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THE PRICING ACCURACY OF THE UNBIASED RIV MODEL

A study on the pricing accuracy of the residual income valuation (RIV) model using unbiased accounting: Evidence on Nordic data

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Abstract

This paper aims to investigate whether the pricing accuracy of the *RIV* model is improved with unbiased accounting. The introduction of the Feltham-Ohlson model has left researchers with an eagerness to propose a *RIV* model with high pricing accuracy. While prior researchers within the field have dedicated their attention to the effects stemming from the choice of value driver, length of explicit forecast horizon and horizon value, the effects stemming from the accounting itself has been left unanswered. We introduce an unbiased *RIV* model, neutralised any accounting policy, and compare its pricing accuracy with the base *RIV* model. Our unbiased *RIV* model is derived by assessing firm-specific accounting measurement bias for each firm in our data sample, comprising listed firms in the Nordics. Our results show that the pricing accuracy of the *RIV* model is consistently higher with unbiased accounting. Thus, we find that the pricing accuracy is improved with the unbiased *RIV* model regardless of model adjustments and across industries, countries and valuation time periods evaluated in this paper. Moreover, our research shows that the pricing accuracy of the *RIV* model changes in different valuation settings, which bring valuable insights for practitioners of the *RIV* model. We evaluate the size of measurement bias as the driving cause for this and find that the largest incremental improvements in the pricing accuracy of the unbiased *RIV* model appear in valuation settings where the accounting measurement bias is inherently higher.

Keywords: Pricing accuracy, Residual income valuation, Unbiased accounting, Accounting measurement bias, Conservative accounting

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1. INTRODUCTION

Fundamental valuation is the process of estimating firm value using accounting information. Three value concepts arise from this process: book value, economic value, and market value, all coinciding in an ‘ideal’ world without uncertainty (e.g., Runsten, 1998; Lee, 1999). Given the uncertainty of the future, fundamental valuation encompasses aspects of both art and science. In the dividend discount model (*PVED*), firm value hinges on expected dividends to shareholders, a concept Penman (1992) finds inconsistent to established finance theory, referencing the influential work of Miller and Modigliani (1961) on dividend policy irrelevancy of value. The residual income valuation (*RIV*) model by Ohlson (1995) and Feltham and Ohlson (1995) resolves 'the dividend conundrum' by anchoring value to accounting information while presuming dividend policy irrelevancy (e.g., Lundholm, 1995; Lo & Lys, 2000). While the Feltham-Ohlson model is a distinctive contribution to the research field in valuation theory, it presents apparent implementation issues concerning forecasting for going concerns to infinity (e.g., Penman, 1997; Dechow *et al.*, 1999; Myers, 1999). This has left researchers eager to find the *RIV* model yielding the highest pricing accuracy.

Prior research on pricing accuracy has positioned the *RIV* model as a high-quality valuation model. Its distinctive strength stems from its ability to link accounting information to firm value (e.g., Lee, 1999; Penman, 2012), although the degree of relevance and reliability of this information in asserting firm value may be less pronounced. Extensive evidence in prior research suggests that the *RIV* model consistently understates contemporaneous market value (see e.g., Francis *et al*., 2000; Anesten *et al*., 2020), indicative of an inherent conservative bias rooted in the adherence to predetermined accounting standards. This accounting measurement bias is unique to each firm and involves unrealised values encapsulated in the past due to conservative measurement of assets and liabilities (e.g., Gjesdal, 1999; Zhang, 2000; Beaver & Ryan, 2000). Several attempts have been made to derive the size of this measurement bias with varied outcomes (see e.g., Fruhan, 1979; Runsten, 1998), with Runsten (1998) defines it as ‘a difficult task’. Runsten (1998) argues that its difficulty arises from the combined mix of investment types and the continuous flows of investments, which are amplified by changes in the general business climate and operational business activities. The extent to which the firm-specific measurement bias affects the pricing accuracy of the *RIV* model remains unanswered in attempts to derive the highest pricing accuracy.

To understand the implication of the measurement bias in a valuation setting, this paper seeks to investigate whether the pricing accuracy of the *RIV* model is enhanced by using unbiased accounting. From what we know, the question is novel, bridging two previously unmerged research fields concerning the pricing accuracy of the *RIV* model and accounting measurement bias. Therefore, this paper has considerable implications on the perception of the *RIV* model as an equity valuation model among researchers, practitioners, regulators, and other common users. The research question for this paper is formulated as follows:

Does unbiased accounting improve the pricing accuracy of the RIV model?

The remainder of this paper is structured as follows; In the second chapter, an introduction to the *RIV* model is provided, along with an overview of prior empirical research on the pricing accuracy of the *RIV* model. In the third chapter, we integrate insights from prior empirical research to develop our research design to answer the research question of this paper. In the fourth chapter, an overview of the sample selection is provided, from the selection criteria to the derived final sample. In the fifth chapter, our results are presented, coupled with a brief discussion on how the results relate to prior empirical research. In the sixth and final chapter of this paper, we offer concluding remarks and implications, and identify areas of interest for further investigation.

2. LITERATURE REVIEW

This chapter reviews three blocks of literature relevant to the present study. The first block offers an exposition of the residual income pricing (*RIV*) model and is delineated to provide a fundamental understanding. The second block presents accounting policy and its implication on the *RIV* model as an accounting-based valuation model. The third block presents prior research on the pricing accuracy of the *RIV* model. Finally, the chapter concludes with our contributions to the research field.

2.1 THE RESIDUAL INCOME VALUATION MODEL

The roots of the *RIV* model trace back to Preinreich (1938), Edwards & Bell (1961), and Peasnell (1982). However, it has gained recognition more contemporarily through versions presented by Ohlson (1995) and Feltham and Ohlson (1995).

2.1.1 Derivation of the RIV model

The *RIV* model links accounting information to firm value (e.g., Preinreich, 1938; Edwards & Bell, 1961; Ohlson, 1995). Book value of owners' equity is the anchor, enabling investors to direct attention on surplus value not acknowledged in the current book value (e.g., Preinreich, 1938; Skogsvik, 2002; Penman, 2012). Elaborating on this, the intrinsic value of equity may be articulated as follows:

$$V_0 \quad = BV_0 + \text{Premium} \tag{1}$$

where:

$V_0 = \text{economic value of owners}'\text{equity at time } t = 0,$

$BV_0 = \text{book value of owners}'\text{equity at time } t = 0,$

$\text{Premium} = \text{value added to book value of owners}'\text{equity at time } t = 1, 2, 3, \ldots \infty.$

Value accrues to the book value when the rate of return surpasses the required return, commonly termed excess profits, abnormal earnings, or residual income (the latter term is adopted here). The concept of residual income can be traced to Preinreich (1938) on depreciation theory, wherein assets necessitate continual evaluation in the context of replacement and opportunity costs. The formulation of residual income, as delineated by Skogsvik (2002), is presented below.

$$RI_t \quad = NI_t - \rho_E * BV_{t-1} = (ROE_t - \rho_E) * BV_{t-1} \tag{2}$$

where:

RI_t = residual income, accrued in period t,

NI_t = accounting net income, accured in period t,

ρ_E = required return on owners′equity,

BV_{t-1} = opening book value of owners′equity at $t = 1$,

ROE_t = book return on owners′equity, accrued in time t.

Combining Eq. (1) and (2) yields the Feltham-Ohlson model, as introduced by Ohlson (1995) and Feltham and Ohlson (1995). The model is articulated as follows:

Feltham-Ohlson model:

$$V_0(RIV_{FOM}) \quad = BV_0 + \sum_{t=1}^{\infty} \frac{(ROE_t - \rho_E) * BV_{t-1}}{(1 + \rho_E)^t} \tag{3}$$

In accordance with the *RIV* model posited by Feltham and Ohlson (1995), the intrinsic value of equity comprises the anchoring value and the present value of expected residual income in perpetuity (e.g., Ohlson, 1995; 2001; Feltham & Ohlson, 1995; Bernard, 1995; Lundholm, 1995; Penman, 1997).

2.1.2 Underlying assumptions

The Feltham-Ohlson model relies primarily on three key assumptions: i) the present value of expected dividends, ii) adherence to the 'clean surplus relation', and iii) linear information dynamics.

Present value of expected dividends

Firstly, the intrinsic value of equity equates to the present value of expected dividends, rooted in the work by Miller and Modigliani (1961) on the irrelevance of dividend policy in determining value (e.g., Bernard, 1995; Lundholm, 1995; Lee *et al.*, 1999). This formulation can be expressed as:

$$V_0(PVED) \; = \sum\nolimits_{t=1}^{\infty} \frac{DIV_t}{(1+\rho_E)^t} \tag{4}$$

where:

$DIV_t =$ dividend paid to the shareholder of the company at time t.

Clean surplus relation

Secondly, the model necessitates the adherence to 'clean surplus relation' (*CSR*) in each period, implying that net income, dividends, and new issuances of share capital account for changes in the book value during a fiscal period (e.g., Bernard, 1995; Lundholm, 1995; Skogsvik, 1998; Johansson & Runsten, 2005). This formulation can be expressed as:

$$D_t - N_t = BV_{t-1} + NI_t - BV_t = BV_{t-1} * ROE_t - (BV_t - BV_{t-1}) \tag{5}$$

where:

$N_t =$ new issue of share capital at time t.

Linear information dynamics

The final assumption pertains to linear information dynamics (*LID*). This assumption posits that expected residual income conforms to a linear function of current residual income and other information pertinent to value (e.g., Ohlson, 1995; 2001; Feltham & Ohlson, 1995). Both residual income and additional value-relevant information are assumed to follow mean-reverting processes in the *LID* assumption, indicated by the persistence parameters ω and γ (e.g., Ohlson, 1995; 2001; Feltham & Ohlson, 1995; Bar-Yosef *et al.*, 1996; Dechow *et* *al.*, 1999; Myers, 1999). Assuming the validity of the *LID* assumption, expected residual income (RI_{t+1}) is subject to the persistence parameter ω and can be expressed as follows:

$$RI_{t+1} \quad = \omega RI_t + v_t + \varepsilon_{t+1} \tag{6}$$

where:

ω = persistence parameter of residual income at time t,

v_t = other relevant information parameter at time t,

ε_{t+1} = residual parameter at time $t+1$.

Conversely, assuming the *LID* assumption holds, the expected additional value-relevant information (v_{t+1}) is subject to the persistence parameter γ and can be expressed as:

$$v_{t+1} \quad = \gamma v_t + \varepsilon_{t+1} \tag{7}$$

where:

γ = pesistence parameter of other relevant information at time t.

The *LID* assumption enables operationalisation of the *RIV* model using historical accounting information without incorporating an expression for horizon value (e.g., Dechow *et al.*, 1999; Myers, 1999; Ali *et al.*, 2003; Choi *et al.*, 2006).

2.2 ACCOUNTING POLICY AND CONCEPTS OF VALUE

Accounting information and stock prices are interconnected through three value concepts (Runsten, 1998). The book value is anchored to accounting information following predefined accounting standards. Conversely, the economic value is rooted in forward-looking assessments derived from accessible accounting information, while market value represents the exchange between investors (e.g., Runsten, 1998; Lee, 1999; Barker, 2015). These concepts of value coincide in an 'ideal' world without uncertainty (Runsten, 1998).

2.2.1 Value creation principles

The *RIV* model operates under two principles of value creation: anchoring principle and value conservation principle.

Anchoring principle

The anchoring principle posits that the economic value of equity cannot surpass the anchoring value, specifically the book value of owners' equity unless there is an anticipation of additional value being augmented to the book value in subsequent periods (e.g., Penman & Zhang, 2002; Skogsvik, 2002; Penman, 2012). Penman (2012) delineates this principle as follows:

'If one forecasts that an asset will earn a return on its book value equal to its required return, it must be worth its book value.'(Penman, 2012, p.145)

The anchoring principle intertwines closely with the value premium in Eq. (1) and the Price-to-Book *(P/B)* ratio, suggesting that a *P/B* ratio exceeding (falling below) one signifies future value creation (deterioration) (see e.g., Fama & French, 1995; Fairfield, 1994; Bernard, 1995; Beaver & Ryan, 2000).

Value conservation principle

The value conservation principle implies that the choice of accounting policy bears no relevance to the economic value (e.g., Lundholm, 1995; Penman, 2012; Koller *et al.*, 2020). This principle within the *RIV* model traces its origins to Preinreich (1938) on depreciation theory, asserting that the bookkeeping of assets cannot impact the intrinsic or 'true' value unless something is done to the asset that influences its capacity to generate income streams. Penman (2012) articulates this principle:

'An accounting method that changes current book value changes future residual income, but it does not change the value calculated because the change in residual income is exactly offset, in present value terms, by the change in current book value' (Penman, 2012, p.558)

The value conservation principle suggests that regardless of accounting policy – conservative or unbiased – the economic value should remain unaffected, *ceteris paribus* (e.g., Lundholm, 1995; Penman & Zhang, 2002; Penman, 2012). This principle is often seen as valid only in theory in a world of uncertainty and complexity (e.g., Runsten, 1998; Lee, 1999).

2.2.2 Accounting policy

As per the guidelines established by the International Accounting Standards Board (IASB), the overarching objective of financial reporting is to furnish pertinent financial information to stakeholders, encompassing current and potential shareholders, lenders, and other creditors, enabling informed decision-making regarding resource allocation to an entity (IASB, 2018, 1.2). Consequently, financial reporting does not directly involve estimating the worth of a business enterprise, but the information it furnishes may bear relevance to assert its value (e.g., Runsten, 1998; Lee, 1999; Barker, 2015).

Conservative accounting

Researchers have presented a wide array of definitions for 'conservative accounting'. For this paper, we adopt the definition by Penman and Zhang (2002): the choice of accounting practices that consistently reduces book values of net assets. Consistent with this definition, conservative accounting favours the ‘last in, first out’ (*LIFO*) method for inventory accounting over the ‘first in, first out’ (*FIFO*) method, expense treatment of research and development (*R&D*) expenses instead of capitalisation and amortisation, and shorter economic asset lives for depreciation of long-lived assets (e.g., Runsten, 1998; Penman & Zhang, 2002). Conservative accounting does also encompass practices that inflate estimations for doubtful accounts, sales returns, warrant liabilities and other liabilities (e.g., Fruhan, 1979; Runsten, 1998; Gjesdal, 1999; Zhang, 2000; Beaver & Ryan, 2000).

Practices that involve conservative accounting leads to accounting measurement bias (referred to as ‘measurement bias’). The measurement bias encapsulates income that has remained unrealised in the past due to conservative accounting policies (e.g., Fruhan, 1979; Runsten, 1998; Penman & Zhang, 2002; Penman, 2012). Different types of business activities result in varying degrees of measurement bias, largely explained by asset structures and common investment types to run day-to-day operations (e.g., Fruhan, 1979; Runsten, 1998; Penman & Zhang, 2002). Runsten (1998) argues that the most significant sources of measurement biases for any firm include:

i) *Inventory and work in progress*: Measurement bias traced to inventory stems from unrealised holding gains on inventory valued by the *FIFO* method (e.g., Runsten, 1998; Penman & Zhang, 2002). Typical examples of firms with measurement bias largely driven by inventory include consumer goods and firms with projects having long production cycles, and significant accumulated income reported through the 'completed contract method' (e.g., building and construction firms).

ii) *Tangible assets*: Measurement bias attributable to tangible assets is mainly related to unrealised holding gains resulting from the value disparity between the carrying amount using historical cost and ‘ideal’ measurement of the asset (e.g., Johansson & Östman, 1995; Runsten, 1998). Typical examples with high measurement biases are firms with large proportions of long-lived assets (e.g., real estate, pulp and paper, shipping, investment companies, capital-intensive services and other typical holders of long-lived assets).

iii) *Intangible assets*: Measurement bias stemming from intangible assets results from expense treatment of investments yielding future benefits for the firm in the shape of a hidden assets (see e.g., Fruhan, 1979; Runsten, 1998; Penman & Zhang, 2002; Penman, 2012). Investments in *R&D* and advertising are considered major drivers of this measurement bias (Runsten, 1998). Runsten (1998) argues that typical *R&D*-intensive firms include pharmaceutical, software and other 'high-tech' firms, while advertising investments are commonly executed by firms within consumer goods, engineering, trading and retail and other brand-intensive firms.

iv) *Deferred tax*: Deferred tax arises from temporary differences between an asset's carrying amount and tax base. Measurement bias traced to understated book values of assets represent unrealised income in the past, leading to additional deferred tax liabilities (*DTL*) (Runsten, 1998). Recorded deferred tax assets (*DTA*) and *DTL* are do also possess inherent measurement bias for firms of any type (Runsten, 1998).

Changes in business climate amplify the size of measurement bias. Typical examples encompass changes in the general economic cycle, inflation rates, foreign exchange rates, trade agreements, tax regulations, and accounting policies (e.g., Fruhan, 1979; Johansson & Östman, 1995; Runsten, 1998). Noteworthy factors for estimating the measurement bias, irrespective of industry, include general economic growth and inflation changes, according to Runsten (1998). Fluctuations in the economic growth not only influence the inclination towards investment in *R&D* and advertising but also impact asset structures through replacing older assets with new (e.g., Johansson & Östman, 1995; Runsten, 1998). Similarly, variations in the inflation rates induce fluctuations in unrealised holding gains from tangible assets on the balance sheet (e.g., Johansson & Östman, 1995; Runsten, 1998).

Unbiased accounting

A benchmark to conservative accounting lies in unbiased accounting, also known as 'neutral accounting'. Unbiased accounting implies that recorded book values are neither understated nor overstated, signifying a complete reflection of the theoretical 'ideal' of economic value (e.g., Runsten, 1998; Zhang, 2000; Penman & Zhang, 2002; Penman, 2012; Barker, 2015). Unbiased accounting leads to no measurement bias being created stemming from the choice of accounting policy (e.g., Runsten, 1998; Skogsvik, 1998; Penman & Zhang, 2002).

