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Complex Parsimony in Equity Valuation

- An Empirical Assessment of Model Design and the Incremental Effects of Complexity

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Abstract

When deciding on a valuation model, an investor must be attentive to the juxtaposition between the *usefulness*, driven by complexity, and the *simplicity* of that particular model. This thesis employs an examination of four parsimonious equity valuation models (dividend discount model [DDM], residual income valuation model [RIV], abnormal earnings growth model [AEG], and the Ohlson-Juettner-Nauroth model [OJ]) and their usefulness in relation to the Nordic stock exchanges. Adding to previous studies, it also evaluates the impact of two different payoff schemes, analysts' estimates and martingales. To elaborate on model performance, this study further investigates both the separate and conjoint effects from adding three complexity adjustments, i) extending the forecast horizon, ii) adjusting for bankruptcy risk, and iii) excluding transitory items from the earnings measure. The analysis is carried out using a proprietary measure, which considers a comprehensive view on accuracy and spread. In general, it is found that RIV consistently outperforms the other models, regardless complexity adjustments. Notably, the impact from adding complexity to the models is largely dependent on the combination of model specification and model inputs, but the models' overall performance is increased. Nevertheless, the increased model performance from complexity adjustments must be assessed in light of the additional effort that such adjustments entail, as their marginal benefits are questionable.

Keywords: *equity valuation, valuation complexity, dividend discount model, residual income valuation model, abnormal earnings growth model*

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Contents

1. Introduction

On the purpose of valuation models, Stephen Penman (2005) discusses that consistency with valuation theory is not alone a sufficient argument for legitimizing the choice of model. He claims that, above all, valuation models have a purpose of *utility*, inasmuch as they should guide practitioners on what model to use, and how to properly use that particular model in the decision-making and assessment of investment opportunities:

> *It is of course imperative that a valuation model be consistent with valuation theory, but it is not sufficient. Valuation models are utilitarian – they serve to guide practice – so the choice between competing technologies ultimately comes down to how useful they are for the practical task of evaluating investments.* (Penman, 2005)

Furthermore, complex models have been argued for being more utilitarian than their simpler counterparts, in the sense that complex models are consistently *more accurate* in relation to observed market prices (Kaplan & Ruback, 1995; Bradshaw, 2004; Gleason, Johnson & Li, 2012). However, although it is important that a chosen valuation technology is useful, the chosen technology must also be *simple*, as investors actively seek ways to simplify their investment processes (Kahneman & Tversky, 1973; Peng & Xiong, 2006; Beunza & Garud, 2007). Penman & Sougiannis (1998) stress the virtue of simplicity in equity valuation, and specifically argue that the allegedly complex discounted cash flow model (DCF) is cumbersome owing to its "untangling" of accruals back and forth to arrive at free cash flows. Consequently, it has been proposed that simpler valuation means, or valuation shortcuts (e.g. multiples), have taken an increasingly prominent place in valuation processes, notwithstanding their inferior performance in accuracy (Berkman, Bradbury & Ferguson, 2000; Asquith, Mikhail & Au, 2005; Demirakos, Strong & Walker, 2010; Cavezzali & Rigoni, 2013). Thus, although simpler means might not be as useful as more complex models, they are still virtuous because of their simplicity. For an investor this implies that the task of model choice ultimately comes down to finding a *golden mean*, which optimizes the trade-off between usefulness and simplicity. Such a model should reasonably be parsimonious in its setup, both in terms of specification and inputs. On the former, parsimony can be expressed in terms of few required parameters, pursued by an easy operation for obtaining an intrinsic value; on the latter, it can be translated into readily available inputs, with no adjustments or untangling required at all. Besides a parsimonious setup, such a model would also have to hinge on theoretically consistent logics, since investors feasibly wish to make decisions based on fundamentally derived values (Penman, 2012).

To evaluate the usefulness of parsimonious models, this thesis aims to study four such setups and their performance relative to observed stock prices in the Nordic stock markets. The emphasis on usefulness is important for capital market practitioners, given the plethora of models available, but also for teachers of equity valuation at universities worldwide (Hickman & Petry, 1990). In addition, as the complexity of complex models has been shown to have a positive association with usefulness in terms of model performance, we will also consider the impact of adding complexity to the parsimonious model specifications. Does complexity increase the overall accuracy of parsimonious valuation models, or are some complexity adjustments more relevant than others in that sense? And is there a sufficient degree of complexity for each parsimonious valuation model respectively? The examined models are the dividend discount model (DDM), the residual income valuation model (RIV), the abnormal earnings growth model (AEG) and the Ohlson-Juettner-Nauroth model (OJ). As they are theoretically equivalent (Bernard, 1995; Ohlson 1995; Penman, 2005; Brief, 2007), we further argue that they are equally parsimonious in their specification and input requirements. This assumption is recognized throughout the thesis. Complexity is investigated by incorporating three complexity adjustments to the model specifications. First, we examine the impact from extending the forecast horizon of each model. Secondly, as has been lacking in similar studies, the explicit linkage between bankruptcy risk and parsimonious valuation is studied. Thirdly, the thesis studies the impact on the models from excluding transitory items in the earnings measure. As a final approach, we examine these complexity adjustments' conjoint impact.

Besides McCrae & Nilsson (2001), the extent to which the usefulness of parsimonious models has been studied on the Nordic markets is limited. In that sense, this thesis adds to the current literature by looking into markets with other characteristics than are commonly studied. Additionally, no other study highlights the trade-offs inherent in altering the *degree of complexity* in valuation models. Related, we introduce a proprietary measure, the AMA-score, which aims to quantify these trade-offs. Using this measure we take a systematic approach and examine the effects from introducing complexity adjustments to the original parsimonious model specifications, both separately and conjointly.

In general, it is found that the performance differs considerably between the models, but that their relative rank persists regardless of complexity adjustment. Furthermore, it is also suggested that complexity, when added to the parsimonious formulations, does increase performance. However, this increase depends highly on specific model combinations. Hence, the empirical results support the view that there is a positive association between complexity and accuracy, but also an inherent trade-off between complexity and effort. This trade-off is at length translated into economic terms as the *elasticity of valuation complexity*, which aims to mirror the relative changes in model performance in terms of effort required for that particular performance.

Section 2 presents an overview of the previous literature related to valuation models, both in terms of theoretical and empirical progressions. Next, we present the method undertaken and the data sample used (section 3 and 4). In section 5 we present the results of the study, and also integrate analytical discussions on the findings, along with some of the implications that the results might render. Finally, section 6 concludes the paper, discusses the more general implications and provides avenues to future research.

2. Previous research

2.1. Dividend Discount Model (DDM)

2.1.1. Theories on DDM

A classic approach to equity valuation is the dividend discount model (Rubinstein, 1976). Williams (1938) made the first explicit association between dividends and stock prices (Gordon, 1959; Damodaran, 2006), stipulating that "a stock is worth the present value of all the dividends *ever* to be paid upon it, no more, no less [...]", or equivalently

$$P_0 = \sum_{t=1}^{\infty} \frac{DPS_t}{(1+\rho_e)^t} \tag{1}$$

where P_0 is the current share price, DPS_t is the expected dividend at time *t*, and ρ_e is the cost of equity capital. The rationale behind the model is intuitive as dividends are the actual payments that an investor expects to receive from investing in a company's stock. On a practical note, as dividend payout ratios generally remain stable over time (Lintner, 1956; Jääskeläinen, 1967), DDM also mitigates any forecasting uncertainty. Despite these benefits, later studies have contended the alleged association between stock prices and dividends, and have also questioned the association of subsequent first order changes in these dividends (e.g. Shiller, 1981). Furthermore, the infinite properties of the model require dividend forecasting into perpetuity, a cumbersome activity, especially given companies' theoretical possibility to last forever. Thus, to apply the model, it is reasonable to make it more manageable, which is subject to discussion next.

Over time, DDM was criticized for having omitted the aspect of *growth*, and how to accommodate for it in the model. Gordon & Shapiro (1956) and Gordon (1959) addressed this, by making growth an explicit parameter in the model[1]. They presented a parsimonious expression including growth,

$$P_0 = \frac{DPS_1}{\rho_e - g} \tag{2}$$

where g is (steady state) growth. Obviously, the single condition that $\rho_e > g$ must hold, as we otherwise would obtain negative or infinite share prices. Henceforward, growth had been accommodated for. Nevertheless, their model suffers from one significant limitation: it only considers *one* growth rate. Consequently, it is only suitable for those companies expected to grow at their current rate into perpetuity, and concurrently neglects those instances where companies experience different growth rates up until *steady state*, i.e. a state where all firm parameters (earnings, dividends, &c) grow at the same rate. Its simplicity thus produces a restriction. Furthermore, given that some companies experience supernormal growth (Rappaport, 1986), such a model becomes obsolete. Clendenin & Van Cleave (1954) conducted a study of stocks for such supernormal growth firms. They used alternative DDM applications with uniform discounting rates, and concluded that this resulted in absurdities, especially in terms of infinite share prices (cf. Gordon & Shapiro, 1956). Durand (1957) also discusses the flaw of applying uniform rates to DDM. Similar to Clendenin & Van Cleave, he argues that "if, [...], $g \geq \rho_e$, the sum of an infinite number of terms would again be infinite – [...] – and a reasonable [investor] might [...] object to paying the price" (p. 351; cf. Bernoulli, 1954)[2]. As a response to the inadequacies of uniform rate assumptions, more dynamic models emerged that considered growth over explicit forecast periods and truncate the valuation model at a steady state (Molodovsky, May & Chottiner, 1965; Bauman, 1969; Fuller & Hsia, 1984; Damodaran, 2006).

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[1] They assumed that a corporation retained a fraction of its net income every year, and earned a rate of return on that retention, in addition to a return on the book value of equity. Furthermore, originally, the model was intended for backing out the cost of equity capital, but other studies won greater acclaim for such endeavours (e.g. Sharpe, 1964; Lintner, 1965; Mossin, 1966; Black, 1972; Fama & French, 1993).

[2] Original notation $g \geq k$, where k is the cost of equity capital.

After deciding on a proper specification for DDM, the next issue becomes deriving the inputs, i.e. dividends. On this, Hawkins (1977) discusses that although geometrically equating dividend growth rates with earnings growth rates might have been previously viable, it is not likely to persist given advances in accounting regimes. As earnings have become more volatile owing to new standards emphasising fair value accounting, this implies that net income has become a function also of "currency, interest rate and market value shifts – random events that create random figures" (p. 48). Regardless the potentially distortive effects, he argues that the source of dividends remains the same, in that forecasting future dividends is largely a matter of cash flow statement analysis (cf. Penman, 2012). Similarly, Rappaport (1986) stated that steady state growth rate assumptions understate stock prices, because the implications do not properly mirror that a "slowdown in sales also precipitates a slowdown in investment requirements" (p. 54), and hence, a focus on cash flows will render correctly specified stock prices. Hurley & Johnson (1994) analysed the geometric approach of Gordon & Shapiro (1956) and the additive approach of Hawkins (1977) and Rappaport (1986), in relation to dividend stability. Using a small sample of utility companies, they concluded that the geometric approach rendered a more accurate estimate of the actual stock price, notwithstanding that the additive model might be more suitable for other industries than utility companies.

2.1.2. Empirics on DDM

Much of the early empirical DDM literature concerned DDM's ability to explain stock market fluctuations. In a DDM setting, advocates of efficient markets would attribute stock price movements to "new information" about future dividends. However, LeRoy & Porter (1981) and Shiller (1981) challenged this view. By using variance bound statistical test, and applying a constant discount rate to DDM, they proposed that stock price indices seemed too volatile to be justified only by changes in dividends. However, Shiller's (1981) variance test was questioned by Flavin (1983), for being estimated with downward bias in small samples and for the calculation of observed P_t^*, inducing a bias toward rejection. Similarly, Marsh & Merton (1986) criticized the assumption of dividends being stationary around time trend, and Kleidon (1986) queried the variance bound tests for not concerning time-series relations, only cross-sectional ones. As a response, Campbell & Shiller (1987) and West (1988) revisited the variance bound tests, and found that, as previously alleged, fluctuations in stock markets are in fact too volatile to be explained by dividends alone.

Albeit market movements might not be associated with dividend movements, Jacobs & Levy (1989) still see financial benefits with using the model, if taking an inefficient market for granted, as they presume that "the more accurate your forecasts, and the faster the expectations of others converge toward yours, the greater your profit" (1989; p. 19). Using a univariate regression, they concluded that DDM explained only a small part of the change in ex-post returns[3]. However, when using a multivariate regression of DDM together with other attributes[4], the regression suggested predictive powers[5]. In an akin study, Sorensen & Williamson (1985) supported evidence that DDM could be useful in identifying mispricing. The authors evaluated ex-post portfolio performance using four different valuation techniques, a P/E-model and three DDM models with varying horizons. Next, the portfolios were ranked to identify under- or

[3] $R^2 = 0{,}037$

[4] E.g. P/E, yield, and size.

[5] $R^2 = 0{,}439$

overvaluation[6]. The rankings were used to construct five portfolios ranging from the most undervalued to the most overvalued stocks in the sample. Over the two succeeding years, the authors showed that annual returns were 30,46% and -5,17% for the most undervalued and overvalued portfolio respectively. In addition, they found a positive association between annual returns and model complexity, with the three-period DDM (P/E) model performing the best (worst).

2.2. Residual Income Valuation model (RIV)

2.2.1. Theories on RIV

In addition to the empirical questioning of DDM's validity, also a theory-based critique emerged coeval with Gordon and Shapiro, through Miller & Modigliani's (1961) dividend irrelevancy proposition, which nullified DDM by neutralizing the value-relevance of dividends. For many years, these contrasting theories created a research stalemate, with few contributions in the capital market research (Bernard, 1995), what Penman (1992) called "the dividend conundrum"; stock prices are based on dividends but dividends contain no information on stock prices. In response, subsequent research focus shifted paradigms, from explaining stock price behaviour to understanding the potential impact of accounting information on valuation (known as *market-based accounting research*; Lev & Ohlson, 1982; Lev, 1989).

The role of accounting and its value relevance in valuation is not novel, however. Daniels (1934) argues that lay readers of financial statements "usually believe[...] that the total asset figure of the balance sheet is indicative, and is intended to be so, of the value of the company" (p. 114), mirrored also in IASB's Conceptual Framework, which emphasizes that accounting should be value-relevant. Ball & Brown (1968) showed an association between accounting and valuation, while also suggesting the existence of efficient markets[7]. But given the mentioned shift in paradigms, their theoretical rationale is based on *explaining* stock price behaviour, which acted counter the emerging research area of accounting information's impact on valuation. RIV was a result of this research, although its underpinnings had been discussed much earlier.

Preinreich (1938) discussed capital value as a function of an asset's book value, and earnings less a required rate of return on that asset's book value, i.e. *residual* or *abnormal earnings*. This became the foundation of capital values translated from accounting information. Besides Preinreich, the original RIV was most prominently advocated by Edwards & Bell (1961) and Peasnell (1981; 1982), albeit the latters' specifications largely resemble the original model. However, the perchance most celebrated RIV application is Ohlson's (1995) and Feltham & Ohlson's (1995). Interestingly, although the RIV idea had existed for some time, Ohlson's and Feltham & Ohlson's contribution played a significant role in academia, particularly with regard to their view on the relation between a firm's value and its accounting data (Bernard, 1995; Dechow, Hutton & Sloan, 1999; Lo & Lys, 1999). Out of the two, the more empirically tested application is Ohlson's (1995)[8]. The backbone of Ohlson (1995) rests upon three assumptions; firstly, the price of a security is equal to the future expected dividends (i.e.

[6] The P/E model ranked firms on relative P/E-ratios (low to high), whereas the DDM applications were ranked based on deviation (DEV) from observed market prices, i.e. (intrinsic value)/price. On average, DEV was 1,577 for the most undervalued stock portfolio and 0,501 for the most overvalued one.

[7] This suggestion has been challenged in similar studies (e.g. Foster, 1979; Bartov, Lindahl & Ricks, 1998).

[8] Ohlson (1995) differs from Feltham & Ohlson (1995), as the latter focus on the separation of a firm's operational and financial activities.

follows DDM). Secondly, the clean surplus relation (CSR) applies, meaning that any changes in the book value of equity are reported as income, dividends or capital contributions (Peasnell, 1981; Penman, 1992; Feltham & Ohlson, 1995). Feltham & Ohlson (1995) concluded that the two assumptions are sufficient to express market values in terms of book value and the present value of future expected abnormal earnings, such that

$$V_0 = BV_0 + \sum_{t=1}^{\infty} \frac{E_0[\tilde{x}_t^a]}{(1+\rho_e)^t} \tag{3}$$

where V_0 is the current intrinsic value of equity, $E_t[\ldots]$ is an expectations operator reflecting all available information at time *t*, ρ_e is the cost of equity capital, BV_0 is the current book value of equity, and $\tilde{x}_t^a$ depicts the (expected) abnormal earnings, defined as the difference between observed earnings, x_t, and a cost of capital charge on the book value of the previous period,

$$x_t^a = x_t - \rho_e \cdot BV_{t-1} \tag{4}$$

Here, it is easy to see that abnormal earnings are separate from normal dittos. "Normal" earnings correspond to a "normal" (or required) return on the capital stock at time t, or equivalently displayed, $x_t^a = 0$. Abnormal earnings imply that actual returns are separate from the required return (i.e. $x_t^a \neq 0$), and positive abnormal returns "indicate a 'profitable' period" (Ohlson, 1995). Additionally, as in Preinreich (1938) and Peasnell (1982), as long as assumption two is honoured, the valuation model works for any accounting regime.

The third and final assumption tends to complicate the model. It presents a RIV adaptation that Feltham & Ohlson (1995) recognize as the *linear information model* or the Ohlson model, where *other* information, than accounting information, is assumed to impact the value of a company's stock. Such an assumption is quite reasonable, as there ought to be other information in the capital markets that affects stock price. Alas, given this assumption, attempts to adhere to simplicity is diluted. Despite RIV's similarity to the Ohlson model, we argue that the difference between the two should to be acknowledged, and that the two models should be treated separately, despite their shared heritage. In fact, many empirical studies of the Ohlson model omit the third assumption, but still refer to Ohlson (1995) as the theoretical basis, as though the effect of this assumption would be negligible. Lo & Lys (1999) argue that omission of the third assumption in many empirical studies (e.g. Frankel & Lee 1998; Dechow, Hutton & Sloan, 1999; Francis, Olsson & Oswald, 2000) is because it is oftentimes viewed as superfluous. As a result, they are ultimately empirical tests of the original RIV, not the Ohlson model. Furthermore, Ohlson himself (1999) deprecates the misspecifications of his model and humbly recognizes that "[o]rigination of RIV cannot be attributed to Feltham or Ohlson" (p. 118), whilst concurrently questioning the empirical significance of applying his model without the information dynamics.

2.2.2. Empirics on RIV

Empirically, RIV appears to be more tested than the Ohlson model, owing perhaps to the difficulty in applying the latter. Additionally, any alleged superiority of the Ohlson model over RIV has been challenged in recent studies, suggesting that simpler models might be equally good or better to replicate actual stock prices (Hand &

Landsman, 1998; Lo & Lys, 1999). However, as noted, Ohlson himself questioned the validity of RIV. Particularly, he queried its heavy reliance on CSR to hold. He pointed to the possibility of changing the number of shares, which in turn causes a theoretical flaw in RIV, as this change is not permitted under CSR. This, in combination with a plethora of dirty surplus items, can cause a situation where changes in book value of equity cannot be attributed to changes in income, dividends or capital contributions (Ohlson, 2000; 2005; Penman, 2005). One way of circumventing this is by applying a plug, other than accounting information, but the solution is unorthodox, especially with regard to how such plugs should be interpreted.

Another issue concerns growth rates. Growth is as relevant for RIV as for DDM, but the two models challenge economic intuition for truncated valuations, as they in steady state assume constant growth rates. As discussed, arriving at proper growth rates is difficult, but given its impact on finite valuation models, the issue is central. Attempts have been made to accommodate the models for growth, and Penman (2005) explains that a "likely" scenario is one where high growth is expected in the short-term, turning "in a geometric fashion" to a lower rate in the long-term (cf. Brief, 2007)[9]. Both RIV and the Ohlson model are unable to integrate this finesse, and consequently forecasting growth remains a manual issue. Related, Ohlson (2005) suggested an alternative model, focused on book values regardless of (residual) earnings, which would capture Penman's (2005) "abnormal book values growth", implying an incremental view of changes in book value.

2.3. Abnormal Earnings Growth model (AEG)

2.3.1. Theories on AEG

Ohlson's (2005) and Penman's (2005) alternative view was most prominently elaborated on by Ohlson & Juettner-Nauroth (2005; henceforth OJ), which rendered the abnormal earnings growth model, or the OJ model. In theory, it evaluates the *growth* of abnormal earnings, not abnormal earnings per se. In addition, an important feature of AEG is its independence on CSR, which allows for more general specifications. Practically, it corresponds to financial analysts' propensity to forecast earnings, not book values of equity or dividends (Sloan, 1996). Within financial accounting there has emerged an increased understanding for capital market's propensity to emphasize earnings, and Walker (2006) stresses that standard setters must be more attentive to this fact by making the measurement of earnings more practically relevant for valuation purposes.

Abnormal earnings growth is defined as a period's earnings plus dividends (theoretically) reinvested, in excess of the previous period's earnings growing at the required rate of return,

$$z_t \equiv [EPS_{t+1} + \rho_e \cdot DPS_t] - (1 + \rho_e) \cdot EPS_t \qquad (5)$$

where $\mathrm{EPS_t}$ is (expected) earnings per share at time t and $\mathrm{DPS_t}$ is (expected) dividend per share at time t. Interestingly, although not necessary for the model, when CSR is assumed in AEG, OJ (2005) show that substituting the abnormal earnings expression above into

[9] For further reference, this comparison can be understood as the difference between RONIC and ROIC (Koller, Goedhart & Wessels, 2010), where RONIC is driven down to a lower rate from a previously higher ditto as time goes on.

