attributable to the financial crisis. We estimate intrinsic firm values at the end of June of each year and incorporate the fact that the explicit forecast horizons $(t = 1,2,...,5)$ might differ as a result of different fiscal year ends.[23] In line with other studies, financial firms (SIC codes 6000 to 6999) are excluded from the sample, due to their different characteristics.

As already outlined, we implement two sets of forecasted items. The first set of items is based on the regression approach of Hou et al. 2010, while the second is provided directly by VL's analyst forecasts. For the mechanical forecasting approach, at the end of June each year from 1987 to 2006, we estimate the pooled cross-sectional regression in equations (19) and (20), using the previous ten years of data. Table 2 reports the summary statistics of the variables in the

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22 CRSP and COMPUSTAT merged data is obtained from Wharton Research Data Service (WRDS), and our sample includes all active and inactive firms listed on the New York Stock Exchange (NYSE), the American Exchange (AMEX) and the National Association of Securities Dealers Automated Quotations (NASDAQ) market. VL data is merged by means of the CUSIP number.

23 For example, if the month of a firm's fiscal year end is December, then point in time of the firm's first forecast will be in six months and therefore, less than one year. In our empirical study, different fiscal year ends are therefore incorporated into the discounting of the forecasts. Moreover, if the fiscal year end is not June, $bv_0$ for the RIM and $debt_0$ for the DCF model will earn in-year returns at a cost of equity ( $r_E$ ).

regression equation, starting in 1977 and ending in 2006, while Table 3 contains the regression results starting in 1987 and ending in 2006.

[Insert TABLE 2 about here]

The variables in Table 2 are winsorized each year at the 0.5 percent and 99.5 percent percentiles to mitigate the effect of outliers. Furthermore, we only use firms which are also found in the VL database, so as to ensure comparability of both approaches. The average enterprise value is 4,319 million US$, indicating that the sample includes mainly large firms. In addition, average earnings calculated according to the clean surplus relation ($x_t^{clean}$) are significantly[24] larger than average earnings before extraordinary items ($x_t^{dirt}$) reported by COMPUSTAT (149 million US$ vs. 125 million US$). Interestingly, the impact of share repurchases and stock issuance seems to be economically significant; the mean percentage of cash dividend payers is far larger than if we include share repurchases and capital increases ($dd_t^{cash}$ = 38 percent vs. $dd_t^{total}$ = 4 percent). Overall, the summary statistics yield well-behaved patterns as in other studies (e.g., Lee et al. 2010).

[Insert TABLE 3 about here]

Based on these input variables, we estimate the seven regression models as tabulated in Table

[24] The significance was analyzed by a simple $t$-test of equal means.

3.[25] Since one-year to five-year-ahead forecasts $(\tau = 1,2,...,5)$ are needed for our modeling, and in order to compare them with the VL forecasts, each regression equation is estimated with the respective left-hand variable leading one-year (*t+1*) and up to five-years ahead (*t+5*). Common regressors in all equations are the enterprise value (*ev*), total assets (*ta*) and accruals (*acc*).[26] However, recall that for regression equations (1) and (2) in Table 3 (dependent variables: $x^{clean}$ and $div^{total}$), the four independent variables ($div^{cash}$, $dd^{cash}$, $x^{dirt}$, and $neg\_x^{dirt}$) of regression equations (3) to (7) are changed to ($div^{total}$, $dd^{total}$, $x^{clean}$, and $neg\_x^{clean}$) to ensure consistency between dependent and explanatory variables. Regarding regression equation (3) in Table 3 (dependent variable: 'dirty' earnings $x^{dirt}$), prior evidence is provided by Hou et al. 2010. We confirm their overall results for our sample. Recall that the estimates are used to provide forecasts. Thus, we highlight the decreasing, but in absolute terms, still promising levels of the in-sample-adjusted $R^2$. For example, while 81 percent of the variation in one-year-ahead 'dirty' earnings ($x^{dirt}_{t+1}$) is explained, 68 percent of the variation of the five-year-ahead forecast is still captured by the regression design.[27] Qualitatively similar results are obtained for all other variables. The only minor concern is shown for working capital as our dependent variable (regression equation (7)), thus, the adjusted $R^2$ for the one-year-ahead forecasts is a moderate 30 percent and decreases to 26 percent for five-year-ahead working capital figures. While other regression specifications could potentially enhance explanatory power, we believe that overall

25 Note that we omit regression forecasts for (*t+2*) to (*t+4*) in Table 3. The results are available upon request.

26 Enterprise value is defined as total assets minus the book value of equity plus the market value of equity. Accruals are defined as changes in current assets plus debt changes in current liabilities minus changes in cash and short term investments and minus changes in current liabilities. For a more detailed variable description, see Appendices 1 and 2.

27 We acknowledge that forecasts of levels, as proposed by Hou et al. 2010, might be susceptible to some noise (Lee et al. 2010) and $R^2$'s in levels are commonly higher than results in changes (e.g., Fama and French 2006). Nevertheless, since the aim of our analysis is to investigate the performance of the extended models, it is the appropriate choice.

consistency in the regression design and employed independent variables outweigh the benefit of attempts to increase the in-sample model fit with other independent variables. In summary, Table 3 indicates that the regression equations show a reasonable model fit, which is necessary in order to obtain sound out-of-sample forecasts.

[Insert TABLE 4 about here]

Table 4 contains summary statistics of the forecast values of the input figures used in the company valuation models to determine whether they are reliable and confirm economic intuition.[28] Overall, this seems to be the case. To illustrate, comparing the results for the mechanical forecasts (Panel A) and VL forecasts (Panel B), shows that the mechanical forecasts of mean clean earnings are closer to VL earnings forecasts, which are also supposed to be "clean", than to the standard earnings (before extraordinary items) from the income statement.[29] Turning to the comparison of the dividend time series, two striking findings emerge. Firstly, within the mechanical forecast approach for all forecast horizons, the standard cash dividends are roughly only half of total dividends forecasted by the regression technique. For example, the mean one-year-ahead cash dividends in Panel A are 10.38 million US$, compared to 19.61 million US$ for total dividends. Secondly, comparing the cash dividend forecasts in Panel A with the corresponding VL dividend forecasts in Panel B indicates that the VL figures are approximately only half. Comparing mean operating assets across Panels A and B shows that

[28] Comprehensive statistics of year-by-year median values for all valuation parameters from 1988 to 2006 are not reported but are available on request.

[29] For example, using the mechanical forecast setting, the average clean earnings forecasts $t = 1,2,\ldots,5$ are: 67, 75, 86, 96, 106 (in million US$) compared to 62, 76, 92, 108, and 123 (in million US$) of the analyst forecasts. This pattern contrasts with 51, 56, 62, 69, 78 (in million US$) for dirty earnings based on the mechanical forecast approach.

analysts forecast, on average, higher operating asset levels than the regression technique, which is consistent with lower dividend forecasts by VL, if a proportion of increases in operating assets is financed through retained earnings. Next, summary statistics for initial values provided by COMPUSTAT are presented in Panel C, while Panel D gives an overview of CAPM cost of equity estimates, market value of equity in million US$ and average firm valuations per year. Again, the data confirms the basic plausibility checks. For example, cost of equity with a mean of 11.05 percent from 1988 to 2006 conforms to expectations.[30] Finally, we obtain data for 15,658 firm valuations from 1988 to 2006, while prior studies (Courteau et al. 2001; Francis et al. 2000) apply less than 3,000 observations using a time span of less than six years.

# 5. Empirical results

***Valuation errors***

In line with prior research (Kaplan and Ruback 1995; Penman and Sougiannis 1998; Francis et al. 2000; and others), we evaluate the valuation techniques by comparing the actual market capitalizations with the intrinsic values calculated from the payoffs derived from the various techniques. Assuming market efficiency, market capitalization is an appropriate criterion for evaluating the model performance. The signed prediction error (bias) denotes the deviation of the intrinsic value estimate ($V$) from the market capitalization ($V^M$) at valuation date *t*. This error is defined as $bias_t = (V_t - V_t^M) / V_t^M$ and the absolute prediction error is calculated as

[30] We calculate the cost of equity with the CAPM, using the five-year Treasury constant maturity rate as the risk-free rate, plus five percent as the market risk premium multiplied by betas (obtained from five-year rolling market model regressions). As a further robustness check, we apply cost of equity based on Fama and French 1997 industry risk premiums (48 industry codes) from the five-year rolling three-factor model. The empirical results for our sample do not react sensitively to the choice of cost of equity, although some minor bias and inaccuracy effects are evident.

$inaccuracy_t = \left| V_t - V_t^M \right| / V_t^M$ . Table 5 reports descriptive statistics on valuation errors, namely bias and inaccuracy, for the three extended valuation approaches, compared to the standard model implementation using cross-sectional regression forecasts and VL forecasts. The bias and inaccuracy for the valuation models using cross-sectional regression forecasts are presented in Panels A1 and A2, and using VL forecasts in Panels B1 and B2, respectively. Our discussion focuses on the median results for the 2 percent growth case.