2.2.3 Valuation implications of accounting policies

Firms are incapable of generating residual income in perpetuity. Competitive forces prevent that from happening, making residual income disappear over time until the competitive advantages are exploited and competition normalised around an equilibrium (see e.g., Ohlson, 1995; Skogsvik, 1998). Robust empirical evidence by Porter (1980) supports that line of argument, but also Fama and French (2000) and Nissim and Penman (2001). The point in time where the so called 'business goodwill' (or badwill) is normalised is referred to as steady state and competitive equilibrium (henceforth $SS\&COMPEQ)$, implying that *0-NPV* projects are the only ones being executed, and thus, no additional residual income is generated (e.g., Runsten, 1998; Skogsvik, 1998; 2002; Penman, 2012). This concept of value creation does only hold in settings with unbiased accounting principles (e.g., Runsten, 1998; Skogsvik, 1998; Penman & Zhang, 2002). It can be expressed in the following way:

'An unbiased accounting regime is defined to imply that in the absence of expected abnormal performance, accounting equity will equal economic value and that expected accounting return will simultaneously equal the required rate of return for all future periods.' (Runsten, 1998, p.25)

Conservative accounting imply that residual income is generated despite no value being created from ‘business goodwill’ (see e.g., Skogsvik, 1998; Beaver & Ryan, 2000; Penman & Zhang, 2002). As a result of conservative accounting, the quality of reported earnings and the numbers reported on the balance sheet is significantly lowered, entailing higher subsequent accounting rates of return despite no further value being created, *ceteris paribus* (e.g., Beaver & Ryan, 2000; Penman & Zhang, 2002; Penman, 2012). Relative measurement bias, also referred to as ‘business-to-goodwill’ or ‘q-value’ by Skogsvik (1998), aggregates the two drivers of abnormal performance for a firm: the business goodwill and accounting measurement bias (e.g., Runsten, 1998; Skogsvik, 1998; 2002; Feltham & Ohlson, 1995). It can be decomposed as follows:

$$q(BV)_T \quad = q(BG)_T + q(MB)_T \qquad (8a)$$

where:

$q(BV)_T =$ total relative measurement bias of owners′equity at time T,

$q(BG)_T =$ relative business goodwill (or badwill) measurement bias at time T,

$q(MB)_T =$ relative accounting measurement bias at time T.

Relative measurement bias stems from Brief and Lawson (1992) and the idea of a ‘horizon premium’ representing the excess absolute value of expected economic value over the book value at the horizon point in time (i.e., $t = T$). The expected horizon premium is set in proportion to the book value to extract the relative measurement bias (e.g., Runsten, 1998; Skogsvik, 1998; 2002). In practice, the horizon premium is commonly estimated at valuation date, implying that $q(BV)_0$ is assumed to be $q(BV)_T$. The derivation of the measure can be expressed in the following way:

$$q(BV)_T \quad = \frac{V_T - BV_T}{BV_T} \rightarrow V_T - BV_T = BV_T * q(BV)_T \qquad (8b)$$

where:

$V_T =$ expected economic value of owners′equity at time T,

$ROE_{ss} =$ book return on owners′equity, accrued in steady state,

g_{ss} = growth of owners′equity, accrued in steady state.

Accounting for the measurement bias in the *RIV* model

Given what has now been stated, the Feltham-Ohlson model can be modified for an expression for horizon value capturing impacts from the applied accounting policy. The first model, using the idea of an expected horizon premium, can be expressed as follows:

$$V_0 \quad = BV_0 + \sum_{t=1}^{T} \frac{(ROE_t - \rho_E) * BV_{t-1}}{(1+\rho_E)^t} + \frac{V_T - BV_T}{(1+\rho_E)^T} \tag{9}$$

Applying the derivation in Eq. ($8b$) with Eq. (9), we derive a second *RIV* model with a horizon value based on the concept of relative measurement bias (henceforth 'base *RIV* model'). The formula can be expressed as follows:

Base model:

$$V_0(RIV_{BM}) \quad = BV_0 + \sum_{t=1}^{T} \frac{(ROE_t - \rho_E) * BV_{t-1}}{(1+\rho_E)^t} + \frac{q(BV)_T * BV_T}{(1+\rho_E)^T} \tag{10}$$

2.3 PRIOR EMPIRICAL RESEARCH ON PRICING ACCURACY

This section covers prior research on the pricing accuracy of the *RIV* model. Several branches have appeared in the *RIV* model literature with distinguished perceptions of the driving cause of mispricing. Despite all branches being critical, this paper directs peculiar attention toward the group of studies on the pricing accuracy of the *RIV* model, assuming market efficiency maintained.

Pricing accuracy of the *RIV* model

One of the first studies to find empirical support for the *RIV* model is Penman and Sougiannis (1998). The authors assume market efficiency maintained to examine the valuation bias of the *RIV* model based on *ex-post* realised values, with analysis conducted at the portfolio level. Penman and Sougiannis (1998) find that the *RIV* model outperforms the *PVED* and *DCF* model in terms of valuation bias, exhibited through lower pricing errors. The authors identify GAAPinduced conservatism to be a key driver behind the empirical findings, leading to adverse effects on the pricing accuracy due to future cash flows integrated in the *PVED* and *DCF* model being pushed forward. More importantly, a significant contribution is made regarding impacts from the length of explicit forecast horizon, with the authors evaluating the models based on forecast periods ranging from one, two, three, six, eight, and ten years of horizon point in time (i.e., $T = 1, 2, 3, 6, 8,$ and 10). The authors observe that the variations in the length of the explicit forecast horizon leads to divergent preferences for valuation models, with the *RIV* model being superior in all but $T = 6$ and $T = 10$.

Francis, Olsson, and Oswald (2000) build on the assumptions of market efficiency maintained to examine the pricing accuracy of the *RIV*, *PVED* and discounted cash flow (*DCF*) model. The authors are among the first researchers to apply analysts' forecasts as value driver in the *RIV* model, with most prior researchers dedicating their interests to the implications of the proposed *LID* assumption in the Feltham-Ohlson model (e.g., Dechow *et al.*, 1999; Myers, 1999). The authors find support for analysts' forecasts leading to smaller pricing errors across all valuation models, later reinforced by the work of Liu, Nissim and Thomas (2002). Francis *et al.* (2000) also provide empirical support for the *RIV* model in terms of pricing accuracy and explainability of stock prices. The authors argue that the *RIV* model's outperformance could be traced to the predictability and magnitude of the anchoring value, accounting for as much as 72% of firm value across firms. In contrast, for the *PVED* and *DCF* model, uncertainty is deferred to the horizon value, explaining 65% (82%) of the firm value with the *PVED* (*DCF*) model, compared to a significantly lower 21% with the *RIV* model. Francis *et al.* (2000) also discover that the pricing accuracy varies among firms with differing levels of *R&D*.

Jorgensen, Lee, and Yoo (2011) apply the insights in prior research to conduct a comprehensive study on the pricing accuracy of three different versions of the *RIV* model. Drawing upon prior research, the authors further research the dynamics related to length of explicit forecast horizon and alternative approaches to derive the horizon value. Applying analysts' forecasts as value driver, Jorgensen *et al.* (2011) confirm what has been inferred by Penman and Sougiannis (1998) and Francis *et al.* (2000), namely that the pricing accuracy of the *RIV* model is superior to other valuation models. The authors find that the *RIV* model understates contemporaneous stock prices, confirming the wide range of researchers making the same observation in the U.S. (e.g., Bernard, 1995; Penman & Sougiannis, 1998; Dechow *et al.*, 1999; Myers, 1999; Francis *et al.*, 2000; Courteau *et al.*, 2001; Choi *et al.*, 2006). The authors find that an extension of the explicit forecast horizon from two (i.e., $T = 2$) to five years (i.e. $T = 5$) increase pricing errors of the *RIV* models, confirming the observations made by Lee, Myers and Swaminathan (1999). The findings on the pricing accuracy of the *RIV* model by Jorgensen *et al.* (2011) stand out among the prior research conducted on U.S. data with pricing errors ranging between 0.01 and 0.07 for mean 'signed' pricing errors.

Anesten, Möller, Skogsvik and Skogsvik (2020) synthesise concepts to extend the empirical research on pricing accuracy of the *RIV* model to the Nordic region. Coupled with McCrae and Nilsson (2001), who focus solely on Swedish data, the area is mainly left unexploited for closer examination of the pricing accuracy of the *RIV* model. Similar to research conducted on U.S. data, Anesten *et al.* (2020) find that the *RIV* model outperforms other models. While agreeing with the advantageous effects of the anchoring value, the authors raise its implications for conservatism. Arguably, one of the main contributions of this paper is related to the model adjustments, encompassing single and multiple-step adjustments for the explicit forecast horizon, bankruptcy risk, and transitory items. In the former, the authors find support for Ohlson and Zhang (1999), Frankel and Lee (1998) and Kuo (2015), indicating that an extension of the explicit forecast horizon from two (i.e., $T = 2$) to five years (i.e., $T = 5$) improve the pricing accuracy of the *RIV* model. This is, however, in contrast to the observations made by other researchers (see e.g., Lee *et al.*, 1999; Jorgensen *et al.*, 2011). Table 1 presents key findings in prior research on the pricing accuracy of the *RIV* model.

Table 1: Prior research on pricing accuracy of the RIV model

Author/-s	Sample	Forecast horizon	Value driver	*'Signed' pricing error (PE)* *Mean PE*	*Median PE*	*SD PE*	Key findings
Penman and Sougiannis (1998)	U.S. 1973-1992	$T = 1 \rightarrow 10$	*Ex*-post realised values	---	---	---	*RIV* model understate contemporaneous stock prices. Higher valuation accuracy compared to *DCF* and *PVED* model every time apart from $T = 6$ and $T = 10$.
Francis, Olsson and Oswald (2000)	U.S. 1989-1993	$T = 5$	Analysts'forecasts & *ex*-post realised values	-0.20 -0.13	-0.28 -0.23	---	*RIV* model outperforms *DCF* and *PVED* model. Smaller pricing errors using analysts' forecasts. Anchoring value driver of superior pricing accuracy for the *RIV* model.
Courteau, Kao and Richardson (2001)	U.S. 1992-1996	$T = 5$	Analysts' forecasts	-0.34 -0.30	-0.38 -0.34	0.28 0.31	*RIV* model does not outperform *DCF* model. Identifies inconsistent applications of horizon value.
McCrae and Nilsson (2001)	Swedish 1987-1997	$T = 3$	Analysts' forecasts	-0.49 -0.31 -0.21	---	0.79 0.51 1.27	*RIV* model with analysts' forecasts improves the pricing accuracy. Higher pricing errors and spreads compared to prior research in the U.S.
Jorgensen, Lee and Yoo (2011)	U.S. 1984-2005	$T = 2$ & 5	Analysts' forecasts	0.09 0.07 0.01	-0.06 -0.08 -0.10	0.59 0.51 0.43	*RIV* model exhibit very low pricing errors. Observe discrepancies across *RIV* models with different horizon values. Extended forecast horizon increases pricing errors.
Chang, Landsman and Monahan (2012)	U.S. 1980-2010	$T = 5$ & 15	Analysts' forecasts & naïve approach	-0.37 -0.26	-0.40 -0.31	0.57 0.98	*RIV* model exhibit low pricing errors. Observe discrepancies across *RIV* models with different value drivers and length of forecast horizon. Directs criticism to Jorgensen, Lee and Yoo (2011) with 'no single best model' in pricing accuracy.
Ho, Lee, Lin and Yu (2017)	U.S. 1985-2013	$T = 5$	Analysts' forecasts	-0.01 0.19	-0.02 0.06	0.30 0.79	*RIV* model exhibit higher pricing errors compared to the *AEG* model.
Anesten, Möller, Skogsvik and Skogsvik (2020)	Nordic 2004-2013	$T = 3$ & 5	Analysts' forecasts & historical approach	-0.11 0.17 -0.29 -0.31	-0.25 -0.04 -0.40 -0.47	0.54 0.92 0.71 0.61	*RIV* model understate contemporaneous stock prices. Superior pricing accuracy most of the time compared to *PVED*, *AEG* and *AEG (OJ)* model. Extended forecast period and analysts' forecast improve pricing accuracy of the *RIV* model.

Notes:
This table presents the key takeaways from prior research on pricing accuracy of the *RIV* model. 'Signed' pricing error (*PE*) have been extracted for the *RIV* models in the papers of interest. *Mean PE*, *Median PE* and standard deviation (*SD*) of *PE* have been evaluated to assess pricing accuracy of the *RIV* model. *Mean PE* and *Median PE* close to zero indicate high pricing accuracy while negative values indicate understatement of contemporaneous stock prices. *SD PE* indicate spread of the observations of *PE*, where a low (high) values indicate high (low) pricing accuracy.

Horizon value

Prior research has witnessed the emergence of a wide range of expressions for the horizon value, a response to the practical challenges associated with going concerns implying an infinite forecast period in the Feltham-Ohlson model (e.g., Penman, 1997; Dechow *et al.,* 1999; Myers, 1999). Courteau, Kao and Richardson (2001) and Lundholm and O'Keefe (2001) take a sceptical stance on the horizon values proposed in prior research, suggesting that support for the *RIV* model can be attributed to the inconsistent measurements of horizon value. When using a price-based terminal value, as advocated by Penman (1997), Courteau *et al.* (2001) find that the *DCF* model outperforms the *RIV* model in terms of pricing accuracy. Jorgensen *et al.* (2011) have further delved into the relevance of horizon value for the pricing accuracy of the *RIV* model. The authors discover that the pricing accuracy of the *RIV* model is contingent on applied horizon value, leading to the range of 0.31 and 0.40 in observed mean 'absolute' pricing errors solely stemming from contingency related to the horizon value.

Market efficiency

The pricing accuracy of the *RIV* model is examined assuming maintained market efficiency. This implies that pricing accuracy is determined by the difference between the economic value generated by the *RIV* model and contemporaneous stock prices, assuming the latter is a proper reflection of 'true' intrinsic value (e.g., Francis *et al.,* 2000; Courteau *et al.,* 2001; Anesten *et al.,* 2020). As such, valuation models exhibiting lower dispersion between the values (referred to as pricing error) indicate higher pricing accuracy and quality of the model (see section 3.6) (e.g., Francis *et al.,* 2000; Jorgensen *et al.,* 2011; Anesten *et al.,* 2020). This implies that variations in market efficiency are disregarded. Skogsvik and Skogsvik (2010) discern the meaning of market mispricing into forecasting and modeling mispricing, indicating incomplete reflection of the information in contemporaneous stock prices. Anesten *et al.* (2020) show in a derivation that high-quality valuation models should exhibit pricing errors close to zero in unbiased pricing and valuation model settings, while higher spreads of pricing errors could indicate lower stock market efficiency.

2.4 CONTRIBUTION

In prior empirical research (summarised in Table 1), the *RIV* model emerges as a high-quality valuation model with superior pricing accuracy compared to other models (e.g., *PVED, AEG, DCF*). Some researchers examine the effects from different value drivers, commonly broken down to analysts' forecasts versus alternative historical approaches (e.g., *LID* approach, three-year historical *ROE* or naïve approach) (e.g., Frankel & Lee, 1998; Lee *et al.*, 1999; Abarbanell & Bernard, 2000). A handful of researchers in the research field examine the implications of extended explicit forecast horizons (see e.g., Jorgensen *et al.*, 2011; Anesten *et al.*, 2020), while others dedicate interests to discussions about horizon value (see e.g., Courteau *et al.*, 2001; McCrae & Nilsson, 2001; Jorgensen *et al.*, 2011). What distinguishes most prior papers from one another is the perception of market efficiency either being assumed to be maintained or not, depending on the purpose of the study. From what we know, no research has been conducted to explore the impacts of measurement bias on the pricing accuracy of the *RIV* model.

In this paper, we aim to investigate whether the pricing accuracy of the *RIV* model improves with unbiased accounting. While acknowledging the significance of prior research branches, this paper directs peculiar attention toward the group of studies presuming maintained market efficiency with contemporaneous stock prices considered as the presumed 'true' intrinsic value of equity (see e.g., Penman & Sougiannis, 1998; Courteau *et al.*, 2001). Thus, questions about market efficiency are left outside the scope of this paper. Our research question is novel, bridging two previously unmerged research fields concerning pricing accuracy and measurement bias. Thus, the main contribution of this paper is related to the disentanglement on how conservative accounting impacts the pricing accuracy of the *RIV* model. In addition, we contribute with further insights on the pricing accuracy of the *RIV* model in the Nordic region (e.g., McCrae & Nilsson, 2001; Anesten *et al.*, 2020) and whether the pricing accuracy is sensible to the applied valuation date, value driver, length of explicit forecast horizon and steady-state growth rate (e.g., Francis *et al.*, 2000; Jorgensen *et al.*, 2011; Chang *et al.*, 2012).

3. RESEARCH DESIGN

This section covers how our research question is examined. It starts with introducing the valuation models before going through them more deeply. The chapter also covers how the firm-specific measurement bias will be extracted in both models. This part will be followed by an overview of the metrics used to assess and compare pricing accuracy. Finally, the chapter will end with a brief introduction to our adjusted models, covering modifications for i) valuation date, ii) value driver, iii) length of explicit forecast horizon and iv) steady-state growth rate.