RIV directly gives the AEG application, or the *non-parsimonious* AEG model (Jennergren & Skogsvik, 2007), as

$$V_0 = \frac{EPS_1}{\rho_e} + \frac{1}{\rho_e}\sum_{t=1}^{T}\frac{1}{(1+\rho_e)^t}\cdot z_t \tag{6}$$

By dissecting the above equation, two terms comprise the intrinsic value; firstly, it is anchored on expected earnings in year one, capitalized with the cost of equity capital. The second term with z_t captures abnormal earnings growth for future years up to a truncation point, *T*. One can imagine a scenario with $z_t = 0$ for all future years, which implies that the value of a security is merely the capitalized earnings of year one[10]. However, when expecting abnormal earnings growth, the security is priced at a premium over the normal earnings performance. With regard to this, Penman (2005) sees that the AEG concept is advantageous over the residual income growth concept, as the former suggests a valuation of the incremental effect on earnings growth, not the growth in itself. Or rather

$$z_t = \Delta(x_t^a)$$

where $\Delta(\dots)$ expresses change of the first order, and x_t^a is the abnormal earnings in RIV[11] (Equation 4). To fully appreciate this, recall that mathematically, this implies that $g_{AEG} \neq g_{x^a}$, where g denotes growth, and the indices depict AEG and residual income respectively. The logic goes that if the level of a variable grows at a rate, so do its changes, but the converse is not true. Recognize that the growth rate, g_{AEG}, is the long-term rate for expected abnormal earnings, and a declining rate seems conceptually plausible given assumptions on competition and steady state. Related, truncation and finite valuation models could benefit from the more incremental growth rates of AEG (Penman 2005). Yet the question remains: how does one capture growth in a finite AEG setting? OJ (2005) set up the original model for one forecast and one truncation period, assuming some properties related to z_t, such that

$$z_{t+1} = \gamma z_t$$

where $1 \leq \gamma < (1+\rho_e)$ and $z_t > 0$. The parameter gamma, γ, aims to capture the growth in abnormal earnings growth in future periods. This assumption, together with the ubiquitous DDM assumption, present a complete application of the AEG model, a *parsimonious* application (Jennergren & Skogsvik, 2007), stating that

$$V_0 = \frac{EPS_1}{\rho_e} + \frac{z_1}{R-\gamma} \tag{7}$$

with $R = (1+\rho_e)$, and $\gamma = (1+g_{AEG})$. Note that the right term of Equation 7 possesses the properties of constant growth (Gordon and Shapiro, 1956), hence subsuming this effect explicitly.

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[10] This scenario also shows that the forward P/E ratio can be calculated by dividing both sides by EPS_1 thus rendering $P/_{EPS_1} = \frac{1}{\rho_e}$ (Ohlson, 2005; Penman, 2012).

[11] Perhaps more clearly as $z_t = x_t^a \cdot g_{x^a}$, where g_{x^a} is the constant growth in abnormal earnings (cf. Penman 2005).

The parameter γ requires some supplementary discussion, as its dynamics are both theoretically appealing and practically relevant, and with the constant growth property in the parsimonious model, the effect of γ is significantly amplified, especially if γ approaches R. But what drives γ? Many things impact the expected abnormal earnings growth, but without conjecturing on this, let us consider the two most important ones. Firstly, as competition reasonably catches up with a firm, this will consequently render a situation where abnormal earnings move towards zero, forcing abnormal earnings down. The succeeding effect on γ is negative (e.g. Penman, 2005). Secondly, a conflicting effect is owing to the choice of accounting regimes reflected in the underlying accounting for the model. With unbiased accounting, there are no substantial differences between market values and book values. Conservative accounting, on the other hand, stresses prudence, generally understating assets and overstating liabilities. Furthermore, because of the reversal properties of accounting (Penman, 2012), these biased assessments must at length reverse. This has an ultimate impact on the expected future growth as eloquently displayed by Feltham & Ohlson (1995) with RIV, and is equally valid for AEG. They note that regardless dividend policy and available information at time *t*, it holds under unbiased accounting that the expected growth is approaching zero towards infinity (cf. Gao, Ohlson & Osztasewski, 2013). Under a conservative accounting regime though, growth will remain greater than zero also towards infinity, because of residual earnings persisting in such regimes[12]. The consequent effect on γ from this amendment is positive. So, when accommodating for the two opposing factors of competition on the one hand, and accounting bias on the other, a plausible assumption is that their respective effects offset, such that $\gamma = 1$ (Skogsvik & Juettner-Nauroth, 2013), i.e. a case of "no growth in eps performance" (OJ, 2005, p. 356). This assumption applied to the parsimonious AEG application, gives rise to a version of the model referred to as the PEG model, alluding to the PEG multiple and its relation to the growth of (expected) EPS. Given the common practice of using multiples for valuation purposes, the reference to PEG in this adaptation becomes particularly relevant (Ohlson & Gao, 2006).

Some important extensions of the AEG model have been presented (e.g. Jennergren & Skogsvik, 2011; Grambovas, Garcia, Ohlson & Walker, 2012). One with particularly theoretical implications for the parsimonious AEG model is presented by Penman (2005) and Jorgensen, Lee & Yoo (2011), in an attempt to determine the validity of AEG versus RIV. In short, their adaptation of AEG concerns the number of forecast periods. It is argued that the accuracy of AEG increases considerably when the number of periods increases, which they explain with that short-term earnings are polluted by some "noise", or transitory items, that can distort a more long-term, sustainable level of earnings. This "noise" is given additional impact through the constant growth property in the model specification. Therefore, they argue, misstatements of earnings in previous years, can skew the value, even though earnings growth and return on equity convert to an expected "mean" in later years. Extending with one period, the model can be formulated as

[12] Ohlson & Gao (2006) also note an "invariance aspect" of accounting regimes that may cancel the effects of the applied accounting standards as $t \to \infty$.

$$V_0 = \frac{EPS_1}{\rho_e} + \frac{z_1/\rho_e}{(1+\rho_e)} + \frac{z_2/\rho_e}{(R-\gamma)(1+\rho_e)} \tag{8}$$

2.3.2. Empirics on AEG

In relative terms, AEG is a new model. For that reason, the model and its applications have not been as empirically validated as older models have, with benefits and disadvantages to be recognized. One of the more eloquent critiques on AEG's flaws is discussed by Penman (2005), where he clearly goes against OJ (2005), by suggesting a return to accounting fundamentals. Given AEG's independence of accounting concepts (e.g. CSR), he asks "where is the accounting?". Such concepts legitimize a model by putting it into an accounting context, but they also offer insight on how to forecast and build pro-forma analyses. Moreover, omitting the balance sheet creates another conceptual caveat in AEG. Firstly, it neglects the notion that "assets beget earnings" (Penman 2005, p. 373), i.e. that balance sheets provide information about future earnings. Secondly, there is a virtue in anchoring value to something known, like book values (cf. Daniels, 1934), which could reduce the need for forecasting all together. Penman argues that anchoring on $\frac{EPS_1}{\rho_e}$ goes against the fundamental analyst's dictate of separating the known from the speculated (Penman, 2012), as the anchor is in itself a matter of speculation, both in the numerator and denominator. Related, he recognizes that AEG largely hinges on determining the cost of capital, which is an issue for RIV and DDM alike, but the capitalization property in AEG amplifies the issue. Additionally, one can question the use of earnings as a value parameter. As Brief (2007) argues, many empirical studies have noted that analysts often refer to other accounting and non-accounting information (other than earnings) as value-relevant[13]. Consequently, other models might better capture the full spectrum of value-relevant aspects, but as mentioned, in light of AEG's relative youth, ruling out the model might be premature.

Empirical assessments of AEG's validity have chiefly been concerned with deriving the costs of capital inherent in observed market prices, and their relation to commonly cited risk-proxies. For instance, to infer the risk premium implied by current prices, Gode & Mohanram (2003) used a two-period AEG, three years of forecasted EPS, and assumed that γ is equal to $(1 + r_f)$. For comparison, Gode & Mohanram also inferred the risk-premiums of two RIV models, differing only in the measurement of industry median ROEs. The risk premium was then evaluated threefold. First, they assessed how well the implied risk-premium correlates with other risk factors, e.g. systematic risk, earnings variability and size. What they found is that AEG-inferred risk-premiums correlate with the commonly cited risk factors, although the overall explanatory power was higher for the RIV application with industry-specific information in ROE. Second, the authors ran risk-premium estimates without using current prices, by observing the association between inferred risk-premium and the estimated ditto. Again, they found that RIV outperformed AEG. Finally, they tested the correlation between ex-ante risk-premium and ex-post realized returns, and discovered significant associations between ex-ante risk premiums and ex-post returns. In summary, AEG predicts three-year-ahead returns relatively well, although the industry-specific RIV model is superior for predictions in year one and two, which ultimately suggests a relative superiority of RIV over AEG

[13] This corresponds to Ohlson (1995) and his information dynamics addition to RIV.

Related to examinations on inferred costs of capital, previous studies have compared this with the PEG model to AEG. Botosan & Plumlee (2005) examined the relative reliability of cost of capital estimates (measured as risk-premium), by equating price with five different types of discounted forecasted future payoffs, out of which two were AEG and PEG applications. The authors initially studied the estimates' ability to capture the same underlying construct, by comparing their average magnitude and relative correlation to a realized risk premium. They found systematic understatements in the estimates, although the AEG estimate provided the closest match. Further, when studying if the variations owed to some underlying construct, the results showed a majority of correlations being greater than 0,6, proposing such a construct. Next, they assessed the estimates' relative reliability by regressing risk-proxies from firm-specific data on observed ex-post costs of equity. The inferred risk premiums were finally examined based on their predictability and association with these risk-proxies. Whereas the findings imply a stable association between inferred risk premiums from the PEG model and the regressed firm-specific risk-proxies, the corresponding results for AEG were neither stable nor in line with theory – in other words, the two-period PEG model dominated the two-period AEG. However, Easton & Monahan (2005) ruled out Botosan & Plumlee (2005) as neither correct nor theoretically exhaustive, with their basing a relative rank of expected return measures on the regressed risk factors. Instead, they examined seven accounting-based proxies imputed from observed market prices and analyst forecasts to evaluate the reliability of the expected return estimates. The seven proxies included an inverse P/E-ratio, two two-year PEG models with different dividend schemes and a perpetual abnormal earnings growth rate of zero, one AEG application with γ based on the risk-free rate (cf. Gode & Mohanram, 2003) and one AEG application allowing for variations in γ[14], plus two RIV models, with differing assumptions on growth. By conducting regressions based on accounting-based proxies' measurement error variance, Easton & Monahan (2005) used Voulteenaho's (2002) linear decomposition of realized returns[15] and found that none of these provide reliable estimates for the cost of equity capital[16]. On a specific level, the two-period PEG model with no dividend payouts performed worst, whereas the second PEG model and the AEG applications were beaten by the inverse P/E and RIV models. Interestingly, this shows that Easton's (2004) 'complex' model performed second to worst, while the parsimonious E/P ratio was found to be as reliable as RIV.

2.4. Empirics on model comparability

2.4.1. Relative model performance

From Ohlson (1995) and Feltham & Ohlson (1995), a new field in valuation research emerged, testing the validity of RIV and related models. Usually these models were evaluated on how well they could explain variations in stock prices, but also on their accuracy compared to observed prices. Bernard (1995) pioneered this field of research, and evaluated RIV and DDM's ability to explain stock price variation. He set up three-year RIV and DDM models (without terminal values) and regressed its *components* on the variations in stock price, with the rationale that if a good approximation can be obtained from RIV, a "large fraction" of price variations should be explained by RIV

[14] The AEG application allowing variations in γ, is derived from Easton (2004) who argued for a more complex estimation of long-rung growth rates, as generally applied PEG models are too simplistic in their long-run assumptions.

[15] Based on i) expected return, ii) cash flow news, and iii) return news.

[16] The conclusion holds, even with robust checks controlling for changes in future payoffs and discount rates.

component estimates[17]. The results indicated that RIV explained 68% of the changes in stock prices, while 28% was explained by DDM (cf. LeRoy & Porter, 1981; Schiller, 1981). According to Bernard, not only did this further accentuate the dividend conundrum (Penman, 1992), but it also highlighted the usefulness of accounting-based valuation. He attributed the regression's deviation from full explainability to his applied assumptions, but also to its lacking ability of accommodating an infinite forecast horizon. When adjusting for the latter, the RIV components could explain up to 80% of the changes in stock price.

Associated, Penman & Sougiannis (1998) examined DDM, RIV, DCF and a capitalized earnings model, but in contrast to Bernard (1995), they considered the issue of *truncation* as essential for finite horizon forecasts. For this purpose, the authors examined the bias in model performance, by including and excluding terminal values[18]. The findings suggested that when excluding the terminal value component, accounting based-models (RIV and capitalized earnings model) performed better than cash flow-based dittos (DDM and DCF). Also when including the terminal value calculation, the relative ranks persisted. The authors attributed the results to the ability of accounting-based model payoffs to 'bring the future forward' with the concept of accruals, with diminishing capital expenditures as charges against realized payoffs. More specifically, the authors ascribed much of RIV's relative domination to that a significant part of its intrinsic value estimate comes from book value of equity, which makes it less susceptible to truncation estimates. Acknowledging terminal values, the results also proposed that the impact of this component was relatively greater in the DDM and DCF models, as a large portion of their intrinsic values lay at truncation.

By extending the results of Penman & Sougiannis (1998), Francis, Olsson & Oswald (2000) performed a study to define the accuracy of DDM, RIV and DCF models, using pricing errors[19]. They argued that biases based on portfolio intrinsic value estimates (i.e. Penman & Sougiannis, 1998) lack informative ability, since fundamental investors ultimately look to accuracy to determine any mispricing of individual securities. The results showed that RIV performed relatively better to DDM and DCF, and that DCF performed better than DDM. The median unsigned pricing error, defined as the absolute percentage deviation between calculated intrinsic value and observed price, or $\left|\frac{V_t - P_t}{P_t}\right|$, was 30% for RIV, and 41% (69%) for DCF (DDM). Performing regression analysis, the results were cemented as RIV estimates explained 71% of cross-sectional price changes, compared to 35% (51%) for DCF (DDM) (cf. Bernard, 1995). Furthermore, substituting forecasted with realized payoffs, the authors found that the relative ranks remained, although pricing errors were smaller using the former. The authors also mimicked Penman & Sougiannis' bias approach, where they could confirm that RIV bias dominates

[17] In the analysis, Bernard (1995) assumed i) constant discount rates across all sample firms, ii) constant conservatism affecting book values across firms, iii) that abnormal earnings and dividend forecasts reflected all available information, and iv) that, in light of that information, the capital markets are efficient.

[18] The performance of the models were evaluated by comparing observed prices with the intrinsic value estimates derived from ex-post *realized* payoffs averaged in portfolios over the period 1973-1990. For each model, ex-post portfolio valuation biases were calculated using signed pricing errors, or equivalently $\frac{V_t - P_t}{P_t}$.

[19] In contrast to the previous study, the authors provided evidence based on *individual* firm value estimates and forecast data, and not on portfolio estimates derived from realized payoffs. Furthermore, another difference was the metric used to quantify performance, using accuracy instead of bias. Moreover, they investigated the accuracy through unsigned pricing errors.

DDM and DCF. However, when substituting realizations with forecasts, the ranking became dependent on terminal growth rate assumptions[20].

With OJ (2005), empirical studies could extend their model comparisons by incorporating AEG as well. A forerunner on this was Penman (2005), who examined two-period AEG and RIV applications and their relation to observed market prices, using consensus ex-ante forecasts[21]. He found that RIV (AEG) had a median intrinsic value to price ratio (V/P) of 1,00 (2,02), but also that the V/P-variance was larger for AEG. Hence, RIV was more accurate and less volatile than AEG[22]. With a similar outset, Brief (2007) used the interquartile range (IQR) to estimate the standard deviation for both the RIV and AEG V/P distributions of Penman (2005)[23]. He found that the standard deviation of AEG (2,07) was four times larger than that of RIV (0,48), highlighting the more volatile outcomes of the former, just like Penman (2005), who explained the overvaluations of AEG in three ways. Firstly, they could be a result of overly optimistic analyst forecasts. Secondly, the second-year growth in abnormal earnings could be inflated by a depressed first-year abnormal earnings growth resulting from transitory items. Finally, he argued that the geometric decay in abnormal earnings growth was not representative for that priced by the market. All in all, he suggested that future research should employ *longer forecast horizons* to circumvent any inflated abnormal earnings growth resulting from *transitory items*.

However, the notion of a single best model (RIV) was contended. Lundholm & O'Keefe (2001a; 2001b) argue that the different models should render the exact same intrinsic value, and findings suggesting otherwise are theoretically inconsistent. On an empirical note, Chang, Landsman & Monahan (2012) show that a proposition supporting a single best model is simply not true. They ranked a number of naïve and more complex RIV and AEG (cf. Grambovas, Garcia, Ohlson & Walker, 2012) applications, and found that AEG and RIV using a five-year horizon had the lowest median and mean unsigned pricing errors respectively. Hence, the model that was best for the typical firm, was not best on average. Furthermore, all models were ranked for each observation in the sample and interestingly, the five-year RIV and AEG only ranked first in 10,41% and 14,41% of the cases. Instead, a fifteen-year AEG ranked first most often (28,53%), with naïve RIV as second (19,10%) and naïve AEG (17,06%) in third. However, these models were also the least accurate for 37,58%, 39,73% and 18,06% of the observations. In addition, only three models ranked first more than 16,67% of the observations, implying that only three of the models frequently had a higher likelihood of placing first, than had the relative ranking been distributed randomly. All in all, these inconsistencies made the authors conclude that there simply is no single best model.

2.4.2. Relative model performance with adjustments

Besides a pure comparison of the actual models, many studies have also included different adjustments to study the impact that these have on different model

[20] Using 0% growth the study confirmed the previous results, whereas using 4% catapulted DCF to the top.

[21] Valuations were made every year over the period 1975-2002 using data with U.S. trading equities, employing a constant cost of capital for all firms.

[22] Furthermore, the results provided evidence for that RIV dominated AEG in accuracy for all, but one, years.

[23] Brief (2005) assumed a normal distribution and set the standard normal deviate for the 25th and 75th percentiles, to equal the deviation between each of these percentiles, and the mean of the observed distributions, divided by the standard deviation.

specifications. One such discussion relates to theoretically "ideal" terminal values. Penman (1997) provided formulations for these and also established the theoretical equivalence of the DDM, RIV and DCF models for finite horizons. The ideal terminal value estimates at the end of forecast horizon, *T*, were formulated as: $E_t(P_{t+T})$ for DDM, $E_t(P - B)_{t+T}$ for RIV and $E_t(P - FA)_{t+T}$ for the DCF model, where P_{t+T}, B_{t+T} and FA_{t+T} denotes the *forecasted* stock price, book value of equity and net financial assets at *T*. Whereas previous studies had omitted such terminal formulations (e.g. Penman & Sougiannis, 1998; Francis, Olsson & Oswald, 2000), Courteau, Kao & Richardson (2001) revisited these studies with the ideal terminal value expressions of Penman (1997), in order to establish "a level playing field" comparison. They compared signed and unsigned pricing errors, using both ideal formulations and the *common* ones relying on constant growth properties. The results indicated that pricing errors were significantly smaller for models with ideal terminal values, where RIV (DCF) had a median signed pricing error of 4,73% (4,82%), whereas the common formulation yielded -37% (-41%) and -34% (-30%), for growth rates of 0% and 2% respectively. The analysis of accuracy yielded results similar to those of bias, confirming that common formulations performed worse than ideal. When testing for robustness, they found that RIV and DCF models applying ideal terminal values, explained a similar proportion of cross sectional stock-returns (93,0% versus 93,7%). Similar to Penman & Sougiannis (1998) and Francis, Olsson & Oswald (2000), the models with common formulations confirmed that RIV dominates cash flow models. Courteau, Kao & Richardson hence complemented the earlier studies, inasmuch as it provided a possible explanation for RIV's domination, by highlighting that sensitivity of the estimates is largely owing to the choice of terminal value formulation.

As discussed by Penman (2005), the consideration of horizon and transitory items is another palpable adjustment in equity valuation. One study that explicitly followed these adjustments, was Jorgensen, Lee & Yoo (2011), who examined RIV and AEG over longer horizons[24]. They justified their approach by criticizing previous AEG studies for being too reliant on the risk-proxies used for evaluating the results, when reverse-engineering an implied cost of capital (e.g. Gode and Mohanram, 2003; Botosan & Plumlee, 2005). They evaluated AEG, a PEG model and three RIV applications (RIVIT, RIVCT, RIVGT), all with two- or five-year forecasts[25]. AEG and PEG were less accurate than RIV, and were systematically overvalued in terms of V/P. Interestingly, PEG yielded lower errors than AEG, with V/Ps of 1,407 (1,298) for the two-year (five-year) PEG, compared with 1,994 (1,749) for the two-year (five year) AEG. Subsequently, increasing AEG's forecast horizon did lower the V/P. However, increasing the forecast horizon in RIV yielded mixed results, indicating RIV's relative insensitivity to choice of forecast horizon (cf. Bernard, 1995). The mean RIV V/Ps were 1,111 (1,113), 0,829 (0,937) and 0,952 (1,081) for the two-year (five-year) RIVIT, RIVCT and RIVGT models respectively. Also with unsigned pricing errors, the relative performance remained. In sum, all variations of AEG again exhibited higher pricing errors than the RIV applications, although the forecast horizon improved the accuracy of AEG, with an unclear effect on

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[24] Expected payoffs were derived using analyst estimates.

[25] The different versions of RIV had been circulating in the empirical literature for a while; (RIVIT) by Lee (1999), Gebhardt, Lee & Swaminathan (2001), and Liu, Nissim & Thomas (2002), assumes ROE to trend linearly from the level implied by analysts earnings forecasts for the end of the forecast horizon, to the industry median ROE by year 12, to yield a constant residual earnings in perpetuity. (RIVCT) was presented by Frankel & Lee (1998), Lee (1999) and Ali, Hwang & Trombley (2003), and assumes that residual incomes stay constant past the forecast horizon. The final (RIVGT), by Claus & Thomas (2000), is one where growth is assumed constant for the years preceding the forecast horizon (cf. OJ, 2005).