[Insert TABLE 5 about here]

Across all four Panels in Table 5, the ranking of the standard approaches is the same; the standard DDM performs worst, the standard DCF model ranks second, and the standard RIM provides the most accurate forecasts.[31] Turning to our research question of whether it is worthwhile to implement the extended valuation model, our answer is unequivocally affirmative. In particular, regarding the mechanical forecasts in Panel A1, the average bias associated with the standard DDM can be reduced substantially by implementing our extended model version (from 80 percent to 29 percent). Similarly, large gains in precision, thus eliminating bias, observed for the DCF model (from 70 percent to 29 percent), and, even for the RIM, the bias reduction is economically significant (43 percent vs. 29 percent). Besides the economic significance, Wilcoxon signed-rank tests indicate that all these differences are also statistically significant at the one percent level. A similar picture emerges with respect to absolute valuation errors (Panel A2). Given the recent attention paid to the mechanical forecast approach in the literature (Hou et al. 2010; Lee et al. 2010), these findings are important to achieving correct

[31] These results confirm the findings of previous studies (e.g., Francis et al. 2000).

conclusions, for example, when applying firm valuation models to estimate the implied cost of capital.

In general, we obtain very similar results for VL forecasts (Table 5, Panel B1 and B2). The only difference is that the standard RIM produces more accurate valuation results, achieving almost the same valuation accuracy as the extended RIM.

Overall, implementing our extended valuation models yields identical valuation results (e.g., a level of inaccuracy of 38 percent for the mechanical forecast approach and 33 percent for the VL sample). In addition to the robustness of standard RIM based on VL inputs, the extended models are associated with substantial (economically and statistically significant) reductions in valuation errors, compared to the corresponding standard model.

***Robustness of valuation results***

In order to evaluate the robustness, we repeat the above analysis on a year-by-year basis.

[Insert Figure 1 about here]

Figure 1 indicates that the advantage of the extended models is that they are remarkably stable. In line with Table 5, we observe through the year-by-year comparison that the extended models provide considerably smaller valuation errors than their standard counterparts, as shown in Figure 1 (Panels A1 (bias) and A2 (inaccuracy) for mechanical forecasts, Panels B1 (bias) and B2 (inaccuracy) for VL forecasts). Again, the only exception is the standard RIM based on VL forecasts, producing virtually the same median bias and inaccuracy as the extended models.

Interestingly, in Panel A1, the standard DDM based on mechanical forecasts produces the largest and most stable median bias, underestimating market values by approximately 80 percent. This result conforms to expectations, because cash dividends are generally smoothed over time and positive by definition. By contrast, the standard DCF model produces more volatile median valuation bias, being marginally more accurate than the standard DDM in most years, whereas the standard RIM is closest to the extended model. In general, the same findings are observed in Panel B1, when VL forecasts are employed to estimate the valuation models. Moreover, the differences between the standard models are more pronounced (i.e., using VL forecasts improves both RIM and DCF model valuation). A similar picture arises for the inaccuracy (Panel A2 and B2). In general, the median inaccuracy of the individual models is remarkably stable across time. Also, the ranking of the models is virtually unchanged. Thus, the standard DDM produces on average the most inaccurate estimates and the standard RIM achieves almost the same level of accuracy as the extended models.

As a final robustness check, Table 6 provides a breakdown of valuation accuracy, by employing the Fama-French industry classification (10 industries, which excludes financial firms by definition). In this context, the same picture emerges, with the performance and ranking of the models being stable across all industries. Finally, the results seem plausible from an economic perspective. For example, we observe a relatively high level of inaccuracy (40 percent to 50 percent) for high-tech and telecommunication firms, which are typically more difficult to evaluate, whereas traditional and regulated industries are valued more precisely (inaccuracy around 30 percent).

[Insert TABLE 6 about here]

In summary, the remarkably robust results suggest that the extended models provide considerable advantages, yielding much smaller valuation errors for different sampling periods, as well as for different industries. Moreover, the relative and absolute valuation errors for the extended versions of the DDM and DCF model are considerably smaller than those previously reported.[32]

***Error decomposition***

Besides yielding lower valuation errors, a second major advantage of the extended models is the restored valuation equivalence. The extended models therefore provide a benchmark for analyzing specific violations of the assumptions underlying the standard models. Table 7 reports the impact of introducing the correction terms step-by-step.

[Insert TABLE 7 about here]

Consider first the valuation results based on the mechanical forecasting approach (Panel A). For example, the standard DDM produces an average bias of around 76 percent (first column). When we subsequently introduce the $netcap^{cor,\ de}$ correction for the explicit forecast period, the bias is reduced by just 0.11 percentage points. When we introduce the $netcap^{cor,\ tv}$ correction for the terminal period in a second step, an additional reduction of 5.13 percentage points is achieved. Moreover, $dirt^{cor,\ tv}$ and $\Delta tv$ reduce the bias by 25.28 percentage points and 30.9 percentage points, respectively. A similar picture is obtained for the other two models. The largest reduction in average valuation error is achieved by the $dirt^{cor,\ tv}$ and/or $\Delta tv$ correction. The picture is

[32] For instance, Penman and Sougiannis (1998) report a bias for the DDM of 31.4 percent and for the DCF model of 111.2 percent assuming a $t+4$ forecast horizon without growth in the terminal period. Francis et al. (2000) report a bias (inaccuracy) based on analyst forecasts of 75.5 percent (75.8 percent) for the DDM and 31.5 percent (48.5 percent) for the DCF model.

slightly different for the VL forecasts. While we again find large error reductions when introducing *Δtv* for the DDM (48 percentage points) and the DCF (19 percentage points), the $dirt^{cor,\ tv}$ corrections produce somewhat smaller improvements (one percentage point for DDM and five percentage points for RIM and DCF model). Moreover, the standard RIM so far employed mostly in empirical studies is in part so robust, because the correction terms capturing consistent terminal value and the impact of dirty surplus almost offset each other when using VL forecasts.

Overall, the results indicate that dirty surplus accounting exerts an important impact on valuation accuracy. This may seem surprising at first glance, because it is generally assumed that dirty surplus accounting effects are only transitory. In particular, positive and negative effects would generally cancel out each other. However, recent work by Chambers et al. 2007 has shown that the pricing multiple of dirty surplus items is significantly greater than one, meaning that dirty surplus exerts a persistent effect on equity values. Furthermore, Hand and Landsman (1999, Table 9) also demonstrate that dirty surplus is priced by a factor of two.[33] In line with these studies, we provide supporting evidence that dirty surplus has a persistent and large impact on equity values conditional on employing the mechanical forecast approach. Furthermore, our error decomposition highlights the importance of a reasonable steady-state assumption within the terminal value calculation of the DDM and DCF model, and demonstrates that a simple extrapolation of the payoff in the period from *T* to infinity leads to substantial distortions of the intrinsic value estimate. Expressed differently, the reasonable steady-state calculation is obtained by accrual accounting.

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[33] In unreported regression results, we replicate their equity valuation setting and find similar results. See also Hand and Landsman (2005).

Note that the above error decomposition supplements previous results (e.g., Penman and Sougiannis 1998; Francis et al. 2000; Courteau et al. 2001). In particular, we find that the ranking of the three models depends on the particular correction terms considered. For example, the RIM is generally more robust and is ranked first without any correction terms, while the DCF model is ranked second. However, if we introduce only the terminal value component into the models, the ranking of these models changes (i.e., RIM is second and DCF model first).[34]

***Regression analysis***

In order to further evaluate the performance of the proposed correction terms, we regress observed market prices on the individual components of the extended valuation equations. Table 8 reports the results from a pooled feasible generalized least squares (FGLS) regression. Regressions are performed on a per share basis to avoid confounding effects due to scaling issues (Barth and Kallapur 1996). Inference is based on clustered standard errors at the firm level.

[Insert TABLE 8 about here]

Panel A (mechanical forecasts) shows that the coefficients for the standard DDM, RIM, and DCF model component (columns 1 to 3) are statistically significant and have the expected positive sign. Nevertheless, for all models, the coefficients of the standard model component are significantly smaller than the theoretically predicted value of one.[35] Furthermore, the additional correction terms (columns 4 to 8) are significantly positive for all three models, except

[34] We willingly acknowledge that this *increases* the bias of the RIM based on VL forecasts. However, this indicates that incorporating consistent financial planning reveals the effect.

[35] Unreported tests of coefficients equal one are all rejected at the one percent significance level.

$netcap^{cor,de}$, indicating their importance in enhancing valuation precision. However, for the RIM, the dirty surplus corrections in the explicit forecast period ($dirt^{cor,\ de}$), as well as in the terminal period ($dirt^{cor,\ tv}$) are negative. This finding confirms the results of the valuation error decomposition, where the RIM accuracy was reduced slightly by employing a consistent terminal value calculation.

In general, a similar picture is obtained for the VL forecasts (Panel B). All of the correction terms are statistically significant. Somewhat surprisingly, the RIM dirty surplus correction in the explicit forecast period seems to be much more important when using VL forecasts. This is probably attributable to the fact that analysts use a different information set.