3.1 MODEL OVERVIEW

The formulas for the models are presented below. The base *RIV* model (RIV_{BM}) aims to capture the *RIV* model advocated across prior research (see e.g., Anesten *et al.*, 2020). The formula is expressed in the following way:

$$V_0(RIV_{BM}) \;= BV_0 + \sum_{t=1}^{T} \frac{(ROE_t - \rho_E) * BV_{t-1}}{(1+\rho_E)^t} \;+ \frac{q(BV)_T * BV_T}{(1+\rho_E)^T} \tag{10}$$

The aim of the unbiased *RIV* model (RIV_{UB}) is to compare RIV_{BM} with an alternative approach where unbiased accounting principles are accounted for in the *RIV* model. This model is critical to answer our research question. The formula is expressed in the following way:

$$V_0(RIV_{UB}) \;= BV_0^{UB} + \sum_{t=1}^{T} \frac{(ROE_t^{UB} - \rho_E) * BV_{t-1}^{UB}}{(1+\rho_E)^t} \tag{16}$$

Model specifications for the respective two models are presented below.

3.2 THE BASE RIV MODEL

The first valuation model in this paper is the base *RIV* model (RIV_{BM}). The purpose of applying RIV_{BM} in this paper is to have a benchmark model used in prior empirical research to assess the implications of unbiased accounting for the pricing accuracy of the *RIV* model.

3.2.1 Derivation of the base RIV model

The following notations are used when presenting the base *RIV* model (RIV_{BM}). We apply the same notations as Skogsvik (1998; 2002) and Anesten *et al.* (2020).

V_0 $= \text{economic value of owners'equity at } t = 0$

BV_0 $= \text{book value of owners'equity at } t = 0 \text{ (anchoring value)}$

BV_{t-1} $= \text{opening book value of owners'at time} = 1$

ROE_t $= \text{book return on owners'equity, accured in time } t$

DIV_t $= \text{dividend paid to the shareholder of the company at time } t$

N_t $= \text{new issue of share capital at time } t$

NI_t $= \text{accounting net income, accured in period } t$

ps_t $= \text{payout share of owners'equity at time } t$

ρ_E $= \text{required return on owners'equity}$

R_f $= \text{expected return on risk} - \text{free asset}$

μ_M $= \text{expected return on market portfolio}$

μ_i $= \text{expected return of holding asset } i$

β_i $= \text{beta of asset } i$

V_T $= \text{expected economic value of owners'equity at time } T$

$q(BV)_T$ $= \text{total measurement bias of owners'equity at time } T$

Model derivation

RIV_{BM} is based on the rationale of an expected horizon premium from Brief and Lawson (1992) to extract the relative measurement bias captured in the horizon value, as presented by Skogsvik (1998). The formula for RIV_{BM} is expressed in the following way:

$$V_0(RIV_{BM}) = BV_0 + \sum_{t=1}^{T} \frac{(ROE_t - \rho_E) * BV_{t-1}}{(1+\rho_E)^t} + \frac{q(BV)_T * BV_T}{(1+\rho_E)^T} \tag{10}$$

Consistent with the application of Eq. (10) is that is maintained at the horizon point in time (i.e., $t = T$). Accordingly, no business goodwill nor badwill are expected to be generated from $T+1$. This implies that Eq. (7) is assumed to be solely driven by $q(MB)_T$ where positive figures indicate conservative bias for the firm (see e.g., Skogsvik; 1998; 2002; Penman, 2012)

3.2.2 Model assumptions in the base RIV model

This section covers model assumptions for the base *RIV* model (RIV_{BM}). Although some are unique, most assumptions are shared with the unbiased *RIV* model (RIV_{UB}). Model assumptions unique for are denoted by 'RIV_{BM}'.

Value driver

Analysts' forecasts are used as value driver to derive residual income in the *RIV* model. This is consistent with a wide array of leading researchers in the field examining the pricing accuracy of the *RIV* model (see e.g., Bernard, 1995; Frankel & Lee, 1998; Francis *et al.,* 2000; McCrae & Nilsson, 2001; Liu *et al.,* 2002; Jorgensen *et al.,* 2011; Ho *et al.,* 2017; Anesten *et al.,* 2020). Consensus estimates on net income are sourced from the database S&P Capital IQ, a motivated database from perspectives of both accuracy of contemporaneous stock prices and extensive analyst coverage to ensure accuracy in forecasts. The motivation of a database is commonly derived from these narratives, although other researchers apply Value Line, I/B/E/S and Factset (see e.g., Bernard, 1995; Lee *et al.,* 1999; Liu *et al.,* 2002). Sensitivity tests have been done to ensure consistency with other databases and accuracy of financial and stock price information.

Valuation date

The valuation point (i.e., $t=0$) is assumed to be on 1 March 2023 (henceforth '2023'). This valuation date is motivated to ensure that financial information from the latest fiscal year (i.e., 2022) is publicly available to investors by the time the models are implemented. From perspectives of market efficiency, a longer duration after the earnings release is motivated to ensure analysts' forecasts and contemporaneous stock prices reflect all publicly available financial information (see e.g., Skogsvik & Skogsvik, 2010; Anesten *et al.,* 2020).

Explicit forecast horizon

An explicit forecast horizon of three years is applied (i.e., $t+3$). Thus, consensus estimates on net income are extracted for three fiscal years into the future. In cases where forecasts are unavailable for the third year, growth (parameter g) is calculated as the five-year historical average, aligned with what is advocated by Liu *et al.* (2002) and Jorgensen *et al.* (2011).

Following the three-year explicit forecast horizon of analysts' forecasts, the remaining years follow linear reversion of ROE for ten years until $SS\&COMPEQ$ is reached at the horizon point in time (i.e., $t = T$), aligned with Skogsvik (2002). Thus, the horizon point in time is set to $T = 12$, and firms are presumed to enter a steady state at $T + 1 = 13$. Our horizon point in time is set further into the future than most researchers who choose to disregard the idea of linear reversion of *ROE* advocated by Skogsvik (2002) (see e.g., Penman & Sougiannis, 1998; Abarbanell & Bernard, 2000; McCrae & Nilsson, 2001). Assumptions related to linear reversion of *ROE* stems from the *LID* assumption and is supported by the robust empirical evidence suggesting mean reversion of profitability (see e.g., Porter, 1980; Fama & French, 2000; Nissim & Penman, 2001).

Cost of equity

The required return on owners' equity, or 'cost of equity,' is the applied discount rate for the *RIV* model. The cost of equity is estimated using the Capital Asset Pricing Model (*CAPM*), which can be derived as the expected return of an asset given its systematic risks (e.g., Sharpe, 1964; Lintner, 1965; Black; 1972). It can be expressed in the following way:

$$\mu_i = R_f + \beta_i * \left(\mu_M - R_f\right) \tag{11}$$

The ten-year government bond yield is used as an approximation for risk-free rate (R_f), extracted for each Nordic country (Trading Economics, 2023a). The government bond of each market is utilised since the risk-free rate needs to be stated in the firm's functional currency i.e., the primary currency used for the economic activities (Koller *et al.*, 2020). Beta (β_i) is estimated for each firm, with three-year returns assessed with weekly frequency and compared to the stock returns from the local market index (see e.g., Liu *et al.*, 2002; Jorgensen *et al.*, 2011). Market risk premium is estimated by applying fixed expected market return (μ_M) based on the historical performance of stock market indices (Koller *et al.*, 2020). As such, the expected market return (μ_M) is set to 7.5% for all markets, aligned with the annual returns generated by stock market returns in each country (Trading Economics, 2023b).

Return on equity – Base *RIV* model (RIV_{BM})

The assumption of clean surplus relation (*CSR*) has prevailed in prior research on the *RIV* model since its introduction in the Feltham-Ohlson model (Ohlson, 1995; Feltham & Ohlson, 1995). *CSR* assumes the following:

$$DIV_t - N_t = BV_{t-1} + NI_t - BV_t = BV_{t-1} * ROE_t - (BV_t - BV_{t-1}) \tag{12}$$

For simplicity, it is assumed that firms are in healthy financial conditions, implying that no additional capital injection is needed to maintain business activities (i.e., $N_t = 0$) (Johansson & Runsten, 2014). Assuming that *CSR* holds in expectation, this implies that the book value of owners' equity can be explained by changes in net income and dividends (Johansson & Runsten, 2014). The implications of the *CSR* assumption can be re-expressed as:

$$BV_t = BV_{t-1} + (ROE_t * BV_{t-1}) - (ps_t * BV_{t-1}) \tag{13}$$

For Eq. (13) to hold, *ROE* can be defined as net income (*NI*) deflated by the opening balance of the book value of owners’ equity (Beaver & Ryan, 2000; Johansson & Runsten, 2014). The formula for *ROE* can be expressed in the following way:

$$ROE_t = \frac{NI_t}{BV_{t-1}} \tag{14}$$

ROE, as expressed in Eq. (14), is the applied definition of the accounting rate of return used for the base *RIV* model (RIV_{BM}). In steady state (i.e., $t = T + 1$), *ROE* is referred to as ROE_{ss} and can be explained as a function of the cost of equity and perpetual growth of measurement bias at the horizon point in time (i.e., $t = T$) (Skogsvik, 1998). The formula is expressed in the following way:

$$ROE_{ss} = \rho_E + q(BV)_T * (\rho_E - g_{ss}) \tag{15}$$

3.3 THE UNBIASED RIV MODEL

The second model in this paper is the unbiased *RIV* model (RIV_{UB}). The model has a different structure than the conventional *RIV* model (RIV_{BM}) applied in prior research due to the implications from unbiased accounting principles at the horizon point in time (i.e., $t = T$).

3.3.1 Model derivation of the unbiased RIV model

All notations presented for RIV_{BM} are also applicable on RIV_{UB}. Nonetheless, some additional clarifications are needed, all of which listed below.

BV_0^{UB} $= \text{unbiased book value of owners}'\text{equity at } t = 0$

BV_{t-1}^{UB} $= \text{opening unbiased book value of owners}'\text{equity at time } t$

$g(BV)_t$ $= \text{growth of book value of owners}'\text{equity, accrued in time } t$

ROE_t^{UB} $= \text{unbiased book return on owners}'\text{equity, accrued at time } t$

MB_t $= \text{total measurement bias at time } t$

$q(MB)_t$ $= \text{relative total measurement bias at time } t$

$g(MB)_t$ $= \text{growth of measurement bias, accrued in time } t$

Model derivation

Deriving the unbiased *RIV* model (RIV_{UB}), the starting point is RIV_{BM}, which is expressed in the following way:

$$V_0(RIV_{BM}) = BV_0 + \sum_{t=1}^{T} \frac{(ROE_t - \rho_E) * BV_{t-1}}{(1 + \rho_E)^t} + \frac{q(BV)_T * BV_T}{(1 + \rho_E)^T} \qquad (10)$$

With the measurement bias accounted for at the valuation point in time (i.e., $t = 0$), the accounting becomes neutral after that, implying that the accounting measurement bias (referred to as $q(MB)$) in Eq. (7) is zero at the horizon point in time (i.e., $t = T$). $SS\&COMPEQ$ still holds, meaning that business goodwill and badwill (referred to as $q(BG)$) is the sole driver of residual income until the horizon point in time (i.e., $t = T$). Unbiased accounting implies that markup on horizon value is transferred to anchoring value. The modifications of RIV_{BM} result in Eq. (15), presented below.

$$V_0 = BV_0^{UB} + \sum_{t=1}^{T} \frac{(ROE_t - \rho_E) * BV_{t-1}}{(1+\rho_E)^t} \tag{16}$$

To retain consistency in the valuation model, profitability and subsequent book values must be modified to account for unbiased accounting policy from the valuation date (i.e., $t = 0$). From this, we derive our expression for the unbiased *RIV* model (RIV_{UB}). The formula is expressed in the following way:

Unbiased model:

$$V_0(RIV_{UB}) \ = BV_0^{UB} + \sum_{t=1}^{T} \frac{(ROE_t^{UB} - \rho_E) * BV_{t-1}^{UB}}{(1+\rho_E)^t} \tag{17}$$

Consistent with the application of Eq. (17) is that $SS\&COMPEQ$ is maintained at the horizon point in time (i.e., $t = T$). As such, no business goodwill nor badwill is generated from $T + 1$.

3.3.2 Model assumptions in the unbiased RIV model

The unbiased *RIV* model (RIV_{UB}) is subject to further assumptions compared to the base *RIV* model (RIV_{BM}). Note that assumptions related to valuation date ($t = 0$), analysts' forecasts as a value driver and three-year explicit forecast horizon (i.e., $t + 3$) and cost of equity capital as discount rate also hold in the application of the unbiased *RIV* model (RIV_{UB}).

Book value on owners' equity – Unbiased *RIV* model ($\boldsymbol{RIV_{UB}}$)

With the measurement bias accounted for at the valuation point in time ($t = 0$), the choice of accounting policy does not impact the unbiased *RIV* model in subsequent periods. Shifting the measurement bias to $t = 0$ implies that the horizon value is wholly erased, that is, offset for a markup on the anchoring value. The effect on the anchoring value can be expressed as follows:

$$BV_0^{UB} = BV_0 + MB_0 = BV_0 + (q(MB)_0 * BV_0) \tag{18}$$

An important notation is that RIV_{BM} assume that the input variables for the measurement bias measured at time $t = 0$ serve as a reliable approximation for the horizon point in time (i.e., $t = T$). Supported by the findings by Runsten (1998), the size of measurement bias could be influenced by macroeconomic factors, regulatory changes and other factors in business climate which harms the validity of this assumption in RIV_{BM}. This assumption is wholly erased in RIV_{UB} when the measurement bias is accounted for already at $t = 0$, as reported by the most recent financial statements. For the explicit forecast horizon, the measurement bias derived at the valuation point in time (i.e., $t = 0$) and reflected in anchoring value is expected to grow in line with the remainder of book value of owners' equity. This is expressed in the following way:

$$BV_t^{UB} = (BV_{t-1} + MB_{t-1}) * \left(1 + g(BV_t)\right) \tag{19}$$

This definition of the anchoring value (BV_0^{UB}) and subsequent book values (BV_t^{UB}) are eligible only for RIV_{UB} application. We find no support for the derivation of Eq. (17) and (18) in the prior research; however, it relies heavily on the underlying value creation principles inherent in the *RIV* model.

Return on owners' equity – Unbiased *RIV* model (RIV_{UB})

Unbiased accounting implies that the sole driver of residual income is goodwill or badwill with impacts from the accounting measurement bias accounted for at $t = 0$ (Skogsvik, 1998). Skogsvik (1998) supports the derivation of 'true' *ROE* with unbiased accounting, showing that it is the expected *ROE* with conservative accounting, adjusted for the unrealised capital gains or the loss component of income stemming from the accounting measurement bias. The formula for the unbiased *ROE* can be expressed in the following way:

$$ROE_t^{UB} = \frac{ROE_t + q(BV)_t * g(MB)_t}{1 + q(BV)_t} \tag{20}$$

Consistent with the definition of unbiased accounting in Eq. (20), 'true' profitability is expected to disappear as firms enter $SS\&COMPEQ$, implying that:

$$ROE_{ss} = \rho_E + q(BV)_T * (\rho_E - g_{ss}) \rightarrow ROE_{ss}^{UB} = \rho_E \tag{21}$$

3.4 ESTIMATING THE MEASUREMENT BIAS

The measurement bias for the base *RIV* model (RIV_{BM}) and the unbiased *RIV* model (RIV_{UB}) is estimated for each firm. This implies that the measurement bias is calibrated for each firm by integrating investment types and flows to form asset structures which are unique for each firm. Our framework on how to estimate the firm-specific measurement bias is presented below.

Total measurement bias

The most significant sources of accounting measurement biases include inventory and work in progress, tangible assets, intangible assets and deferred taxes (see e.g., Fruhan, 1979; Runsten, 1998; Penman & Zhang, 2002; Penman, 2012). Thus, the total measurement bias for a firm can be expressed in the following way:

$$MB_{TOT,t} = MB_{Inv,t} + MB_{TA,t} + MB_{IA,t} - MB_{NDTL,t} \tag{22}$$

where:

$MB_{TOT,t}$ = total accounting measurement bias accrued until time t,

$MB_{Inv,t}$ = measurement bias of inventory accrued until time time t,

$MB_{TA,t}$ = measurement bias of tangible assets accured until time t,

$MB_{IA,t}$ = measurement bias of intangible assets accrued until time t,

$MB_{NDTL,t}$ = net DTL arising from additional and recorded deferred tax at time t.

To derive the relative measurement bias (i.e., $q(MB)_t$), the total accounting measurement bias (i.e., $MB_{TOT,t}$) is deflated by the opening balance of book value of owners' equity, accrued during the same period t. The formula can be expressed in the following way:

$$q(MB)_t = \frac{MB_{TOT,t}}{BV_t} \tag{23}$$

Inventory and work in progress

Measurement bias traced to inventory stems from unrealised holding gains on inventory valued by the *FIFO* ('first in, first out') method (Penman & Zhang, 2002). Assuming the *FIFO* method for inventory, finished goods (*FG*) and work in progress (*WIP*) is expected to exhibit the largest unrealised holdings gains, while raw materials are assumed to reflect contemporaneous replacement costs. Firms with long-term projects extending over fiscal periods typically exhibit larger value discrepancies between raw materials and finished goods. A markup on inventory is applied to finished goods to reflect these unrealised holdings gains. The formula can be expressed in the following way:

$$MU_{FG,t} = \frac{Operating\ profit_t}{Manufacturing\ cost_t} \tag{24}$$

where:

$MU_{FG,t}$ = markup on finished goods, accrued in time t.