Table 1. Summary: Empirics on model comparability

Author(s)	*Market and period*	*Models specification*	*Method and payoff specification*	*Key findings*
Bernard (1995)	U.S 1978-1993	-RIV (3Y) excl. term value -RIV (3Y) incl. term value -DDM (3Y) excl. term value	-Regressing of model components on cross-sectional stock price variations -Ex-ante analyst estimates	-RIV dominates DDM -RIV incl. term value dominates RIV excl. term value
Penman & Sougiannis (1995)	U.S 1973-1992	-RIV (1,2,3,6,8,10Y) excl./incl. term values -DDM (1,2,3,6,8,10Y) excl./incl. term values -DCF (1,2,3,6,8,10Y) excl./incl. term values -Cap earnings (1,2,3,6,8,10Y) excl./incl. term values	-Portfolio valuation bias -Ex-post realized payoffs	-Accounting based models dominate (RIV and Cap earnings) -RIV dominates for all but two horizons (6 and 10Y) -Incl. of term value did not chage relative perfromane ranks
Francis, Oswald & Olsson (2000)	U.S 1989-1993	-RIV (5Y) incl. term value -DDM (5Y) incl. term value -DCF (5Y) incl. term value	-Unsigned pricing errors -Univariate and multivariate regressions -Ex-ante analyst estimates -Ex-post realized payoffs	-RIV dominates DCF and DDM -DCF dominate DDM -Smaller pricing errors using analyst estimates as opposed to relaized
Courtreau, Kao & Richardson (2001)	U.S 1992-1996	-RIV (5Y) incl. 'ideal' and 'common' term value -DCF (5Y) incl. 'ideal' and 'common' term value	-Singned and unsigned pricing errors -Intrinsic value and model components regressed on cross-sectional stock-price variations -Ex-ante analyst forecasts	-RIV dominates DCF and DDM -DCF dominate DDM -Smaller pricing errors using analyst estimates as opposed to relaized
Penman (2005)	U.S 1975-2002	-RIV (2Y) incl. term value -AEG (2Y) incl. term value	-V/P-ratios -Ex-ante analyst forecasts	-RIV dominates AEG (median V/P) -V/P distribution smaller for RIV (Brief 2007)
Jorgensen, Lee & Yoo (2011)	U.S 1984-2005	-RIV(IT) (2,5Y) incl. term values -RIV(CT) (2,5Y) incl. term values -RIV(GT) (2,5Y) incl. term values -AEG (2,5Y) incl. term values -PEG (2,5Y) incl. term values	-V/P-ratios -Unsigned pricing error -Ex-ante analyst forecasts	-RIV dominates AEG (median V/P) -PEG dominates AEG -Increased horizon benefit AEG and PEG, but not RIV -AEG and PEG overvaluation due to ROE overestimation gap
Chang, Landsman & Monahan (2012)	U.S 1980-2010	-RIV (1Y) BV only -RIV (5Y) incl. term value -RIV(15Y) incl. term value -AEG (1Y) Cap earnings only -AEG (5Y) incl. term value -AEG (15Y) incl. term value	-Unsigned pricing errors -Signed pricing error -Accuracy ranks -Ex-ante analyst forecasts	-RIV best on average -AEG best for typical firm (median) -AEG (15Y), RIV(1Y) and AEG (1Y) most frequently ranked first *and* last

RIV. Like many previous studies, Jorgensen, Lee & Yoo praised RIV and attributed its consistency to its anchoring on book values of equity, whereas AEG sensitivity, on the other hand, emanated particularly from transitory items.

In order to explain the overvaluations of AEG (and PEG) and its increased performance when extending the horizon, Jorgensen, Lee & Yoo (2011) evaluated the trend of expected future ROEs that were implied by the AEG valuations. These expected ROEs were compared to observed realized ROEs, and absolute (future) ROE errors were calculated. Dividing the sample firms into quintiles based on current ROE, they found that the short-term AEG and PEG models' lower valuation accuracy was most distinct for the firms in the lowest ROE quintile. Furthermore, it was found that firms in this quintile largely overestimated ROE compared to the realized (future) ROE. In other words, increasing the forecast horizon, from two to five years, significantly improved the accuracy of these firms, and additionally mitigated large parts of the ROE overestimation gap.

2.5. Elaborating on the empirical insights

The previous literature provides some interesting findings; RIV is seemingly a stronger model across the studies, whereas AEG systematically generates large overvaluations and deviations and DDM ends up somewhere in between the two. Further, to improve model performance, extending the horizon and reflecting over the terminal value formulations are two particularly stressed adjustments. Although previous studies offer valuable considerations to investors for assessing investments, the methodological differences between them make it difficult to draw any bigger conclusions, as they differ too much to justify such conclusions. In addition, previous studies only consider realized or analysts' estimates as payoffs. The former might be a neat theoretical approach, but the practical relevance can be questioned since stock prices reflect *unrealized* payoffs, and the latter can be queried on the basis of ordinary investors' alternatives. On the one hand, analysts forecast some financial items more distinctly than others, which benefit only the valuation models using those items, but on the other, the access to such forecasts is mainly restricted to institutional investors, or else only at a high price. Considering payoff schemes that are intuitive, easily constructed and thus more commonly used would be of interest for ordinary investors. Given the inconclusive results from the mutually inconsistent methodologies of previous studies, an investor would benefit from a more uniform and comprehensive review that takes the findings of the previous literature into account, by providing a "level playing field" in terms of specifications and inputs.

Furthermore, previous literature has not *explicitly* considered model complexity. Instead, their theoretical underpinnings suggest that model complications are merely tests of robustness (e.g. horizon extension; Penman & Sougiannis, 1998), and not tools for increased model performance. However, since such "tests of robustness" have been proven to increase the performance of valuation models, we argue for a shift in paradigms, where research should investigate complexity adjustments as performance-enhancing rather than as means to induce statistical significance. A more structured approach, for adding complexity to valuation models, would also allow for a more granular evaluation of performance in relation to complexity. In addition, this would provide valuable insights for investors, since such complexity adjustments are pervasive in all investment decisions.

All in all, a study that integrates a more comprehensive stance regarding model specifications, evaluation methodologies and payoff schemes would facilitate a level playing field comparison. Together with findings from previous studies, this would ultimately provide useful insights and tools for investors and academia alike. Such a structured approach has also been requested in previous research, perchance most eloquently by Jorgensen, Lee & Yoo (2011):

> *A theoretical approach might help more systematically identify conditions under which a specific implementation of a valuation model improves or deteriorates the valuation accuracy of resulting equity value estimates.* (p. 469)

Following the emphasis on *conditions* in the above quote, we argue that a structured approach, to assess the benefits from adding complexity, would shed light on a neglected, yet relevant, part of valuation modeling, while also help investors to consider the level of complexity sufficient for their discretionary needs.

3. Method

Because of the need for a comprehensive study employing a level playing field comparison across parsimonious valuation models, we set out to perform a uniform examination of the DDM, RIV, AEG and OJ models *[a]*. In addition, we cater to an ordinary investor's need for simpler means to arrive at forecasted payoff attributes. For this reason, we equip the models with two types of payoff schemes, *estimates* and *martingales*. Finally, we consider two consecutive three-year forecast periods (2009-2011 and 2014-2016), implying two different valuation points in time. These points in time occur three days after reporting date in 2009 and 2014. Incorporating the above, intrinsic values are subsequently calculated for each model, payoff and valuation date, resulting in 16 model combinations, four for each model.

Viewing complexity as a potentially performance-enhancing tool, we further consider the effects of different complexity adjustments on the above models' performance. For this, we investigate the effects of three such adjustments, i) extension of the horizon *[b]*, ii) incorporation of bankruptcy risk *[c]*, and iii) exclusion of transitory items *[d]*. In turn, this investigation looks at the effects of these adjustments both separately and conjointly. Consequently, the examination renders three different, but still additive, studies; i) study of the non-adjusted parsimonious models, ii) study of the single-adjusted parsimonious models, and iii) study of the multi-adjusted parsimonious models. Figure 1 presents a summary of the addressed model combinations in the three studies. All studies calculate intrinsic values in 2009 and 2014 respectively.

Figure 1. Summary of tested model combinations

	Parsimonious	Single adjustments			Multiple adjustments			
Inputs	*Non-adjusted* *[a]*	*Horizon* *[b]*	*Bankruptcy* *[c]*	*Transitory items* *[d]*	*Horizon +* *Bankruptcy*	*Horizon +* *Transitory items*	*Bankruptcy +* *Transitory items*	*Horizon +* *Bankruptcy +* *Transitory items*
Payoff								
Martingale	✓	✓	✓	✓	✓	✓	✓	✓
Estimates	✓	✓	✓	✓	✓	✓	✓	✓
Horizon		✓			✓	✓		✓
Bankruptcy			✓		✓		✓	✓
Transitory items				✓		✓	✓	✓

3.1. Model specifications

For the parsimonious, single- and multi-adjusted studies, we calculate model specific intrinsic values using the specifications of DDM, RIV, AEG and OJ as presented in the literature review. Owing to the different applications of AEG, we perform two competing specifications; AEG that is a three-year model, and OJ, which is a one-year model (cf. OJ, 2005). The model formulations on which we base our calculations are as follows:

DDM:

$$V_0 = \sum_{t=1}^{T} \frac{DPS_t}{(1+\rho_e)^t} + \frac{\frac{DPS_{T+1}}{\rho_e - g_{ss}}}{(1+\rho_e)^T} \tag{9}$$

RIV:

$$V_0 = BVPS_0 + \sum_{t=1}^{T} \frac{(ROE_t - \rho_e) \cdot BVPS_{t-1}}{(1+\rho_e)^t} + \frac{q_T \cdot BVPS_T}{(1+\rho_e)^T} \tag{10}$$

OJ:

$$V_0 = \frac{EPS_1}{\rho_e} + \frac{z_1/\rho_e}{R-\gamma} \tag{11a}$$

$$z_t = \left[EPS_{t+1} + \rho_e \cdot DPS_t\right] - \left(1+\rho_e\right) \cdot EPS_t \tag{11b}$$

AEG:

$$V_0 = \frac{EPS_1}{\rho_e} + \sum_{t=1}^{T} \frac{z_t/\rho_e}{(1+\rho_e)^t} + \frac{z_{T+1}/\rho_e}{(R-\gamma)(1+\rho_e)^T} \tag{12}$$

where

V_0	= the intrinsic value of equity at valuation date, time 0;
DPS_t	= dividend per share at time t;
ROE_t	= return on owners' equity at time t;
$BVPS_t$	= book value per share at time t;
EPS_t	= earnings (net income) per share at time t;
z_t	= the abnormal earnings growth at time t;
q_T	= the permanent measurement bias at time T;
ρ_e	= cost of equity capital at valuation date;
g_{ss}	= perpetual growth rate in steady state;
γ	= (1 + g_{AEG}); and
R	= (1 + ρ_e).

** all per share items are calculated using undiluted common shares outstanding.*

Intrinsic value calculations and discounting procedures

Using the DDM, RIV, AEG and OJ models, intrinsic values are calculated for each firm three days after its annual *reporting date* in 2009 and 2014, henceforth the *valuation date*. In order to calculate intrinsic values at valuation date while keeping the models theoretically equivalent, we need to consider two specific adjustments with respect to the accounting-based RIV, AEG and OJ specifications above. Firstly, these three models' theoretical equivalence with DDM is only obtained when their payoffs "arrive" at *dividend payout date* for every forecasted year. Hence, using the original specifications above (see Equations 10-12) would yield *ex-dividend* intrinsic values for RIV, AEG and OJ, at dividend payout date in year zero, or rather V_{0+f}^{EX}. However, as we wish to compare intrinsic values with observed prices at *valuation date*, we need to consider the fraction of a year, *f*, that remains from valuation date until dividend payout date, as dividends are paid roughly three months after valuation date for our sample firms. When adjusting for this timing difference, we need to discount the calculated ex-dividend intrinsic values to valuation date. This amendment is ultimately shown as

$$V_0^{EX} = \frac{V_{0+f}^{EX}}{(1+\rho_e)^{0+f}} \tag{13}$$

Secondly, even though the first adjustment is necessary, the intrinsic values become theoretically inconsistent, since it would render *ex*-dividend intrinsic values at valuation date. This inconsistency stems from the fact that we at valuation date observe stock prices that are *cum-dividend*, reflecting the next upcoming dividend, DPS_{0+f}. For this reason, a second adjustment is necessary to make the intrinsic values *cum-dividend*, and thus reflective of the upcoming dividend, by adding it to V_0^{EX} in Equation 13. To perform this second adjustment, we simply discount the upcoming dividend, DPS_{0+f} to valuation date, $t = 0$, using the same fraction, f, in the same manner as with V_{0+f}^{EX}, or equivalently

$$\frac{DPS_{0+f}}{(1+\rho_e)^{0+f}} \tag{14}$$

Equations 13 and 14 can be combined into one, summarized in Equation 15 as

$$V_0^{CUM} = \frac{V_{0+f}^{EX}}{(1+\rho_e)^{0+f}} + \frac{DPS_{0+f}}{(1+\rho_e)^{0+f}} = \left[\frac{V_{0+f}^{EX} + DPS_{0+f}}{(1+\rho_e)^{0+f}}\right] \tag{15}$$

where V_0^{CUM} is the cum-dividend intrinsic value at valuation date, V_{0+f}^{EX} is the ex-dividend intrinsic value at dividend payout date, and DPS_{0+f} the upcoming dividend at dividend payout date, in year 0. Moving forward, we refer to intrinsic values as V_0^{CUM}, as calculated in Equation 15. DDM is not subject to the dividend adjustment, as the intrinsic value obtained is cum-dividend by definition (see Equations 9 and 16). With respect to the model specifications as presented in the literature review and above, some specification updates due to our intrinsic value calculation procedure are appropriate before proceeding.

Updated model specifications

DDM:

$$V_0 = \sum_{t=0}^{2} \frac{DPS_{t+f}}{(1+\rho_e)^{t+f}} + \frac{\frac{DPS_{3+f}}{\rho_e - g_{ss}}}{(1+\rho_e)^{2+f}} \tag{16}$$

For DDM, no cum-dividend adjustment is necessary, as we simply discount the next three estimated dividends per share at valuation date $t = 0$. However, we still need to adjust the power of our discount factors to incorporate the fact that intrinsic values are calculated at valuation date, not dividend payout date. In turn, and as evident from Equation 9 and 16, the first forecasted dividend occurs in year 0, and only needs discounting with the discount factor raised to fraction *f*, or $0 + f$.

RIV:

$$V_{0+f}^{EX} = BVPS_0 + \sum_{t=1}^{3} \frac{(ROE_t - \rho_e) \cdot BVPS_{t-1}}{(1+\rho_e)^t} + \frac{q_T \cdot BVPS_3}{(1+\rho_e)^3} \tag{17}$$

$$V_0^{CUM} = \left[\frac{V_{0+f}^{EX} + DPS_{0+f}}{(1+\rho_e)^{0+f}}\right]$$

As opposed to the DDM formulation, RIV needs updating to incorporate the cum-dividend adjustment, i.e. Equation 15. To simplify our approach, we follow our discussion above and first calculate an ex-dividend intrinsic value at dividend payout date in year 0, $(t = 0 + f)$. Another difference from DDM, is that the first payoff in the RIV model is obtained year 1. For this reason, ROE and BVPS carry the indices $(t + f)$ and $(t - 1 + f)$ respectively, only to highlight the ex-dividend properties required for the RIV model to be theoretically consistent.

OJ:

$$V_{0+f}^{EX} = \frac{EPS_1}{\rho_e} + \frac{z_1/\rho_e}{R - \gamma} \tag{18}$$

$$V_0^{CUM} = \left[\frac{V_{0+f}^{EX} + DPS_{0+f}}{(1+\rho_e)^{0+f}}\right]$$

AEG:

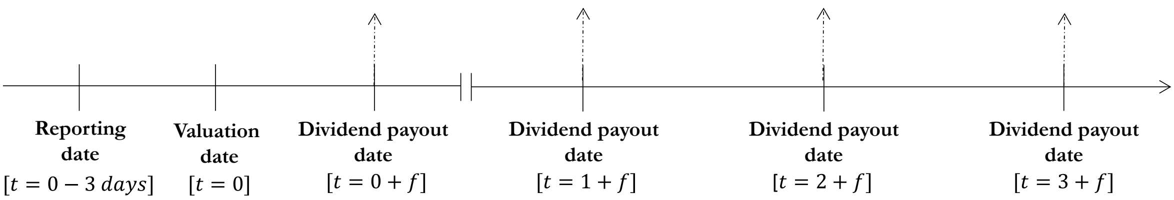
$$V_{0+f}^{EX} = \frac{EPS_1}{\rho_e} + \sum_{t=1}^{3} \frac{z_t/\rho_e}{(1+\rho_e)^t} + \frac{z_4/\rho_e}{(R-\gamma)(1+\rho_e)^3} \tag{19}$$

$$V_0^{CUM} = \left[\frac{V_{0+f}^{EX} + DPS_{0+f}}{(1+\rho_e)^{0+f}}\right]$$

Similar to RIV, the AEG and OJ models are also updated to incorporate the cum-dividend and adjustment, rendering two updated formulations. In addition and like RIV, the first forecasted payoffs occur in year 1. We recognize that AEG and OJ consider the cum-dividend earnings by definition (cf. Equation 11b; Penman, 2012), but as we initiate these models from $\mathrm{t} = 1$, we omit $\mathrm{DPS}_{0+\mathrm{f}}$ and must consequently add it by using Equation 14, ultimately Equation 15. Figure 2 summarizes the payoffs and the relevant dates for all models.

Figure 2. Forecasted payoffs and respective dates

Model	Cum-div adj.	Payoff			
DDM	No	DPS_{0+f}	DPS_{1+f}	DPS_{2+f}	
RIV	Yes		$(ROE_1 - \rho_e) \cdot BVPS_{0+f}$	$(ROE_2 - \rho_e) \cdot BVPS_{1+f}$	$(ROE_3 - \rho_e) \cdot BVPS_{2+f}$
AEG	Yes		$^{z_1}/_{\rho_e}$	$^{z_2}/_{\rho_e}$	$^{z_3}/_{\rho_e}$
OJ	Yes		$^{z_1}/_{\rho_e}$	$^{z_2}/_{\rho_e}$	$^{z_3}/_{\rho_e}$



Valuation date

Market efficiency has been subject to much debate and research (e.g. Fama, 1965; 1970; Ball & Brown, 1968; Grossman & Stiglitz, 1976; 1980; Shiller, 1981; Haugen, 2012), and consensus on whether such a phenomenon exists has not been reached. We use a three-day absorption window to allow for possible frictions in the capital markets. However, given the arbitrary nature of this assumption, we calculate intrinsic value estimates for all models also *at* reporting date and five days after. This procedure is *not* intended to test the absorption effects from new information, but is solely done for the sake of testing the robustness of our findings.

3.2. Model inputs

Payoff forecasting procedures

For the respective models, payoffs come in two variations, with different forecasting rationales. These payoff variations are either *estimates* or *martingale*. We refer to estimates as payoffs constructed from median financial item estimates provided by the analysts that cover the firms in our sample (e.g. EPS and BVPS). Due to the difficulty of finding historical analysts' estimates, we follow Penman & Sougiannis (1998) and Francis, Olsson & Oswald (2000) and take *realized* payoffs as a proxy for estimates for the valuation period 2009-2013.

Martingale, on the other hand, are payoffs obtained through a simple forecasting procedure based on *historical* financial item observations at valuation date, $\mathrm{t} = 0$. The martingale rationale basically states that events of the past help inform events of the future, such that the conditional expected value of the next observation, given all the past observations, is equal to the last observation, or equivalently

$$E[X_{t+1}|X_1, \dots, X_t] = X_t \tag{20}$$

In our case, the martingale properties of Equation 20 is elaborated on further, as we take an average of a firm's financial performance over the past five years, and assume that this performance is representative for the firm's performance also moving forward, in terms of a financial item X (e.g. EPS and DPS), such that

$$E[X_{0+\tau}|X_{-5}, \dots, X_{-1}] = \frac{1}{5}\sum_{t=-5}^{-1} X_t \tag{21}$$

This further implies that there are no upward or downward slopes of the model inputs. In some cases, such slopes are economically sensible, but for the sake of simplicity in the martingale operation, this consciously overlooked. Along the lines of Equations 20 and 21, martingale $\mathrm{ROE_t}$ estimates are obtained by equating $\mathrm{ROE_t}$ with the pre-valuation date five-year historical $\mathrm{ROEaverage}$, $\left[\frac{1}{5}\sum_{\tau=-5}^{-1} \mathrm{ROE}_\tau = \mathrm{ROE_t}\right]$, keeping $\mathrm{ROE_t}$ constant across the forecast period. EPS estimates are then derived with the application of the estimated $\mathrm{ROE_t}$ on $\mathrm{BVPS_{t-1}}$. Following this procedure, martingale $\mathrm{DPS_t}$ are obtained by the application of the pre-valuation date five-year historical payout-ratios (pr), $\left[\frac{1}{5}\sum_{\tau=-5}^{-1} \mathrm{pr}_\tau = \mathrm{pr_t}\right]$ on the derived $\mathrm{EPS_t}$. Finally, we adhere to keeping CSR intact when we derive $\mathrm{BVPS_t}$ with the help of our $\mathrm{EPS_t}$ and $\mathrm{DPS_t}$ martingale estimates. Following this rationale, all martingale payoffs are consistent regardless the choice of valuation model, as they rely on the same underlying assumptions. Additionally, we limit our martingale $\mathrm{ROE_t}$ estimates to values in the range of 0% to 100%, as we argue that values being systematically outside of this range are at odds with both economic sensibility and prior performance. However, and for the sake of robustness, we also calculate intrinsic values using a $\mathrm{ROE_t}$ range of $\rho_{e,j}$ to 100%, where $\rho_{e,j}$ refers to the cost of equity capital for firm j in the sample.

Cost of equity capital

In this study, we use the *capital asset pricing model* (CAPM; Sharpe, 1964; Lintner, 1965; Mossin, 1966)[26] to arrive at firm-specific costs of equity capital, i.e.

$$\rho_e = r_f + \beta_j \cdot [E(r_m) - r_f] \tag{22}$$

where r_f is the intermediate-term treasury bond yield, and is based on the 10-year government bond yield for the country in which each firm denominates its reporting currency (Koller, Goedhart & Wessels, 2010). For example, firms using SEK as their reporting currency are assigned the 10-year Swedish government bond yield as a proxy for

[26] Hence omitting other models for determining the cost of equity capital. This is consciously done for two reasons. Firstly, it is outside the scope of this study to examine the accuracy of cost of capital models; for the sake of focus, considering several models could be an undermining procedure. Secondly, Jorgensen, Lee & Yoo (2011) embrace several such models (CAPM and Fama & French (1993)) in their study, and conclude that their results of the relative performances of the valuation models' were not affected by this choice. Thus, the impact of the choice of cost of capital model is allegedly indifferent for the results.

r_f. β_j is firm-specific[27] and obtained by regressing 60 months of stock price variations on the index to which the corresponding stock belongs. The final term, $[E(r_m) - r_f]$, captures the market risk-premium, and is assumed to be 5% (cf. Francis, Olsson & Oswald, 2000; Fernandez, Linares & Fernández Acin, 2014). We further assume that ρ_e is constant across the forecast horizon, for any given firm and valuation date.

Truncation values

Truncation values are calculated using *common* terminal value formulations (cf. Penman, 1997; Courteau, Kao & Richardson, 2001), but still differ somewhat depending on model. For DDM (Equation 16), DPS_{T+1+f} is derived by bringing the last forecasted dividend DPS_{T+f} forward, using the perpetual steady state growth rate used for the truncation value. In line with previous studies (e.g. Francis, Olsson & Oswald, 2000), we set this perpetual growth rate to 4%. The truncation value of RIV (Equation 17), is obtained by multiplying book value per share for the last forecast year, $T + f$, with a permanent measurement bias, q_T[28]. To obtain firm-specific q_T, we confer Runsten (1998) who developed industry-specific dittos, and assign these to each firm in our sample using SIC-codes provided in the data set. Finally, we consider the perpetual abnormal earnings growth parameter γ when truncating AEG and the OJ model (Equations 18 and 19). Following the discussion in the literature review, we assume that the different impacts of competition on the one hand, and conservative accounting on the other (cf. Skogsvik & Juettner-Nauroth, 2013), offset so that the effect on γ is zero, or equivalently $\gamma = 1$.