Overall, the above results indicate that additional components comprising the extended models are significantly related to market prices and that dirty surplus and net capital contributions play an important role.[36] While the relative importance of the correction terms differs for the two forecasting methods, consistent financial planning enables an explicit recognition of these effects.

# 6. Conclusion

This study extends the most important company valuation methods (DDM, RIM and DCF model) by correcting for dirty surplus accounting and employing consistent terminal value calculations, including comprehensive dividend definitions. Most importantly, the extended

[36] We also run unreported fixed-effects regression and obtain similar results. In addition, we emphasize that our sample size is roughly five times those of related prior studies. Recall that our sample consists of more than 15,000 observations from 1988 to 2006, while Courteau et al. (2001) investigate a random balanced panel of 500 firms with 2,500 observations over five years and the study of Francis et al. 2000 is based on 2,907 observations from 1989-1993.

models yield smaller valuation errors if VL analyst data is employed and even if we use a regression based forecast approach. Robustness tests indicate that our findings are not driven by a particular industry or time span.

Besides the advantage of obtaining more precise value estimates, the adjusted models reestablish empirical equivalence by yielding identical valuation results under less than ideal conditions. Consequently, they provide a benchmark framework, which enables us to analyze the extent to which the standard models are affected by specific violations of ideal conditions. Hence, our results have some implications for capital market research and for practical implementations of the models. Regarding capital market research, there is a need to deal with data which is affected by non-ideal conditions. Here, we have shown that incorporating all the information contained in given data provides important insights. In particular, if dirty surplus, share repurchases, and so on influence payout ratios and thus growth rates and finally shareholder value, then it is important to develop and use models that are capable of capturing these components. Even more significantly, growing research on the implied cost of capital estimates might benefit from our findings through understanding why certain specifications of intrinsic value models lead to more accurate cost of capital estimates.

Finally, our results have implications for regulatory standard setters, because the derivations of fair value estimates are encountered in many circumstances under IFRS and US-GAAP. In particular, firm valuation based on these projected firm accounts should be conducted using a forecasting approach which is based on consistent financial planning, including the proposed corrections.

However, as in the literature, our implementation of intrinsic value models is based on simplifying assumptions and thus leaves room for further research. For example, it seems promising to analyze whether different time series properties for dirty surplus, earnings, and book value could further improve intrinsic valuation estimates based on the proposed consistent financial planning approach.

# Appendix 1

Variable definitions

Variables in the cross-sectional regression forecast models (Panel A)

| Item | Description | Measurement for regressions in Panel A |
|---|---|---|
| $x_t^{dirt}$ | Dirty earnings at date $t$ | IB |
| $x_t^{clean}$ | Clean earnings at date $t$ | ΔCEQ + DVC + PRSTKC - SSTK |
| $ev_t$ | Enterprise value at date $t$ | AT - CEQ + PRC · SHROUT |
| $ta_t$ | Total assets at date $t$ | AT |
| $capex_t$ | Capital expenditures at date $t$ | CAPX |
| $dep_t$ | Depreciation and amortization at date $t$ | DP |
| $wc_t$ | Working capital at date $t$ | WCAP |
| $acc_t$ | Total accruals at date $t$ | ΔACT + ΔDLC - ΔCHE - ΔLCT |
| $div_t^{cash}$ | Cash dividends at date $t$ | DVC |
| $div_t^{total}$ | Total dividends incl. equity capital transfers at date $t$ | DVC + PRSTKC - SSTK |
| $dd_t^{cash}$ | Dummy variable that equals 0 for cash dividend payers and 1 for non-cash dividend payers | |
| $dd_t^{total}$ | Dummy variable that equals 0 for total dividend payers and 1 for non-total dividend payers | |
| $neg\_x_t^{dirt}$ | Dummy variable that equals 1 for firms with positive or zero dirty earnings and 0 for firms with negative dirty earnings | |
| $neg\_x_t^{clean}$ | Dummy variable that equals 1 for firms with positive or zero clean earnings and 0 for firms with negative clean earnings | |

Forecast variables using cross-sectional regression forecast models (Panel A)

| Item | Description | Measurement in Panel A |
|---|---|---|
| $E(x_t^{dirt})$ | Expected dirty earnings for $t = 1,2,\ldots,T$ | Derived from regression forecast model (20) |
| $E(x_t^{clean})$ | Expected clean earnings for $t = 1,2,\ldots,T$ | Derived from regression forecast model (19) |
| $E(div_t^{cash})$ | Expected cash dividends for $t = 1,2,\ldots,T$ | Derived from regression forecast model (20) |
| $E(div_t^{total})$ | Expected total dividends incl. equity transfers for $t = 1,2,\ldots,T$ | Derived from regression forecast model (19) |
| $E(capex_t)$ | Expected capital expenditures for $t = 1,2,\ldots,T$ | Derived from regression forecast model (20) |
| $E(dep_t)$ | Expected depreciation and amortization for $t = 1,2,\ldots,T$ | Derived from regression forecast model (20) |
| $E(wc_t)$ | Expected working capital for $t = 1,2,\ldots,T$ | Derived from regression forecast model (20) |

This appendix is continued on the next page.

# Appendix 1 (continued)

Forecast variables using Value Line data (Panel B)

| Item | Description | Measurement in Panel B |
|---|---|---|
| $E(x_t^{clean})$ | Expected clean earnings for $t = 1,2,\ldots,T$ | Earningspershare · Commonshsoutstanding |
| $E(div_t^{cash})$ | Expected cash dividends for $t = 1,2,\ldots,T$ | Divdeclaredpershare · Commonshsoutstanding |
| $E(div_t^{total})$ | Expected total dividends incl. equity transfers for $t = 1,2,\ldots,T$ | $E(x_t^{clean}) \cdot k$ |
| $E(capex_t)$ | Expected capital expenditures for $t = 1,2,\ldots,T$ | Capitalspendingpershare · Commonshsoutstanding |
| $E(dep_t)$ | Expected depreciation and amortization for $t = 1,2,\ldots,T$ | Deprecdepletionamort |
| $E(wc_t)$ | Expected working capital for $t = 1,2,\ldots,T$ | Workingcapital |

Further variables of valuation models (Panel A and Panel B)

| Item | Description | Measurement in Panel A and Panel B |
|---|---|---|
| $E(oa_t)$ | Expected net operating assets for $t = 1,2,\ldots,T$ | $E(oa_{t-1}) + E(capex_t) - E(dep_t) + \Delta E(wc_t)$ |
| $E(bv_t^{dirt})$ | Expected book value of common equity for $t = 1,2,\ldots,T$ | $E(bv_{t-1}^{dirt}) + E(x_t^{(dirt)}) - E(div_t^{cash})$ |
| $E(bv_t^{clean})$ | Expected clean book value of common equity for $t = 1,2,\ldots,T$ | $E(bv_{t-1}^{clean}) + E(x_t^{clean}) - E(div_t^{total})$ |
| $bv_0$ | Book value of equity at valuation date $t= 0$ | CEQ |
| $debt_0$ | Debt at valuation date $t= 0$ | DLC + DLTT + PSTK |
| $oa_0$ | Net operating assets at valuation date $t= 0$ | CEQ + DLC + DLTT + PSTK |
| $k$ | Current dividend payout ratio | $\dfrac{DVC+PRSTKC-SSTK}{\Delta CEQ + DVC + PRSTKC - SSTK}$ |
| $r_E$ | Cost of equity at valuation date $t= 0$ | $r_F + 0.05 \cdot \beta$ |
| $r_F$ | Risk free rate at valuation date $t= 0$ | Five year Treasury constant maturity rate |
| $\beta$ | Firm-specific beta at valuation date $t= 0$ | Historical beta derived from regression over last 5 years |
| $V_0^M$ | Market capitalization at valuation date $t= 0$ | PRC · SHROUT (from CRSP) |
| $V_0$ | Intrinsic value estimate of market equity value at valuation date $t= 0$ | |
| $s$ | Corporate tax rate | |

# Appendix 2

Data sources of items

**COMPUSTAT**

| Mnemonic | Description |
| --- | --- |
| ACT | Current Assets - Total |
| AT | Assets - Total |
| CAPX | Capital Expenditures |
| CEQ | Common Equity - Total |
| CHE | Cash and Short-Term Investments |
| DLC | Debt in Current Liabilities - Total |
| DLTT | Long-Term Debt - Total |
| DP | Depreciation and Amortization |
| DVC | Common Cash Dividends |
| IB | Income before Extraordinary Items |
| LCT | Current Liabilities - Total |
| PRSTKC | Purchase of Common and Preferred Stock |
| PSTK | Preferred Stock - Total |
| SSTK | Sale of Common and Preferred Stock |
| WCAP | Working Capital |

**Federal Reserve Statistical Release**

| Mnemonic | Description |
| --- | --- |
| not available | Five-year Treasury constant maturity rate |