The markup is applied to reported finished goods, but also half of the items reported as work in progress since being assumed to be finished by the valuation point in time (i.e., $t = T$). As such, total measurement bias attributable to inventory can be expressed as in the following way:

$$MB_{Inv,t} = \left[(FG_t * MU_{FG,t}) + (WIP_t * \frac{MU_{FG,t}}{2})\right] \tag{25}$$

where:

FG_t = finished goods recorded on balance sheet at time t,

WIP_t = work in progress recorded on balance sheet at time t.

Tangible assets

Tangible assets are generally valued at historical cost and linearly depreciated over a predefined economic life (e.g., Johansson & Östman, 1995; Runsten, 1998; Penman & Zhang, 2002). The accounting measurement bias attributable to tangible assets is mainly related to the unrealised holding gains resulting from the value disparity between the carrying amount using historical cost and the 'ideal' measurement of the asset (e.g., Johansson & Östman, 1995; Runsten, 1998). This 'ideal' measurement typically refers to the current cost method proposed by Edwards and Bell (1961) (see e.g., Runsten, 1998). Johansson and Östman (1995) argue that capital-intensive firms, common holders of longer-lived assets, may accumulate significant unrealised holding gains over extended periods, especially in high-inflationary environments.

Given an identified deprecation pattern (f), the measurement bias in the tangible assets can be extracted by setting the carrying amount using historical cost relative to its estimated value using the current cost method (e.g., Fruhan, 1979; Johansson & Östman, 1995; Runsten, 1998). The formula can be expressed in the following way:

$$MB_{TA,t} = \sum_{n=0}^{N} \left(\left(1 + i_{i,t}\right)^{n} - 1 \right) * \frac{A_{n,k}^{(r)}}{acc\left[A_{n,k}^{(r)}\right]} \tag{26}$$

where:

$i_{i,t}$ = local inflation rate for company i accured in time t,

n = age of asset where $n = 0, 1, 2, \dots N$,

$A_{n,k}^{(r)}$ = book value of n year old asset of type k (after depreciation),

$acc\left[A_{n,k}^{(r)}\right]$ = accumulated book value of k assets (after acc. depreciation).

We use the Consumer Price Index (*CPI*) as a measure for the inflation rate (i) in Eq. (26), consistent with Runsten (1998). For the application of Eq. (26), the following criteria need to be strictly fulfilled: i) investments are assumed to be executed at the beginning of each period, ii) assets are assumed to follow *FIFO* principles (i.e., assets still in the firm are classified as new while disposed assets are classified as old), iii) linear depreciation patterns for all assets and iv) economic life of each asset is determined by its depreciation pattern *f*.

Intangible assets

The measurement bias attributable to intangible assets is derived from hidden reserves in off-balance sheet items. These items commonly originate from investments in *R&D* or advertising, which consistently act as major influences on the measurement bias observed in firms operating in pharmaceutical, consumer goods and other 'high-tech' and brand-intensive firms (Runsten, 1998). The total measurement bias for the intangible assets is a function of i) already capitalised investments and ii) expensed but not capitalised investments.

Firstly, capitalised investments are visible in the recorded book values and must be estimated at their current cost from an identified deprecation pattern (f). The formula for measurement bias attributed to this source of intangible assets can be expressed as follows:

$$MB_{IA\,cap,t} = \sum_{n=0}^{N} \left[Inv_{IA,t} * (1 - t * f)\right] * (1 + i_{i,t})^{t} \tag{27}$$

where:

$MB_{IA\,cap,t} = measurement\ bias\ of\ capitalized\ investments\ accrued\ in\ time\ t,$

$Inv_{IA,t} =$ investment in intangibles made in time t.

Secondly, expensed investments are assumed to represent a value which should be capitalised. With no depreciation pattern (f) accessible, the first action requires capitalisation of previously expensed investments taking a predefined economic life (Runsten, 1998). Fruhan (1979) and Runsten (1998) both assert an economic life of ten years for the *R&D* investments and six years for the advertising investments, and we will do the same in our paper. After this, the value will be estimated using the current cost method (Runsten, 1998). The formula for the measurement bias attributed to this component of the intangible assets can be expressed as follows:

$$MB_{IA\,exp,t} = \sum_{n=0}^{N} Inv_{IA,t} * \frac{Remaining\ economic\ life}{Total\ economic\ life} * (1 + i_{i,t})^{t} \tag{28}$$

where:

$MB_{IA\,exp,t} = measurement\ bias\ of\ expensed\ investments\ accrued\ in\ time\ t.$

The total measurement bias related to intangible assets is the sum of these two sources of measurement bias. The formula can be expressed in the following way:

$$MB_{IA,t} = MB_{IA\,cap,t} + MB_{IA\,exp,t} \tag{29}$$

Assumptions for tangible assets related to *CPI* as inflation rate (i) and the same criteria must be fulfilled to derive the investment patterns for intangible assets as for tangible assets.

Deferred taxes

Deferred taxes arise from the temporary differences between the carrying amount and tax bases of a given asset. With the measurement biases representing unrecognised holding gains for assets, this gives arise to an additional deferred tax liability (*DTL*), which is not recorded on the balance sheet (Runsten, 1998). This component of deferred tax should be considered together with the recorded *DTL* and deferred tax assets (*DTA*) on the balance sheet, resulting in net deferred tax liabilities (*NDTL*). The formula can be expressed in the following way:

$$MB_{NDTL,t} = MB_{DTL,t} - MB_{DTA,t} + MB_{ADTL,t} \tag{30}$$

where:

$MB_{DTL,t}$ = measurement bias from recorded DTL accrued in time t,

$MB_{DTA,t}$ = measurement bias from recorded DTA accrued in time t,

$MB_{ADTL,t}$ = measurement bias from additional DTL accrued in time t.

Measurement bias related to the components of deferred taxes in Eq. (28) can be estimated using the annuity formula with the present value of annual reversals of tax payments, discounted by the after-tax cost of debt (Runsten, 1998). The annual reversals of the deferred taxes are determined by the economic life of the asset type (k), implying that, for example, deferred taxes from inventory are assumed to have one year in reversal time. The formula can be expressed in the following way for recorded *DTL* given asset type k:

$$DTL_{k,t} = \left(\frac{MB_{k,t} * \tau}{n}\right) * \frac{\left[1 - \left(\frac{1}{(1+r_D)^n}\right)\right]}{r_D} \tag{31}$$

where:

$DTL_{k,t}$ = deferred tax liabilities for asset k in time t,

r_D = cost of debt (after tax),

τ = statutory tax rate.

The measurement bias derived from recorded *DTL* is the sum of all asset types *k*, which can be expressed in the following way with inventory, tangible assets and intangible assets as assets:

$$MB_{DTL,t} = DTL_{Inv,t} + DTL_{TA,t} + DTL_{IA,t} \tag{32}$$

The same procedure to derive the measurement bias is applied for the recorded *DTL* in Eq. (31) and (32) as for *ADTL* and recorded *DTA.*

3.5 ASSESSMENT OF PRICING ACCURACY

To assess the pricing accuracy of the base *RIV* model (RIV_{BM}) and the unbiased *RIV* model (RIV_{UB}), six metrics are measured and evaluated for each model. These metrics are divided into three separate areas of interest to assess pricing accuracy: precision, spread and performance.

Precision

The most central metrics in the pricing accuracy literature are related to precision, examined through 'signed' pricing error (*PE*) and 'absolute' pricing error (*APE*). Pricing errors close to zero indicate high precision of the model and high pricing accuracy of the model. Following its importance in assessing the accuracy of a valuation model, *PE* and *APE* are widely used among researchers to determine the pricing accuracy of the *RIV* model (see e.g., Francis *et al.,* 2000; Courteau *et al.,* 2001; Choi *et al.,* 2006; Jorgensen *et al.,* 2011; Chang *et al.,* 2012, Anesten *et al.,* 2020).

'Signed' pricing error (PE)

The 'signed' pricing error (*PE*) captures the pricing error and is the value discrepancy between economic value (*V*) and contemporaneous stock price (*P*) (e.g., Francis *et al.,* 2000; Courteau *et al.,* 2001; McCrae & Nilsson, 2001). The formula for *PE* can be expressed in the following way:

$$PE_{0,j} = \frac{V_{0,j}(RIV) - P_{0,j}}{P_{0,j}} \tag{33}$$

where:

$V_{0,j}(RIV) = \text{value of owners}'\text{equity using } RIV \text{ model for company } j \text{ at } t = 0,$

$P_{0,j} = \text{observed market value of owners}'\text{equity for company } j \text{ at } t = 0.$

'Absolute' pricing error (APE)

The 'absolute' pricing error (*APE*) captures the size of the pricing error in absolute terms (Beatty *et al.*, 1999). A common application of the *APE* metric is by looking at the mean, also referred to as *'MAPE'* (Beatty *et al.*, 1999). Compared to the *PE*, the *APE* metric is unsensitive to positive and negative pricing errors stemming from the mixture of overstatements and understatements of stock prices, which eliminates risks related to offsetting each other. The *APE* formula can be expressed in the following way if the *RIV* model is applied to derive economic value:

$$APE_{0,j} = \left| \frac{V_{0,j}(RIV) - P_{0,j}}{P_{0,j}} \right| \tag{34}$$

Spread

Spread is examined in this paper by examination of the standard deviation of *PE* and *APE*, but also sample above 15% *APE* (*15%APE*) and interquartile range of *PE* (*IQRPE*). Lower spreads and, thus, higher pricing accuracy is signified in lower numbers across all these metrics.

Sample fraction above 15% APE (15%APE)

The *15%APE* metric reflects the number of observations with *APE* exceeding 15% (Kim & Ritter, 1999). The formula is presented in the following way:

$$15\%APE_0 = \frac{1}{n}\sum_{i=1}^{n}\left[APE_{0,j} > 15\%\right] \tag{35}$$

Interquartile range of 'signed' pricing error (IQRPE)

The interquartile range (*IQRPE*) captures the difference between the third (Q_3) and first quartile (Q_1) of the observations of *PE* (Liu *et al.*, 2002). The formula for the metric is expressed in the following way:

$$IQRPE_0 = Q_3(PE)_0 - Q_1(PE)_0 \tag{36}$$

Performance

The metric covering performance is the *A-score*. *A-score* integrates precision and spread to formulate a score reflecting overall pricing performance of the model (Faber, 1999; Newbold *et al.*, 2022). The formula is expressed in the following way:

$$A_{0,j} = \frac{[1/IQRPE_0]}{Mean(APE_{0,j})} \tag{37}$$

Table 2 presents an overview of the observed range of given metrics in prior empirical research of the *RIV* model.

Table 2. Pricing accuracy of the RIV model

Author/-s	Sample	Approach	Forecast horizon	*Precision*			*Spread*			*Performance*
				Mean PE	***Median PE***	***MAPE***	***SD PE***	***IQRPE***	***15%APE***	***A-score***
Francis, Olsson and Oswald (2000)	U.S. 1989-1993	GGM0%	$T = 5$	-0.20	-0.28	--	--	--	0.80	--
		GGM4%		-0.13	-0.23	--	--	--	0.78	--
Courteau, Kao and Richardson (2001)	U.S. 1992-1996	GGM0%	$T = 5$	-0.34	-0.38	0.39	0.28	--	--	--
		GGM2%		-0.30	-0.34	0.37	0.31	--	--	--
McCrae and Nilsson (2001)	Swedish 1987-1997	NAÏVE	$T = 3$	-0.49	--	0.74	0.79	--	--	--
		ANR		-0.31	--	0.57	0.51	--	--	--
		GGM2%		-0.21	--	0.77	1.27	--	--	--
Jorgensen, Lee and Yoo (2011)	U.S. 1984-2005	GLS	$T = 2$	0.01	-0.10	0.40	0.59	0.55	0.77	4.52
		GGM0%		0.07	-0.06	0.31	0.43	0.44	0.68	7.38
		CT		0.08	-0.08	0.34	0.47	0.48	0.72	6.15
		GLS	$T = 5$	0.01	-0.10	0.39	0.56	0.53	0.75	4.89
		GGM0%		0.07	-0.07	0.32	0.45	0.45	0.69	7.03
		CT		0.09	-0.09	0.36	0.51	0.50	0.74	5.60
Chang, Landsman and Monahan (2012)	U.S. 1980-2010	FOR5	$T = 5$	-0.37	-0.40	0.47	0.57	0.57	--	3.74
		FOR10	$T = 10$	-0.26	-0.31	0.51	0.98	0.52	--	3.81
Ho, Lee and Lin (2017)	U.S. 1995-2013	GLS	$T = 5$	0.19	0.06	1.83	0.79	--	--	--
		CT		-0.01	-0.02	0.82	0.30	--	--	--
Anesten, Möller, Skogsvik and Skogsvik (2020)	Nordic 2004-2013	ANR2009	$T = 3$	-0.11	-0.25	0.42	0.54	0.59	0.79	4.04
		HIS2009		0.17	-0.04	0.58	0.92	0.80	0.77	2.16
		ANR2014		-0.29	-0.40	0.53	0.71	0.46	0.90	4.10
		HIS2014		-0.31	-0.47	0.56	0.61	0.49	0.92	3.64
Mean				**-0.12**	**-0.17**	**0.54**	**0.59**	**0.50**	**0.74**	**5.39**
Median				**-0.13**	**-0.17**	**0.42**	**0.56**	**0.51**	**0.77**	**4.31**

Notes:
This table presents an overview of observed pricing accuracy of the *RIV* model from selected metrics split into three areas of interest: precision, spread and performance. Precision close to zero, low spreads and high performance indicate high pricing accuracy of the valuation model. Approaches to horizon value applied in prior research: *GGM0%/GGM2%/GGM4%* (Gordon Growth Model with 0%, 2% and 4% growth), *GLS* (Linear reversion adovated by Gebhart, Lee and Swaminahan, 2001), *CT* (GGM with 3% premium advocated by Claus and Thomas, 2001). Approaches to value driver applied in prior research: *ANR* (analysts' forecast), *HIS* (historical approach), *NAÏVE* (naive

3.6 MODEL ADJUSTMENTS

To capture additional insights on pricing accuracy of the base *RIV* model (RIV_{BM}) and the unbiased *RIV* model (RIV_{UB}), adjustments are conducted which target sensitivity to i) valuation date, ii) value driver, iii) length of explicit forecast horizon and iv) steady-state growth rate.

Valuation date

An additional valuation date ($t = 0$) is examined to assess the sensitivity to time period. The adjustments aim to capture various changes in the business climate, which could influence the size of measurement bias, as shown by Runsten (1998). Anesten *et al.* (2020) comprises an example in prior empirical research on the pricing accuracy of the *RIV* model where a second valuation point in time is examined. The authors find that pricing errors (in terms of *PE*) are lower when conducting their study in 2009 compared to 2014, which further motivates an evaluation of a second valuation date in this paper. The second valuation date ($t = 0$) is set to 1 March 2017 (henceforth '2017').

Value driver

Prior research on the pricing accuracy of the *RIV* model places overwhelming emphasis on analysts' forecasts as the preferable value driver in the *RIV* model (see e.g., Frankel & Lee, 1998; Dechow *et al.*, 1999; Lee *et al.*, 1999, Francis *et al.*, 2000; Liu *et al.*, 2002). However, concerns are also raised about using analysts' forecasts as a value driver, mainly related to sell-side analyst irrationality (e.g., Frankel & Lee, 1998; Lee *et al.*, 1999; Abarbanell & Bernard, 2000) and their inclusion of other value relevant information (e.g., Liu *et al.*, 2002; Skogsvik, 2008). Anesten *et al.* (2020) provide an example where analysts' forecasts are supplemented by a historical approach built on the findings of Skogsvik (2008). Interestingly, the authors observe that by using the three-year historical average of *ROE*, the pricing accuracy of the *RIV* model can be enhanced, which motivates the application of this approach in our paper. The formula is presented in the following way:

$$ROE_{Avg,t} = \frac{ROE_{t-1} + ROE_{t-2} + ROE_{t-3}}{3} \qquad (38)$$

Eq. (36) is the historical approach referred to hereafter in the adjusted *RIV* models.

Explicit forecast horizon

The length of the explicit forecast horizon is a common adjustment in prior empirical research (see e.g., Penman & Sougiannis, 1998; Jorgensen *et al.*, 2011; Chang *et al*., 2012; Kuo, 2015; Anesten *et al.*, 2020). Most findings support that a longer explicit forecast horizon induces enhanced pricing accuracy of the *RIV* model (see e.g., Penman & Sougiannis, 1998; Anesten *et al.*, 2020). Interestingly, however, Jorgensen *et al.* (2011) find that pricing errors are higher for the *RIV* model when extending the explicit forecast horizon from $T = 2$ to $T = 5$. The inconsistent findings in prior research highlight the relevance of assessing the sensitivity of a longer explicit forecast horizon for our *RIV* models. Thus, a longer explicit forecast horizon of two years is evaluated, implying that the explicit forecast horizon ranges to $t = t + 5$ before the ten-year linear reversion of *ROE* is applied toward $T = 14$ with $T + 1 = 15$.

Steady state growth rate ($\boldsymbol{RIV_{BM}}$)

The Gordon growth model (*GGM*) is one of finance theory's most well-established expressions for horizon value. Initially presented by Gordon and Shapiro (1956) and Gordon (1959), the underlying rationale of *GGM* is that a defined value driver is assumed to grow at a constant rate in perpetuity. *GGM* with constant or growing residual income at the horizon point in time are common applications of the horizon value for the *RIV* model (e.g., Kaplan & Ruback, 1995; Francis *et al.*, 2000; Jorgensen *et al.*, 2011). This is, however, inconsistent with the definition of horizon point (i.e., $t = T$) applied in our paper assuming *SS&COMPEQ*. This implies that the horizon value is unaffected by assumptions about growth in steady state (referred to as g_{ss}) as long as *SS&COMPEQ* holds (Skogsvik; 1998). However, changing g_{ss} influences ROE_{ss}, as presented in Eq. (15), which subsequently influence the linear reversion of *ROE* across firms. To test the impact on pricing accuracy stemming from this factor, an additional scenario where zero growth in perpetuity (i.e., $g_{ss} = 0\%$) is assessed.