3.3. Advanced model derivation and inputs

After conducting the initial parsimonious study, we add three different complexity adjustments to our models. These are added in three separate steps and concern i) the forecast horizon, ii) bankruptcy risk, and iii) transitory items. Finally, we add these adjustments conjointly and examine their collective impact in four additional steps; horizon and bankruptcy risk; horizon and transitory items; bankruptcy risk and transitory items; and horizon, bankruptcy risk and transitory items. Whereas the parsimonious study renders 16 model combinations (four for each model), these additions (together with our robustness calculations) results in a total of 192 different model combinations, 48 for each type of model or rather 16 for each of the three additions.

3.3.1. Extension of forecast horizon

As a first step, we extend all models to incorporate a longer forecast horizon. The DDM, RIV and AEG models are extended to five-year instead of a three-year forecast horizons, whereas OJ is extended from a one-year to a two-year horizon (cf. Jorgensen, Lee & Yoo, 2011; see Equations 16-19). Hence, the only difference from the parsimonious approach is that DDM, RIV and AEG payoffs are forecasted over the periods 2009-2013 and 2014-2018, whereas OJ incorporates forecasted payoffs for the periods 2009-2010 and 2014-2015.

[27] Although arguments have been presented of the superiority of industry-betas in models like CAPM (e.g. Fama & French, 1997), we have decided to pursue this firm-specific approach, as the data is more readily available one the one hand, but also as arbitrary judgments on industry categorization are not required.

[28] The permanent measurement bias reflects that a conservative accounting regime conceals the market values of the assets in the firm, and hence also the "true" value of equity (cf. Brainard & Tobin, 1968; Tobin, 1969). At length, this renders a situation where residual incomes persist in steady state and in zero-NPV contexts.

3.3.2. Incorporation of bankruptcy risk

Previous similar studies have omitted the fact that companies face the risk of going bankrupt (e.g. Penman & Sougiannis, 1998; Frankel & Lee, 1998; Penman, 2005; Jorgensen, Lee & Yoo, 2011), or have assumed so only implicitly. However, we argue that to better mirror the reality of capital markets, it makes sense to include this particular risk explicitly. Moreover, both realized payoffs and analysts' estimates are by definition conditioned on survival, and thus, the intrinsic values of each model must be adjusted for with bankruptcy risk, to make the numerator and denominator theoretically consistent.

There exists a plethora of studies discussing bankruptcy risk models, out of which Beaver (1966) and Altman (1968) are particularly renowned. However, they suffer from two drawbacks; firstly, their samples consist of equally many failing as surviving firms, which could cause bias in the results, since the actual failure ratio reasonably ought to be smaller than one in two (cf. Ohlson, 1980). Secondly, they look at US industrial firms only. This can in turn cause another bias, since Nordic firms could differ from their US counterparts, and consequently the models might produce inaccurate estimations of the risk of bankruptcy. For these two reasons, we use the bankruptcy prediction model by Skogsvik (1988), in which he studied a sample of medium to large Swedish manufacturing companies, comprising a relatively greater part of surviving firms than failing dittos. The model allows for predicting bankruptcy risk up to six years ahead, which in addition will make a valid contribution since the forecasts for each firm in the sample will run for one, two, three or five years from valuation date.

The bankruptcy risk can be incorporated into the study by adjusting the equity cost of capital for each company with their respective bankruptcy risks. This adjustment is ultimately depicted as

$$\rho_e^* = \frac{\rho_e + p(fail)}{1 - p(fail)} \tag{23}$$

where ρ_e is the firm-specific cost of equity capital and p(fail) is the firm-specific bankruptcy risk (Skogsvik, 2006). For the bankruptcy-adjusted models, the cost of equity capital from Equation 23 replaces those of Equations 11b and 16-19, for each firm. The bankruptcy risks used in the models are averages of the calculated p(fail), such that $\frac{1}{n}\sum_{t=1}^{n} p(fail)_t$; e.g. a three-year model will use the average of p(fail) for year 1, 2, and 3. Furthermore, we will adjust the firm-specific bankruptcy risks to accommodate for any skewedness in the sample behind the Skogsvik model[29]. This will render more accurate bankruptcy risks, and hence also contribute to the overall accuracy in the cost of equity capital for each respective firm. Apart from the proportion of failure companies in the original sample, the adjustment requires an a priori probability of failure companies in the population of companies. This probability is calculated as the average firm-specific bankruptcy risk for the firms in the sample.

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[29] Calculated as: $p(fail)_{POP} = p(fail)_{ES} \cdot \left[\frac{\pi \cdot (1-prop)}{prop \cdot (1-\pi) + p(fail)_{ES} \cdot (\pi - prop)}\right]$

where $p(fail)_{ES}$ is the probability of failure as predicted in the one-year model by Skogsvik (1988), π is the a priori probability of failure in the population of companies (i.e. 0.3%, 0,9%, 1.5% or 2.8% for this study [depending on horizon]), and prop is the proportion of failure companies in the estimation sample of companies, which in Skogsvik's (1988) sample is $\frac{51}{379} = 0{,}1346$ (Skogsvik & Skogsvik, 2013).

3.3.3. Earnings excluding transitory items

As many authors have concluded, transitory items can have significant and distortive effects on valuation models in general, and AEG in particular (e.g. Penman, 2005; Jorgensen, Lee & Yoo, 2011; Gao, Ohlson & Ostaszewski, 2013). For that reason, we intend to operate the valuation models with regard to earnings measures that are including *and* excluding transitory items, to see whether the exclusion of that "noise" in earnings could improve the models[30]. This implies that we replace the normal $\mathrm{EPS_t}$ with the earnings per share excluding transitory items, $\mathrm{EPS_t^{xt}}$. This affects the Equations 11b and 17-19. In addition, it impacts our martingale estimates, since $\left[\frac{1}{5}\sum_{\tau=-5}^{-1}\mathrm{ROE_\tau^{xt}} = \mathrm{ROE_t^{xt}}\right]$ will reflect and incorporate the exclusion of transitory items implicitly.

3.4. Means for model evaluation

To evaluate the performance of the models and their different combinations, we have chosen seven measures that have been commonly used in previous literature. These measures aim to capture two important aspects of assessing model performance, namely *accuracy* and *spread*. Accuracy captures how close to observed stock prices a model's intrinsic value is, and spread aims to capture the deviation in accuracy. The accuracy measures are: mean V/P, mean PE, median PE, and MAPE. V/P is short for the intrinsic value for each model specification (V), scaled by observed stock price (P), such that

$$\left[{}^{V}\!/_{P}\right]_{0,j} = \frac{V_{0,j}}{P_{0,j}} \tag{24}$$

for each firm j, at valuation date, $\mathrm{t} = 0$. The mean of V/P is simply obtained by summing up the V/P for all firms, and dividing by the number of firms, n, or rather

$$\left[{}^{V}\!/_{P}\right]_{0,i} = \frac{1}{n}\sum_{j=1}^{n}\left[{}^{V}\!/_{P}\right]_{0,j} \tag{25}$$

for any model i, at valuation date, $\mathrm{t} = 0$.

Next, PE is short for *signed* pricing error, and is calculated as intrinsic value subtracted by observed stock price, and then deflated with observed stock price:

$$PE_{0,j} = \frac{V_{0,j} - P_{0,j}}{P_{0,j}} \tag{26}$$

for each firm j, at valuation date, $\mathrm{t} = 0$. The PE variable is subject to both *mean* (similar to Equation 25, but with $\mathrm{PE_{0,j}}$ ($\mathrm{PE_{0,i}}$) instead of $\left[{}^{\mathrm{V}}\!/_{\mathrm{P}}\right]_{0,j}$ ($\left[{}^{\mathrm{V}}\!/_{\mathrm{P}}\right]_{0,i}$)) and *median* calculations.

The final accuracy measure is the mean of *unsigned* (or absolute) pricing errors, MAPE (Beatty, Riffe & Thompson, 1999; Jorgensen, Lee & Yoo, 2011). Whereas PE above aims to capture the direction of the pricing error, MAPE is a measure for determining the magnitude or size of the pricing error – the smaller value of MAPE, the more accurate the model. MAPE is calculated as

[30] The chosen data for this procedure is EPS excluding transitory items in the FACTSET database.

$$MAPE_{0,i} = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{V_{0,j} - P_{0,j}}{P_{0,j}}\right| \quad (27)$$

for any model i, at valuation date, $t = 0$.

In terms of spread, we have chosen three measures, standard deviation of PE, 15% APE, and IQRPE. The standard deviation of PE is simply the standard deviation of Equation 26 above. The second measure, 15% APE (Kim & Ritter, 1999), represents the fraction of the total sample that obtains an unsigned pricing error (APE) that exceeds 15%. A smaller fraction indicates a less deviating model. This measure is mathematically formulated as

$$15\%\ APE_{0,i} = \frac{1}{n}\sum_{j=1}^{n} Y_j \quad (28)$$

for any model i, at valuation date, $t = 0$. Y_j is a binomial discrete variable, that aims to capture the number of firms that generate unsigned pricing errors larger than 15%. Hence, the variable possesses the complementary properties that

$$Y_j = \begin{cases} 1 & APE_j \geq 15\% \quad \text{for all } j = \{1, \dots, n\} \\ 0 & APE_j < 15\% \quad \text{for all } j = \{1, \dots, n\} \end{cases}$$

where j denotes the firms in the sample of total n firms. In total, the variable Y_j will only include those firms that obtain unsigned pricing errors (APE) equal to or in excess of 15%, in which case Y_j will assume value 1.

The last measure of spread is IQRPE, short for inter-quartile range of signed pricing errors, i.e. PE (Liu, Nissim & Thomas, 2002). The measure aims to reflect the range between the third and first quartiles in PE, where lower scores suggests less spread in the model. IQRPE can be ultimately be depicted as

$$IQRPE_{0,i} = Q_3[PE_{0,i}] - Q_1[PE_{0,i}] \quad (29)$$

for any model i, at valuation date, $t = 0$, where $Q_q[\dots]$ denotes the quartile q for which the variable is calculated.

3.4.1. The AMA-score

Assessing a model's performance along both accuracy and spread is not a clear-cut task. Similar to us, prior studies handle this by interchangeably considering accuracy and spread (e.g. Frankel & Lee, 1998; Penman, 2005; Brief, 2007). However, looking at these two dimensions simultaneously would be advantageous, as it would provide a more comprehensive picture of a model's performance; a model is not necessarily good because it scores well in one of the dimensions. Furthermore, given that there is an inherent trade-off between the two dimensions (Faber, 1999; Newbold, Carlson & Thorne, 2012), it is wishful to consider the two concurrently. Therefore, before proceeding with a comparison of the models' performances, we here introduce a measurement score to make such a comparison more accessible (see Appendix 1). In order to overcome the cumbersome activity of looking at accuracy and spread successively, the performance assessment is simplified by looking at the two dimensions simultaneously. This is the basis for the AMA-score[31], which considers both the accuracy and spread, by combining the MAPE (accuracy) and IQRPE (spread) measures, or mathematically

$$AMA_{0,i} = \frac{\left[{}^{1}/_{IQRPE_{0,i}}\right]}{MAPE_{0,i}} \tag{30}$$

for each model i at valuation date, $t = 0$. The AMA-score provides a measure of the relative (out)performance of a model and payoff combination, where the score (and hence model performance) increases with low values of MAPE (i.e. high accuracy) and IQRPE (i.e. tight or low spread). Consequently, a higher AMA-score suggests a relatively better model, in terms of both accuracy *and* spread.

4. Data

Data is collected from FACTSET, a comprehensive database of historical and forecasted financial statement items commonly used by investment banks, private equity firms and media. Using one database, this paper benefits from a uniform source of both forecasted and historical data, as all items in the financial statements are assessed similarly, and hence the risk of working with variables of differing bases is mitigated. The selected data comprise the five Nordic stock exchanges'[32] large- and mid-cap lists, which total 303 firms. Financial firms[33] are consciously omitted from the sample, as their common key financial items are influenced by more unorthodox accounting conventions. We also omit those firms that do not possess the data required for our model calculations. These exclusions render a final sample of 233 firms. This sample consists mainly of Swedish firms (49%) and are fairly equally distributed across sectors with slight overweight for manufacturing, process industry and medical technology firms (see Appendix 6).

For these firms, we collect fourteen income statement[34] and balance sheet items[35]. These items are used to obtain the model payoffs and bankruptcy risks for each year. Furthermore, we gather additional financial and non-financial data necessary for the CAPM and model computations[36]. FACTSET also provides exact reporting dates and dividend payout dates. The reporting date is the date at which a firm's annual report becomes publicly available. The dividend payout date denotes the date where the proposed dividend from a firm's most recent annual report is paid out to its shareholders. All of the above are gathered over 2004-2013 for historical inputs, and over 2014-2018 for forecasted inputs. Forecasted financial items are the median forecasts of the analysts covering each respective firm. On average, each firm in the sample is covered by six brokers. The availability of data differs between firms and financial statement items, which results in a variation of firm-year observations depending on the model

[31] Anesten-Möller Accuracy score

[32] Nasdaq-owned stock exchanges in Denmark, Finland, Iceland, Norway, and Sweden.

[33] Financial institutions, investment companies and real-estate firms.

[34] Revenues, EBIT, interest expense, EBT, tax expense, net income, net income excluding transitory items.

[35] Shareholders' equity, total assets, total liabilities, inventory, cash assets, current assets and current liabilities.

[36] CAPM: 10-year treasury bond yield for Denmark, Finland, Iceland, Norway and Sweden for the risk.
Other items: dividend per share, (common) shares outstanding, stock prices.

specification. For this thesis, this implies average firm-year observations of 590, 345, 485, and 311 for RIV, DDM, AEG, and OJ respectively.

4.1. Descriptive statistics

Table 2 reports a summary of the median of key variables used throughout this study. For the 233 firms the median market cap ranges from 3 156 to 3 832 EURm, mirroring the large size of the firms in our sample. Historically, these firms have experienced somewhat sluggish growth, but analysts expect these firms to grow stably at

Table 2. Sample statistics of key variables

Year t	*2009*	*2010*	*2011*	*2012*	*2013*	*2014*	*2015*	*2016*	*2017*	*2018*
No. of firms	233	233	233	233	233	233	233	233	233	233
Firm characteristics (EURm)										
Market cap$_t$	3 213	3 823	3 156	3 431	3 832	n.a	n.a	n.a	n.a	n.a
Revenues$_t$	3 998	4 033	4 353	4 587	4 562	4 892	5 379	5 865	5 599	16 048
YoY growth$_t$ (%)	-7%	7%	8%	4%	1%	5%	5%	4%	5%	6%
EBIT$_t$	208	341	369	289	388	435	524	584	929	2122
Margin$_t$ (%)	7%	9%	9%	8%	8%	9%	10%	12%	14%	20%
Discount rate (%)										
CAPM disc. rate$_t$	8,0%	7,3%	6,7%	6,1%	6,7%	5,7%	5,7%	5,7%	5,7%	5,7%
Risk-free rate$_t$	3,2%	2,7%	2,1%	1,5%	2,3%	1,2%	1,2%	1,2%	1,2%	1,2%
One-year bankruptcy risk$_t$	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%	0,0%
Two-year bankruptcy risk$_t$	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%	0,1%
Three-year bankruptcy risk$_t$	0,2%	0,2%	0,2%	0,2%	0,2%	0,2%	0,2%	0,2%	0,2%	0,2%
Five-year bankruptcy risk$_t$	0,6%	0,7%	0,6%	0,7%	0,6%	0,6%	0,6%	0,6%	0,6%	0,6%
Payoffs (EUR)										
Estimates										
BVPS$_t$	23	25	26	26	26	27	30	33	16	63
EPS$_t$	2,9	4,0	3,6	3,6	3,7	4,0	4,8	5,7	5,6	3,0
EPS$^{xt}_t$	2,4	3,8	3,5	3,4	3,4	3,9	4,7	5,4	5,7	2,8
DPS$_t$	1,5	2,0	2,5	2,3	2,6	2,5	3,0	3,1	4,2	6,1
ROE$_t$ (%)	10%	16%	14%	13%	13%	15%	17%	18%	17%	18%
pr$_t$ (%)	50%	54%	53%	57%	60%	57%	51%	50%	53%	51%
Martingale										
BVPS$_t$	25	29	31	37	42	27	29	30	29	37
EPS$_t$	4,7	5,4	6,2	7,1	8,0	6,8	4,4	4,7	4,8	3,9
EPS$^{xt}_t$	5,4	5,4	6,1	6,7	7,9	5,7	4,1	4,4	4,5	4,5
DPS$_t$	1,4	1,9	1,9	1,9	1,6	2,9	3,3	3,8	2,7	6,1
ROE$_t$ (%)	21%	21%	21%	21%	21%	15%	15%	15%	15%	15%
pr$_t$ (%)	30%	35%	29%	28%	19%	41%	68%	74%	72%	61%

Notes:
Table 2 presents yearly medians for key variables in the study. Year t is the year to which key variables refer. 2009 and 2014 are years in which valuations are performed, all other years in the study are used for forecasting purposes. Market cap, Revenues and EBIT are denominated in millions of Euro. Estimates for 2009-2013 refer to realized observations whereas those between 2014 and 2018 are the median of analyst forecasts. BVPS$_t$ is the book value per share, EPS$_t$ is the earnings per share, EPS$^{xt}_t$ is the earnings per share excluding transitory items, DPS$_t$ is the dividend per share, ROE$_t$ is the return on owners equity and is calculated as EPS$_t$/BVPS$_{t-1}$, finally pr$_t$ is the payout ratio and is calculated as DPS$_t$/EPS$_t$.

4-6% approaching 2018. In terms of profitability, the large firms have shown stable profitability over 2009-2013, with EBIT-margins of 7-9%. Looking forward, analysts anticipate this profitability to improve slightly towards 2018. Before proceeding, it is additionally worth mentioning that the reason for why revenues and EBIT catapult in 2018, is because firms that have analysts' estimates thus far into the future, are also the largest in the sample.

Costs of equity capital (CAPM disc. rate$_t$) range between 6,1% and 8,0% for 2009-2013. Further, they decrease over the period due to a decrease in the risk-free rates, as betas and risk-premiums are held constant. The costs of equity capital for 2014-2018 are the same as that computed for the 2014 valuation. One-, two-, three- and five-year bankruptcy risks are relatively small, which reflects the large size of firms, and span across 0,01% (one-year) to 0,73% (five-year). Furthermore, as expected, the longer the forecast, the higher the risk of bankruptcy. Again, the bankruptcy risk at the valuation of 2014, is held stable for the period 2014-2018 for all horizons.

With regards to payoff inputs, these will differ with the distinction of estimates versus martingale. In addition, estimates are based on realized payoffs (cf. Francis, Olsson & Oswald, 2000; Jorgensen, Lee & Yoo, 2011) for the period 2009-2013 and on analysts' estimates over 2014-2018. To begin with, as book values per share ($\mathrm{BVPS_t}$) and dividends per share ($\mathrm{DPS_t}$) are functions of $\mathrm{EPS_t}$, $\mathrm{ROE_t}$ and payout ratios ($\mathrm{pr_t}$), it becomes a question of observing the development of the latter. Firstly, ROEs for estimates' payoffs range between 10-16% over the period 2009-2013, whereas martingale ROEs are held constant at 21% for the same period. Hence, martingale ROEs by large exceed those of estimates, as the former are based on the ROE development prior to 2009. For the period 2014-2018, estimates' ROEs pick up somewhat for a span of 15-18%, compared to the constant martingale of 15%, which once again are based on the prior five-year average (i.e. 2009-2013). Secondly, looking at payout ratios, they are stable around 50-60% for estimate payoffs for 2009-2013 and 2014-2018. For martingale, there is a significant difference in payout ratios over the two periods, stemming from the martingale forecast routine as discussed previously. Finally, Table 2 also includes EPS excluding transitory items ($\mathrm{EPS_t^{xt}}$). We see that, compared to normal EPS, there are systematic median transitory gains. Collectively, the statistics of Table 2 illustrate the stability of estimates' key variables over our sample period, whereas their martingale counterparts show a larger variation.

5. Results and discussion

5.1. Study of the non-adjusted parsimonious models

Table 3 presents the results for the study of the non-adjusted parsimonious models. Panel A orders the results in terms of Model and Period, whereas Panel B orders by Payoff and Period. As discussed, we use seven measures that aim to evaluate both accuracy (mean V/P, mean PE, median PE, MAPE) and spread (std. dev. PE, 15% APE, IQRPE) for each model combination.