**Value Line**

| Mnemonic | Description |
| --- | --- |
| Beta | Firm-specific beta |
| Capitalspendingpershare | Capital expenditures per share |
| Commonshsoutstanding | Common shares outstanding |
| Deprecdepletionamort | Depreciation and amortization |
| Divdeclaredpershare | Common dividends per share |
| Earningspershare | Earnings per share |
| Workingcapital | Working capital |

**CRSP**

| Mnemonic | Description |
| --- | --- |
| PRC | Stock price (adjusted for stock splits, etc.) |
| SHROUT | Shares outstanding (adjusted for stock splits, etc.) |

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TABLE 1

The different correction terms – an overview

| | | *netcap* | ***dirt**$^{cor}$* **(Mechanical forecast approach)** | ***dirt**$^{cor}$* **(VL forecasts)** | ***Δtv*** |
|---|---|---|---|---|---|
| **explicit forecast period** | **DDM$^{extended}$** | $\sum_{t=1}^{T}\frac{div_t^{total}-div_t^{cash}}{(1+r_E)^t}$ | | | |
| | **RIM$^{extended}$** | | $\sum_{t=1}^{T}\frac{x_t^{clean}-x_t^{dirt}-r_E\left(bv_{t-1}^{clean}-bv_{t-1}^{dirt}\right)}{(1+r_E)^t}$ | $\sum_{t=1}^{T}\frac{-r_E\left(bv_{t-1}^{clean}-bv_{t-1}^{dirt}\right)}{(1+r_E)^t}$ | |
| | **DCF$^{extended}$** | | $\sum_{t=1}^{T}\frac{x_t^{clean}-x_t^{dirt}-r_E\left(bv_{t-1}^{clean}-bv_{t-1}^{dirt}\right)}{(1+r_E)^t}$ | $\sum_{t=1}^{T}\frac{-r_E\left(bv_{t-1}^{clean}-bv_{t-1}^{dirt}\right)}{(1+r_E)^t}$ | |
| **terminal period** | **DDM$^{extended}$** | $\frac{(1+g)(div_T^{total}-div_T^{cash})}{(1+r_E)^T(r_E-g)}$ | $\frac{(1+g)(x_T^{clean}-x_T^{dirt})-g\left(bv_T^{clean}-bv_T^{dirt}\right)}{(1+r_E)^T(r_E-g)}$ | $\frac{-g\left(bv_T^{clean}-bv_T^{dirt}\right)}{(1+r_E)^T(r_E-g)}$ | $\frac{(1+g)x_T^{dirt}-g\cdot bv_T^{dirt}-(1+g)div_T^{total}}{(1+r_E)^T(r_E-g)}$ |
| | **RIM$^{extended}$** | | $\frac{(1+g)(x_T^{clean}-x_T^{dirt})-r_E\left(bv_T^{clean}-bv_T^{dirt}\right)}{(1+r_E)^T(r_E-g)}$ | $\frac{-r_E\left(bv_T^{clean}-bv_T^{dirt}\right)}{(1+r_E)^T(r_E-g)}$ | $\frac{-r_E\left(bv_T^{dirt}-(1+g)bv_{T-1}^{dirt}\right)}{(1+r_E)^T(r_E-g)}$ |
| | **DCF$^{extended}$** | | $\frac{(1+g)(x_T^{clean}-x_T^{dirt})-r_E\left(bv_T^{clean}-bv_T^{dirt}\right)}{(1+r_E)^T(r_E-g)}$ | $\frac{-r_E\left(bv_T^{clean}-bv_T^{dirt}\right)}{(1+r_E)^T(r_E-g)}$ | $\frac{(1+r_E)(oa_T-(1+g)oa_{T-1})-r_E\left(bv_T^{dirt}-(1+g)bv_{T-1}^{dirt}\right)}{(1+r_E)^T(r_E-g)}$ |

The table reports the different correction terms, used by the extended models in order to correct the standard models. *netcap* is the correction for stock repurchases and capital contributions calculated as the difference between total dividends and cash dividends given in (7), $dirt^{cor}$ is the correction for dirty surplus accounting according to (9) and (6) and differs in column two (modeling based on mechanical forecasts) and column three (modeling based on Value Line forecasts), and *Δtv* is the terminal value correction according to (16), (17), and (18).

TABLE 2

Summary statistics of the variables in the cross-sectional regression forecast models

| Variable | Mean | 1% | 25% | Median | 75% | 99% | Std. Dev. | No. Firms |
|---|---|---|---|---|---|---|---|---|
| $x_t^{dirt}$ | 124.77 | -407.99 | 5.64 | 25.70 | 88.25 | 2,353.93 | 447.94 | 1,044 |
| $x_t^{clean}$ | 149.13 | -488.09 | 5.04 | 27.92 | 99.27 | 3,000.95 | 557.93 | 1,044 |
| $ev_t$ | 4,319.38 | 42.40 | 387.84 | 946.49 | 2,927.92 | 68,292.70 | 11,617.85 | 1,044 |
| $ta_t$ | 2,380.31 | 24.11 | 218.47 | 546.07 | 1,677.38 | 34,492.29 | 6,042.44 | 1,044 |
| $capex_t$ | 153.23 | 0.15 | 8.35 | 26.90 | 99.47 | 2,454.31 | 447.06 | 1,044 |
| $dep_t$ | 109.79 | 0.48 | 7.67 | 21.74 | 75.84 | 1,595.84 | 315.75 | 1,044 |
| $wc_t$ | 252.63 | -543.80 | 32.04 | 97.35 | 250.23 | 3,171.95 | 580.49 | 1,044 |
| $acc_t$ | 4.82 | -512.34 | -8.02 | 2.11 | 19.04 | 473.42 | 133.12 | 1,044 |
| $div_t^{cash}$ | 46.21 | 0.00 | 0.13 | 2.14 | 19.30 | 1,005.93 | 174.77 | 1,044 |
| $div_t^{total}$ | 71.68 | -272.81 | -2.38 | 3.43 | 33.53 | 1,797.80 | 328.02 | 1,044 |
| $dd_t^{cash}$ | 0.38 | 0.00 | 0.00 | 0.23 | 0.77 | 1.00 | 0.46 | 1,044 |
| $dd_t^{total}$ | 0.04 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.20 | 1,044 |
| $neg\_x_t^{dirt}$ | 0.14 | 0.00 | 0.00 | 0.00 | 0.07 | 1.00 | 0.33 | 1,044 |
| $neg\_x_t^{clean}$ | 0.14 | 0.00 | 0.00 | 0.00 | 0.07 | 0.97 | 0.33 | 1,044 |

This table reports summary statistics of the variables between 1977 and 2006 used in the seven cross-sectional regression forecast models. It presents the time series averages of the used variables of the cross-sectional mean, median, standard deviation, different percentiles, and number of firms. We winsorize all variables of the cross-sectional regression forecast models each year at the 0.5% and 99.5% percentiles. The variables are expressed in million US$, except the four dummy variables. Variable definitions and data sources of items are provided in Appendices 1 and 2.

TABLE 3

Cross-sectional regression forecast models and average regression coefficients

$$x^{clean}_{i,t+\tau} = \beta_0 + \beta_1 ev_{i,t} + \beta_2 ta_{i,t} + \beta_3 div^{total}_{i,t} + \beta_4 dd^{total}_{i,t} + \beta_5 x^{clean}_{i,t} + \beta_6 neg\_x^{clean}_{i,t} + \beta_7 acc_{i,t} + \varepsilon_{i,t+\tau} \quad (1)$$

| *LHS* | *intercept* | $ev_t$ | $ta_t$ | $div^{total}_t$ | $dd^{total}_t$ | $x^{clean}_t$ | $neg\_x^{clean}_t$ | $acc_t$ | *adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| $x^{clean}_{t+1}$ | 13.72*** | 0.04*** | -0.02*** | 0.18*** | -26.43 | 0.22*** | -22.19 | 0.09*** | 0.62 |
| $x^{clean}_{t+5}$ | 17.02*** | 0.08*** | -0.04*** | 0.06 | 10.39 | 0.04 | -1.43 | -0.02* | 0.51 |

$$div^{total}_{i,t+\tau} = \beta_0 + \beta_1 ev_{i,t} + \beta_2 ta_{i,t} + \beta_3 div^{total}_{i,t} + \beta_4 dd^{total}_{i,t} + \beta_5 x^{clean}_{i,t} + \beta_6 neg\_x^{clean}_{i,t} + \beta_7 acc_{i,t} + \varepsilon_{i,t+\tau} \quad (2)$$

| *LHS* | *intercept* | $ev_t$ | $ta_t$ | $div^{total}_t$ | $dd^{total}_t$ | $x^{clean}_t$ | $neg\_x^{clean}_t$ | $acc_t$ | *adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| $div^{total}_{t+1}$ | -8.40*** | 0.01*** | -0.00 | 0.42*** | -15.13* | 0.09*** | -2.28 | -0.04*** | 0.69 |
| $div^{total}_{t+5}$ | -13.25*** | 0.04*** | -0.02*** | 0.22*** | -13.59 | 0.11*** | 5.08 | -0.01 | 0.64 |