4. SAMPLE SELECTION

This section covers the sample selection, from the fixed selection criteria and missing data to derived final sample.

4.1 SELECTION CRITERA

The data is retrieved from S&P Capital IQ. The following screening criteria are used:

i. Company type: Public company (70,329 firms)
ii. Market capitalisation: Minimum of SEK 1.0bn (23,365 firms)
iii. Industry classifications: "Banks", "Financial Services", "Insurance", "Equity Real Estate Investment Trusts", "Real Estate Management and Development" are excluded (19,765 firms)
iv. Geographic locations: Sweden, Denmark, Finland, Norway or Iceland (516 firms)
v. Company status: Active (465 firms)

A total of 465 firm-year observations is available based on the initial selection criteria listed in i) to v). These selection criteras are assumed to be necessary to achieving a balanced and robust measurement of measurement bias while forming a representative sample for assessment of pricing accuracy. As shown, criteria ii) entails a noticeable reduction of firms but is motivated to form a coherent sample in terms of *size* i.e., displaying similar signs of maturity in business activities with stable profitability, growth and risks. Runsten (1998) and Fruhan (1979) implement similar criteria to establish robust measures of firm-specific measurement bias. Consistent with the approach adopted by Ahmed, Morton and Schaefer (2000) as well as Anesten *et al.* (2020), financial firms (i.e., financial institutions, investment companies and real-estate firms) are excluded in criteria iv) to ensure alignment of the financial reporting standards and business activities.

4.2 MINIMUM DISCLOSURE REQUIREMENTS

For each firm, data is retrieved from S&P Capital IQ on market capitalisation ($P_{0,j}$), book value of owners' equity at the valuation date (BV_0), operating profit, manufacturing costs, finished goods (FG), work in progress (WIP), book value and executed investments in tangible assets (*TA*), book value and executed investments in intangible assets (*IA*) (i.e., *R&D* and advertising) and beta values (β). Analysts' forecasts are also retrieved on consensus estimates on earnings (NI). All items are retrieved in constant currency to mitigate risks of foreign currency exposures driving excess profits unequally across the sample. The ten-year government bond yield (R_f) is retrieved from Trading Economics and CPI (i) from each country's national statistics bureau.

To extract beta values (β) and analysts' forecasts, additional criteras are needed. In the former, the firms must be listed for at least three years to extract measurement of three-year historical beta values, benchmarked against the local stock market indices. This additional layer of criteria is applied by Anesten *et al.* (2020) and Runsten (1998). For analysts' forecasts, firms need to have analyst coverage to enable extraction of consensus estimates for a minimum two fiscal years ahead (i.e., $t + 2$). A total of 368 firm-year observations remains after adjusting for these two criteria, representing a loss of 97 observations, or 21% of the initial sample. Finally, after a careful review of financial information of remaining firms, a loss of 25 firm-year observations, or 5% of the initial sample, is registered due to a lack of minimum requirements to estimate the measurement bias. This yields our final sample of 343 firm-year observations for the valuation date on 1 March 2023.

4.3 FINAL SAMPLE

Table 3 and 4 represents the geographical and industry split of the firm-year observations in the final sample. As exhibited in Tables 3 and 4, the final sample is mainly represented by Swedish firms (48%), consistent with Anesten *et al.* (2020), with 49% of the final sample represented by Swedish firms. In terms of industry, we deploy 16 different industry definitions presented by Runsten (1998). Applying these industry definitions, an overwhelming proportion of the final sample is found to be represented by firms within *engineering*, *consumer goods*, and *other service* (i.e., mainly 'high-tech' firms with software systems). A domination of *engineering* is observed in Runsten (1998), but also Anesten *et al.* (2020); however, lower propositions of firms within *pulp and paper*, *chemical industry* and *shipping* are observed in our sample. This can be partly explained by the higher proposition of sample firms in *pharmaceutical*, *consumer goods, consultants and consumer* and *other service*.

Table 3. Sample characteristics – Industry

Industry sector	**Firm obs.**	***% of total***
Engineering	60	*17%*
Other service	53	*15%*
Consumer goods	52	*15%*
Pharmaceutical	32	*9%*
Capital-intensive firms	29	*8%*
Building and construction	27	*8%*
Other production	26	*8%*
Trading and retail	23	*8%*
Consultants and computer	12	*3%*
Pulp and paper	11	*3%*
Shipping	10	*3%*
Chemical industry	7	*2%*
Cong. & mix. inv.	1	*1%*
Total	**343**	***100%***

Notes:
This table presents the industry breakdown of the final sample. Sample size is 343 firm-year observations. Industries have been defined based on Runsten's (1998) 16 industry definitions. Firms falling under the definition of *investment companies*, *real estate* and *mixed building and real estate* have been excluded in this paper.

Table 4. Sample characteristics – Country

Country	**Firm obs.**	***% of total***
Sweden	164	*48%*
Finland	71	*21%*
Norway	69	*20%*
Denmark	39	*11%*
Iceland	0	*0%*
Total	**343**	***100%***

Notes:
This table presents the country breakdown of the final sample. Sample size is 343 firm-year observations.

Table 5 presents the pooled distributions of key variables in the final sample. As exhibited in Table 5, the sample has a mean market cap ranging between 2 192 and 5 466 MEUR in 2013-2022. Sales figures range between 1 826 and 3 096 MEUR in the sample period. Profitability margins fluctuated from 2013 to 2022, particularly from 2020 to 2022, with the mean EBIT margin ranging between 9% and 19%. The mean inflation of 7.5% in 2022 also stands out from the remaining sample period, trending between 0.8% and 2.8% during 2013-2021. All variables are presented in the table below.

Table 5. Descriptive statistics

In EURm	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Market capitalisation	2 192	2 355	2 681	2 747	3 020	2 818	3 507	4 303	5 466	4 545
Sales	1 826	1 893	1 945	1 870	1 956	2 158	2 225	2 184	2 447	3 096
Growth y/y (%)		*4%*	*3%*	*-4%*	*5%*	*10%*	*3%*	*-2%*	*12%*	*27%*
EBIT	205	214	195	174	212	249	250	198	391	600
EBIT margin (%)	*11%*	*11%*	*10%*	*9%*	*11%*	*12%*	*11%*	*9%*	*16%*	*19%*
ROE (%)	*8%*	*8%*	*10%*	*11%*	*12%*	*11%*	*11%*	*11%*	*14%*	*13%*
Beta	--	--	--	--	--	--	--	--	--	1.2
Cost of equity (%)	--	--	--	--	--	--	--	--	--	*8.2%*
CPI (%)	*1.6%*	*1.1%*	*0.8%*	*1.4%*	*1.5%*	*1.9%*	*1.8%*	*1.0%*	*2.8%*	*7.5%*
Risk-free rate (%)	--	--	--	--	--	--	--	--	--	*2.6%*

Notes:
This table presents the descriptive statistics of the final sample. Sample size is 343 firm-year observations. All items are expressed in EURm, if not stated otherwise.

5. RESULTS AND DISCUSSION

In this part, a presentation and analysis of the empirical findings are carried out to answer our research question. The chapter is structured in three main parts. The first part covers the pricing accuracy of the unbiased *RIV* model (RIV_{UB}) compared to the base *RIV* model (RIV_{BM}). For the second part, adjustments to both models are conducted to test sensitivity to underlying configurations in the *RIV* model as found in prior research (see e.g., Jorgensen *et al.*, 2011; Anesten *et al.*, 2020), such as valuation date, length of the explicit forecast horizon, choice of value driver and steady-state growth rates. Finally, a discussion is outlined on observed measurement bias and pricing accuracy of the *RIV* model in different valuation settings.

5.1 PRICING ACCURACY OF THE UNBIASED RIV MODEL

Table 6 presents the pricing precision, spread and performance (i.e., *A-score*) of the *RIV* models. Our results in Table 6 indicate that the pricing accuracy of the *RIV* model is enhance´d when using unbiased accounting (i.e., RIV_{UB}). This is exhibited with pricing errors closer to zero, lower pricing spreads and higher *A-score* for RIV_{UB} compared to RIV_{BM}.

Table 6. Pricing accuracy assessment

	Precision			*Spread*			*Performance*
Model	***Mean PE***	***Median PE***	***MAPE***	***SD PE***	***IQRPE***	***15%APE***	***A-score***
RIV_{BM}	0.27	-0.01	0.66	1.08	0.92	0.79	1.65
RIV_{UB}	-0.01	-0.14	0.48	0.65	0.76	0.81	2.75

Notes:
This table presents the pricing accuracy results of the unbiased *RIV* model (RIV_{UB}) and base *RIV* model (RIV_{BM}) with valuation point in time is set to 1 March 2023 ($t = 0$). Sample size is 333 firm-year observations. A three-year explicit forecast horizon (i.e., $t + 3$ and $T = 12$) is applied and analysts' forecasts is used as value driver for both models. For RIV_{BM}, a steady-state growth rate of 2% (i.e., $g_{ss} = 2\%$) is applied. The results are disclosed in accordance with our three areas of interest for assessment of the pricing accuracy: precision, spread and performance. To reduce the effects of outliers, the top and bottom 1% exhibited observations were omitted for each model.

Precision

As exhibited in Table 6, the unbiased *RIV* model (RIV_{UB}) exhibits a *mean PE* of -0.01, *median PE* of -0.14 and *MAPE* of 0.48. This can be compared to *a mean PE* of 0.27, *median PE* of -0.01 and *MAPE* of 0.66 using the base *RIV* model (RIV_{BM}). This infers that the pricing precision of RIV_{UB} is superior to RIV_{BM}. With negative *median PE* in both models, our results indicate that the *RIV* model understates contemporaneous stock prices, supporting the narrative of the

RIV model being a conservative model in prior empirical research (see e.g., Francis *et al.*, 2000; Courteau *et al.*, 2001; Chang *et al.*, 2012). Compared to prior empirical research evaluating the metrics *PE* and *APE* (summarised in Table 2), our results suggest comparable precision of the *RIV* model. Compared to research conducted on Nordic data (see e.g., McCrae & Nilsson, 2001; Anesten *et al.*, 2020), our results indicate similar precision with *MAPE* ranging between 0.42 and 0.77. Our results are also aligned with the prior research conducted on U.S. data, with *MAPE* observed between 0.31 and 1.83 (see Table 2).

Spread

The unbiased *RIV* model (RIV_{UB}) exhibits a mean *SD PE* of 0.65, *IQRPE* of 0.76 and *15%APE* of 0.81. This can be compared to the *SD PE* of 1.08, *IQRPE* of 0.92 and *15%APE* of 0.79 using the base *RIV* model (RIV_{BM}), as exhibited in Table 6. This infers that pricing spreads are higher with the application of RIV_{BM} relative to the RIV_{UB}, excluding the slightly lower observed *15%APE*. Positioning our findings compared to the prior research (summarised in Table 2), we derive higher pricing spreads for both *RIV* models in our empirical data. This infers that, given our assumptions, our results indicate higher volatility of pricing errors. Nonetheless, our results are aligned with the observations made by McCrae and Nilsson (2001) on Swedish data with *SD PE* being in the range of 0.51 and 1.27. This supports Anesten *et al.* (2020), who infer that a higher spreads in valuation models could be an indication of lower stock market efficiency. Nonetheless, as this paper assumes that market efficiency is maintained, questions about variations in stock market efficiency are disregarded.

Performance

As exhibited in Table 6, the unbiased *RIV* model (RIV_{UB}) performs *an A-score* of 2.75, while the base *RIV* model (RIV_{BM}) exhibits *an A-score* of 1.65. This infers that RIV_{UB} has higher pricing accuracy than RIV_{BM}. It indicates what previously has been inferred concerning the precision and spread of the models, namely that the pricing accuracy of RIV_{UB} is superior to RIV_{BM} when integrating aspects of both precision and spread. Positioning our findings compared to prior research presenting an *A-score* of the *RIV* model (i.e., Jorgensen *et al.*, 2011; Anesten *et al.*, 2020), with observed range between 2.16 and 7.38, our empirical data indicates *A-scores* of the *RIV* model in the lower bound for RIV_{UB} (2.75) and below this range for RIV_{BM} (1.65). That said, one may question the comparability of the *A-score* with Jorgensen *et al.* (2011) positioned as the paper finding the best pricing accuracy of the *RIV* model on U.S.

data with a mean *A-score* of 5.93 across its six versions of the *RIV* model. We argue that the comparability of our results is more accurate with Anesten *et al.* (2020) as they conducted their research on Nordic data, applying analysts' forecasts among the value drivers with a three-year explicit forecast horizon. Compared to this paper, our research indicates lower pricing accuracy of the *RIV* model with valuation date in 2023.

5.2 PRICING ACCURACY OF THE ADJUSTED MODELS

Table 7 presents the pricing accuracy (referred to as *A-score*) when adjusting the *RIV* models for i) valuation date, ii) value driver, iii) explicit forecast horizon, and iv) steady-state growth rate. Our results indicate that the pricing accuracy of the unbiased *RIV* model (RIV_{UB}) consistently outperforms the base *RIV* model (RIV_{BM}) regardless of adjustment. The highest *A-score* across all *RIV* model versions is exhibited by RIV_{UB} using analysts' forecasts (referred to as *ANR*) with a three-year explicit forecast (i.e., $t+3$) horizon with a valuation date set to 2017 ($t = 0$). The lowest *A-score* across all model versions is exhibited by RIV_{BM} using analysts' forecasts when combined with a five-year explicit forecast horizon (i.e., $t+5$) and $g_{ss} = 0\%$. A presentation of all the pricing accuracy metrics for the adjusted *RIV* models are presented in Appendix 1.

Table 7. A-score of adjusted RIV models

	2017		2023	
Model adjustments	RIV_{BM}	RIV_{UB}	RIV_{BM}	RIV_{UB}
ANR + $t+3$ ($T = 12$) + $g_{ss} = 2\%$	3.42	5.64	1.65	2.75
HIS + $t+3$ ($T = 12$) + $g_{ss} = 2\%$	3.33	5.61	1.57	2.12
ANR + $t+5$ ($T = 14$) + $g_{ss} = 2\%$	1.54	4.86	1.32	2.10
HIS + $t+5$ ($T = 14$) + $g_{ss} = 2\%$	2.36	5.21	1.53	2.19
ANR + $t+3$ ($T = 12$) + $g_{ss} = 0\%$	3.16	n/a	1.61	n/a
HIS + $t+3$ ($T = 12$) + $g_{ss} = 0\%$	3.19	n/a	1.39	n/a
ANR + $t+5$ ($T = 14$) + $g_{ss} = 0\%$	1.42	n/a	1.28	n/a
HIS + $t+5$ ($T = 14$) + $g_{ss} = 0\%$	2.02	n/a	1.32	n/a

Notes:
This table presents the results from the *RIV* model adjustment with *A-score* as deployed indication for pricing accuracy. Sample size is 343 firm-year observations in 2023 and 223 firm-year observations in 2017 A total of 24 model versions are presented, two of which (marked with grey background) comprises the valuation setting presented in section 5.1. Changes in steady-state growth rate is irrelevant for the unbiased model (marked with n/a wherever necessary). *ANR* represents analysts' forecasts and *HIS* the alternative historical approach. To reduce the effects of outliers, the top and bottom 1% exhibited *A-score* were omitted for each model.

Valuation date

As exhibited in Table 7, all *RIV* models indicate a significant uplift of the *A-score* in 2017 compared to its equivalents in 2023 (see Appendix 1A and illustration in Appendix 3F). Our empirical results show an *A-score* of the *RIV* models between 1.28 and 2.75 in 2023 compared to the range of 1.42 and 5.64 in 2017. Our results indicate considerable improvements in the *A-score* of the unbiased *RIV* model (RIV_{UB}) compared to the base *RIV* model (RIV_{BM}). This implies that the pricing accuracy of the *RIV* model is sensitive to the chosen date, consistent with Anesten *et al.* (2020). Assuming market efficiency maintained, discrepancies in the pricing accuracy between different valuation points in time could be interconnected with various changes in the business climate and the size of measurement bias, as suggested by Runsten (1998). This is supported by a higher observed mean $q(MB)_0$ of 0.68 in 2017 compared to 0.46 in 2023. There are various explanations for this shift in measurement bias for firms, which we link to changes in the business climate and operational activities, in line with Runsten (1998).

Value driver

The *RIV* model exhibits the highest *A-score* when combined with analysts' forecasts, as shown in Table 7. This supports the wide array of empirical research supporting analysts' forecasts as the preferred value driver over alternative historical approaches (see e.g., Dechow *et al.*, 1999; Lee *et al.*, 1999; Francis *et al.*, 2000; Liu *et al*., 2002). This observation is indicated for both the unbiased *RIV* model (RIV_{UB}) and the base *RIV* model model (RIV_{BM}). Our empirical data further indicate that when combined with a shorter explicit forecast horizon of $t + 3$, analysts' forecasts yield higher *A-score* almost every time for the *RIV* model. In contrast, the historical approach (referred to as *HIS*) produces a higher *A-score* when combined with a longer explicit forecast horizon of $t + 5$. This supports Abarbanell and Bernard (2000), suggesting that analysts are affected by overly optimistic outlooks on short-term profits. This, while notions about profitability following mean-reverting processes imply lower profitability in subsequent periods (e.g., Frankel & Lee, 1998; Abarbanell & Bernard, 2000; Skogsvik, 2008). This could explain why the *RIV* model exhibit higher pricing accuracy with analysts' forecasts combined with short explicit forecast and the historical approach with the longer explicit forecast horizon.