Our primary results in Panel A suggest that, in terms of accuracy, DDM and OJ systematically overstates observed prices. On the other hand, RIV shows consistent understatements of observed prices, whereas the accuracy of AEG depends on the type of payoff; overstatement with martingale, and understatement with estimates. Looking at spread, Panel A further suggests that RIV outperforms the other models, but that DDM

Table 3. Results: Non-adjusted parsimonious model specifications

Panel A

Ordered by Model and Period

Model	*Valuation year*	*Payoff*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
DDM	2009	Estimates	1,19	0,19	0,03	0,86	0,54	0,78	0,78	351	2,36
DDM	2009	Martingale	1,17	0,17	-0,08	0,91	0,63	0,85	0,88	339	1,80
DDM	2014	Estimates	1,23	0,23	0,08	0,72	0,53	0,79	0,78	477	2,41
DDM	2014	Martingale	1,39	0,39	0,29	0,89	0,69	0,85	1,06	432	1,37
RIV	2009	Estimates	0,88	-0,11	-0,25	0,54	0,42	0,79	0,59	546	4,09
RIV	2009	Martingale	1,16	0,17	-0,04	0,92	0,58	0,77	0,80	567	2,17
RIV	2014	Estimates	0,71	-0,29	-0,40	0,71	0,53	0,90	0,46	651	4,09
RIV	2014	Martingale	0,69	-0,31	-0,47	0,61	0,56	0,92	0,49	651	3,68
AEG	2009	Estimates	0,81	-0,14	-0,10	12,69	5,58	0,88	4,93	621	0,04
AEG	2009	Martingale	11,31	10,32	2,68	33,90	10,40	0,93	5,79	405	0,02
AEG	2014	Estimates	-5,70	-6,70	-0,53	17,31	11,93	0,97	17,65	657	0,00
AEG	2014	Martingale	6,59	5,59	1,16	19,85	5,74	0,91	3,26	378	0,05
OJ	2009	Estimates	4,65	3,57	1,41	20,81	8,13	0,92	5,70	211	0,02
OJ	2009	Martingale	3,80	3,43	1,21	9,53	3,68	0,91	3,51	176	0,08
OJ	2014	Estimates	7,57	6,99	3,19	19,58	9,36	0,98	5,76	220	0,02
OJ	2014	Martingale	3,35	3,20	0,57	12,56	3,48	0,89	2,25	185	0,13

Panel B

Ordered by Payoff and Period

Payoff	*Valuation year*	*Model*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
Estimates	2009	DDM	1,19	0,19	0,03	0,86	0,54	0,78	0,78	351	2,36
Estimates	2009	RIV	0,88	-0,11	-0,25	0,54	0,42	0,79	0,59	546	4,09
Estimates	2009	AEG	0,81	-0,14	-0,10	12,69	5,58	0,88	4,93	621	0,04
Estimates	2009	OJ	4,65	3,57	1,41	20,81	8,13	0,92	5,70	211	0,02
Estimates	2014	DDM	1,23	0,23	0,08	0,72	0,53	0,79	0,78	477	2,41
Estimates	2014	RIV	0,71	-0,29	-0,40	0,71	0,53	0,90	0,46	651	4,09
Estimates	2014	AEG	-5,70	-6,70	-0,53	17,31	11,93	0,97	17,65	657	0,00
Estimates	2014	OJ	7,57	6,99	3,19	19,58	9,36	0,98	5,76	220	0,02
Martingale	2009	DDM	1,17	0,17	-0,08	0,91	0,63	0,85	0,88	339	1,80
Martingale	2009	RIV	1,16	0,17	-0,04	0,92	0,58	0,77	0,80	567	2,17
Martingale	2009	AEG	11,31	10,32	2,68	33,90	10,40	0,93	5,79	405	0,02
Martingale	2009	OJ	3,80	3,43	1,21	9,53	3,68	0,91	3,51	176	0,08
Martingale	2014	DDM	1,39	0,39	0,29	0,89	0,69	0,85	1,06	432	1,37
Martingale	2014	RIV	0,69	-0,31	-0,47	0,61	0,56	0,92	0,49	651	3,68
Martingale	2014	AEG	6,59	5,59	1,16	19,85	5,74	0,91	3,26	378	0,05
Martingale	2014	OJ	3,35	3,20	0,57	12,56	3,48	0,89	2,25	185	0,13

Notes:

Table 3, Panel A and B, present valuation accuracy measures and their distributions for the DDM, RIV, AEG and OJ-models. Models further vary by type of payoff and period in which these payoffs are forecasted. V/P refers to intrinsic values scaled by the observed prices. PE is the *signed* pricing error, and MAPE is the mean absolute (*unsigned*) pricing error. 15%APE is the percentage of sample whose absolute pricing errors is over 15%. IQRPE is the inter-quartile range of pricing errors. Finally, AMA-score is the inverse of IQRPE divided by MAPE.

finds itself comfortably second. Both AEG and OJ show considerable spread. Panel B enables comparisons between payoff attributes. Considering both accuracy and spread, estimates appear to be better than martingale. Furthermore, looking solely at the estimate payoffs, ex-post (realized) is marginally better, along both accuracy and spread, than ex-ante (analyst forecasts).

By adding the AMA-scores to Table 3, we can more easily quantify and rank the models' relative performance. Looking at the performance of each model with respect to payoff attributes (Panel B), the AMA-score suggests that RIV is considerably better than the other models, for all periods and payoffs. The AMA-score cements the proposition that DDM is better than both AEG and OJ. For the latter, the results are inconclusive, although it appears as though OJ more often than not scores higher than AEG. These findings mirror the pre-AMA results.

When testing the robustness of these findings by altering the valuation date and underlying payoff assumptions with regard to ROE, we see that the relative model performance persists as do our previous results (see Appendix 2 and 5).

Analysis

Both the relative strength of RIV over other models and its understating tendencies are in line with previous studies (Bernard, 1995; Penman, 1995; Penman & Sougiannis, 1998; Francis, Olsson & Oswald, 2000; Courteau, Kao & Richardson, 2001). Its relative strength has been attributed to its ability to anchor on something "real", by anchoring on book values of equity. This appears to be true also in our case, where we can see that 61%[37] of the intrinsic values from RIV emanate from the anchor, compared with 0%, 2% and 5% for DDM, AEG and OJ respectively. Hence, in the latter models, more value resides in estimations and speculations. Looking at terminal values, only 31% of RIV's intrinsic values are captured by this term, whereas the equivalents for the other models range between 90-95%[38]. RIV's anchoring on book values could also provide an explanation for the systematic understatement of prices. Given a ubiquitous use of conservative accounting and the characteristics this implies, book values of equity will mirror this conservatism, and be suppressed. A theoretically correct q-value would serve to mitigate this accounting bias, but given the understatement that we see, it appears as though the assigned q-values (to our sample firms) could be insufficient to correctly account for the "true" conservatism.

We also see substantial overestimations and spreads for the AEG and OJ applications, which is in line with Jorgensen, Lee & Yoo (2011). Observing the terminal values for the two models, these comprise 92% and 95% of the intrinsic values, in AEG and OJ respectively. As these models depend on the *growth* of abnormal earnings, not abnormal earnings per se, a constant growth in abnormal earnings would create an exponential evolution of the abnormal earnings growth[39]. Hence, a constant ROE estimate would drive a smooth development of a firm's abnormal earnings, but at the same time an exponential one of the abnormal earnings *growth*. This would in turn create an overstated expected abnormal earnings growth at truncation, i.e. z_4 in Equation 19. Given this, we can observe that in our sample (see Table 2) there are on average not only constant (martingale payoffs) but also increasing ROEs (estimate payoffs), possibly

[37] Median

[38] DDM 90%, AEG 92%, and OJ 95%.

[39] Remember that $z_t = \Delta(x_t^a)$ (Penman, 2005).

explaining the overestimations that we see. Further, the AEG and OJ applications display markedly larger spreads than their DDM and RIV counterparts (cf. Brief, 2007). Like DDM and RIV, the AEG and OJ payoffs are uncertain, but given the models reliance on growth capitalization, any deviations from the *realized future* abnormal earnings growth are given a more distinct weight in the intrinsic value calculations. Additionally, owing to the capitalization properties, the intrinsic value becomes increasingly sensitive also to the cost of equity capital (Penman, 2005).

In terms of payoff inputs, we observe that estimates serve as a better payoff for all models, than does martingale. Related, Francis, Olsson & Oswald (2000) find that estimates from analysts' forecasts are more accurate than realized payoffs, but we cannot claim any such difference between the two. We attribute the relative advantage of estimates over martingale to the intricacies of generating payoff inputs, as our results suggest that our martingale inputs are too simplistic in their assumptions. Even when adjusting our ROE estimate limitation range[40], martingale's inferiority to estimates is cemented. Consequently, simple martingale forecasting, relying on five years of historical accounting data, is simply not adequate. Possibly, other information would have to be incorporated into the payoffs, to mirror other market events that cannot be properly reflected by accounting data, just as suggested by Ohlson (1995) and Feltham & Ohlson (1995) (e.g. Dechow, Hutton & Sloan, 1999).

5.2. Study of the single-adjusted parsimonious models

Next, we adjust the parsimonious models *[a]* to accommodate for three complexity attributes, i) extension of forecast horizon *[b]*, ii) incorporation of bankruptcy risk *[c]*, and iii) earnings excluding transitory items *[d]*. Table 4 provides the AMA-scores for these different variations.

5.2.1. Extension of forecast horizon [b]

Overall, 50% of the models are improved by the extension of forecast horizon[41]. The question on whether to extend this horizon or not, is largely a matter of what payoff inputs one uses, estimates or martingales. For all models but DDM, we see that when using estimates, extended horizons renders higher AMA-scores. Especially the RIV model shows an increase in AMA, impressive given its high initial score. AEG and OJ follow the same pattern, but the results are inconclusive, due to their low scores to begin with. However, when using martingale payoffs in these three models, the AMA-scores decrease. On the other hand, DDM acts counter, where martingale (estimates) increases (decrease) its relative performance with extended horizons. Yet, overall we observe that the relative performance between the models persist, with the exception for the martingale payoffs of 2009, where DDM supersedes RIV as the best model. In addition, we also observe slight intra-model changes, especially true for DDM, which seems to become less sensitive to the choice of payoff input following the adjustment.

Analysis

Previous studies have argued for extended horizons, as this is supposed to yield better accuracy (e.g. Jorgensen, Lee & Yoo, 2011). However, what we find contradicts such a proposition, and instead suggests that an extension is validated by the

[40] From 0% to a minimum of cost of equity capital, implying non-negative NPV investments.

[41] Also confirmed when elaborating on valuation dates and ROE forecasting limitations (Appendix 3)

Table 4. Results: AMA-scores after single-adjustment

Panel A

Ordered by Model and Period

			Adjustments			
Model	*Valuation year*	*Payoff*	*Parsimonious [a]*	*Horizon [a] + [b]*	*Bankruptcy [a] + [c]*	*Transitory items [a] + [d]*
DDM	2009	Estimates	2,36	2,20	**2,58**	2,36
DDM	2009	Martingale	1,80	**2,03**	1,83	1,80
DDM	2014	Estimates	2,41	2,38	**2,57**	2,41
DDM	2014	Martingale	1,37	**2,49**	1,64	1,37
RIV	2009	Estimates	4,09	**5,16**	4,07	4,31
RIV	2009	Martingale	2,17	1,23	2,18	**2,35**
RIV	2014	Estimates	4,09	**5,12**	4,12	4,07
RIV	2014	Martingale	**3,68**	3,53	3,49	3,67
AEG	2009	Estimates	0,04	0,05	0,04	**0,06**
AEG	2009	Martingale	0,02	0,00	0,02	**0,03**
AEG	2014	Estimates	0,00	0,00	**0,01**	0,00
AEG	2014	Martingale	0,05	0,01	**0,06**	0,05
OJ	2009	Estimates	0,02	0,03	0,01	**0,03**
OJ	2009	Martingale	0,08	0,05	0,09	**0,10**
OJ	2014	Estimates	0,02	**0,05**	0,02	0,02
OJ	2014	Martingale	0,13	0,09	**0,14**	0,10

Panel B

Ordered by Payoff and Period

			Adjustments			
Payoff	*Valuation year*	*Model*	*Parsimonious [a]*	*Horizon [a] + [b]*	*Bankruptcy [a] + [c]*	*Transitory items [a] + [d]*
Estimates	2009	DDM	2,36	2,20	**2,58**	2,36
Estimates	2009	RIV	4,09	**5,16**	4,07	4,31
Estimates	2009	AEG	0,04	0,05	0,04	**0,06**
Estimates	2009	OJ	0,02	0,03	0,01	**0,03**
Estimates	2014	DDM	2,41	2,38	**2,57**	2,41
Estimates	2014	RIV	4,09	**5,12**	4,12	4,07
Estimates	2014	AEG	0,00	0,00	**0,01**	0,00
Estimates	2014	OJ	0,02	**0,05**	0,02	0,02
Martingale	2009	DDM	1,80	**2,03**	1,83	1,80
Martingale	2009	RIV	2,17	1,23	2,18	**2,35**
Martingale	2009	AEG	0,02	0,00	0,02	**0,03**
Martingale	2009	OJ	0,08	0,05	0,09	**0,10**
Martingale	2014	DDM	1,37	**2,49**	1,64	1,37
Martingale	2014	RIV	**3,68**	3,53	3,49	3,67
Martingale	2014	AEG	0,05	0,01	**0,06**	0,05
Martingale	2014	OJ	0,13	0,09	**0,14**	0,10

Notes:

Table 4 shows model performance by AMA-score for the DDM, RIV, AEG and OJ-models. AMA-scores are calculated for each and every adjustment; hence, the adjustements are added separately in relation to the parsimounious models, and not additively (e.g. [a] + [c] hence implies a three-year, bankruptcy adjusted model). AMA-scores in bold and underscore highlight the best outcome for each model and adjustment combination.

combined choice of payoff and model. With regards to payoff, our martingale exercise once again highlights the drawbacks with such simplified assumptions. These drawbacks are consistently apparent in the accounting-based models, suggesting a difficulty in forecasting accounting-based payoffs using a martingale approach. In DDM, on the other hand, a simple martingale forecasting of dividends appears to suffice. This could mirror the common notion that payout ratios are stable over time, and hence, that historical accounting data should capture such stable ratios also moving forward[42]. On a similar note, RIV's terminal value as a fraction of total intrinsic value decreases from 31% to 13%, with a redistribution to the benefit of the explicit forecast periods. Hence, more emphasis is placed on the payoffs between valuation date and truncation point, a period in which the leverage from using analysts' estimates should reasonably be substantial, given the nature of the profession. This could further explain why the simplistic martingale operations perform worse in the accounting-based models, given their reliance on EPS and ROE, which in turn demand far more in-depth firm-specific knowledge than can be accommodated for using simple historical regressions.

5.2.2. Incorporation of bankruptcy risk [c]

When adjusting the parsimonious models for the risk of bankruptcy, the relative model performance rank remains. Looking at AMA's development compared to the parsimonious setup, 79% of the model combinations benefit from including bankruptcy risk[43]. On a more granular level, we observe that all models but RIV benefit from this adjustment. RIV on the other hand is on average unchanged, if only slightly weakened. In terms of payoffs, no pattern is altered when adjusting for bankruptcy risk, in turn echoing the relative strength of estimates over martingale.

Analysis

The benefit of the bankruptcy risk adjustment for DDM, AEG and OJ models can reasonably stem from the systematic intrinsic value overstatements from their respective parsimonious model specification (Table 4). As the introduction of the bankruptcy risk increases the cost of equity capital (cf. Skogsvik, 2006), MAPE will subsequently decrease, by the improvement of the V/P-ratio. In other words, with respect to the consistent overstatements, it appears feasible to include this adjustment in DDM, AEG and OJ. In terms of RIV, its low sensitivity to bankruptcy risk incorporation can be explained by that book values of equity (61% of intrinsic value) are unaffected by this adjustment.

5.2.3. Earnings excluding transitory items [d]

The relative performance rank of the models from the parsimonious study persists also when excluding transitory items from EPS. With this adjustment, we deduce that 50% of the models benefit, with resulting higher AMA-scores[44,45]. Overall, we observe that this adjustment primarily impacts AEG and OJ, although there is a slight impact also on RIV. Furthermore, there appears to be no obvious distinction between estimate and martingale payoffs in terms of the change in AMA, but when examining the valuation years *in combination* with these payoffs, there is a clear pattern where payoffs of 2009

[42] The downside from using estimates instead is slight, which implies that analysts' forecasts are equally good also with longer forecasting horizons.
[43] Also confirmed when elaborating on valuation dates and ROE forecasting limitations (Appendix 3)
[44] DDM is excluded, due to its indifference from excluding transitory items, as it relies on normal EPS for their payout ratios.
[45] Also confirmed when elaborating on valuation dates and ROE forecasting limitations (Appendix 3)

Table 5. Results from transitory items-adjustments: MAPE, IQRPE and AMA-scores

Ordered by Payoff and Period

			Parsimonious		**Transitory items**		**Δ%**		**AMA-score**		**EPS^{xt}-adj**	**V/P**
Payoff	*Valuation year*	*Model*	*MAPE*	*IQRPE*	*MAPE*	*IQRPE*	*MAPE*	*IQRPE*	*Parsimonious*	**Δ%**	*Effect*	
Estimates	2009	DDM	0,54	0,78	0,54	0,78	0%	0%	2,36	0%	n.a	n.a
Estimates	2009	RIV	0,42	0,59	0,41	0,57	-2%	-3%	4,09	5%	positive	< 1
Estimates	2009	AEG	5,58	4,93	4,19	4,29	-25%	-13%	0,04	53%	positive	< 1
Estimates	2009	OJ	8,13	5,70	5,67	5,19	-30%	-9%	0,02	57%	positive	> 1
Estimates	2014	DDM	0,53	0,78	0,53	0,78	0%	0%	2,41	0%	n.a	n.a
Estimates	2014	RIV	0,53	0,46	0,53	0,46	0%	1%	4,09	0%	negative	< 1
Estimates	2014	AEG	11,93	17,65	13,39	18,89	12%	7%	0,00	-17%	negative	< 1
Estimates	2014	OJ	9,36	5,76	9,45	5,95	1%	3%	0,02	-4%	negative	> 1
Martingale	2009	DDM	0,63	0,88	0,63	0,88	0%	0%	1,80	0%	n.a	n.a
Martingale	2009	RIV	0,58	0,80	0,55	0,77	-5%	-3%	2,17	8%	negative	> 1
Martingale	2009	AEG	10,40	5,79	7,76	4,85	-25%	-16%	0,02	60%	negative	> 1
Martingale	2009	OJ	3,68	3,51	3,16	3,30	-14%	-6%	0,08	24%	negative	> 1
Martingale	2014	DDM	0,69	1,06	0,69	1,06	0%	0%	1,37	0%	n.a	n.a
Martingale	2014	RIV	0,56	0,49	0,57	0,48	2%	-2%	3,68	0%	positive	< 1
Martingale	2014	AEG	5,74	3,26	6,89	2,91	20%	-11%	0,05	-7%	positive	> 1
Martingale	2014	OJ	3,48	2,25	3,77	2,63	8%	17%	0,13	-21%	positive	> 1

Notes:

Table 5 shows MAPE, IQRPE, AMA-score and the change of these with regard to the parsimonious and transitory items-adjusted DDM, RIV, AEG, and OJ models. EPS*-adj represents the transitory adjustments made to the normal EPS, where a positive (negative) effect means that the normal EPS is lower (higher) than the corresponding EPS exluding transitory items. V/P is the intrinsic value, scaled by observed price. A value of <1 (>1) implies undervaluation (overvaluation) distinctly improve AMA-scores, whereas those of 2014 decrease it. Hence, RIV, AEG and OJ are all improved using valuation year 2009, whereas the opposite is true for 2014.

Analysis

Previous literature has discussed the potential impact of EPS adjusted for transitory items, but knowingly no study has tested the models for this. Instead, in order to adjust for these items, other studies have extended the horizon, with the rationale that such extensions would overcome the distortive effects, as transitory items are assumed to diminish over time. However, our data suggests that this is not the case, since a large proportion of the firms in our sample display transitory items both historically but also in analyst estimates moving forward (Table 2). As expected, the adjustment improves the performance of the AEG and OJ applications, but only for the valuation year of 2009, and not for 2014. These inconsistent results call for a more granular analysis.

In Table 5, we plot MAPE, IQRPE and AMA, along with their respective changes, for both the parsimonious applications and those including transitory items. In addition, the second far-right column depicts the effects on EPS, when adjusted for transitory items; a positive effect implies that EPS excluding transitory items has been adjusted upward compared to normal EPS. In the far-right column, we add V/P-ratios, which serve to note the under- or overvaluation from the parsimonious study (*[a]*: Table 3). In other words, a V/P smaller (greater) than 1, would benefit from an EPS uplift (suppression), as this would increase (decrease) the intrinsic value, and consequently push the V/P-ratio towards 1. Considering the martingale payoffs in Table 5, we see that the models with valuation year 2009 display negative EPS adjustments combined with V/P-ratios greater than 1. As expected, these models render increases in terms of AMA. Elaborating on the martingale operation, its negative EPS-effect emanates from that the historical five-year average of EPS excluding transitory items, has been distorted by transitory *gains*. The same line of reasoning holds for the martingale payoffs for valuation year 2014, but with opposite effects, i.e. historical transitory *losses*.

As with martingale, the inter-year differences of estimates can be explained with differing EPS adjustments in combination with over- or undervaluation. But since estimates are obtained from three-year ahead forecasts, rather than five-year historical averages, the periods in which we have to consider any transitory items are different. Along these line, and as opposed to martingale, we see that estimates include transitory losses for models calculating intrinsic values in 2009, but transitory gains for those calculating in 2014. In sum, the observed inconsistent pattern, of the 2009 and 2014 martingale and estimates valuations, are due to inherent differences in transitory gains or losses, and their respective effect on EPS, but also on the over- or undervaluations obtained from the parsimonious study.

However, the above rationale is not consistent for the OJ application when using estimates. By investigating our sample of analysts' estimate payoffs, we observe that, unlike martingale[46], the estimate payoffs show variations in transitory items (in terms of size and sign) from one year to another. For instance, the 2009 EPS and 2010 EPS are both positively adjusted for transitory losses, but differ in size where the 2010 EPS is greater than its 2009 counterpart. *Ceteris paribus,* this would imply that the intrinsic value of OJ would increase, and in turn negatively affect MAPE. Nevertheless, we see that the

[46] Martingales are based on historical averages, and hence any transitory items of the past will persist moving forward, rendering smaller variations.

effect is opposite, and that MAPE of the 2009 OJ is strikingly improved. Looking at the basis of OJ (2005), such an effect can only be realized when $[(1+\rho_e)\cdot transitory\ items_t > transitory\ items_{t+1} + \rho_e \cdot DPS_t]$, implying that the numerator at truncation is decreased, hence also decreasing the intrinsic value[47]. We find evidence for such relations in our sample, providing an explanation for the initially inconsistent finding. To conclude, the effect from excluding transitory items has opposing effects on AMA, depending on which period our payoffs are based on (martingale) or forecasted over (estimates), stemming from different transitory adjustments to our sample firms over the studied period.

5.2.4. Implications of the single-adjustment study

Previously, the study of the parsimonious models concluded the outperformance of RIV in relation to the other model specifications. Adding the complexity adjustments of horizon extension, bankruptcy risk and exclusion of transitory items, we observe that this outperformance remains. Notwithstanding the persistence of the relative inter-model performance, there are positive effects in the *intra*-model performances, suggesting gains from adding complexity to the parsimonious model formulations. Quantifying these gains, we see that, out of the 16 possible model and payoff combinations, the adjustments of horizon, bankruptcy risk and transitory items render the relatively best performing applications in five instances respectively, leaving only one best application in its parsimonious setup (Table 4). In other words, the complexity attributes all contribute to increase the accuracy and decrease the spread of the models.

Looking solely at the best performing combinations, Table 6 displays their respective AMA-scores and relative change compared to their best performing parsimonious counterpart. Interestingly, being the relatively best model to begin with, RIV still displays the largest improvement in AMA-scores when adding complexity. Furthermore, adjusting for bankruptcy seems to be the most prominent adjustment for three out of the four best performing models.

Table 6. Results Summary: Best performing single-adjusted model setups

	Model setup		**AMA-score**	
Model	*Payoff*	*Adjustment*	*Score*	Δ%
DDM	Estimates	Bankruptcy [a] + [c]	2,58	7%
RIV	Estimates	Horizon [a] + [b]	5,16	26%
AEG	Martingale	Bankruptcy [a] + [c]	0,06	6%
OJ	Martingale	Bankruptcy [a] + [c]	0,14	12%

Notes:
Table 6 shows the best performing model setups with respect to AMA score. The percentage change in AMA-score reflects the increase (decrease) in relation to their respective parsimonious setups.