$$x^{dirt}_{i,t+\tau} = \beta_0 + \beta_1 ev_{i,t} + \beta_2 ta_{i,t} + \beta_3 div^{cash}_{i,t} + \beta_4 dd^{cash}_{i,t} + \beta_5 x^{dirt}_{i,t} + \beta_6 neg\_x^{dirt}_{i,t} + \beta_7 acc_{i,t} + \varepsilon_{i,t+\tau} \quad (3)$$

| *LHS* | *intercept* | $ev_t$ | $ta_t$ | $div^{cash}_t$ | $dd^{cash}_t$ | $x^{dirt}_t$ | $neg\_x^{dirt}_t$ | $acc_t$ | *adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| $x^{dirt}_{t+1}$ | 3.76* | 0.02*** | -0.01*** | 0.26*** | -7.47** | 0.55*** | 4.98 | -0.05*** | 0.81 |
| $x^{dirt}_{t+5}$ | 2.83** | 0.06*** | -0.04*** | 0.64*** | 6.83 | 0.24*** | 6.12 | -0.07*** | 0.68 |

$$div^{cash}_{i,t+\tau} = \beta_0 + \beta_1 ev_{i,t} + \beta_2 ta_{i,t} + \beta_3 div^{cash}_{i,t} + \beta_4 dd^{cash}_{i,t} + \beta_5 x^{dirt}_{i,t} + \beta_6 neg\_x^{dirt}_{i,t} + \beta_7 acc_{i,t} + \varepsilon_{i,t+\tau} \quad (4)$$

| *LHS* | *intercept* | $ev_t$ | $ta_t$ | $div^{cash}_t$ | $dd^{cash}_t$ | $x^{dirt}_t$ | $neg\_x^{dirt}_t$ | $acc_t$ | *adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| $div^{cash}_{t+1}$ | -2.57*** | 0.00*** | 0.00 | 0.76*** | -0.99 | 0.06*** | 3.52*** | 0.00 | 0.93 |
| $div^{cash}_{t+5}$ | -3.48* | 0.01*** | -0.01*** | 0.81*** | -1.71 | 0.08*** | 6.40* | 0.01 | 0.88 |

$$capex_{i,t+\tau} = \beta_0 + \beta_1 ev_{i,t} + \beta_2 ta_{i,t} + \beta_3 div^{cash}_{i,t} + \beta_4 dd^{cash}_{i,t} + \beta_5 x^{dirt}_{i,t} + \beta_6 neg\_x^{dirt}_{i,t} + \beta_7 acc_{i,t} + \varepsilon_{i,t+\tau} \quad (5)$$

| *LHS* | *intercept* | $ev_t$ | $ta_t$ | $div^{cash}_t$ | $dd^{cash}_t$ | $x^{dirt}_t$ | $neg\_x^{dirt}_t$ | $acc_t$ | *adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| $capex_{t+1}$ | 7.95 | -0.01*** | 0.06*** | 0.22*** | 2.82 | 0.39*** | 12.66** | -0.02 | 0.77 |
| $capex_{t+5}$ | 16.72*** | 0.02*** | 0.05*** | 0.21*** | 19.44** | 0.25*** | 11.97 | -0.10*** | 0.70 |

$$dep_{i,t+\tau} = \beta_0 + \beta_1 ev_{i,t} + \beta_2 ta_{i,t} + \beta_3 div^{cash}_{i,t} + \beta_4 dd^{cash}_{i,t} + \beta_5 x^{dirt}_{i,t} + \beta_6 neg\_x^{dirt}_{i,t} + \beta_7 acc_{i,t} + \varepsilon_{i,t+\tau} \quad (6)$$

| *LHS* | *intercept* | $ev_t$ | $ta_t$ | $div^{cash}_t$ | $dd^{cash}_t$ | $x^{dirt}_t$ | $neg\_x^{dirt}_t$ | $acc_t$ | *adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| $dep_{t+1}$ | 0.06 | -0.01*** | 0.05*** | 0.28*** | 3.23* | 0.03*** | 7.71* | 0.02* | 0.85 |
| $dep_{t+5}$ | 8.85* | -0.00 | 0.05*** | 0.11*** | 12.45** | 0.28*** | 15.68* | -0.03 | 0.78 |

$$wc_{i,t+\tau} = \beta_0 + \beta_1 ev_{i,t} + \beta_2 ta_{i,t} + \beta_3 div^{cash}_{i,t} + \beta_4 dd^{cash}_{i,t} + \beta_5 x^{dirt}_{i,t} + \beta_6 neg\_x^{dirt}_{i,t} + \beta_7 acc_{i,t} + \varepsilon_{i,t+\tau} \quad (7)$$

| *LHS* | *intercept* | $ev_t$ | $ta_t$ | $div^{cash}_t$ | $dd^{cash}_t$ | $x^{dirt}_t$ | $neg\_x^{dirt}_t$ | $acc_t$ | *adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| $wc_{t+1}$ | 140.06*** | 0.02*** | -0.00 | -0.27*** | -31.63*** | 0.31*** | 9.07 | 0.47*** | 0.30 |
| $wc_{t+5}$ | 161.19*** | 0.05*** | -0.03*** | -0.35*** | -2.52 | 0.28*** | 19.76 | 0.53*** | 0.26 |

This table reports the seven cross-sectional regression forecast models. It also presents the average regression coefficients from the annual pooled cross-section regressions of one-year-ahead $(\tau = 1)$ and five-year-ahead forecasts $(\tau = 5)$ of the forecast variables $x^{clean}_{t+\tau}$, $div^{total}_{t+\tau}$, $x^{dirt}_{t+\tau}$, $div^{cash}_{t+\tau}$, $capex_{t+\tau}$, $dep_{t+\tau}$, and $wc_{t+\tau}$. The regressions are estimated as of June 30th each year *t* from 1987 to 2006, using the previous ten years of data. We winsorize all variables of the cross-sectional regression forecast models annually at the 0.5% and 99.5% percentiles. The stars indicate the significance level based on time-series *t*-statistics (* significant at 10%; ** significant at 5%; *** significant at 1%). adj. $R^2$ is the time-series average adjusted R-squared from the annual regressions. Variable definitions and data sources of items are provided in Appendices 1 and 2. Note that this table does not present regression forecasts for (*t+2*) to (*t+4*), but the results are available upon request.

TABLE 4

Summary statistics of valuation parameters

Panel A: Cross-sectional regression forecasts

| | $E(x_1^{clean})$ | $E(x_2^{clean})$ | $E(x_3^{clean})$ | $E(x_4^{clean})$ | $E(x_5^{clean})$ | $E(x_1^{dirt})$ | $E(x_2^{dirt})$ | $E(x_3^{dirt})$ | $E(x_4^{dirt})$ | $E(x_5^{dirt})$ | $E(oa_1)$ | $E(oa_2)$ | $E(oa_3)$ | $E(oa_4)$ | $E(oa_5)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 66.72 | 74.76 | 86.27 | 95.94 | 105.96 | 50.73 | 55.50 | 61.87 | 69.43 | 78.39 | 667.18 | 711.52 | 755.91 | 808.83 | 860.17 |
| Std. Dev. | 26.26 | 28.12 | 32.50 | 37.68 | 40.23 | 15.42 | 16.54 | 17.83 | 19.95 | 24.65 | 198.05 | 205.80 | 214.90 | 226.14 | 236.15 |

| | $E(div_1^{cash})$ | $E(div_2^{cash})$ | $E(div_3^{cash})$ | $E(div_4^{cash})$ | $E(div_5^{cash})$ | $E(div_1^{total})$ | $E(div_2^{total})$ | $E(div_3^{total})$ | $E(div_4^{total})$ | $E(div_5^{total})$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 10.38 | 12.63 | 14.79 | 17.39 | 19.58 | 19.61 | 24.95 | 29.07 | 34.77 | 41.71 |
| Std. Dev. | 3.64 | 4.51 | 5.27 | 6.65 | 8.12 | 6.42 | 6.97 | 7.89 | 9.55 | 10.94 |

Panel B: Value Line forecasts

| | $E(x_1^{clean})$ | $E(x_2^{clean})$ | $E(x_3^{clean})$ | $E(x_4^{clean})$ | $E(x_5^{clean})$ | $E(div_1^{cash})$ | $E(div_2^{cash})$ | $E(div_3^{cash})$ | $E(div_4^{cash})$ | $E(div_5^{cash})$ | $E(oa_1)$ | $E(oa_2)$ | $E(oa_3)$ | $E(oa_4)$ | $E(oa_5)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 62.15 | 76.30 | 92.34 | 107.81 | 122.65 | 5.78 | 6.33 | 7.46 | 8.34 | 9.21 | 729.61 | 774.66 | 837.99 | 889.12 | 946.95 |
| Std. Dev. | 23.12 | 26.32 | 30.27 | 34.52 | 37.71 | 3.26 | 3.47 | 4.02 | 4.52 | 5.06 | 233.26 | 246.06 | 262.29 | 273.37 | 289.57 |