Explicit forecast horizon

We find that the *RIV* model exhibits higher *A-score* when combined with a shorter explicit forecast horizon of $t + 3$, as exhibited in Table 7. This is inconsistent with what is inferred by Anesten *et al.* (2020), suggesting that the pricing accuracy of the *RIV* model is enhanced with an extension of explicit forecast horizon. However, our results support findings by Lee *et al.* (1999) and Jorgensen *et al.* (2011) conducted on U.S. data, showing that an extension of explicit forecast does not enhance the pricing accuracy of the *RIV* model, but rather increases pricing errors. Our research indicates that the *RIV* model with the shorter explicit forecast horizon of $t + 3$ exhibits higher *A-score* in combination with the analysts' forecast. The *RIV* model using a shorter explicit forecast horizon show a higher *A-score* in almost every adjustment. However, the outperformance of a shorter explicit forecast horizon is lower with the historical approach as a value driver.

Steady state growth rate – Base *RIV* model ($\boldsymbol{RIV_{BM}}$)

We found that assumptions about steady-state growth rates do not have any material impact on the *A-score* for the base *RIV* model (RIV_{BM}), as is exhibited in Table 7. This is consistent with the implications of assuming *SS&COMPEQ* at a horizon point in time (i.e., $t = T$) (e.g., Skogsvik, 2002; Penman, 2012). Nonetheless, our empirical data indicate slight improvements in the *A-score* when applying a higher steady state growth rate of 2% (i.e., $g_{ss} = 2\%$). This is aligned with the prior empirical research using different steady-state growth rates with *GGM* in the horizon value (e.g., Francis *et al.,* 2000; Courteau *et al.,* 2001). Our research indicates that steady-state growth rate of $g_{ss} = 2\%$ yields higher improvements effects on the *A-score* when combined with the historical approach and longer explicit forecast horizon of $t + 5$. An overview of the impact on pricing accuracy of the *RIV* model is summarised in Appendix 1.

5.3 MEASUREMENT BIAS AND PRICING ACCURACY

In this section, further analysis is conducted on the implications of measurement bias on the pricing accuracy of the *RIV* model. Three areas of interests are included in this examination, adhering to three different valuation settings: industry, country, and time period.

5.3.1 Breakdown of the measurement bias

As exhibited in Table 8, our results show that measurement bias is highest in *pharmaceutical*, followed by *consumer goods, engineering*, *other service* and *capital-intensive service*. Firms falling under Runsten's (1998) definitions for these industries exhibit a measurement bias (i.e., $q(MB)_0$) between 0.72 (0.52) and 2.51 (1.04) in 2023 (2017). Consistent with Runsten (1998), our empirics data show that *pharmaceutical, consumer goods* and capital-intensive service are among the industries with the highest measurement bias. As exhibited in Table 8, the lowest measurement bias is observed within *building and construction*, *conglom. & mix. inv*, *pulp and paper* and *other production*, with $q(MB)_0$ ranging between 0.05 (0.18) and 0.28 (0.31) on 2023 (2017). This is in alignment with Runsten (1998), albeit our measurement bias related to *pulp and paper* and *shipping* differ notably in comparison. The measurement bias for each industry is presented below.

Table 8: Measurement bias per industry

	2017			*2023*		
Industry sector	**Firm obs.**	***% of total***	$q(MB)_0$	**Firm obs.**	***% of total***	$q(MB)_0$
Pharmaceutical	22	*10%*	**2.51**	32	*9%*	**1.04**
Consumer goods	30	*13%*	**0.82**	52	*15%*	**0.94**
Engineering	45	*20%*	**0.80**	60	*17%*	**0.69**
Capital-intensive service	24	*11%*	**0.72**	29	*8%*	**0.52**
Other service	29	*13%*	**0.63**	53	*15%*	**0.49**
Trading and retail	11	*5%*	**0.60**	23	*8%*	**0.43**
Chemical industry	6	*3%*	**0.48**	7	*2%*	**0.40**
Shipping	6	*3%*	**0.45**	10	*3%*	**0.35**
Consultants and computer	9	*4%*	**0.38**	12	*3%*	**0.32**
Building and construction	16	*7%*	**0.31**	27	*8%*	**0.28**
Other production	18	*8%*	**0.29**	26	*8%*	**0.26**
Pulp and paper	7	*3%*	**0.18**	11	*3%*	**0.25**
Conglom. & and mix. inv.	n/a	*n/a*	**n/a**	1	*1%*	**0.05**
Total	**223**	***100%***		**343**	***100%***	

Notes:
This table presents the industry breakdown of measurement bias derived on 1 March 2017/2023 ($t = 0$). $q(MB)_0$ represent the average of firm-specific measurement bias falling under each industry in the same industry definitions as Runsten (1998) derived at $t = 0$. Sample size is 343 (223) firm-year observations in 2023 (2017). Latest financial reports used includes the fiscal year 2022 (2016) for derivation of $q(MB)_0$ on 2023 (2017).

The deviations compared to Runsten's table could be explained by changes in business climate. Starting with measurement biases arising from *FIFO* of inventory, no significant markups are observed. For *building and construction,* among the typical holders of large unrealised holding gains related to inventory, according to Runsten (1998), exhibit among the lowest $q(MB)$ of 0.28 (0.31) in 2023 (2017). For the typical holders of long-lived assets (e.g., *pulp and paper* and *shipping*) low measurement bias is observed. This is despite the Nordic region having mean inflation rates of 7.5% during 2022. However, it should be inferred that the inflation was consistently lower during 2013-2021 than Runsten (1998), as exhibited in Table 5. Nonetheless, the combination of lower measurement bias traced to long-lived assets and a high-inflationary environment contrasts with what Runsten (1998) and Johansson and Östman (1995) predict. That said, it should be noted that the periods leading up to the derivation of Runsten's table exhibited consistently higher inflation, trending between 4% and 10% seven-year averages in the period 1967-1993. This indicates that Runsten's table could arguably be considered invalid when comparing the measurement bias of tangible assets in low-inflationary environments.

For the proportion of measurement bias arising from *R&D* and advertising, Table 8 indicates significant discrepancies compared to Runsten's table. In the former, lower measurement bias is observed, especially in 2023, for firms falling under definitions of *pharmaceutical*, *other service* and *consultants and computer*. The lower measurement bias could be traced to overall lower investments of this type during this time period. However, other factors related to changes in business climate cannot be disregarded as potential drivers for the observed discrepancies. Fluctuations in general economic growth and introductions of new accounting rules, for example, could also play an essential role in the source of this measurement bias, impacting both the willingness to deploy *R&D* investments and to what extent these types of investments are expensed or capitalised (see e.g., Runsten, 1998). In contrast to *R&D*-intensive firms, higher measurement bias is derived from the brand-intensive firms (i.e., mainly *consumer goods*). Changes in business climate cannot be excluded as a potential driver of this development, and neither can it for any of the other observed discrepancies in the measurement bias.

Following the industry breakdown, we derive the measurement bias per country, presented in Table 9. As exhibited, Denmark exhibits the highest measurement bias (i.e., $q(MB)_0$) of 1.00 (1.03) in 2023 (2017). This is primarily driven by the varied exposures to high-bias industries such as *pharmaceutical*, *consumer goods* and *engineering,* accounting for 50% (57%) of the firm-year observations in 2023 (2017) (breakdown accessible in Appendix 2). Followed by Denmark is Sweden and Finland with observed $q(MB)_0$ of 0.58 (0.68) and 0.54 (0.55), respectively, in 2023 (2017). The measurement bias inherent in these countries is largely attributed to the exposures to *consumer goods*, *other service and engineering* (see Appendix 2). Lastly, Norway exhibits the lowest measurement bias across the Nordic countries with $q(MB)_0$ of 0.43 (0.47) in 2023 (2017). Lower measurement bias in Norway is attributed to the exposures to heavy industry with longer-lived assets (e.g., *capital-intensive service, other production* and *shipping*) exhibiting consistently lower measurement bias in our empirical data. As shown in Table 4, no firm-year observations are derived in Iceland.

Table 9: Measurement bias per country

	2017			*2023*		
Country	**Firm obs.**	***% of total***	$q(MB)_0$	**Firm obs.**	***% of total***	$q(MB)_0$
Denmark	30	*13%*	**1.03**	39	*11%*	**1.00**
Sweden	101	*45%*	**0.68**	164	*48%*	**0.58**
Finland	53	*24%*	**0.55**	71	*21%*	**0.54**
Norway	39	*17%*	**0.47**	69	*20%*	**0.43**
Total	**223**	***100%***		**343**	***100%***	

Notes:
This table presents the country breakdown of measurement bias derived on 1 March 2017/2023 ($t = 0$). $q(MB)_0$ represent the measurement bias derived at $t = 0$. Sample size is 343 (223) firm-year observations for 2023 (2017). Latest financial reports used includes the fiscal year 2022 (2016) for derivation of $q(MB)_0$ in 2023 (2017).

5.3.2 Measurement bias and pricing accuracy in different valuation settings

Table 10 presents the pricing accuracy (*A-score*) for industry categories reflecting the size of measurement bias in an industry (see breakdown in Appendix 4). As exhibited, the unbiased *RIV* model (RIV_{UB}) yields a higher *A-score* compared to the base *RIV* model (RIV_{BM}) for all industry categories in both periods while having an *A-score* aligned with prior research (summarised in Table 2). This confirms what previously has been inferred, i.e., that the pricing accuracy of the *RIV* model is enhanced with unbiased accounting. As shown in Table 10, the size of *A-score* cannot be derived from solely the size of measurement bias. However, it may be derived that the magnitude of the incremental improvements in using RIV_{UB} is larger for 'High-bias industries' compared to 'Low-bias industries' (see Appendix 3D and 3E). As shown in Table 10, the high-bias industries exhibit incremental *A-score* improvements of 81% (72%) in 2023 (2017) by using RIV_{UB} instead for RIV_{BM}. These figures can be compared to 'Mid-bias industries' and 'Low-bias industries' with incremental improvements of 29% (3%) and 19% (9%) in 2023 (2017). All results are presented below.

Table 10. Industries categorised by measurement bias and improvement in A-score

	2017				*2023*			
	Measurement bias	***A-score***		**Δ%**	**Measurement bias**	***A-score***		**Δ%**
Industry category	$q(MB)_0$	RIV_{UB}	RIV_{BM}	$\frac{RIV_{UB}}{RIV_{BM}} - 1$	$q(MB)_0$	RIV_{UB}	RIV_{BM}	$\frac{RIV_{UB}}{RIV_{BM}} - 1$
High-bias industries	0.95	4.36	2.54	*72%*	0.74	2.60	1.43	*81%*
Mid-bias industries	0.47	5.02	4.88	*3%*	0.40	7.59	5.88	*29%*
Low-bias industries	0.28	3.17	2.91	*9%*	0.28	5.21	4.36	*19%*

Notes:
This table presents the measurement bias and *A-score* for the unbiased *RIV* model (RIV_{UB}) and base *RIV* model (RIV_{BM}) per industry category in 2017 and 2023. All models apply analysts' forecasts as value driver (*ANR*), three-year explicit forecast horizon (i.e., $t + 3$) and steady-state growth rate of 2% for the base *RIV* (RIV_{BM}). Industries have been broken down depending on the size of measurement bias for each year (see breakdown in Appendix 4). A positive (negative) incremental improvement (referred to as Δ%) implies that the industry category benefit more (less) from the use of the unbiased *RIV* model (RIV_{UB}) compared to the base *RIV* (RIV_{BM}) model. Sample size is 343 (223) firm-year observations for 2023 (2017). To reduce the effects from outliers, the top and bottom 1% observations of *A-score* are omitted for each model.

Table 11 presents the pricing accuracy (referred to as *A-score*) for each country. As exhibited in the table, RIV_{UB} yields higher *A-score* for all countries in 2017 and 2023. This indicates that the pricing accuracy of the *RIV* model improves with unbiased accounting at the country level. The highest *A-score* using RIV_{UB} is exhibited in Finland (3.15) in 2023 and Denmark (7.76) in 2017. RIV_{BM} yields an *A-score* in the lower bound compared to prior research (see Table 2). The lowest *A-score* using RIV_{UB} is exhibited in Norway across both valuation dates. Compared to the industry breakdown, the incremental improvements of using RIV_{UB} is more visible at country-level with the lower comparable *A-score* of RIV_{BM}. The discrepancy is visual across all Nordic countries, including Norway, with enhancements of *A-score* ranging between 38% (22%) and 270% (578%) in 2023 (2017). Considerable incremental improvements in *A-score* are observed in countries with high measurement bias, such as Denmark, Sweden, and Finland (see Appendix 3B and 3C for illustration). This is aligned with the observations made in the separate industry categories in Table 10. All results are presented below.

Table 11. Measurement bias and pricing accuracy per country

	2017				2023			
	Measurement bias	***A-score***		Δ%	**Measurement bias**	***A-score***		Δ%
Country	$q(MB)_0$	RIV_{UB}	RIV_{BM}	$\frac{RIV_{UB}}{RIV_{BM}} - 1$	$q(MB)_0$	RIV_{UB}	RIV_{BM}	$\frac{RIV_{UB}}{RIV_{BM}} - 1$
Denmark	1.03	7.76	1.14	*578%*	1.00	3.03	0.82	*270%*
Sweden	0.68	5.80	3.62	*60%*	0.52	3.01	1.87	*61%*
Finland	0.55	7.47	4.14	*80%*	0.47	3.15	1.96	*61%*
Norway	0.47	3.51	2.88	*22%*	0.42	1.79	1.30	*38%*

Notes:
This table presents the measurement bias and *A-score* for the unbiased *RIV* model (RIV_{UB}) and base *RIV* model (RIV_{BM}) per country in 2017 and 2023. All models apply analysts' forecasts as value driver (*ANR*), three-year explicit forecast horizon (i.e., $t + 3$) and steady-state growth rate of 2% for the base *RIV* (RIV_{BM}). A positive (negative) incremental improvement (referred to as Δ%) implies that the country benefit more (less) from use of the unbiased *RIV* model (RIV_{UB}) compared to the base *RIV* (RIV_{BM}) model. Sample size is 332 (214) firm-year observations in 2023 (2017) where the top and bottom 1% outliers of *A-score* is omitted for each model. No countries have been excluded as a result of the minimum requirements. No firm-year observations are available in Iceland.

6. CONCLUSION AND IMPLICATIONS

In this section, we will first summarise and discuss our findings and conclusions, followed by a comment on its implications for the research field. Lastly, we share our suggestions for further research.

This paper aims to investigate whether the pricing accuracy of the RIV model improves by using unbiased accounting. Indeed, the pricing accuracy of the *RIV* model is enhanced with unbiased accounting. Our results show that the unbiased *RIV* model (RIV_{UB}) consistently outperforms the base *RIV* model (RIV_{BM}) with lower pricing errors, spreads, and higher *A-scores* exhibited by the former. This observation stands regardless of adjustment for valuation date, value driver, length of explicit forecast horizon and steady-state growth rate. We find that pricing accuracy is improved with the unbiased *RIV* model (RIV_{UB}) across the industries, countries and periods evaluated in this paper. Across the 24 different model versions of the *RIV* model (see Appendix 1), it exhibits the highest *A-score* of 5.64 (RIV_{UB}) and 3.42 (RIV_{BM}). The *A-score* of the base *RIV* model (RIV_{BM}) is measured between 1.28 and 3.42, which is aligned with the established range in prior research on pricing accuracy of the *RIV* model (Jorgensen *et al.,* 2011; Anesten *et al.,* 2020).

We find that the pricing accuracy of the *RIV* model (referred to as *A-score*) is sensible to a few underlying assumptions tested in prior research on pricing accuracy of the *RIV* model (see e.g., Francis *et al.,* 2000; Jorgensen *et al.,* 2011; Anesten *et al.,* 2020). We observe largest effects on the *A-score* from the valuation date, which we attribute to a higher mean measurement bias of 0.68 in 2017 compared to 0.46 in 2023. We derive improvements in the *A-score* from analysts' forecasts as the value driver, consistent with prior empirical research (e.g., Dechow *et al.,* 1999; Lee *et al.,* 1999; Francis *et al.,* 2000; Liu *et al.,* 2002). In addition, we derive improvements in the *A-score* from the shorter explicit forecast horizon of three years, consistent with the research by Lee *et al.* (1999) and Jorgensen *et al.* (2011). Although having a higher *A-score* using analysts' forecasts coupled with a shorter explicit forecast horizon, the historical approach outperforms whenever combined with the longer forecast horizon of five years. Lastly, we find no material effects on the pricing accuracy attributed to changes in steady-state growth rates, indicating low sensitivity to the slope of linear reversion of *ROE* across firms assuming $SS\&COMPEQ$.

Our research shows that the pricing accuracy of the *RIV* model changes in different settings. We evaluate the size of measurement bias as the driving cause for this. No apparent effects on the level of *A-score* can be derived from the size of measurement bias in a specific industry or country. However, it is derived that the magnitude of the incremental improvements of *the A-score* using the unbiased *RIV* model (RIV_{UB}) stands out in valuation settings with high inherent measurement bias (see Appendix 3 for illustrations). In terms of industries, this is observed for the ones categorised as 'High-bias industries' exhibiting incremental improvements of the *A-score* of 81% (72%) in 2023 (2017) when using the unbiased *RIV* model (RIV_{UB}). This can be compared to 'Low-bias industries' on the opposite end with substantially lower incremental improvements of 19% (9%) in 2023 (2017). At a country-level, incremental improvements in the *A-score* are observed in Denmark, Sweden, and Finland. This is attributed to the exposure to firms in 'High-bias industries', such as *pharmaceutical* and *consumer goods*. Thus, largest incremental improvements in the pricing accuracy using the unbiased *RIV* model (RIV_{UB}) appear to be in settings where the measurement bias is inherently higher.