For an investor looking to make no more than one adjustment to a parsimonious model, Table 6 provides significant guidance but also depicts the relative gains from such an adjustment. However, it should be duly noted that adjustments come at a price, as they reasonably require some degree of effort. Hence, there is an inherent trade-off between increased model performance on the one hand, and effort (e.g. because

[47] Or equivalently $[(1+\rho_e)\cdot \Delta EPS_t > \Delta EPS_{t+1} + \rho_e \cdot DPS_t]$ (cf. Equation 11b).

of cognitive and temporal limitations[48]) on the other. Therefore, a rational investor would wish to maximize the relation between the two, or in economic terms, wish to maximize the *elasticity of valuation complexity*, i.e. $max\left[\frac{\Delta\% AMA}{\Delta\% \, effort}\right]$(cf. Equation 30). Along these lines, it makes sense to consider not only the increase in AMA-scores, but also the relative effort required for each adjustment. In our opinion, the effort of extending the horizon is smaller relative to adjusting for bankruptcy or transitory items, as the latter require additional information and/or technical ability, whereas the former merely requires a mechanical extension of the original setup. Consequently, the horizon-adjusted RIV adheres to the maximization of the elasticity of valuation complexity better than the other models, illuminating its strength in terms of performance *and* effort required.

5.3. Study of the multi-adjusted parsimonious models

Given the benefits that the models experienced from single adjustments, one could expect an even larger benefit from conjoint adjustments. For this reason, Table 7 displays four additional complexity combinations and their respective AMA-scores. We observe that the relative inter-model performance remains from the study of the single adjustments, namely that RIV is best in three cases, whereas DDM is strongest with the 2009 martingale[49]. When adding complexity adjustments to the single-adjusted models, we see that AMA is improved for 30% of the outcomes.

In terms of specific adjustments, the conjoint addition of extended horizon *and* bankruptcy risk (*[a] + [b] + [c]*) comprise a majority of the enhanced outcomes. Furthermore, the benefit from introducing [*[a] + [b] + [c]*] is much more apparent when using estimate payoffs, and particularly those derived from analysts' forecasts, as we see unanimous improvement for all models using this payoff. The [*[a] + [b] + [c]*] adjustment also noticeably improves the performance of DDM, since three out of the four best DDM applications hinge upon the [*[a] + [b] + [c]*] combination. The relatively strong performance of this multiple combination casts a shadow over the other combinations, where the bankruptcy and transitory item adjusted applications (*[a] + [b] + [d]*) are particularly weak[50]. Fully adjusted models (*[a] + [b] + [c] + [d]*), improve performance in 13% of cases compared to its single-adjusted counterparts. However, any actual additional performance over the double-adjusted (e.g. *[a] + [b] + [c])* combinations occur in only 3% of the possible outcomes.

Analysis

The [*[a] + [b] + [c]*] combination highlights two interesting results; its positive effect on DDM and its positive effect on models employing analysts' forecast. For DDM, we saw that the single-adjustment of extending the horizon (*[b]*) made the AMA-scores more uniform across the DDM variations. When adding bankruptcy risk (*[c]*) the previous uniforming effect is amplified, with the negative effect on MAPE and IQRPE that the bankruptcy risk adjustment single-handedly brings. As for analysts' forecast, their effect on MAPE and IQRPE in the [*[a] + [b] + [c]*] setting is similarly positive to that of DDM. Simply put, this is an effect emerging from two AMA-increasing adjustments combined into one, i.e. horizon extension and bankruptcy risk collectively. On a more granular level, we attribute the extended horizon's positive effect to our previous

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[48] See among others Kahneman & Tversky, 1973, March, 1978 and Beunza & Garud, 2006.

[49] Also confirmed when elaborating on valuation dates and ROE forecasting limitations (Appendix 4 and 5)

[50] Yielding only one best model.

Table 7. Results: Model AMA-score's after single and multiple adjustments

Panel A

Ordered by Model and Period

			Parsimonious	Single adjustments			Multiple adjustments			
Model	*Valuation year*	*Payoff*	*[a]*	*[a] + [b]*	*[a] + [c]*	*[a] + [d]*	*[a] + [b] + [c]*	*[a] + [b] + [d]*	*[a] + [c] + [d]*	*[a] + [b] + [c] + [d]*
DDM	2009	Estimates	2,36	2,20	**2,58**	2,36	2,58	2,20	2,58	2,58
DDM	2009	Martingale	1,80	2,03	1,83	1,80	**2,52**	2,03	1,83	2,52
DDM	2014	Estimates	2,41	2,38	2,57	2,41	**3,07**	2,38	2,57	3,07
DDM	2014	Martingale	1,37	2,49	1,64	1,37	**3,24**	2,49	1,64	3,24
RIV	2009	Estimates	4,09	5,16	4,07	4,31	5,38	5,34	4,26	**5,55**
RIV	2009	Martingale	2,17	1,23	2,18	2,35	1,34	1,37	**2,35**	1,46
RIV	2014	Estimates	4,09	5,12	4,12	4,07	**5,28**	4,72	4,08	5,00
RIV	2014	Martingale	**3,68**	3,53	3,49	3,67	3,02	3,67	3,60	3,16
AEG	2009	Estimates	0,04	0,05	0,04	0,06	0,07	0,06	0,06	**0,09**
AEG	2009	Martingale	0,02	0,00	0,02	0,03	0,01	0,01	**0,03**	0,01
AEG	2014	Estimates	0,00	0,00	0,01	0,00	**0,01**	0,00	0,00	0,01
AEG	2014	Martingale	0,05	0,01	**0,06**	0,05	0,04	0,01	0,05	0,02
OJ	2009	Estimates	0,02	0,03	0,01	0,03	0,01	**0,06**	0,02	0,04
OJ	2009	Martingale	0,08	0,05	0,09	0,10	0,06	0,07	**0,11**	0,07
OJ	2014	Estimates	0,02	0,05	0,02	0,02	**0,06**	0,04	0,02	0,06
OJ	2014	Martingale	0,13	0,09	**0,14**	0,10	0,11	0,07	0,12	0,08

Notes:

Table 7 shows model performance by AMA-score for the DDM, RIV, AEG and OJ-models. AMA-scores are calculated for each and every adjustment. For the single adjustment, these are added separately, whereas the multi-adjusted adds additively. AMA-scores in bold and underscore highight the best outcome for each model and adjustment combination. [a] denotes the parsimonious setups, [b] the horizon extended setups, [c] the bankruptcy adjusted setups, and [d] the transitory item adjusted setups.

Table 7. cont'd. Results: Model AMA-score's after single and multiple adjustments

Panel B

Ordered by Payoff and Period

			Parsimonious	Single adjustments			Multiple adjustments			
Payoff	*Valuation year*	*Model*	*[a]*	*[a] + [b]*	*[a] + [c]*	*[a] + [d]*	*[a] + [b] + [c]*	*[a] + [b] + [d]*	*[a] + [c] + [d]*	*[a] + [b] + [c] + [d]*
Estimates	2009	DDM	2,36	2,20	**<u>2,58</u>**	2,36	2,58	2,20	2,58	2,58
Estimates	2009	RIV	4,09	5,16	4,07	4,31	5,38	5,34	4,26	**<u>5,55</u>**
Estimates	2009	AEG	0,04	0,05	0,04	0,06	0,07	0,06	0,06	**<u>0,09</u>**
Estimates	2009	OJ	0,02	0,03	0,01	0,03	0,01	**<u>0,06</u>**	0,02	0,04
Estimates	2014	DDM	2,41	2,38	2,57	2,41	**<u>3,07</u>**	2,38	2,57	3,07
Estimates	2014	RIV	4,09	5,12	4,12	4,07	**<u>5,28</u>**	4,72	4,08	5,00
Estimates	2014	AEG	0,00	0,00	0,01	0,00	**<u>0,01</u>**	0,00	0,00	0,01
Estimates	2014	OJ	0,02	0,05	0,02	0,02	**<u>0,06</u>**	0,04	0,02	0,06
Martingale	2009	DDM	1,80	2,03	1,83	1,80	**<u>2,52</u>**	2,03	1,83	2,52
Martingale	2009	RIV	2,17	1,23	2,18	2,35	1,34	1,37	**<u>2,35</u>**	1,46
Martingale	2009	AEG	0,02	0,00	0,02	0,03	0,01	0,01	**<u>0,03</u>**	0,01
Martingale	2009	OJ	0,08	0,05	0,09	0,10	0,06	0,07	**<u>0,11</u>**	0,07
Martingale	2014	DDM	1,37	2,49	1,64	1,37	**<u>3,24</u>**	2,49	1,64	3,24
Martingale	2014	RIV	**<u>3,68</u>**	3,53	3,49	3,67	3,02	3,67	3,60	3,16
Martingale	2014	AEG	0,05	0,01	**<u>0,06</u>**	0,05	0,04	0,01	0,05	0,02
Martingale	2014	OJ	0,13	0,09	**<u>0,14</u>**	0,10	0,11	0,07	0,12	0,08

Notes:

Table 7 shows model performance by AMA-score for the DDM, RIV, AEG and OJ-models. AMA-scores are calculated for each and every adjustment. For the single adjustment, these are added separately, whereas the multi-adjusted adds additively. AMA-scores in bold and underscore highight the best outcome for each model and adjustment combination. [a] denotes the parsimonious setups, [b] the horizon extended setups, [c] the bankruptcy adjusted setups, and [d] the transitory item adjusted setups.

discussion, where we argued that this adjustment illuminated analysts' skills in a longer explicit forecast period. Secondly, the improvement from bankruptcy risk adjustments could stem from that analysts' estimates are conditioned on survival, by definition. Hence, without adjusting the cost of equity capital for the risk of bankruptcy, the models will operate with inputs of differing assumptions.

5.3.1. Implications of the multi-adjustment study

Even though the [*[a] + [b] + [c]*] adjustment is the most positively contributing adjustment, one should be cautious about adding complexity to the single-adjusted models, as 70% of *all* model combinations do *not* benefit from such adjustments. Of the remaining adjustments (30%) that increase the AMA-score, there are clear differences in how much they actually add in AMA-terms. For example, the [*[a] + [b] + [c]*] and [*[a] + [b] + [c] + [d]*] adjustments add roughly 25% in performance, as opposed to the [*[a] + [b] + [d]*] and [*[a] + [c] + [d]*] adjustments, which only contribute 7%. This leaves us to conclude that the effort of adjusting for transitory items (*[d]*) might not be worthwhile, whereas the previously alleged strong combination of *[b]* and *[c]* does provide additional performance, considering all model combinations. From a practical point of view, these conclusions provide general insights to an investor facing the choice of adding complexity to any single-adjusted model. More specifically, if an investor would pursue such adjustments, he or she should also consider the fact that they add particular value to DDM in terms of model, and analysts' forecasts in terms of payoffs.

Though one can question the addition of further complexity to the single-adjusted models, we still see benefits from such adjustments for the *best* performing model combinations, where DDM, RIV and AEG all gain from such additions. Table 8 highlights this, and also displays AMA-scores for the best model combinations. We see that the relative performance rank remain, but also that optimal payoffs have changed (compared to Table 6) for DDM and AEG. In summary, the best performing DDM use martingale payoffs, and is adjusted by extending the horizon and adding bankruptcy risk. RIV and AEG ideally use estimate payoffs and all complexity adjustments ([*[a] + [b] + [c] + [d]*]), whereas OJ requires only the bankruptcy risk adjustment and martingale payoffs. Hence, Table 8 provides a more specific and comprehensive recipe for how to optimally construct the DDM, RIV, AEG and OJ applications.

Table 8. Results Summary: Best performing model setups and marginal change in AMA

	Model setup		**AMA-score**	**Additive AMA-score Δ%**		
Model	*Payoff*	*Adjustment*	*Score*	*Single*	*Double*	*Full*
DDM	Martingale	[a] + [b] + [c]	3,24	7%	25%	0%
RIV	Estimates	[a] + [b] + [c] + [d]	5,55	26%	4%	3%
AEG	Estimates	[a] + [b] + [c] + [d]	0,09	6%	28%	30%
OJ	Martingale	[a] + [c]	0,14	12%	-18%	-32%

Notes:
Table 8 shows the best performing model setups with respect to AMA score for all models and adjustments. The percentage change in the additive AMA-score reflects the increase (+) or decrease (-) in relation to their respective parsimonious, single-adjusted and double-adjusted setups.

In the far-right section of Table 8, the relative changes in AMA that come from one additional complexity adjustment is displayed. Firstly, DDM sees an AMA increase from adding one complexity adjustment to the best parsimonious application (+7%), but particularly so to the best single-adjusted model (+25%). Further, the fully adjusted one is unaffected[51]. Secondly, RIV sees a large AMA increase from adjusting the best parsimonious model (+26%), and positive yet smaller effects for the other adjustments (4% and 3% respectively). Finally, the AEG and OJ applications display different patterns, as the former sees an increase in AMA from each and every complexity adjustment, whereas the latter has an opposing effect from increasing complexity. However, this difference reasonably resides in the fact that they rely on different payoff schemes. In addition, the results of AEG and OJ are less noteworthy than those of DDM and RIV, as a rational investor would not pursue the use of any of the models given their relatively poor performance. Hence, AEG and OJ show inconclusive results, but DDM and RIV see benefits from adding complexity.

Furthermore, Table 8 can act as a compass for when to stop adjusting the models with complexity. Nevertheless, as has been previously discussed, adding complexity comes at a price, and a rational investor should be considerate of the trade-off between increased performance of a model and the effort required to obtain that performance. By consequently adhering to the maximization of the elasticity of valuation complexity, the far-right section of Table 8 suggests that a double-adjustment is justified for DDM, as this renders a momentous increase compared to the single-adjustment, but also as there are no additional gains from adjusting fully. RIV on the other hand has a different pattern, where a single-adjustment could be argued as sufficient, at least in terms of elasticity. Although we see additional gains from making RIV more complex than only by a single-adjustment, these gains are only marginal, shedding light on the efforts required for these complexity adjustments. Given the subjective nature of effort, the complexity adjustment of RIV (and DDM) depends on several factors, e.g. investor skill, size of investment, temporal constraints, &c. For instance, the effort of performing a double-adjustment to RIV might be relatively lower for an investor with strong accounting skills, which in turn could justify the additional gain of 4% that this adjustment implies. However, despite the reliance on investor discretion, we deem that the extended horizon adjustment (*[h]*) requires less skill than do adjusting for bankruptcy risk and transitory items. For this reason, we argue that the single-adjusted RIV displays the best characteristics from an elasticity point of view, as it obtains a relatively high AMA for a relatively simple complexity adjustment.

6. Conclusion and implications

A review of previous literature provides some valuable insight to ordinary investors as it cements the importance of truncation values, payoff schemes and horizon length in valuation modelling. In addition, the previous literature shows that complexity adjustments increase the performance of valuation models. Interestingly though, this literature does not explicitly address complexity adjustments (e.g. horizon extension), but rather use them as tests of robustness to underpin its suggested findings. Owing to the literature's inconsistency in terms of inputs used and means to evaluate the performance of models, ordinary investors would benefit from a comprehensive study, setting the record straight in a "level playing field" comparison. Because of the increased performance of models incorporating complexity adjustments, ordinary investors would also benefit from an exposition of what these adjustments do to model performance, by using a more structured approach.

For this reason, we in a first step investigated the performance of the DDM, RIV, AEG and OJ models under uniform assumptions and periods in a *study of the non-*

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[51] As expected, given DDM's indifference to transitory items as previously discussed.

adjusted parsimonious models. In addition, we developed a uniform evaluation measure, the AMA-score, which considers both accuracy and spread in an attempt to more easily quantify and enable conclusions regarding model performance. Using this AMA-score, we found that RIV outperforms the other models, that DDM comes comfortably second and that the AEG and OJ models overvalue observed stock prices to the extent that they become inadequate to ordinary investors. Similar to Penman (2005; 2012), we attribute RIV's outperformance to its ability to anchor on book value of equity, or something "real", whereas the relative inferior results of DDM, AEG and OJ are attributed to their respective large parts of intrinsic value residing at truncation (90-95%). For AEG and OJ, the large truncation values are attributed to constant ROE estimates approaching truncation, in turn creating an exponential development of abnormal earnings growth.

The *study of the non-adjusted parsimonious models* also facilitates a comparison between payoffs relying on *estimates* and those relying on a simpler forecasting procedure hinging on recent historical performance, *martingale*. The results suggests that estimates serve as the better payoff scheme for all models, accentuating the relative advantage of a more complex forecasting procedure, or access to it.

Building on the level playing field comparison, we set out to investigate the effects and potential benefits from the addition of complexity adjustments, given the lack of previous research in the area but also because of the practical implications such an investigation would provide to ordinary investors' modeling process. This addition was carried out in two steps, where in the first, adjustments for horizon, bankruptcy risk and transitory items were added separately to the parsimonious model formulations. The second step investigated the effects from combining these complexity adjustments, both in relation to the parsimonious and the single-adjusted formulations. The *study of single-adjusted parsimonious models* suggests that the addition of complexity adjustments to the parsimonious formulations contribute to increased performance, but that this increase often comes with restrictions with respect to payoff and model. For example, an extension of the horizon benefitted the RIV model using estimate payoffs, and DDM using martingale. Furthermore, the incorporation of bankruptcy risk was the adjustment that increased the performance of most models, expected as a majority of model variations overestimated intrinsic values with respect to observed prices. Interestingly, the top-performing model combinations incorporated a complexity adjustment, once again highlighting the benefits from such adjustments but also the knowledge of the specific formulation in which these are present.

In the final *study of multi-adjusted parsimonious models*, the results and conclusions were in line with those provided by the single-adjusted, since any performance gains from including adjustments depended on specific model combinations. The adjustments that to the greatest extent contributed to performance were those including horizon extension and bankruptcy risk incorporation conjointly, i.e. ([a] + [b] + [c]). By adding the complexity adjustments in steps, we could also analyze the marginal performance gain or loss from one additional adjustment to the best-performing combination of each model. This analysis showed that DDM benefits from double-adjustments, and RIV from single-adjustments.

No specific guidance is given on whether, or to which extent, investors should pursue such adjustments, but the results highlight the inherent trade-offs from such a pursuit. In our view, complexity adjustments come at different costs to different investors, as there is reason to believe that the effort to accommodate for the adjustments will differ depending on investor constraints. For this reason, we introduced the concept of *elasticity of valuation complexity*, with the notion that a rational investor would wish to maximize the performance of the valuation model given the investor's constraints *at* valuation date. In light of this, our analysis of the marginal performance increase from one additional adjustment can work as a compass for investors facing the choice of complexity adjustments.

With respect to the above, this paper contributes to existing research in three important ways. In a first step, the paper facilitates a "level playing field" comparison between models, necessary for an ordinary investor facing the choice of multiple valuation models and payoff methodologies. Secondly, the paper accentuates a yet neglected area within valuation research, as it structurally highlights the inherent gains from the addition of complexity, and provides recipes for optimally designing valuation models with regards to both accuracy and spread. Finally, the paper touches upon the concept of model performance in relation to the effort necessary to accommodate for complexity adjustments.

For future research, the last point on effort in relation to complexity adjustment could be elaborated on further. For instance, the AMA-score provides a quantifiable measure on the accuracy and spread of a complexity-adjusted model, but as long as effort is kept a qualitative parameter, the discussion on elasticity becomes more hypothetical in nature. In a scenario where an average investor's effort could be quantified (e.g. an effort index, time, or number of adjustments), would help quantify the relationship $\left[\frac{\Delta\%\ AMA}{\Delta\%\ effort}\right]$ and consequently provide more guidance on the topic. However, this venture has been outside the scope of this study, but having introduced a means for capturing the relative performance of valuation models also in contexts of increased complexity, we look forward to fruitful attempts to take this elasticity approach even further.

Furthermore, following the scope of this paper, we also see an opportunity for future studies to consider other complexity attributes than those presented in this thesis. Here, we have discussed quantifiable adjustments made to model inputs, in terms of e.g. bankruptcy risk. Future research could continue on this path, but could also consider any inherent complexity in the original model specification per se. In other words, instead of assuming that the models are equally parsimonious and simple to begin with, one could argue that some models are more complex in their mere parsimonious specification than others, and would in turn have a greater effort associated with its application already in a non-adjusted parsimonious study.

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8. Appendix

Appendix 1: The AMA-score rationale

The AMA-score is inspired and deduced from the common statistical property that there exists an inherent trade-off between *accuracy* and *spread*. This notion is particularly discussed in terms of the relationship between model performance and model complexity (Faber, 1999; Newbold, Carlson & Thorne, 2012). The rationale goes that as model complexity increases, the accuracy improves but with the cost of increased spread, such that the first-order relationships can be viewed as

$$\frac{\delta Accuracy}{\delta Complexity} = \left[-\frac{\delta Spread}{\delta Complexity}\right]$$

The AMA-score is a means of capturing both accuracy and spread into one, and more specifically doing so by considering two common measures for these phenomena, namely the mean of absolute pricing errors (MAPE) for the accuracy dimension, and the inter-quartile range of pricing errors (IQRPE) for the spread dimension, such that for a model i the ultimate performance in terms of AMA can be expressed as

$$AMA_i = \frac{\left[{}^{1}/_{(Q_3[PE_i] - Q_1[PE_i])}\right]}{\frac{1}{n}\sum_{j=1}^{n}\left|\frac{V_j - P_j}{P_j}\right|} = \frac{\left[{}^{1}/_{IQRPE_i}\right]}{MAPE_i}$$

for any model i, considering firms j = $\{1, \dots, n\}$. Considering these effects, the above lines of reasoning can be more eloquently depicted graphically, as considered below

Figure A1. The accuracy-spread trade-off and the AMA evolution

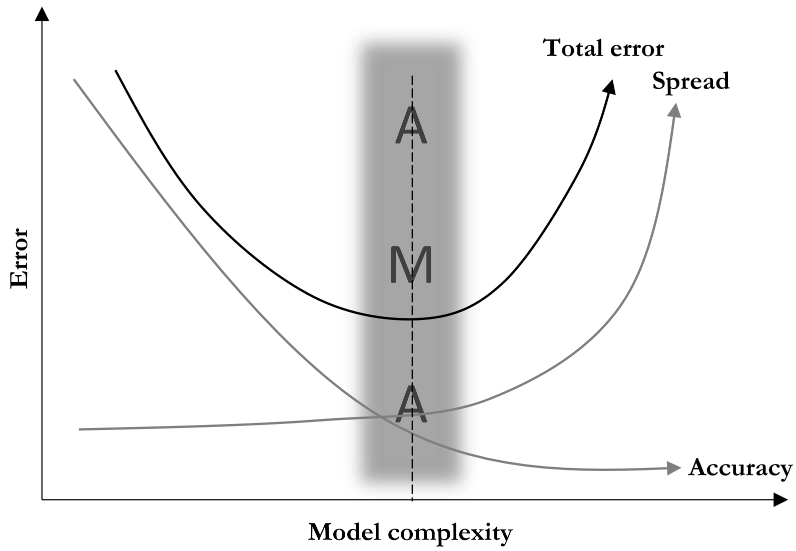

Figure A1 captures that as complexity increases, accuracy goes down but spread goes up. In total, these two are mutually exclusive in comprising the notion of a *total error*, which in turn is aimed to be minimized (dotted line in figure). The AMA-scores mitigates the risk of looking solely at accuracy or spread, as there is an inherent relationship between them. Instead, the AMA-score helps by considering both dimensions and hence maximize the relative performance of these dimensions, such that the total error is moving towards its minimum (shaded AMA-area). This renders that well-performing models will perform well along both these dimensions and any increase in complexity, will not necessarily render an increased total error.