Panel C: COMPUSTAT initial values

| | $k$ | $bv$ | $debt$ | $oa$ | $wc$ |
|---|---|---|---|---|---|
| Mean | 0.2176 | 429.37 | 205.11 | 693.03 | 159.75 |
| Std. Dev. | 0.0824 | 153.25 | 69.06 | 243.11 | 48.15 |

Panel D: Cost of equity, market value and no. of firm valuations

| | $r_E$ | $V^M$ | *No. firms* |
|---|---|---|---|
| Mean | 0.1105 | 1,148,124 | 824 |
| Std. Dev. | 0.0187 | 493,341 | 118 |

This table reports the mean and standard deviation of the yearly median statistics for the sample firms. In total, there is data available for 15,658 firm valuations and 109,606 firm-year observations. Values are given in million US$, except percentages. The forecasts are presented for $t = 1,2,...,5.$ Panel A presents the values estimated by the cross-sectional models according to (19) and (20), using data available up to the previous fiscal year end. Expected operating assets $E(oa_t)$ are calculated by previous operating assets, plus expected capital expenditures, less expected depreciation and amortization, plus expected working capital changes. Panel B presents VL forecast data as of June of each year. Negative cash dividends are set to zero. In Panel C, $k$ is the current dividend payout ratio estimated by dividing the current total dividends by clean earnings. For firms with negative clean earnings, total dividends are divided by six percent of total assets. We constrain $k$ to be between 0 and 100% and to be constant over the forecast horizon. The realized data of $bv$, $debt$, $oa$ (defined as the sum of $bv$ and $debt$), and $wc$ are commonly known at valuation date and used as initial values. Furthermore, in Panel D, $r_E$ is the cost of equity computed with the CAPM, using the five-year Treasury constant maturity rate as the risk-free rate, plus five percent as the market risk premium multiplied by betas (obtained from five-year rolling market model regressions). $V^M$ is the market value of equity calculated from CRSP as price times number of shares outstanding. *No. firms* presents the mean and standard deviation of yearly median firm valuations. Detailed description of variable definitions and data sources are provided in Appendices 1 and 2.

TABLE 5

Valuation errors for the three standard models and the extended models

Panel A1: **Bias** for the valuation models using cross-sectional regression forecasts

| | | standard models | | | |
|---|---|---|---|---|---|
| | | **DDM** | **RIM** | **DCF** | **extended models** |
| $g = 2\%$ | Mean | -75.99% | -34.62% | -62.90% | -14.57% |
| | **Median** | **-80.10%***** | **-43.49%***** | **-69.65%***** | **-28.75%** |
| | Std. Dev. | 34.19% | 62.86% | 52.51% | 72.31% |
| $g = 4\%$ | Mean | -69.33% | -27.76% | -42.77% | 0.92% |
| | **Median** | **-75.71%***** | **-40.82%***** | **-57.47%***** | **-21.91%** |
| | Std. Dev. | 53.79% | 89.42% | 110.51% | 195.27% |

Panel A2: **Inaccuracy** for the valuation models using cross-sectional regression forecasts

| | | standard models | | | |
|---|---|---|---|---|---|
| | | **DDM** | **RIM** | **DCF** | **extended models** |
| $g = 2\%$ | Mean | 77.83% | 51.13% | 70.33% | 46.09% |
| | **Median** | **80.27%***** | **47.09%***** | **70.49%***** | **38.35%** |
| | Std. Dev. | 29.76% | 50.35% | 42.04% | 57.60% |
| $g = 4\%$ | Mean | 73.80% | 55.10% | 66.45% | 55.97% |
| | **Median** | **76.24%***** | **47.72%***** | **61.64%***** | **39.60%** |
| | Std. Dev. | 47.48% | 75.70% | 98.11% | 187.07% |

This table is continued on the next page.

TABLE 5 (continued)

Panel B1: **Bias** for the valuation models using Value Line forecasts

| | | standard models | | | |
|---|---|---|---|---|---|
| | | **DDM** | **RIM** | **DCF** | **extended models** |
| *g* = 2% | Mean | -79.44% | -8.89% | -32.39% | -9.46% |
| | **Median** | **-84.13%***** | **-20.12%** | **-45.47%***** | **-20.30%** |
| | Std. Dev. | 23.36% | 56.60% | 75.30% | 57.04% |
| *g* = 4% | Mean | -73.45% | 5.91% | -0.95% | 6.54% |
| | **Median** | **-80.46%***** | **-12.07%** | **-27.73%***** | **-11.04%** |
| | Std. Dev. | 37.44% | 84.10% | 193.51% | 84.70% |

Panel A2: **Inaccuracy** for the valuation models using Value Line forecasts

| | | standard models | | | |
|---|---|---|---|---|---|
| | | **DDM** | **RIM** | **DCF** | **extended models** |
| *g* = 2% | Mean | 79.97% | 38.65% | 56.18% | 39.48% |
| | **Median** | **84.17%***** | **31.95%** | **52.06%***** | **33.23%** |
| | Std. Dev. | 21.49% | 42.29% | 59.70% | 42.24% |
| *g* = 4% | Mean | 76.32% | 46.82% | 66.35% | 48.25% |
| | **Median** | **80.85%***** | **33.30%** | **49.77%***** | **34.94%** |
| | Std. Dev. | 31.18% | 70.10% | 181.78% | 69.92% |

Panel A1 shows mean, median, and standard deviation of the bias for the three standard valuation models and the extended model implementation using cross-sectional regression forecasts while Panel A2 reports the figures of the inaccuracy, respectively. Panel B1 shows the mean, median, and standard deviation of the bias using Value Line forecasts and Panel B2 reports the figures of the inaccuracy, respectively. The valuation errors are based on 2% and 4% growth rates in the terminal period. The extended models are given in (7) for the DDM, (9) for the RIM, and (12) for the DCF model. The standard models represent the model implementations according to (13) - (15). Negative intrinsic value estimates are set to zero. The signed prediction errors (bias) are calculated as (intrinsic value estimate – market capitalization)/market capitalization. The absolute prediction errors (inaccuracy) are calculated as |intrinsic value estimate – market capitalization|/market capitalization. All calculations are based on 15,658 firm valuations. Stars indicate significance levels of the Wilcoxon nonparametric sign test which tests that the median valuation errors are the same for the respective standard model and the extended model. In Panels A1 and B1, we test the null hypothesis that the median bias of the extended model is equal to the median bias of the respective standard model and the alternative hypothesis that the median bias of the extended model is larger than the median bias of the respective standard model. In Panels A2 and B2, we test the null hypothesis that the median inaccuracy of the extended model is equal to the median inaccuracy of the respective standard model and the alternative hypothesis that the median inaccuracy of the extended model is smaller than the median inaccuracy of the respective standard model. For example '47.09%***' for the standard RIM (Panel A2, $g = 2\%$) indicates that it performs statistically significantly worse at the 1% level than the extended model. * significant at 10%; ** significant at 5%; *** significant at 1%.

TABLE 6

Median valuation error by industry

Panel A: Cross-sectional regression forecasts

| No. | Industry | *N* | Bias: standard models DDM | Bias: standard models RIM | Bias: standard models DCF | Bias: extended models | Inaccuracy: standard models DDM | Inaccuracy: standard models RIM | Inaccuracy: standard models DCF | Inaccuracy: extended models |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Non Durables | 1,926 | -70.90% | -34.20% | -60.10% | -20.57% | 71.22% | 39.63% | 61.72% | 34.35% |
| 2 | Consumer Durables | 659 | -72.50% | -36.11% | -63.83% | -24.73% | 72.54% | 39.92% | 65.36% | 35.04% |
| 3 | Manufacturing | 4,512 | -71.08% | -36.84% | -61.74% | -24.11% | 71.22% | 40.37% | 62.91% | 34.69% |
| 4 | Energy | 814 | -73.43% | -34.77% | -58.12% | -19.33% | 73.58% | 38.87% | 58.94% | 30.70% |
| 5 | High Tech | 3,172 | -93.18% | -62.98% | -87.56% | -48.06% | 93.18% | 64.43% | 87.92% | 51.48% |
| 6 | Telecom | 236 | -86.25% | -58.71% | -73.97% | -28.01% | 86.25% | 59.32% | 75.40% | 40.64% |
| 7 | Shops | 1,090 | -85.36% | -43.50% | -73.33% | -23.59% | 85.44% | 46.29% | 74.18% | 37.45% |
| 8 | Healthcare | 817 | -88.90% | -50.39% | -73.25% | -36.33% | 88.90% | 51.36% | 73.30% | 41.08% |
| 9 | Utilities | 169 | -52.74% | -15.42% | -40.36% | -6.12% | 53.90% | 31.68% | 44.94% | 29.37% |
| 10 | Other | 2,263 | -86.21% | -47.33% | -73.20% | -27.33% | 86.30% | 50.85% | 73.72% | 36.81% |