This paper contributes to the research field showing that the accounting policy influences the pricing accuracy of the *RIV* model. Our paper bridges the two previously unmerged research fields of pricing accuracy and accounting measurement bias. Our results show that the pricing accuracy of the *RIV* model is enhanced with unbiased accounting, especially in industries, countries, and time periods where the inherent measurement bias is larger. Our findings imply two things for practitioners, researchers, regulators, and other users of the *RIV* model. Firstly, the inherent accounting measurement bias in the *RIV* model affects the pricing accuracy of the model. Secondly, the pricing accuracy of the *RIV* model could be improved with unbiased accounting, but the magnitude of the improvement depends largely on its valuation setting (illustrated in Appendix 3). We suggest a holistic view in the application of the *RIV* model where it is adapted and executed for its valuation setting. To gain a deeper understanding of our discoveries, we encourage further research into how the accounting measurement bias impacts the pricing accuracy of the *RIV* model. Our suggestions for further research are presented in the final chapter of this paper.

6.1 SUGGESTIONS FURTHER RESEARCH

We have detected three primary topics related to the dynamics between pricing accuracy and measurement bias that could be of interest to research further. Firstly, to gain a deeper understanding of observed changes in the pricing accuracy across different valuation settings, it is of interest to direct attention toward fundamental changes in the business climate which affect most firms. Examples include changes in accounting rules, such as the implementation of IFRS 16, which is likely to have increased the measurement bias stemming from the tangible assets since the inception on 1 January 2019. Nonetheless, other changes in business climate (e.g., inflation, general economic cycle, and trade agreements) cannot be disregarded in any of the observed changes in the size of measurement bias across valuation settings. This has been left outside the scope of our paper, leaving a gap for future research to explore further. Secondly, the implications of applying the same measurement bias for $q(MB)_0$ in the unbiased *RIV* model (RIV_{UB}) and $q(MB)_T$ in the base *RIV* model (RIV_{BM}) remain unanswered. Thus, we welcome further research where *ex-post* realised values of $q(MB)_T$ are used to disentangle the 'true' effects from this underlying assumption in the *RIV* model.

Our paper presumes maintained market efficiency when using contemporaneous stock prices as a benchmark value for the intrinsic value of equity. Building on the assumptions by Penman and Souginannis (1998) and Francis *et al.* (2001), this is considered among the simplest and most conventional ways of asserting a benchmark in the assessment of pricing accuracy for a valuation model. Nevertheless, the implication of assuming market efficiency maintained is that variations in market efficiency are disregarded in this paper. Anesten *et al.* (2020) present higher pricing spreads of a valuation model as a potential indicator of low market efficiency. In our paper, we observe consistently higher spreads compared to prior empirical research conducted on U.S. data (see e.g., Courteau *et al.*, 2001; Jorgensen *et al*., 2011) but, on the other hand, it is in line with the findings by McCrae and Nilsson (2001) on Swedish data. Thus, to better understand the underlying drivers of pricing accuracy and the validity of observed superiority of the unbiased *RIV* model (RIV_{UB}), we welcome further research across lower-sized firms, in other jurisdictions and during another period to capture these contingencies in the assessment of pricing accuracy of the *RIV* model.

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APPENDIX

Appendix 1: Pricing accuracy of the *RIV* model

Appendix 1A: Pricing accuracy of the RIV model

Model	Valuation date	Value driver	Firm obs.	Forecast horizon	g_{SS}	*Precision*			*Spread*			*Performance*
						Mean PE	***Median PE***	***MAPE***	***SD PE***	***IQRPE***	***15%APE***	***A-score***
RIV_{RM}	01 March 2017	*ANR*	214	*t + 3 (T=12)*	2%	0.14	-0.05	0.47	0.73	0.62	0.75	3.42
RIV_{BM}	01 March 2017	*HIS*	216	*t + 3 (T=12)*	2%	-0.03	-0.22	0.49	-0.22	0.61	0.82	3.33
RIV_{BM}	01 March 2017	*ANR*	214	*t + 3 (T=12)*	0%	0.18	-0.03	0.50	0.79	0.64	0.75	3.16
RIV_{BM}	01 March 2017	*HIS*	216	*t + 3 (T=12)*	0%	-0.02	-0.22	0.50	0.73	0.63	0.82	3.19
RIV_{BM}	01 March 2017	*ANR*	214	*t + 5 (T=14)*	2%	0.42	0.42	0.71	1.23	0.92	0.77	1.54
RIV_{BM}	01 March 2017	*HIS*	216	*t + 5 (T=14)*	2%	0.15	-0.12	0.58	0.96	0.73	0.79	2.36
RIV_{BM}	01 March 2017	*ANR*	214	*t + 5 (T=14)*	0%	0.47	0.07	0.75	1.33	0.94	0.78	1.42
RIV_{BM}	01 March 2017	*HIS*	216	*t + 5 (T=14)*	0%	0.19	-0.11	0.61	1.05	0.81	0.78	2.02
RIV_{UB}	01 March 2017	*ANR*	214	*t + 3 (T=12)*	n.a.	-0.07	-0.16	0.38	0.56	0.47	0.74	5.64
RIV_{UB}	01 March 2017	*HIS*	216	*t + 3 (T=12)*	n.a.	-0.26	-0.35	0.44	0.45	0.41	0.85	5.61
RIV_{UB}	01 March 2017	*ANR*	214	*t + 5 (T=14)*	n.a.	0.00	-0.14	0.42	0.85	0.49	0.70	4.86
RIV_{UB}	01 March 2017	*HIS*	216	*t + 5 (T=14)*	n.a.	-0.23	-0.34	0.45	0.49	0.43	0.87	5.21
RIV_{BM}	01 March 2023	*ANR*	333	*t + 3 (T=12)*	2%	0.27	-0.01	0.66	1.08	0.92	0.79	1.65
RIV_{BM}	01 March 2023	*HIS*	332	*t + 3 (T=12)*	2%	0.14	-0.17	0.67	1.10	0.95	0.85	1.57
RIV_{BM}	01 March 2023	*ANR*	332	*t + 3 (T=12)*	0%	0.30	0.00	0.67	1.11	0.93	0.80	1.61
RIV_{BM}	01 March 2023	*HIS*	332	*t + 3 (T=12)*	0%	0.23	-0.14	0.76	1.48	0.95	0.85	1.39
RIV_{BM}	01 March 2023	*ANR*	332	*t + 5 (T=14)*	2%	0.39	0.06	0.76	1.26	0.99	0.82	1.32
RIV_{BM}	01 March 2023	*HIS*	331	*t + 5 (T=14)*	2%	0.15	-0.15	0.68	1.13	0.96	0.85	1.53
RIV_{BM}	01 March 2023	*ANR*	331	*t + 5 (T=14)*	0%	0.41	0.07	0.77	1.24	1.02	0.82	1.28
RIV_{BM}	01 March 2023	*HIS*	332	*t + 5 (T=14)*	0%	0.23	-0.13	0.76	1.38	1.00	0.84	1.32
RIV_{UB}	01 March 2023	*ANR*	333	*t + 3 (T=12)*	n.a.	-0.01	-0.14	0.48	0.65	0.76	0.81	2.75
RIV_{UB}	01 March 2023	*HIS*	332	*t + 3 (T=12)*	n.a.	-0.03	-0.28	0.63	1.19	0.75	0.83	2.12
RIV_{UB}	01 March 2023	*ANR*	331	*t + 5 (T=14)*	n.a.	0.06	-0.11	0.57	0.84	0.84	0.79	2.10
RIV_{UB}	01 March 2023	*HIS*	332	*t + 5 (T=14)*	n.a.	-0.10	-0.29	0.58	0.83	0.79	0.82	2.19

Notes:
This table presents a summary of the results, in terms of *precision* (i.e., *mean PE, median PE and MAPE*), *spread* (i.e., *SD PE, IQRP* and *15%APE*) and *pricing accuracy performance* (i.e., *A-score*). for all our model adjustments.

Appendix 1B. The valuation date (2017 vs 2023) with largest improvement in A-score

Model adjustments	RIV_{BM}		RIV_{UB}	
ANR + $t+3$ + $g_{ss}=2\%$	2017	*107%*	2017	*105%*
HIS + $t+3$ + $g_{ss}=2\%$	2017	*112%*	2017	*165%*
ANR + $t+5$ + $g_{ss}=2\%$	2017	*17%*	2017	*131%*
HIS + $t+5$ + $g_{ss}=2\%$	2017	*54%*	2017	*138%*
ANR + $t+3$ + $g_{ss}=0\%$	2017	*96%*	n.a.	*n.a.*
HIS + $t+3$ + $g_{ss}=0\%$	2017	*130%*	n.a.	*n.a.*
ANR + $t+5$ + $g_{ss}=0\%$	2017	*11%*	n.a.	*n.a.*
HIS + $t+5$ + $g_{ss}=0\%$	2017	*53%*	n.a.	*n.a.*

Notes:
This table presents the effects on the *A-score* when adjusting for valuation date in the *RIV* models. The columns that display the year represent the valuation date that yields the highest *A-score* when comparing the two valuation dates (i.e., 2017 or 2023), followed by the improvement in *A-score*. All Improvments are positive for 2017 when compared to 2023. Model versions exhibiting largest incremental improvements for each line (i.e., RIV_{BM} or RIV_{UB}) is marked with grey background.

Appendix 1C. Adjusting for value driver, explicit forecast horizon and steady state growth

Model adjustment	**Approach**	*2017* RIV_{BM}		*2017* RIV_{UB}		*2023* RIV_{BM}		*2023* RIV_{UB}	
Value driver (*ANR/HIS*)	$g_{ss}=2\%$ $t+3$	*ANR*	*3%*	*ANR*	*1%*	*ANR*	*5%*	*ANR*	*30%*
	$g_{ss}=2\%$ $t+5$	*HIS*	*53%*	*HIS*	*7%*	*HIS*	*16%*	*HIS*	*4%*
	$g_{ss}=0\%$ $t+3$	*HIS*	*1%*	*n.a.*	*n.a.*	*ANR*	*16%*	*n.a.*	*n.a.*
	$g_{ss}=0\%$ $t+5$	*HIS*	*42%*	*n.a.*	*n.a.*	*HIS*	*3%*	*n.a.*	*n.a.*
Explicit forecast horizon ($t+3/t+5$)	*ANR* $g_{ss}=2\%$	$t+3$	*122%*	$t+3$	*16%*	$t+3$	*25%*	$t+3$	*31%*
	HIS $g_{ss}=2\%$	$t+3$	*41%*	$t+3$	*8%*	$t+3$	*3%*	$t+5$	*3%*
	ANR $g_{ss}=0\%$	$t+3$	*123%*	*n.a.*	*n.a.*	$t+3$	*26%*	*n.a.*	*n.a.*
	HIS $g_{ss}=0\%$	$t+3$	*58%*	*n.a.*	*n.a.*	$t+3$	*5%*	*n.a.*	*n.a.*
Steady state growth rate (0%/2%)	*ANR* $t+3$	$g_{ss}=2\%$	*8%*	*n.a.*	*n.a.*	$g_{ss}=2\%$	*3%*	*n.a.*	*n.a.*
	HIS $t+3$	$g_{ss}=2\%$	*4%*	*n.a.*	*n.a.*	$g_{ss}=2\%$	*13%*	*n.a.*	*n.a.*
	ANR $t+5$	$g_{ss}=2\%$	*9%*	*n.a.*	*n.a.*	$g_{ss}=2\%$	*3%*	*n.a.*	*n.a.*
	HIS $t+5$	$g_{ss}=2\%$	*17%*	*n.a.*	*n.a.*	$g_{ss}=2\%$	*16%*	*n.a.*	*n.a.*

Notes:
This table presents the effects on the *A-score* when adjusting for value driver, explicit forecast horizon and steady state growth rate in the *RIV* model. The table is horizontally divided into three sections, each adjusting for one factor (i.e., value driver, explicit forecast, horizon and steady-state growth rate) at the time while keeping everything else constant. For instance, the first section adjusts for value driver (i.e., *ANR* or *HIS*) while explicit forecast and steady state growth are kept constant. Model versions exhibiting the largest improvements for each line (i.e., RIV_{BM} or RIV_{UB} for 2017/2023) are marked with grey background.

Appendix 2: Measurement bias per country

Table 2A. Industry exposure per country, 2023

Industry	Denmark	Sweden	Finland	Norway
Pharmaceutical	*21%*	*10%*	*4%*	*6%*
Consumer goods	*21%*	*15%*	*23%*	*6%*
Engineering	*8%*	*23%*	*18%*	*7%*
Capital-intensive service	*0%*	*5%*	*4%*	*25%*
Other service	*3%*	*15%*	*23%*	*16%*
Trading and retail	*5%*	*9%*	*6%*	*4%*
Chemical industry	*5%*	*1%*	*1%*	*3%*
Shipping	*8%*	*1%*	*0%*	*9%*
Consultants and computer	*3%*	*3%*	*6%*	*3%*
Building and construction	*18%*	*7%*	*4%*	*9%*
Other production	*8%*	*7%*	*6%*	*10%*
Pulp and paper	*0%*	*3%*	*6%*	*3%*
Conglomerates and mixed investments	*0%*	*1%*	*0%*	*0%*
Total	***100%***	***100%***	***100%***	***100%***

Notes:
This table presents the industry exposures in each Nordic country. Sample size is 343 firm-year observations with no observations in Iceland, as presented in Table 4.

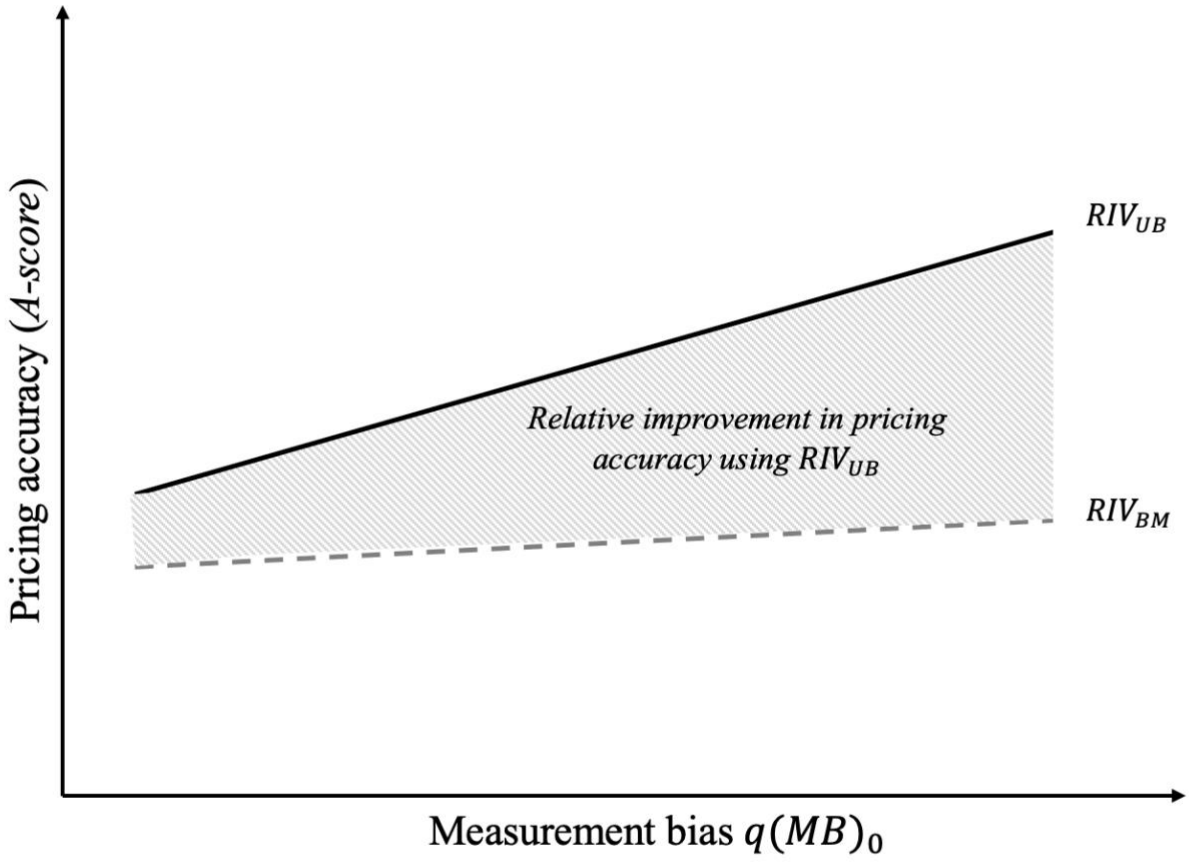
Table 2B. Industry exposure per country, 2017

Industry	Denmark	Sweden	Finland	Norway
Pharmaceutical	*27%*	*9%*	*4%*	*8%*
Consumer goods	*23%*	*11%*	*19%*	*5%*
Engineering	*7%*	*28%*	*21%*	*10%*
Capital-intensive service	*0%*	*9%*	*6%*	*31%*
Other service	*3%*	*14%*	*21%*	*8%*
Trading and retail	*0%*	*7%*	*6%*	*3%*
Chemical industry	*7%*	*1%*	*2%*	*5%*
Shipping	*10%*	*0%*	*0%*	*8%*
Consultants and computer	*0%*	*4%*	*6%*	*5%*
Building and construction	*17%*	*7%*	*2%*	*8%*
Other production	*7%*	*8%*	*8%*	*10%*
Pulp and paper	*0%*	*3%*	*8%*	*0%*
Conglomerates and mixed investments	*0%*	*0%*	*0%*	*0%*
Total	***100%***	***100%***	***100%***	***100%***

Notes:
This table presents the industry exposures in each Nordic country. Sample size is 223 firm-year observations with no observations in Iceland.