Appendix 2: Non-adjusted parsimonious model specifications

Table B3. Results: Non-adjusted parsimonious model specifications (ROE: +100 & Coc)

Panel A

Ordered by Model and Period

Model	*Period*	*Payoff*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
DDM	2009-2011	Estimates	1,19	0,19	0,03	0,86	0,54	0,78	0,78	351	2,36
DDM	2009-2011	Martingale	1,17	0,17	-0,08	0,91	0,63	0,85	0,88	339	1,80
DDM	2014-2016	Estimates	1,23	0,23	0,08	0,72	0,53	0,79	0,78	477	2,41
DDM	2014-2016	Martingale	1,39	0,39	0,29	0,89	0,69	0,85	1,06	432	1,37
RIV	2009-2011	Estimates	0,88	-0,11	-0,25	0,54	0,42	0,79	0,59	546	4,09
RIV	2009-2011	Martingale	1,20	0,21	-0,02	0,97	0,61	0,79	0,83	567	1,98
RIV	2014-2016	Estimates	0,71	-0,29	-0,40	0,71	0,53	0,90	0,46	651	4,09
RIV	2014-2016	Martingale	0,73	-0,27	-0,45	0,71	0,58	0,92	0,50	651	3,43
AEG	2009-2011	Estimates	0,81	-0,14	-0,10	12,69	5,58	0,88	4,93	621	0,04
AEG	2009-2011	Martingale	10,63	9,64	2,28	32,69	9,73	0,92	5,28	438	0,02
AEG	2014-2016	Estimates	-5,70	-6,70	-0,53	17,31	11,93	0,97	17,65	657	0,00
AEG	2014-2016	Martingale	5,67	4,67	0,95	17,62	4,89	0,89	3,41	486	0,06
OJ	2009-2010	Estimates	4,65	3,57	1,41	20,81	8,13	0,92	5,70	211	0,02
OJ	2009-2010	Martingale	3,97	3,22	1,19	9,15	3,46	0,90	3,40	193	0,08
OJ	2014-2015	Estimates	7,57	6,99	3,19	19,58	9,36	0,98	5,76	220	0,02
OJ	2014-2015	Martingale	3,82	3,07	0,50	11,65	3,35	0,88	2,82	218	0,11

Panel B

Ordered by Payoff and Period

Payoff	*Period*	*Model*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
Estimates	2009-2011	DDM	1,19	0,19	0,03	0,86	0,54	0,78	0,78	351	2,36
Estimates	2009-2011	RIV	0,88	-0,11	-0,25	0,54	0,42	0,79	0,59	546	4,09
Estimates	2009-2011	AEG	0,81	-0,14	-0,10	12,69	5,58	0,88	4,93	621	0,04
Estimates	2009-2010	OJ	4,65	3,57	1,41	20,81	8,13	0,92	5,70	211	0,02
Estimates	2014-2016	DDM	1,23	0,23	0,08	0,72	0,53	0,79	0,78	477	2,41
Estimates	2014-2016	RIV	0,71	-0,29	-0,40	0,71	0,53	0,90	0,46	651	4,09
Estimates	2014-2016	AEG	-5,70	-6,70	-0,53	17,31	11,93	0,97	17,65	657	0,00
Estimates	2014-2015	OJ	7,57	6,99	3,19	19,58	9,36	0,98	5,76	220	0,02
Martingale	2009-2011	DDM	1,17	0,17	-0,08	0,91	0,63	0,85	0,88	339	1,80
Martingale	2009-2011	RIV	1,20	0,21	-0,02	0,97	0,61	0,79	0,83	567	1,98
Martingale	2009-2011	AEG	10,63	9,64	2,28	32,69	9,73	0,92	5,28	438	0,02
Martingale	2009-2010	OJ	3,97	3,22	1,19	9,15	3,46	0,90	3,40	193	0,08
Martingale	2014-2016	DDM	1,39	0,39	0,29	0,89	0,69	0,85	1,06	432	1,37
Martingale	2014-2016	RIV	0,73	-0,27	-0,45	0,71	0,58	0,92	0,50	651	3,43
Martingale	2014-2016	AEG	5,67	4,67	0,95	17,62	4,89	0,89	3,41	486	0,06
Martingale	2014-2015	OJ	3,82	3,07	0,50	11,65	3,35	0,88	2,82	218	0,11

Notes:

Table B3, Panel A and B, present valuation accuracy measures and their distributions for the DDM, RIV, AEG and OJ-models. Models further vary by type of payoff and period in which these payoffs are forecasted. V/P refers to intrinsic values scaled by the observed prices. PE is the *signed* pricing error, and MAPE is the mean absolute (*unsigned*) pricing error. 15%APE is the percentage of sample whose absolute pricing errors is over 15%. IQRPE is the inter-quartile range of pricing errors. Finally, AMA-score is the inverse of IQRPE divided by MAPE.

Appendix 3: Single-adjusted parsimonious model specifications

Table A4[b]. Results: Horizon-adjusted model specifications (single-adjusted)

Panel A

Ordered by Model and Period

Model	*Period*	*Payoff*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. Dev PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
DDM	2009-2013	Estimates	1,16	0,16	0,03	0,69	0,53	0,80	0,86	555	2,20
DDM	2009-2013	Martingale	1,03	0,03	-0,10	0,76	0,56	0,84	0,88	535	2,03
DDM	2014-2018	Estimates	1,12	0,12	0,03	0,73	0,50	0,86	0,84	175	2,38
DDM	2014-2018	Martingale	1,21	0,21	0,14	0,66	0,51	0,73	0,78	185	2,49
RIV	2009-2013	Estimates	0,88	-0,12	-0,21	0,51	0,39	0,76	0,50	890	5,16
RIV	2009-2013	Martingale	1,54	0,55	0,19	1,98	0,89	0,85	0,92	930	1,23
RIV	2014-2018	Estimates	0,63	-0,37	-0,39	0,57	0,45	0,83	0,44	415	5,12
RIV	2014-2018	Martingale	0,72	-0,28	-0,42	0,57	0,52	0,88	0,55	645	3,53
AEG	2009-2013	Estimates	2,84	1,90	0,64	13,03	5,19	0,91	4,19	1020	0,05
AEG	2009-2013	Martingale	28,45	27,46	3,59	108,30	27,52	0,94	8,67	635	0,00
AEG	2014-2018	Estimates	-8,50	-9,50	-10,84	12,13	11,21	0,97	17,98	175	0,00
AEG	2014-2018	Martingale	13,61	12,61	1,98	54,76	12,65	0,92	5,27	180	0,01
OJ	2009-2011	Estimates	1,92	0,92	0,12	15,09	6,64	0,92	5,55	424	0,03
OJ	2009-2011	Martingale	5,05	4,89	1,34	16,23	5,13	0,90	3,78	352	0,05
OJ	2014-2016	Estimates	4,77	4,77	2,40	7,91	5,05	0,97	4,29	440	0,05
OJ	2014-2016	Martingale	4,06	4,10	0,53	17,69	4,38	0,91	2,43	370	0,09

Panel B

Ordered by Payoff and Period

Payoff	*Period*	*Model*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
Estimates	2009-2013	DDM	1,16	0,16	0,03	0,69	0,53	0,80	0,86	555	2,20
Estimates	2009-2013	RIV	0,88	-0,12	-0,21	0,51	0,39	0,76	0,50	890	5,16
Estimates	2009-2013	AEG	2,84	1,90	0,64	13,03	5,19	0,91	4,19	1020	0,05
Estimates	2009-2011	OJ	1,92	0,92	0,12	15,09	6,64	0,92	5,55	424	0,03
Estimates	2014-2018	DDM	1,12	0,12	0,03	0,73	0,50	0,86	0,84	175	2,38
Estimates	2014-2018	RIV	0,63	-0,37	-0,39	0,57	0,45	0,83	0,44	415	5,12
Estimates	2014-2018	AEG	-8,50	-9,50	-10,84	12,13	11,21	0,97	17,98	175	0,00
Estimates	2014-2016	OJ	4,77	4,77	2,40	7,91	5,05	0,97	4,29	440	0,05
Martingale	2009-2013	DDM	1,03	0,03	-0,10	0,76	0,56	0,84	0,88	535	2,03
Martingale	2009-2013	RIV	1,54	0,55	0,19	1,98	0,89	0,85	0,92	930	1,23
Martingale	2009-2013	AEG	28,45	27,46	3,59	108,30	27,52	0,94	8,67	635	0,00
Martingale	2009-2011	OJ	5,05	4,89	1,34	16,23	5,13	0,90	3,78	352	0,05
Martingale	2014-2018	DDM	1,21	0,21	0,14	0,66	0,51	0,73	0,78	185	2,49
Martingale	2014-2018	RIV	0,72	-0,28	-0,42	0,57	0,52	0,88	0,55	645	3,53
Martingale	2014-2018	AEG	13,61	12,61	1,98	54,76	12,65	0,92	5,27	180	0,01
Martingale	2014-2016	OJ	4,06	4,10	0,53	17,69	4,38	0,91	2,43	370	0,09

Notes:
Table A4[b], Panel A and B, present valuation accuracy measures and their distributions for the DDM, RIV, AEG and OJ-models. Models further vary by type of payoff and period in which these payoffs are forecasted. V/P refers to intrinsic values scaled by the observed prices. PE is the *signed* pricing error, and MAPE is the mean absolute (*unsigned*) pricing error. 15%APE is the percentage of sample whose absolute pricing errors is over 15%. IQRPE is the inter-quartile range of pricing errors. Finally, AMA-score is the inverse of IQRPE divided by MAPE.

Table B4[b]. Results: Horizon-adjusted model specifications (ROE: +100 & Coc)

Panel A

Ordered by Model and Period

Model	*Period*	*Payoff*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. Dev PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
DDM	2009-2013	Estimates	1,16	0,16	0,03	0,69	0,53	0,80	0,86	555	2,20
DDM	2009-2013	Martingale	1,03	0,03	-0,10	0,76	0,56	0,84	0,88	535	2,03
DDM	2014-2018	Estimates	1,12	0,12	0,03	0,73	0,50	0,86	0,84	175	2,38
DDM	2014-2018	Martingale	1,21	0,21	0,14	0,66	0,51	0,73	0,78	185	2,49
RIV	2009-2013	Estimates	0,88	-0,12	-0,21	0,51	0,39	0,76	0,50	890	5,16
RIV	2009-2013	Martingale	1,61	0,62	0,25	2,00	0,93	0,87	0,95	930	1,13
RIV	2014-2018	Estimates	0,63	-0,37	-0,39	0,57	0,45	0,83	0,44	415	5,12
RIV	2014-2018	Martingale	0,77	-0,23	-0,41	0,64	0,53	0,89	0,58	645	3,24
AEG	2009-2013	Estimates	2,84	1,90	0,64	13,03	5,19	0,91	4,19	1020	0,05
AEG	2009-2013	Martingale	26,32	25,33	3,21	104,11	25,41	0,91	8,14	690	0,00
AEG	2014-2018	Estimates	-8,50	-9,50	-10,84	12,13	11,21	0,97	17,98	175	0,00
AEG	2014-2018	Martingale	10,30	9,30	1,45	46,62	9,46	0,88	4,11	250	0,03
OJ	2009-2011	Estimates	1,92	0,92	0,12	15,09	6,64	0,92	5,55	424	0,03
OJ	2009-2011	Martingale	5,21	4,55	1,21	15,55	4,79	0,90	3,50	386	0,06
OJ	2014-2016	Estimates	4,77	4,77	2,40	7,91	5,05	0,97	4,29	440	0,05
OJ	2014-2016	Martingale	4,50	3,80	0,48	16,35	4,08	0,89	2,55	436	0,10

Panel B

Ordered by Payoff and Period

Payoff	*Period*	*Model*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
Estimates	2009-2013	DDM	1,16	0,16	0,03	0,69	0,53	0,80	0,86	555	2,20
Estimates	2009-2013	RIV	0,88	-0,12	-0,21	0,51	0,39	0,76	0,50	890	5,16
Estimates	2009-2013	AEG	2,84	1,90	0,64	13,03	5,19	0,91	4,19	1020	0,05
Estimates	2009-2011	OJ	1,92	0,92	0,12	15,09	6,64	0,92	5,55	424	0,03
Estimates	2014-2018	DDM	1,12	0,12	0,03	0,73	0,50	0,86	0,84	175	2,38
Estimates	2014-2018	RIV	0,63	-0,37	-0,39	0,57	0,45	0,83	0,44	415	5,12
Estimates	2014-2018	AEG	-8,50	-9,50	-10,84	12,13	11,21	0,97	17,98	175	0,00
Estimates	2014-2016	OJ	4,77	4,77	2,40	7,91	5,05	0,97	4,29	440	0,05
Martingale	2009-2013	DDM	1,03	0,03	-0,10	0,76	0,56	0,84	0,88	535	2,03
Martingale	2009-2013	RIV	1,61	0,62	0,25	2,00	0,93	0,87	0,95	930	1,13
Martingale	2009-2013	AEG	26,32	25,33	3,21	104,11	25,41	0,91	8,14	690	0,00
Martingale	2009-2011	OJ	5,21	4,55	1,21	15,55	4,79	0,90	3,50	386	0,06
Martingale	2014-2018	DDM	1,21	0,21	0,14	0,66	0,51	0,73	0,78	185	2,49
Martingale	2014-2018	RIV	0,77	-0,23	-0,41	0,64	0,53	0,89	0,58	645	3,24
Martingale	2014-2018	AEG	10,30	9,30	1,45	46,62	9,46	0,88	4,11	250	0,03
Martingale	2014-2016	OJ	4,50	3,80	0,48	16,35	4,08	0,89	2,55	436	0,10

Notes:

Table B4[b], Panel A and B, present valuation accuracy measures and their distributions for the DDM, RIV, AEG and OJ-models. Models further vary by type of payoff and period in which these payoffs are forecasted. V/P refers to intrinsic values scaled by the observed prices. PE is the *signed* pricing error, and MAPE is the mean absolute (*unsigned*) pricing error. 15%APE is the percentage of sample whose absolute pricing errors is over 15%. IQRPE is the inter-quartile range of pricing errors. Finally, AMA-score is the inverse of IQRPE divided by MAPE.

Table A4[c]. Results: Bankruptcy-adjusted model specifications (single-adjusted)

Panel A

Ordered by Model and Period

Model	*Period*	*Payoff*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. Dev PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
DDM	2009-2011	Estimates	1,15	0,15	-0,04	0,85	0,53	0,75	0,72	351	2,58
DDM	2009-2011	Martingale	1,13	0,13	-0,14	0,89	0,62	0,88	0,88	339	1,83
DDM	2014-2016	Estimates	1,17	0,17	0,02	0,70	0,51	0,79	0,77	477	2,57
DDM	2014-2016	Martingale	1,33	0,33	0,18	0,86	0,65	0,81	0,94	432	1,64
RIV	2009-2011	Estimates	0,88	-0,11	-0,25	0,54	0,42	0,80	0,59	546	4,07
RIV	2009-2011	Martingale	1,16	0,16	-0,04	0,92	0,58	0,76	0,80	567	2,18
RIV	2014-2016	Estimates	0,72	-0,28	-0,39	0,71	0,53	0,88	0,46	651	4,12
RIV	2014-2016	Martingale	0,73	-0,27	-0,43	0,65	0,55	0,91	0,52	651	3,49
AEG	2009-2011	Estimates	0,79	-0,15	-0,13	12,52	5,36	0,87	4,61	621	0,04
AEG	2009-2011	Martingale	10,72	9,73	2,41	32,43	9,81	0,93	5,45	405	0,02
AEG	2014-2016	Estimates	-5,20	-6,20	-0,52	15,93	11,03	0,97	17,20	657	0,01
AEG	2014-2016	Martingale	6,20	5,20	1,05	18,40	5,36	0,90	3,30	378	0,06
OJ	2009-2010	Estimates	4,21	3,15	1,31	17,77	17,77	0,91	5,54	211,00	0,01
OJ	2009-2010	Martingale	3,62	3,23	1,18	9,18	3,48	0,90	3,38	176,00	0,09
OJ	2014-2015	Estimates	6,54	5,90	2,90	17,10	8,10	0,98	5,34	220,00	0,02
OJ	2014-2015	Martingale	3,15	2,96	0,52	11,94	3,25	0,95	2,16	185,00	0,14

Panel B

Ordered by Payoff and Period

Payoff	*Period*	*Model*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
Estimates	2009-2011	DDM	1,15	0,15	-0,04	0,85	0,53	0,75	0,72	351	2,58
Estimates	2009-2011	RIV	0,88	-0,11	-0,25	0,54	0,42	0,80	0,59	546	4,07
Estimates	2009-2011	AEG	0,79	-0,15	-0,13	12,52	5,36	0,87	4,61	621	0,04
Estimates	2009-2010	OJ	4,21	3,15	1,31	17,77	17,77	0,91	5,54	211	0,01
Estimates	2014-2016	DDM	1,17	0,17	0,02	0,70	0,51	0,79	0,77	477	2,57
Estimates	2014-2016	RIV	0,72	-0,28	-0,39	0,71	0,53	0,88	0,46	651	4,12
Estimates	2014-2016	AEG	-5,20	-6,20	-0,52	15,93	11,03	0,97	17,20	657	0,01
Estimates	2014-2015	OJ	6,54	5,90	2,90	17,10	8,10	0,98	5,34	220	0,02
Martingale	2009-2011	DDM	1,13	0,13	-0,14	0,89	0,62	0,88	0,88	339	1,83
Martingale	2009-2011	RIV	1,16	0,16	-0,04	0,92	0,58	0,76	0,80	567	2,18
Martingale	2009-2011	AEG	10,72	9,73	2,41	32,43	9,81	0,93	5,45	405	0,02
Martingale	2009-2010	OJ	3,62	3,23	1,18	9,18	3,48	0,90	3,38	176	0,09
Martingale	2014-2016	DDM	1,33	0,33	0,18	0,86	0,65	0,81	0,94	432	1,64
Martingale	2014-2016	RIV	0,73	-0,27	-0,43	0,65	0,55	0,91	0,52	651	3,49
Martingale	2014-2016	AEG	6,20	5,20	1,05	18,40	5,36	0,90	3,30	378	0,06
Martingale	2014-2015	OJ	3,15	2,96	0,52	11,94	3,25	0,95	2,16	185	0,14

Notes:

Table A4[c], Panel A and B, present valuation accuracy measures and their distributions for the DDM, RIV, AEG and OJ-models. Models further vary by type of payoff and period in which these payoffs are forecasted. V/P refers to intrinsic values scaled by the observed prices. PE is the *signed* pricing error, and MAPE is the mean absolute (*unsigned*) pricing error. 15%APE is the percentage of sample whose absolute pricing errors is over 15%. IQRPE is the inter-quartile range of pricing errors. Finally, AMA-score is the inverse of IQRPE divided by MAPE.

Table B4[c]. Results: Bankruptcy-adjusted model specifications (ROE: +100 & Coc)
Panel A
Ordered by Model and Period

Model	*Period*	*Payoff*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. Dev PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
DDM	2009-2011	Estimates	1,15	0,15	-0,04	0,85	0,53	0,75	0,72	351	2,58
DDM	2009-2011	Martingale	1,13	0,13	-0,14	0,89	0,62	0,88	0,88	339	1,83
DDM	2014-2016	Estimates	1,17	0,17	0,02	0,70	0,51	0,79	0,77	477	2,57
DDM	2014-2016	Martingale	1,33	0,33	0,18	0,86	0,65	0,81	0,94	432	1,64
RIV	2009-2011	Estimates	0,88	-0,11	-0,25	0,54	0,42	0,80	0,59	546	4,07
RIV	2009-2011	Martingale	1,20	0,21	-0,03	0,97	0,61	0,79	0,82	567	2,00
RIV	2014-2016	Estimates	0,72	-0,28	-0,39	0,71	0,53	0,88	0,46	651	4,12
RIV	2014-2016	Martingale	0,78	-0,22	-0,42	0,75	0,58	0,91	0,53	651	3,24
AEG	2009-2011	Estimates	0,79	-0,15	-0,13	12,52	5,36	0,87	4,61	621	0,04
AEG	2009-2011	Martingale	10,24	9,25	2,24	31,57	9,35	0,92	5,13	429	0,02
AEG	2014-2016	Estimates	-5,20	-6,20	-0,52	15,93	11,03	0,97	17,20	657	0,01
AEG	2014-2016	Martingale	5,28	4,28	0,91	16,34	4,53	0,88	3,43	486	0,06
OJ	2009-2010	Estimates	4,21	3,15	1,31	17,77	17,77	0,91	5,54	211	0,01
OJ	2009-2010	Martingale	3,78	3,02	1,12	8,80	3,27	0,89	3,08	193	0,10
OJ	2014-2015	Estimates	6,54	5,90	2,90	17,10	8,10	0,98	5,34	220	0,02
OJ	2014-2015	Martingale	3,54	2,77	0,45	11,05	3,08	0,95	2,48	218	0,13

Panel B
Ordered by Payoff and Period

Payoff	*Period*	*Model*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
Estimates	2009-2011	DDM	1,15	0,15	-0,04	0,85	0,53	0,75	0,72	351	2,58
Estimates	2009-2011	RIV	0,88	-0,11	-0,25	0,54	0,42	0,80	0,59	546	4,07
Estimates	2009-2011	AEG	0,79	-0,15	-0,13	12,52	5,36	0,87	4,61	621	0,04
Estimates	2009-2010	OJ	4,21	3,15	1,31	17,77	17,77	0,91	5,54	211	0,01
Estimates	2014-2016	DDM	1,17	0,17	0,02	0,70	0,51	0,79	0,77	477	2,57
Estimates	2014-2016	RIV	0,72	-0,28	-0,39	0,71	0,53	0,88	0,46	651	4,12
Estimates	2014-2016	AEG	-5,20	-6,20	-0,52	15,93	11,03	0,97	17,20	657	0,01
Estimates	2014-2015	OJ	6,54	5,90	2,90	17,10	8,10	0,98	5,34	220	0,02
Martingale	2009-2011	DDM	1,13	0,13	-0,14	0,89	0,62	0,88	0,88	339	1,83
Martingale	2009-2011	RIV	1,20	0,21	-0,03	0,97	0,61	0,79	0,82	567	2,00
Martingale	2009-2011	AEG	10,24	9,25	2,24	31,57	9,35	0,92	5,13	429	0,02
Martingale	2009-2010	OJ	3,78	3,02	1,12	8,80	3,27	0,89	3,08	193	0,10
Martingale	2014-2016	DDM	1,33	0,33	0,18	0,86	0,65	0,81	0,94	432	1,64
Martingale	2014-2016	RIV	0,78	-0,22	-0,42	0,75	0,58	0,91	0,53	651	3,24
Martingale	2014-2016	AEG	5,28	4,28	0,91	16,34	4,53	0,88	3,43	486	0,06
Martingale	2014-2015	OJ	3,54	2,77	0,45	11,05	3,08	0,95	2,48	218	0,13

Notes:
Table B4[c], Panel A and B, present valuation accuracy measures and their distributions for the DDM, RIV, AEG and OJ-models. Models further vary by type of payoff and period in which these payoffs are forecasted. V/P refers to intrinsic values scaled by the observed prices. PE is the *signed* pricing error, and MAPE is the mean absolute (*unsigned*) pricing error. 15%APE is the percentage of sample whose absolute pricing errors is over 15%. IQRPE is the inter-quartile range of pricing errors. Finally, AMA-score is the inverse of IQRPE divided by MAPE.