Panel B: Value Line forecasts

| No. | Industry | *N* | Bias: standard models DDM | Bias: standard models RIM | Bias: standard models DCF | Bias: extended models | Inaccuracy: standard models DDM | Inaccuracy: standard models RIM | Inaccuracy: standard models DCF | Inaccuracy: extended models |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Non Durables | 1,926 | -73.51% | -11.57% | -28.63% | -7.57% | 73.56% | 30.34% | 41.38% | 30.82% |
| 2 | Consumer Durables | 659 | -72.01% | -9.11% | -36.47% | -5.89% | 72.01% | 24.84% | 42.90% | 26.48% |
| 3 | Manufacturing | 4,512 | -72.77% | -12.29% | -34.28% | -12.15% | 72.79% | 27.00% | 43.74% | 28.15% |
| 4 | Energy | 814 | -79.00% | -17.64% | -46.24% | -22.20% | 79.00% | 28.41% | 53.75% | 31.43% |
| 5 | High Tech | 3,172 | -100.00% | -38.00% | -66.31% | -39.59% | 100.00% | 42.86% | 67.74% | 43.53% |
| 6 | Telecom | 236 | -100.00% | -40.82% | -50.89% | -42.42% | 100.00% | 48.79% | 64.59% | 50.64% |
| 7 | Shops | 1,090 | -89.36% | -14.53% | -47.44% | -11.66% | 89.44% | 27.80% | 54.00% | 30.21% |
| 8 | Healthcare | 817 | -100.00% | -31.49% | -55.68% | -32.17% | 100.00% | 38.34% | 59.00% | 40.44% |
| 9 | Utilities | 169 | -55.32% | -10.34% | -45.03% | -17.67% | 56.08% | 24.19% | 50.04% | 30.01% |
| 10 | Other | 2,263 | -92.77% | -23.39% | -50.90% | -23.57% | 92.84% | 32.85% | 55.96% | 33.94% |

Panel A shows the median bias and median inaccuracy by Fama-French industry for the three standard models and the extended model implementation using cross-sectional regression forecasts while Panel B reports the median bias and median inaccuracy by Fama-French industry using Value Line forecasts. The firms are classified into industries by Fama-French 10-industry portfolios. Detailed information about the industry classification is available at the website of Kenneth R. French, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french. *N* indicates the number of valuations per industry. The calculations are based on a 2% growth rate in the terminal period. The extended models are given in (7) for the DDM, (9) for the RIM, and (12) for the DCF model. The standard models represent the model implementations according to (13) - (15). Negative intrinsic value estimates are set to zero. The signed prediction errors (bias) are calculated as (intrinsic value estimate – market capitalization)/market capitalization. The absolute prediction errors (inaccuracy) are calculated as | intrinsic value estimate – market capitalization|/market capitalization.

TABLE 7

Mean change in bias by introducing the proposed correction terms

Panel A: Cross-sectional regression forecasts

| | Bias standard model | Change in bias $netcap^{cor, de}$ | $netcap^{cor, tv}$ | $dirt^{cor, de}$ | $dirt^{cor, tv}$ | $\Delta tv$ | Bias extended model |
|---|---|---|---|---|---|---|---|
| $DDM^{extended}$ | -75.99% | 0.11% | 5.13% | | 25.28% | 30.90% | -14.57% |
| $RIM^{extended}$ | -34.62% | | | 5.84% | 16.64% | -2.43% | -14.57% |
| $DCF^{extended}$ | -62.90% | | | -3.67% | 16.64% | 35.36% | -14.57% |

Panel B: Value Line forecasts

| | Bias standard model | Change in bias $netcap^{cor, de}$ | $netcap^{cor, tv}$ | $dirt^{cor, de}$ | $dirt^{cor, tv}$ | $\Delta tv$ | Bias extended model |
|---|---|---|---|---|---|---|---|
| $DDM^{extended}$ | -79.44% | 5.05% | 15.59% | | 1.06% | 48.28% | -9.46% |
| $RIM^{extended}$ | -8.89% | | | 0.76% | 5.34% | -6.68% | -9.46% |
| $DCF^{extended}$ | -32.39% | | | -1.53% | 5.34% | 19.12% | -9.46% |

Panel A shows the mean change in bias using cross-sectional regression forecasts and Panel B reports the mean change in bias using Value Line forecasts. All calculations are based on a 2% growth rate in the terminal period. The extended models are given in (7) for the DDM, (9) for the RIM, and (12) for the DCF model. The standard models represent the model implementations according to (13) - (15). The variables $netcap^{cor, de}$ and $netcap^{cor, tv}$ are the corrections for stock repurchases and capital increases calculated as the difference between total dividends and cash dividends, $dirt^{cor, de}$ and $dirt^{cor, tv}$ are the corrections for dirty surplus accounting according to (9) and (6) and differ in Panel A and Panel B depending on the forecasting approach (regression based forecasts versus Value Line analyst forecasts), and $\Delta tv$ is the terminal value correction according to (16), (17), and (18). The superscripts *de* and *tv* indicate the two phases; explicit forecast period and terminal period. The mean bias of the extended and standard valuation models is calculated as the mean of (intrinsic value estimate – market capitalization)/ market capitalization. The mean bias of the correction terms is determined as the difference between the mean present value of the correction terms and the mean market capitalization divided by the mean market capitalization.

TABLE 8

Pooled feasible generalized least squares (FGLS) panel regression of share price on per share components of intrinsic value estimates

Panel A: Cross-sectional regression forecasts

| | | **standard DDM** | **standard RIM** | **standard DCF** | ***netcap*$^{cor, de}$** | ***netcap*$^{cor, tv}$** | ***dirt*$^{cor, de}$** | ***dirt*$^{cor, tv}$** | **$\Delta tv$** | ***intercept*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **DDM$^{extended}$** | Coefficient | 0.7238 | | | -0.0376 | 1.0380 | | 0.1524 | 0.5154 | 17.3637 |
| | *P*-value of test statistic: Coef. = 0 | 0.0000 | | | 0.0590 | 0.0000 | | 0.0000 | 0.0000 | 0.0000 |
| **RIM$^{extended}$** | Coefficient | | 0.5215 | | | | -0.1094 | 0.4570 | -2.8809 | 14.8107 |
| | *P*-value of test statistic: Coef. = 0 | | 0.0000 | | | | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| **DCF$^{extended}$** | Coefficient | | | 0.6592 | | | 0.1191 | 0.3429 | 0.3550 | 17.7797 |
| | *P*-value of test statistic: Coef. = 0 | | | 0.0000 | | | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Panel B: Value Line forecasts

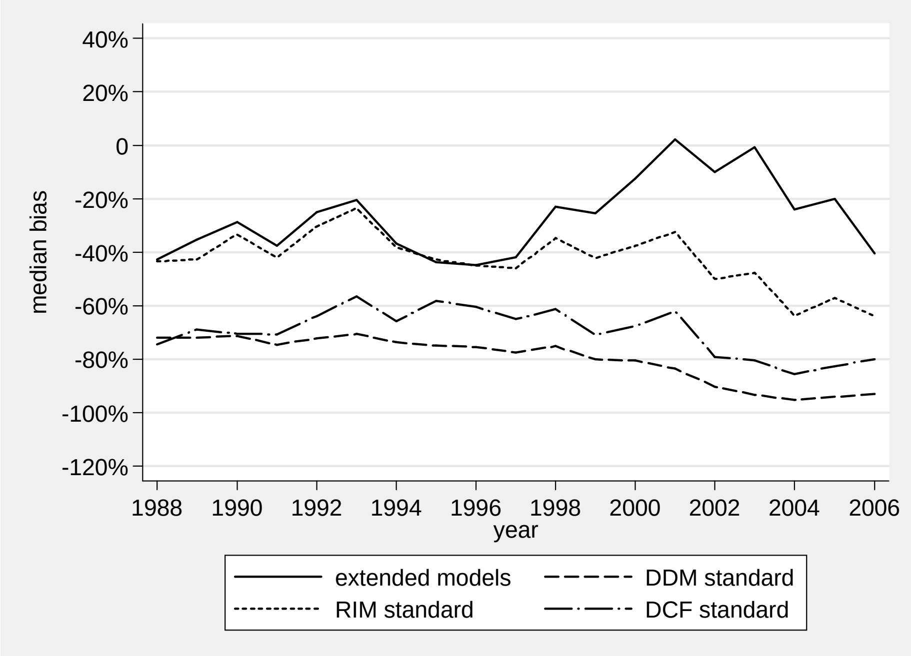
| | | **standard DDM** | **standard RIM** | **standard DCF** | ***netcap*$^{cor, de}$** | ***netcap*$^{cor, tv}$** | ***dirt*$^{cor, de}$** | ***dirt*$^{cor, tv}$** | **$\Delta tv$** | ***intercept*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **DDM$^{extended}$** | Coefficient | 0.8823 | | | 1.5116 | -0.1556 | | 3.2441 | 0.6538 | 13.5877 |
| | *P*-value of test statistic: Coef. = 0 | 0.0000 | | | 0.0000 | 0.0000 | | 0.0000 | 0.0000 | 0.0000 |
| **RIM$^{extended}$** | Coefficient | | 0.4757 | | | | 5.2822 | -0.8711 | -3.8851 | 11.1912 |
| | *P*-value of test statistic: Coef. = 0 | | 0.0000 | | | | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| **DCF$^{extended}$** | Coefficient | | | 0.6610 | | | 8.0015 | -1.1772 | 0.5471 | 14.8251 |
| | *P*-value of test statistic: Coef. = 0 | | | 0.0000 | | | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