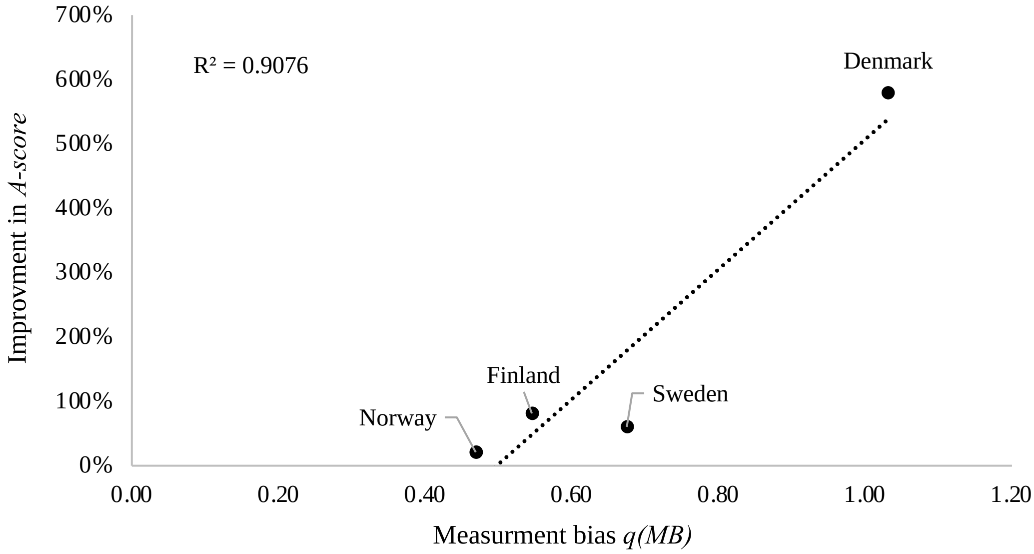
Appendix 3: Measurement bias and pricing accuracy

Figure 3A. Incremental improvements in A-score, illustrated



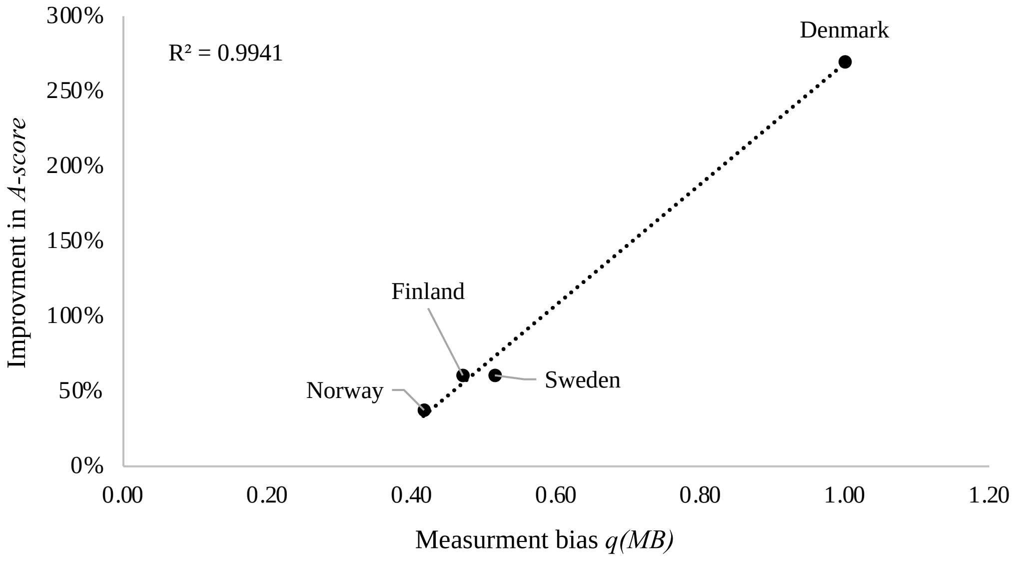
Notes:
Figure 3A illustrates the incremental improvements of using the unbiased *RIV* model (RIV_{UB}) in valuation settings where the measurement bias is inherently higher (e.g., country, industry or period). The figure shows our findings, indicating that as the measurement bias increases, the pricing accuracy (*A-score*) of the RIV_{UB} goes up, while being substantially lower for the base *RIV* model (RIV_{BM}). This leads to a larger discrepancy (delta) between the two models, the larger the measurement bias (referred to as $q(MB)_0$) is, illustrated by our figure.

Figure 3B. Improvement in A-score and mean measurement bias per country, 2017



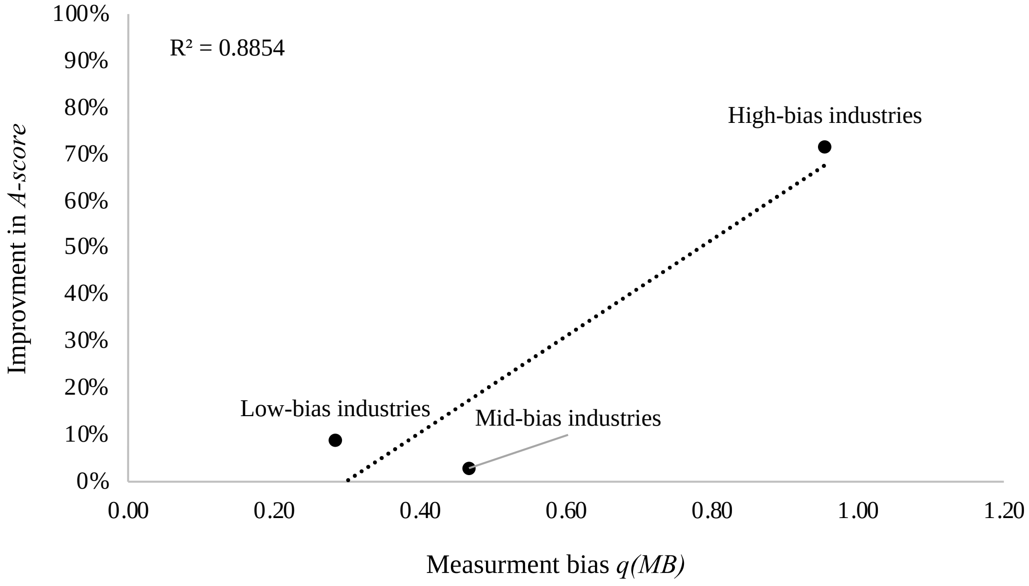
Notes:
Figure 3B illustrates the incremental improvement of *A-score* by using the unbiased *RIV* model (RIV_{UB}) on 1 March 2017 per country (i.e., Denmark, Finland, Sweden and Norway). The figure is based on the model that uses three-year explicit forecast period coupled with ANR and steady state growth of 2%. The figure shows, illustrated in *Figure 3A*, that the incremental improvements of using the unbiased *RIV* model (RIV_{UB}) is greater in countries where measurement bias is inherently higher (e.g., Denmark). Observations in the top-right corner indicates high measurement bias and large incremental improvement of *A-score* using the unbiased *RIV* model (RIV_{UB}) instead for the unbiased *RIV* model (RIV_{BM}). Sample size is 223 firm-year observations on 1 March 2017.

Figure 3C. Improvement in A-score and mean measurement bias per country, 2023



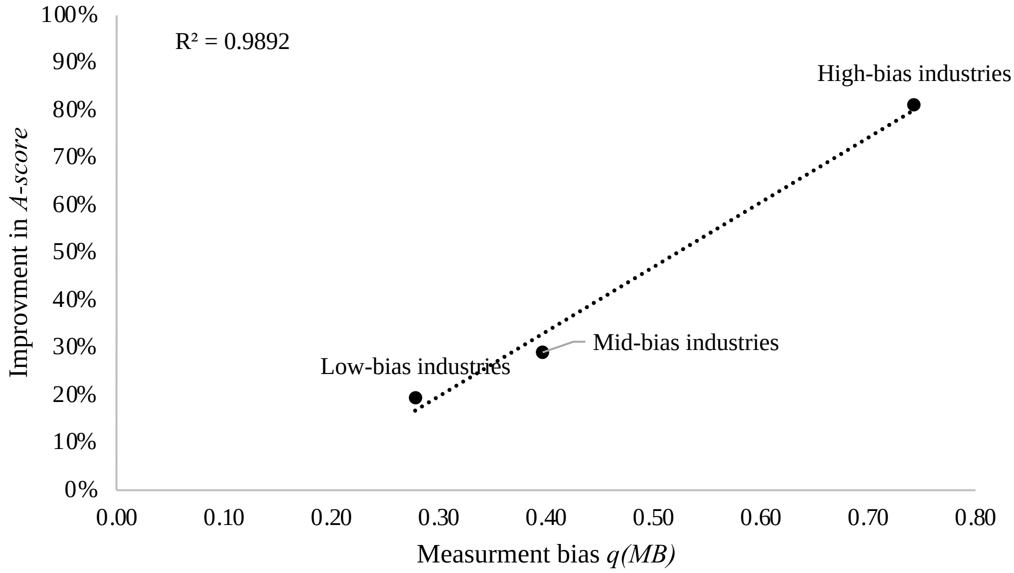
Notes:
Figure 3C illustrates the incremental improvement of *A-score* by using the unbiased *RIV* model (RIV_{UB}) on 1 March 2023 per country (i.e., Denmark, Finland, Sweden and Norway). The figure is based on the model that uses three-year explicit forecast period coupled with ANR and steady state growth of 2%. The figure shows, illustrated in *Figure 3A*, that the incremental improvements of using the unbiased *RIV* model (RIV_{UB}) is greater in countries where measurement bias is inherently higher (e.g., Denmark). Observations in the top-right corner indicates high measurement bias and large incremental improvement of *A-score* using the unbiased *RIV* model (RIV_{UB}) instead for the unbiased *RIV* model (RIV_{BM}). Sample size is 343 firm-year observations on 1 March 2023.

Figure 3D. Improvement in A-score and mean measurement bias per industry, 2017



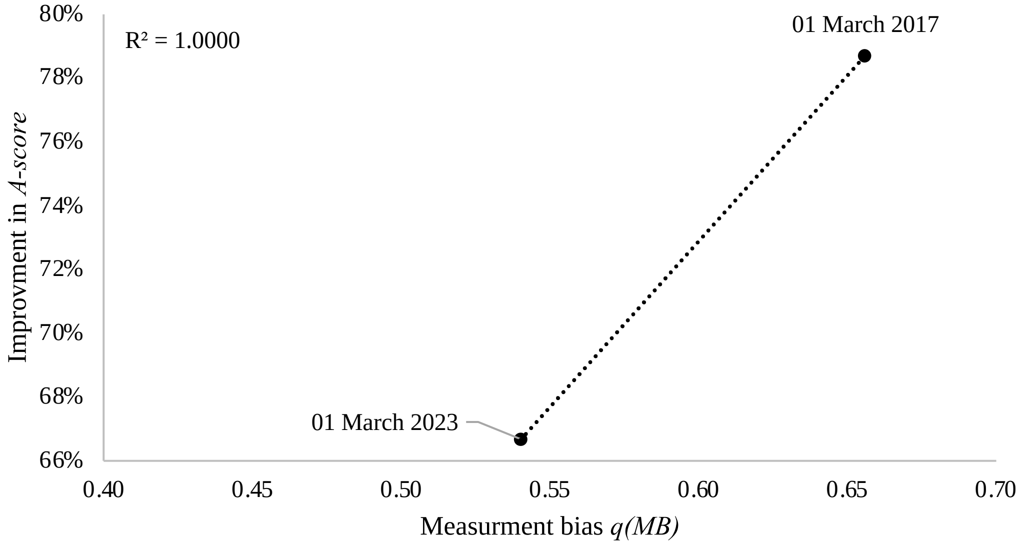
Notes:
Figure 3D illustrates the incremental improvement of *A-score* by using the unbiased *RIV* model (RIV_{UB}) on 1 March 20217 per industry category (i.e., 'High-bias industries', 'Mid-bias industries' and 'Low-bias industries'*)*. The figure is based on the model that uses three-year explicit forecast period coupled with *ANR* and steady state growth of 2%. The figure shows, illustrated in *Figure 3A*, that the incremental improvements of using the unbiased *RIV* model (RIV_{UB}) is greater in the 'High-bias industries' where measurement bias is inherently higher. Observations in the top-right corner indicates high measurement bias and large incremental improvement of *A-score* using the unbiased *RIV* model (RIV_{UB}) instead for the unbiased *RIV* model (RIV_{BM}). Sample size is 223 firm-year observations on 1 March 2017.

Figure 3E. Improvement in A-score and mean measurement bias per industry, 2023



Notes:
Figure 3E illustrates the incremental improvement of *A-score* by using the unbiased *RIV* model (RIV_{UB}) on 1 March 2023 per industry category (i.e., 'High-bias industries', 'Mid-bias industries' and 'Low-bias industries'*)*. The figure is based on the model that uses three-year explicit forecast period coupled with *ANR* and steady state growth of 2%. The figure shows, illustrated in *Figure 3A*, that the incremental improvements of using the unbiased *RIV* model (RIV_{UB}) is greater in the 'High-bias industries' where measurement bias is inherently higher. Observations in the top-right corner indicates high measurement bias and large incremental improvement of *A-score* using the unbiased *RIV* model (RIV_{UB}) instead for the unbiased *RIV* model (RIV_{BM}). Sample size is 343 firm-year observations on 1 March 2023.

Figure 3F. Improvement in A-score and mean measurement bias per valuation date



Notes:
Figure 3F illustrates the incremental improvement of *A-score* by using the unbiased *RIV* model (RIV_{UB}) per valuation date (i.e., 1 March 2017 and 1 March 2023). The figure is based on a three-year explicit forecast period coupled with ANR and steady state growth of 2% for RIV_{BM} and RIV_{UB} for each respective valuate date. The figure shows, illustrated in *Figure 3A*, that the incremental improvements of using the unbiased *RIV* model (RIV_{UB}) is greater on 1 March 2017 when the measurement bias is inherently higher. Observations in the top-right corner indicates high measurement bias and large incremental improvement of *A-score* using the unbiased *RIV* model (RIV_{UB}) instead for the unbiased *RIV* model (RIV_{BM}). Sample size is 223 firm-year observations on 1 March 2017 and 343 on 1 March 2023.

Appendix 4: Industry categorisation

Exhibit 4A. Categorisation of industries, 2017

Industry	$q(MB)_0$	RIV_{UB}	RIV_{BM}	Δ%
High-bias industries				
Pharmaceutical	1.65	2.10	1.78	*18%*
Consumer goods	0.82	7.51	2.18	*245%*
Engineering	0.74	4.54	4.32	*5%*
Capital-intensive service	0.60	3.29	1.87	*76%*
Average	**0.95**	**4.36**	**2.54**	***72%***
Mid-bias industries				
Trading and retail	0.56	2.59	2.14	*21%*
Chemical industry	0.48	3.81	2.69	*41%*
Other service	0.45	6.79	8.80	*-23%*
Shipping	0.38	6.90	5.88	*17%*
Average	**0.47**	**5.02**	**4.88**	***3%***
Low-bias industries				
Consultants & computer	0.37	2.59	2.77	*-6%*
Building and construction	0.29	4.86	3.91	*24%*
Other production	0.29	0.96	0.79	*21%*
Pulp and paper	0.18	4.25	4.15	*3%*
Average	**0.28**	**3.17**	**2.91**	***9%***

Notes:
Exhibit 4B presents the categorisation of industries on 1 March 2017. The industries are grouped depending on size of measurement bias (i.e., 'High-bias industries', 'Mid-bias industries', 'Low-bias industries'). The rationale with the categorisation is to provide a more representative reflection of the inherent measurement bias and the improvement in *A-score* by using the unbiased *RIV* model (RIV_{UB}) compared to the base *RIV* model (RIV_{BM}). Sample size is 223 firm-year observations.

Exhibit 4B. Categorisation of industries, 2023

Industry	$q(MB)_0$	RIV_{UB}	RIV_{BM}	Δ%
High-bias industries				
Pharmaceutical	1.05	2.43	1.57	*55%*
Consumer goods	0.76	2.60	0.99	*161%*
Engineering	0.67	3.99	2.15	*85%*
Capital-intensive service	0.49	1.37	1.02	*35%*
Average	**0.74**	**2.60**	**1.43**	***81%***
Mid-bias industries				
Trading and retail	0.43	6.30	4.43	*42%*
Chemical industry	0.40	20.33	16.15	*26%*
Other service	0.40	2.83	2.05	*38%*
Shipping	0.35	0.88	0.91	*-3%*
Average	**0.40**	**7.79**	**5.88**	***29%***
Low-bias industries				
Consultants & computer	0.32	6.51	8.48	*-23%*
Building and construction	0.29	2.90	2.71	*7%*
Other production	0.26	4.36	2.91	*50%*
Pulp and paper	0.25	7.08	3.37	*110%*
Average	**0.28**	**5.21**	**4.36**	***19%***

Notes:
Exhibit 4B presents the categorisation of industries on 1 March 2023. The industries are grouped depending on size of measurement bias (i.e., 'High-bias industries', 'Mid-bias industries', 'Low-bias industries'). The rationale with the categorisation is to provide a more representative reflection of the inherent measurement bias and the improvement in *A-score* by using the unbiased *RIV* model (RIV_{UB}) compared to the base *RIV* model (RIV_{BM}). Sample size is 343 firm-year observations.