Table A4[d]. Results: Transitory item-adjusted model specifications (single-adjusted)

Panel A

Ordered by Model and Period

Model	*Period*	*Payoff*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. Dev PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
DDM	2009-2011	Estimates	1,19	0,19	0,03	0,86	0,54	0,78	0,78	351	2,36
DDM	2009-2011	Martingale	1,17	0,17	-0,08	0,91	0,63	0,85	0,88	339	1,80
DDM	2014-2016	Estimates	1,23	0,23	0,08	0,72	0,53	0,79	0,78	477	2,41
DDM	2014-2016	Martingale	1,39	0,39	0,29	0,89	0,69	0,85	1,06	432	1,37
RIV	2009-2011	Estimates	0,90	-0,10	-0,23	0,54	0,41	0,79	0,57	546	4,31
RIV	2009-2011	Martingale	1,12	0,12	-0,06	0,86	0,55	0,77	0,77	546	2,35
RIV	2014-2016	Estimates	0,71	-0,29	-0,40	0,71	0,53	0,91	0,46	651	4,07
RIV	2014-2016	Martingale	0,70	-0,30	-0,46	0,67	0,57	0,92	0,48	630	3,67
AEG	2009-2011	Estimates	0,89	-0,05	-0,01	7,14	4,19	0,89	4,29	591	0,06
AEG	2009-2011	Martingale	8,68	7,69	2,26	22,38	7,76	0,93	4,85	405	0,03
AEG	2014-2016	Estimates	-8,16	-9,16	-7,74	16,85	13,39	0,96	18,89	642	0,00
AEG	2014-2016	Martingale	7,73	6,73	1,16	35,10	6,89	0,89	2,91	408	0,05
OJ	2009-2010	Estimates	3,86	3,01	1,67	10,24	5,67	0,91	5,19	200,00	0,03
OJ	2009-2010	Martingale	3,34	2,92	1,10	7,19	3,16	0,92	3,30	175,00	0,10
OJ	2014-2015	Estimates	7,42	7,01	3,17	20,03	9,45	0,99	5,95	215,00	0,02
OJ	2014-2015	Martingale	3,63	3,53	0,72	14,99	3,77	0,88	2,63	186,00	0,10

Panel B

Ordered by Payoff and Period

Payoff	*Period*	*Model*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
Estimates	2009-2011	DDM	1,19	0,19	0,03	0,86	0,54	0,78	0,78	351	2,36
Estimates	2009-2011	RIV	0,90	-0,10	-0,23	0,54	0,41	0,79	0,57	546	4,31
Estimates	2009-2011	AEG	0,89	-0,05	-0,01	7,14	4,19	0,89	4,29	591	0,06
Estimates	2009-2010	OJ	3,86	3,01	1,67	10,24	5,67	0,91	5,19	200	0,03
Estimates	2014-2016	DDM	1,23	0,23	0,08	0,72	0,53	0,79	0,78	477	2,41
Estimates	2014-2016	RIV	0,71	-0,29	-0,40	0,71	0,53	0,91	0,46	651	4,07
Estimates	2014-2016	AEG	-8,16	-9,16	-7,74	16,85	13,39	0,96	18,89	642	0,00
Estimates	2014-2015	OJ	7,42	7,01	3,17	20,03	9,45	0,99	5,95	215	0,02
Martingale	2009-2011	DDM	1,17	0,17	-0,08	0,91	0,63	0,85	0,88	339	1,80
Martingale	2009-2011	RIV	1,12	0,12	-0,06	0,86	0,55	0,77	0,77	546	2,35
Martingale	2009-2011	AEG	8,68	7,69	2,26	22,38	7,76	0,93	4,85	405	0,03
Martingale	2009-2010	OJ	3,34	2,92	1,10	7,19	3,16	0,92	3,30	175	0,10
Martingale	2014-2016	DDM	1,39	0,39	0,29	0,89	0,69	0,85	1,06	432	1,37
Martingale	2014-2016	RIV	0,70	-0,30	-0,46	0,67	0,57	0,92	0,48	630	3,67
Martingale	2014-2016	AEG	7,73	6,73	1,16	35,10	6,89	0,89	2,91	408	0,05
Martingale	2014-2015	OJ	3,63	3,53	0,72	14,99	3,77	0,88	2,63	186	0,10

Notes:
Table A4[d], Panel A and B, present valuation accuracy measures and their distributions for the DDM, RIV, AEG and OJ-models. Models further vary by type of payoff and period in which these payoffs are forecasted. V/P refers to intrinsic values scaled by the observed prices. PE is the *signed* pricing error, and MAPE is the mean absolute (*unsigned*) pricing error. 15%APE is the percentage of sample whose absolute pricing errors is over 15%. IQRPE is the inter-quartile range of pricing errors. Finally, AMA-score is the inverse of IQRPE divided by MAPE.

Table B4[d]. Results: Transitory item-adjusted model specifications (ROE: +100 & Coc)

Panel A

Ordered by Model and Period

Model	*Period*	*Payoff*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. Dev PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
DDM	2009-2011	Estimates	1,19	0,19	0,03	0,86	0,54	0,78	0,78	351	2,36
DDM	2009-2011	Martingale	1,14	0,14	-0,04	0,75	0,57	0,89	0,82	339	2,14
DDM	2014-2016	Estimates	1,23	0,23	0,08	0,72	0,53	0,79	0,78	477	2,41
DDM	2014-2016	Martingale	1,33	0,33	0,17	0,87	0,66	0,86	0,93	438	1,65
RIV	2009-2011	Estimates	0,88	-0,11	-0,25	0,54	0,42	0,79	0,59	546	4,09
RIV	2009-2011	Martingale	1,20	0,21	-0,02	0,97	0,61	0,79	0,83	567	1,98
RIV	2014-2016	Estimates	0,71	-0,29	-0,40	0,71	0,53	0,90	0,46	651	4,09
RIV	2014-2016	Martingale	0,73	-0,27	-0,45	0,71	0,58	0,92	0,50	651	3,43
AEG	2009-2011	Estimates	0,89	-0,05	-0,01	7,14	4,19	0,89	4,29	591	0,06
AEG	2009-2011	Martingale	8,25	7,25	2,11	21,73	7,34	0,93	4,59	432	0,03
AEG	2014-2016	Estimates	-8,16	-9,16	-7,74	16,85	13,39	0,96	18,89	642	0,00
AEG	2014-2016	Martingale	6,74	5,74	0,98	31,65	5,94	0,87	3,05	504	0,06
OJ	2009-2010	Estimates	3,86	3,01	1,67	10,24	5,67	0,91	5,19	200	0,03
OJ	2009-2010	Martingale	3,49	2,71	1,07	6,88	2,94	0,90	2,97	193	0,11
OJ	2014-2015	Estimates	7,42	7,01	3,17	20,03	9,45	0,99	5,95	215	0,02
OJ	2014-2015	Martingale	4,07	3,33	0,63	13,92	3,59	0,88	2,95	218	0,09

Panel B

Ordered by Payoff and Period

Payoff	*Period*	*Model*	*Mean V/P*	*Mean PE*	*Median PE*	*Std. dev. PE*	*MAPE*	*15% APE*	*IQRPE*	*Firm-year obs.*	*AMA-score*
Estimates	2009-2011	DDM	1,19	0,19	0,03	0,86	0,54	0,78	0,78	351	2,36
Estimates	2009-2011	RIV	0,88	-0,11	-0,25	0,54	0,42	0,79	0,59	546	4,09
Estimates	2009-2011	AEG	0,89	-0,05	-0,01	7,14	4,19	0,89	4,29	591	0,06
Estimates	2009-2010	OJ	3,86	3,01	1,67	10,24	5,67	0,91	5,19	200	0,03
Estimates	2014-2016	DDM	1,23	0,23	0,08	0,72	0,53	0,79	0,78	477	2,41
Estimates	2014-2016	RIV	0,71	-0,29	-0,40	0,71	0,53	0,90	0,46	651	4,09
Estimates	2014-2016	AEG	-8,16	-9,16	-7,74	16,85	13,39	0,96	18,89	642	0,00
Estimates	2014-2015	OJ	7,42	7,01	3,17	20,03	9,45	0,99	5,95	215	0,02
Martingale	2009-2011	DDM	1,14	0,14	-0,04	0,75	0,57	0,89	0,82	339	2,14
Martingale	2009-2011	RIV	1,20	0,21	-0,02	0,97	0,61	0,79	0,83	567	1,98
Martingale	2009-2011	AEG	8,25	7,25	2,11	21,73	7,34	0,93	4,59	432	0,03
Martingale	2009-2010	OJ	3,49	2,71	1,07	6,88	2,94	0,90	2,97	193	0,11
Martingale	2014-2016	DDM	1,33	0,33	0,17	0,87	0,66	0,86	0,93	438	1,65
Martingale	2014-2016	RIV	0,73	-0,27	-0,45	0,71	0,58	0,92	0,50	651	3,43
Martingale	2014-2016	AEG	6,74	5,74	0,98	31,65	5,94	0,87	3,05	504	0,06
Martingale	2014-2015	OJ	4,07	3,33	0,63	13,92	3,59	0,88	2,95	218	0,09

Notes:

Table B4[d], Panel A and B, present valuation accuracy measures and their distributions for the DDM, RIV, AEG and OJ-models. Models further vary by type of payoff and period in which these payoffs are forecasted. V/P refers to intrinsic values scaled by the observed prices. PE is the *signed* pricing error, and MAPE is the mean absolute (*unsigned*) pricing error. 15%APE is the percentage of sample whose absolute pricing errors is over 15%. IQRPE is the inter-quartile range of pricing errors. Finally, AMA-score is the inverse of IQRPE divided by MAPE.

Appendix 4: Multi-adjusted parsimonious model specifications (100% & ρ_e)

Table B7. Results: Model AMA-score's after single and multiple adjustments (ROE: +100 & Coc)

Panel A

Ordered by Model and Period

			Parsimonious	Single adjustments			Multiple adjustments			
Model	*Valuation year*	*Payoff*	*[a]*	*[a] + [b]*	*[a] + [c]*	*[a] + [d]*	*[a] + [b] + [c]*	*[a] + [b] + [d]*	*[a] + [c] + [d]*	*[a] + [b] + [c] + [d]*
DDM	2009	Estimates	2,36	2,20	**2,58**	2,36	2,58	2,20	2,58	2,58
DDM	2009	Martingale	1,80	2,03	1,83	2,14	**2,52**	2,03	1,83	2,52
DDM	2014	Estimates	2,41	2,38	2,57	2,41	**3,07**	2,38	2,57	3,07
DDM	2014	Martingale	1,37	2,49	1,64	1,65	**3,24**	2,49	1,64	3,24
RIV	2009	Estimates	4,09	5,16	4,07	4,09	5,38	5,34	4,26	**5,55**
RIV	2009	Martingale	1,98	1,13	2,00	1,98	1,24	1,28	**2,19**	1,35
RIV	2014	Estimates	4,09	5,12	4,12	4,09	**5,28**	4,72	4,08	5,00
RIV	2014	Martingale	3,43	3,24	3,24	3,43	2,91	**3,50**	3,33	3,10
AEG	2009	Estimates	0,04	0,05	0,04	0,06	0,07	0,06	0,06	**0,09**
AEG	2009	Martingale	0,02	0,00	0,02	0,03	0,01	0,01	**0,03**	0,01
AEG	2014	Estimates	0,00	0,00	0,01	0,00	**0,01**	0,00	0,00	0,01
AEG	2014	Martingale	0,06	0,03	**0,06**	0,06	0,04	0,01	0,06	0,02
OJ	2009	Estimates	0,02	0,03	0,01	0,03	0,01	**0,06**	0,02	0,04
OJ	2009	Martingale	0,08	0,06	0,10	0,11	0,06	0,08	**0,12**	0,09
OJ	2014	Estimates	0,02	0,05	0,02	0,02	**0,06**	0,04	0,02	0,06
OJ	2014	Martingale	0,11	0,10	**0,13**	0,09	0,10	0,07	0,11	0,08

Notes:

Table B7 shows model performance by AMA-score for the DDM, RIV, AEG and OJ-models. AMA-scores are calculated for each and every adjustment. For the single adjustment, these are added separately, whereas the multi-adjusted adds additively. AMA-scores in bold and underscore highight the best outcome for each model and adjustment combination. [a] denotes the parsimonious setups, [b] the horizon extended setups, [c] the bankruptcy adjusted setups, and [d] the transitory item adjusted setups.

Table B7. cont'd. Results: Model AMA-score's after single and multiple adjustments (ROE: +100 & Coc)

Panel B

Ordered by Payoff and Period

			Parsimonious	Single adjustments			Multiple adjustments			
Payoff	*Valuation year*	*Model*	*[a]*	*[a] + [b]*	*[a] + [c]*	*[a] + [d]*	*[a] + [b] + [c]*	*[a] + [b] + [d]*	*[a] + [c] + [d]*	*[a] + [b] + [c] + [d]*
Estimates	2009	DDM	2,36	2,20	**<u>2,58</u>**	2,36	2,58	2,20	2,58	2,58
Estimates	2009	RIV	4,09	5,16	4,07	4,09	5,38	5,34	4,26	**<u>5,55</u>**
Estimates	2009	AEG	0,04	0,05	0,04	0,06	0,07	0,06	0,06	**<u>0,09</u>**
Estimates	2009	OJ	0,02	0,03	0,01	0,03	0,01	**<u>0,06</u>**	0,02	0,04
Estimates	2014	DDM	2,41	2,38	2,57	2,41	**<u>3,07</u>**	2,38	2,57	3,07
Estimates	2014	RIV	4,09	5,12	4,12	4,09	**<u>5,28</u>**	4,72	4,08	5,00
Estimates	2014	AEG	0,00	0,00	0,01	0,00	**<u>0,01</u>**	0,00	0,00	0,01
Estimates	2014	OJ	0,02	0,05	0,02	0,02	**<u>0,06</u>**	0,04	0,02	0,06
Martingale	2009	DDM	1,80	2,03	1,83	2,14	**<u>2,52</u>**	2,03	1,83	2,52
Martingale	2009	RIV	1,98	1,13	2,00	1,98	1,24	1,28	**<u>2,19</u>**	1,35
Martingale	2009	AEG	0,02	0,00	0,02	0,03	0,01	0,01	**<u>0,03</u>**	0,01
Martingale	2009	OJ	0,08	0,06	0,10	0,11	0,06	0,08	**<u>0,12</u>**	0,09
Martingale	2014	DDM	1,37	2,49	1,64	1,65	**<u>3,24</u>**	2,49	1,64	3,24
Martingale	2014	RIV	3,43	3,24	3,24	3,43	2,91	**<u>3,50</u>**	3,33	3,10
Martingale	2014	AEG	0,06	0,03	**<u>0,06</u>**	0,06	0,04	0,01	0,06	0,02
Martingale	2014	OJ	0,11	0,10	**<u>0,13</u>**	0,09	0,10	0,07	0,11	0,08

Notes:
Table B7 shows model performance by AMA-score for the DDM, RIV, AEG and OJ-models. AMA-scores are calculated for each and every adjustment. For the single adjustment, these are added separately, whereas the multi-adjusted adds additively. AMA-scores in bold and underscore highight the best outcome for each model and adjustment combination. [a] denotes the parsimonious setups, [b] the horizon extended setups, [c] the bankruptcy adjusted setups, and [d] the transitory item adjusted setups.

Appendix 5: Multi-adjusted parsimonious model specifications (+0 and +5 days)

Table C7. Results: Model AMA-score's after single and multiple adjustments (Valuation date +0 days)

Panel A

Ordered by Model and Period

			Parsimonious		Single adjustments		Multiple adjustments			
Model	*Valuation year*	*Payoff*	*[a]*	*[a] + [b]*	*[a] + [c]*	*[a] + [d]*	*[a] + [b] + [c]*	*[a] + [b] + [d]*	*[a] + [c] + [d]*	*[a] + [b] + [c] + [d]*
DDM	2009	Estimates	2,50	2,24	**2,66**	2,50	2,59	2,24	**2,66**	2,59
DDM	2009	Martingale	1,76	2,04	1,76	2,08	**2,57**	1,86	2,20	2,35
DDM	2014	Estimates	2,41	2,38	2,57	2,41	**3,08**	2,38	2,57	**3,08**
DDM	2014	Martingale	1,37	2,49	1,64	1,65	**3,24**	2,10	1,83	2,61
RIV	2009	Estimates	4,12	4,87	4,01	4,14	5,02	5,24	4,16	**5,45**
RIV	2009	Martingale	2,11	1,25	2,10	**2,28**	1,37	1,38	2,27	1,46
RIV	2014	Estimates	4,09	5,12	4,12	4,08	**5,28**	4,72	4,08	5,00
RIV	2014	Martingale	**3,68**	3,53	3,49	3,67	3,02	3,66	3,60	3,16
AEG	2009	Estimates	0,04	0,05	0,04	0,06	0,07	0,06	0,06	**0,09**
AEG	2009	Martingale	0,02	0,00	0,02	0,03	0,01	0,01	**0,03**	0,01
AEG	2014	Estimates	0,00	0,01	0,01	0,00	**0,01**	0,00	0,00	0,01
AEG	2014	Martingale	0,05	0,02	**0,06**	0,05	0,04	0,01	0,05	0,02
OJ	2009	Estimates	0,02	0,03	0,01	0,03	0,01	**0,03**	0,02	0,03
OJ	2009	Martingale	0,08	0,05	0,09	0,10	0,06	0,05	**0,11**	0,07
OJ	2014	Estimates	0,02	0,05	0,02	0,02	**0,07**	0,05	0,02	0,06
OJ	2014	Martingale	0,13	0,09	**0,14**	0,10	0,11	0,09	0,12	0,08

Notes:

Table B7 shows model performance by AMA-score for the DDM, RIV, AEG and OJ-models. AMA-scores are calculated for each and every adjustment. For the single adjustment, these are added separately, whereas the multi-adjusted adds additively. AMA-scores in bold and underscore highight the best outcome for each model and adjustment combination. [a] denotes the parsimonious setups, [b] the horizon extended setups, [c] the bankruptcy adjusted setups, and [d] the transitory item adjusted setups.

Table C7. Results: Model AMA-score's after single and multiple adjustments (Valuation date +5 days)

Panel A

Ordered by Model and Period

			Single adjustments				Multiple adjustments			
Model	*Valuation year*	*Payoff*	*[a]*	*[a] + [b]*	*[a] + [c]*	*[a] + [d]*	*[a] + [b] + [c]*	*[a] + [b] + [d]*	*[a] + [c] + [d]*	*[a] + [b] + [c] + [d]*
DDM	2009	Estimates	2,34	2,21	2,69	2,34	2,56	2,21	**<u>2,69</u>**	2,56
DDM	2009	Martingale	1,82	2,09	1,83	2,09	**<u>2,54</u>**	1,87	2,15	2,31
DDM	2014	Estimates	2,41	2,37	2,57	2,41	**<u>3,07</u>**	2,37	2,57	3,07
DDM	2014	Martingale	1,37	2,49	1,64	1,65	**<u>3,24</u>**	2,09	1,83	2,60
RIV	2009	Estimates	4,08	5,00	4,04	4,20	5,46	5,38	4,18	**<u>5,66</u>**
RIV	2009	Martingale	2,17	1,24	2,16	2,31	1,37	1,36	**<u>2,33</u>**	1,44
RIV	2014	Estimates	4,09	5,12	4,12	4,07	**<u>5,28</u>**	4,72	4,07	5,00
RIV	2014	Martingale	**<u>3,68</u>**	3,53	3,49	3,67	3,02	3,67	3,60	3,16
AEG	2009	Estimates	0,04	0,05	0,04	0,06	0,07	0,06	0,06	**<u>0,09</u>**
AEG	2009	Martingale	0,02	0,00	0,02	0,03	0,01	0,01	**<u>0,03</u>**	0,01
AEG	2014	Estimates	0,00	0,00	0,01	0,00	**<u>0,01</u>**	0,00	0,00	0,01
AEG	2014	Martingale	0,05	0,01	**<u>0,06</u>**	0,05	0,04	0,01	0,05	0,02
OJ	2009	Estimates	0,02	0,03	0,01	0,03	0,01	**<u>0,05</u>**	0,02	0,04
OJ	2009	Martingale	0,08	0,05	0,09	0,10	0,06	0,07	**<u>0,11</u>**	0,07
OJ	2014	Estimates	0,02	0,05	0,02	0,02	**<u>0,06</u>**	0,04	0,02	0,06
OJ	2014	Martingale	0,13	0,09	**<u>0,14</u>**	0,10	0,11	0,07	0,12	0,08

Notes:

Table B7 shows model performance by AMA-score for the DDM, RIV, AEG and OJ-models. AMA-scores are calculated for each and every adjustment. For the single adjustment, these are added separately, whereas the multi-adjusted adds additively. AMA-scores in bold and underscore highight the best outcome for each model and adjustment combination. [a] denotes the parsimonious setups, [b] the horizon extended setups, [c] the bankruptcy adjusted setups, and [d] the transitory item adjusted setups.

Appendix 6: Summary of sample firm statistics

Table A8. Summary of sample firm statistics

Sector of sample firms

Orderd by No. of firms	*No. of firms*	*% of sample*
Producer Manufacturing	37	16%
Health Technology	27	12%
Process Industries	21	9%
Consumer Non-Durables	14	6%
Industrial Services	13	6%
Electronic Technology	12	5%
Retail Trade	12	5%
Transportation	12	5%
Consumer Services	11	5%
Commercial Services	10	4%
Consumer Durables	10	4%
Energy Minerals	10	4%
Non-Energy Minerals	10	4%
Energy Minerals	9	4%
Technology Services	9	4%
Communications	7	3%
Distribution Services	7	3%
Utilities	2	1%
Total	**233**	**100%**

Geographic origin of sample firms

Orderd by Country	*No. of firms*	*% of sample*
Denmark	52	22%
Finland	35	15%
Iceland	11	5%
Norway	21	9%
Sweden	114	49%
Total	**233**	**100%**