This table reports the results of feasible generalized least squares (FGLS) regression of share price on the per share components of intrinsic values estimates. We specify a heteroskedastic error structure across panels and AR (1) autocorrelation within panels. The extended models are given in (7) for the DDM, (9) for the RIM, and (12) for the DCF model. The standard models represent the model implementations according to (13) - (15). All calculations are based on a 2% growth rate in the terminal period. In addition to the present value of the standard model, the present values of the correction terms are implemented as the explanatory variables. *netcap*$^{cor, de}$ and *netcap*$^{cor, tv}$ are the corrections for stock repurchases and capital increases, *dirt*$^{cor, de}$ and *dirt*$^{cor, tv}$ are the corrections for dirty surplus accounting according to (9) and (6) and differ in Panel A and Panel B depending on the forecasting approach (regression based forecasts versus Value Line analyst forecasts), and $\Delta tv$ is the terminal value correction according to (16), (17), and (18). The superscripts *de* and *tv* indicate the two phases; explicit forecast period and terminal period. The original sample is reduced to a subsample for each extended model by deleting observations with studentized residuals exceeding an absolute value of 2.5. We test the hypotheses that a coefficient equals 0 or a coefficient equals 1 and report the *p*-values. Since $R^2$ are not meaningful for GLS regressions, R-squared is not computed. Unreported tests of coefficients equal 1 are all rejected at the 1% significance level.

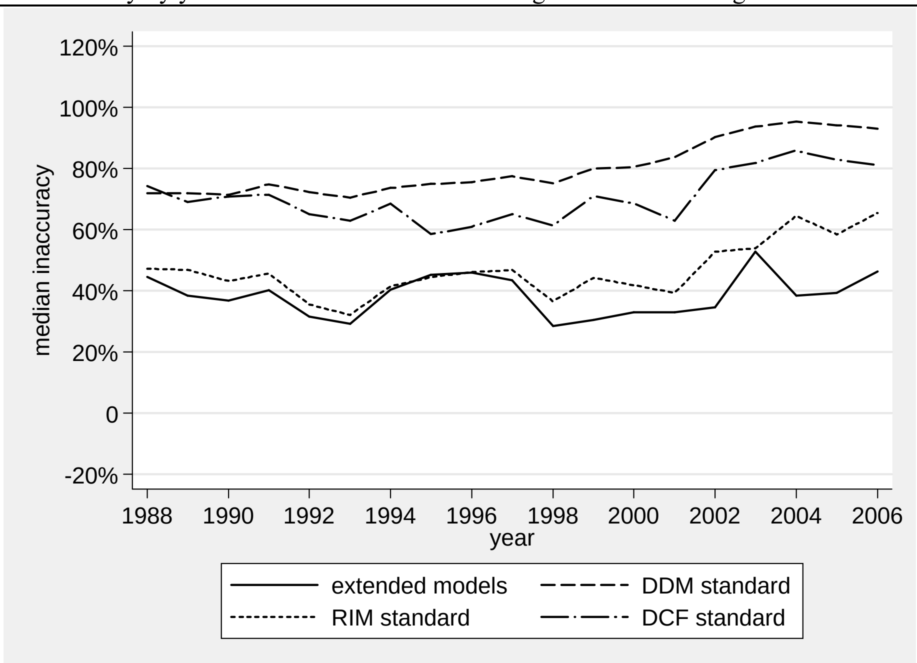
Figure 1

Year-by-year results: Median bias and median inaccuracy

Panel A1: Median bias by year for the valuation models using cross-sectional regression forecasts



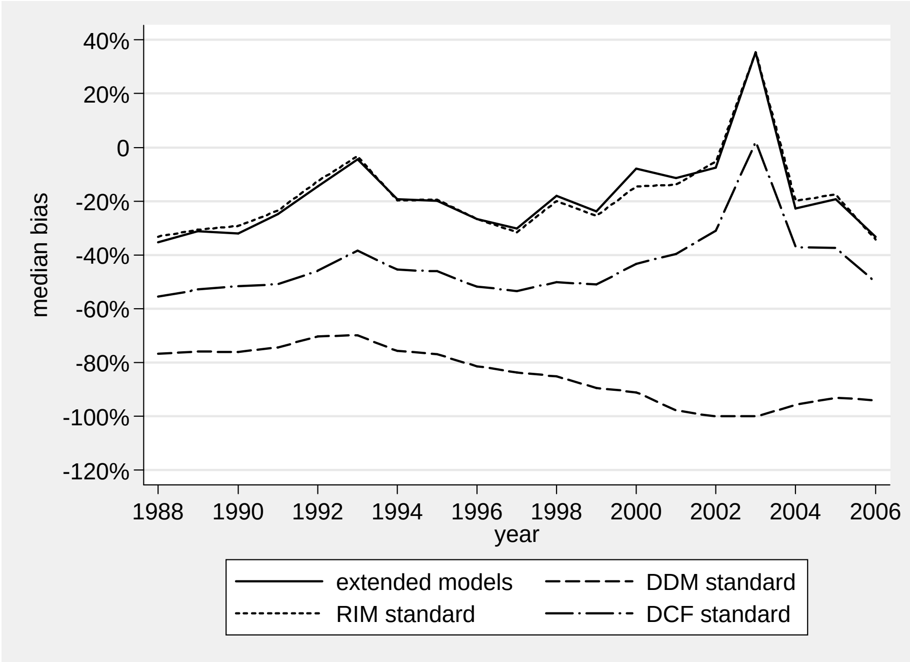

Panel A2: Median inaccuracy by year for the valuation models using cross-sectional regression forecasts



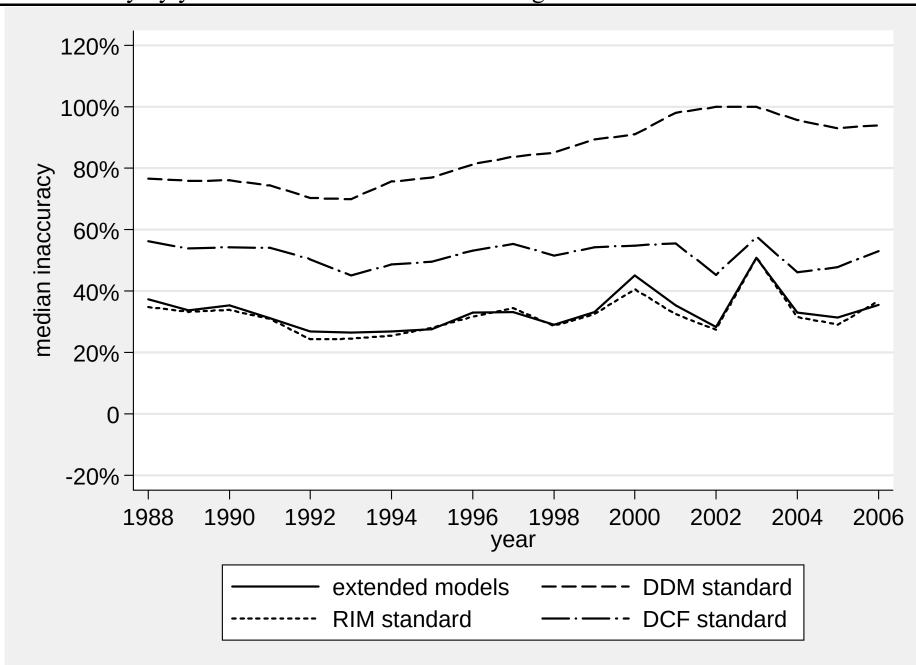

This figure is continued on the next page.

Figure 1, continued

Panel B1: Median bias by year for the valuation models using Value Line forecasts




Panel B2: Median inaccuracy by year for the valuation models using Value Line forecasts




Panel A1 shows the median bias by year for the valuation models using cross-sectional regression forecasts and Panel A2 reports the median inaccuracy by year for the valuation models using cross-sectional regression forecasts, Panels B1 und B2 show the median valuation errors by year using Value Line forecasts, respectively. All calculations are based on a 2% growth rate in the terminal period. The extended models are given in (7) for the DDM, (9) for the RIM, and (12) for the DCF model. The standard models represent the model implementations according to (13) - (15). Negative intrinsic value estimates are set to zero. The signed prediction errors (bias) are calculated as the difference between intrinsic value estimate and market capitalization divided by market capitalization. The absolute prediction errors (inaccuracy) are calculated as |intrinsic value estimate – market capitalization|/market capitalization.

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