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Mark Bruun

ESSAYS ON EARNINGS PREDICTABILITY

The PhD School of LIMAC

PhD Series 12.2016

CBS  **COPENHAGEN BUSINESS SCHOOL**
HANDELSHØJSKOLEN

Essays on Earnings Predictability

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Preface

Thanks to my supervisors Thomas Plenborg, Kim Pettersson, Ole Sørensen and Jesper Banghøj. Furthermore thanks to Per Olsson and Jeppe Christoffersen for acting as my discussants at my final WIP seminar and for the useful comments. Also, thanks to Hans Frimor, Peter Ove Christensen and Jan Marton for providing useful comments. Thanks to Wayne Landsman for helping me make my messages in the articles clearer as well as for useful comments. Thanks to my colleagues at the Department of Accounting and Auditing at Copenhagen Business School.

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Finally, thanks to my friends and family for moral support and their patience through the whole process. Thank you, especially Ragnhild E. Gundersen for taking care of me and our daughter Cornelia.

Summary

This dissertation addresses the prediction of corporate earnings. The thesis aims to examine whether the degree of precision in earnings forecasts can be increased by basing them on historical financial ratios. Furthermore, the intent of the dissertation is to analyze whether accounting standards affect the accuracy of analysts' earnings forecasts. Finally, the objective of the dissertation is to investigate how the stock market is affected by the accuracy of corporate earnings projections.

The dissertation contributes to a deeper understanding of these issues. First, it is shown how earnings forecasts can be generated based on historical timeseries patterns of financial ratios. This is done by modeling the return on equity and the growth-rate in equity as two separate but correlated timeseries processes which converge to a long-term, constant level. Empirical results suggest that these earnings forecasts are not more accurate than the simpler forecasts based on a historical timeseries of earnings. Secondly, the dissertation shows how accounting standards affect analysts' earnings predictions. Accounting conservatism contributes to a more volatile earnings process, which lowers the accuracy of analysts' earnings forecasts. Furthermore, the dissertation shows how the stock market's reaction to the disclosure of information about corporate earnings depends on how well corporate earnings can be predicted. The dissertation indicates that the stock market's reaction to the disclosure of earnings information is stronger for firms whose earnings can be predicted with higher accuracy than it is for firms whose earnings can not be predicted with the same degree of accuracy.

Resumé (Summary in Danish)

Denne afhandling omhandler forudsigelse af virksomheders indkomst. Afhandlingen har til formål at undersøge, hvorvidt graden af præcision i indkomstprognoser for virksomheder kan øges ved at basere indkomstprognoser på historiske, finansielle nøgletal. Ydermere, er hensigten med afhandlingen at analysere hvorvidt regnskabsstandarder påvirker nøjagtigheden i analytikeres forudsigelser om virksomheders indkomst. Endelig, er målet med afhandlingen at undersøge, hvordan aktiemarkedet påvirkes af præcisionen i indkomstprognoser for virksomheder.

Afhandlingen bidrager til en dybere indsigt i disse problemstillinger. For det første, vises hvordan indkomstprognoser kan genereres ud fra historiske tidsseriemønstre for finansielle nøgletal. Dette gøres ved at modellere egenkapitalsforrentningen og vækstraten i egenkapitalen, som to separate, men korrelerede tidsserieprocesser, som konvergerer mod et langsigtet, konstant niveau. Empiriske resultater antyder, at disse indkomstprognoser ikke er mere nøjagtige end simple prognoser baseret på historiske tidsserier for indkomst. For det andet, viser afhandlingen, hvordan regnskabsstandarder påvirker analytikeres indkomstforudsigelser. Regnskabsmæssig konservatisme bidrager til en mere volatil indkomstproces, hvilket sænker nøjagtigheden i analytikeres indkomstprognoser. Desuden viser afhandlingen, hvordan aktiemarkedets reaktion på offentliggørelse af information om virksomheders indkomst, afhænger af i hvilken grad af præcision virksomheders indkomst kan predikteres. Afhandlingen indikerer, at aktiemarkedets reaktion på offentliggørelse af indkomstinformation, er kraftigere for virksomheder hvis indkomst kan forudsiges med højere nøjagtighed, sammenlignet med virksomheder hvis indkomst ikke kan forudsiges med samme grad af nøjagtighed.

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1 Research objective

For decades, the accounting literature (starting with Ball and Brown (1968) and Beaver (1968)) has studied whether earnings announcements are relevant or informative to investors, by looking at how prices (or market transactions) change when earnings are announced. The informativeness of earnings announcements is important for the stock market because it enhances the efficiency of capital allocation across firms in society. The informativeness of earnings announcements is closely related to the accuracy of earnings forecasting (which is also known as earnings predictability). If earnings were perfectly predictable, earnings announcements should not create a stock price movement, because there would be no earnings surprises (i.e. no new information content in the earnings). Likewise, stock price movements should only emerge because of the time value of money (i.e. less discounting of earnings)¹. Earlier studies disagree about whether more accurate earnings forecasting increases or decreases the informativeness of earnings announcements.

Another branch of the literature has studied how accurate earnings forecasts are. Lacina et al. (2011) and Bradshaw et al. (2012) compare analysts' forecasts to time-series based earnings forecasts. They find that analyst forecasts are only superior to a simple Random Walk (RW) time-series model in the short-run (i.e. one or two years ahead). Bansal et al. (2012) and Ball et al. (2014) focus on how the short-run accuracy of time-series based earnings forecasts can be enhanced. In the same way as informativeness in earnings announcements is important for the stock market, so are accurate earnings forecasts, because earnings forecasts implicitly determine the capital allocation across firms. However, as far as my

¹For this reason, increasing the accuracy of earnings forecasting should reduce the volatility of the stock market.

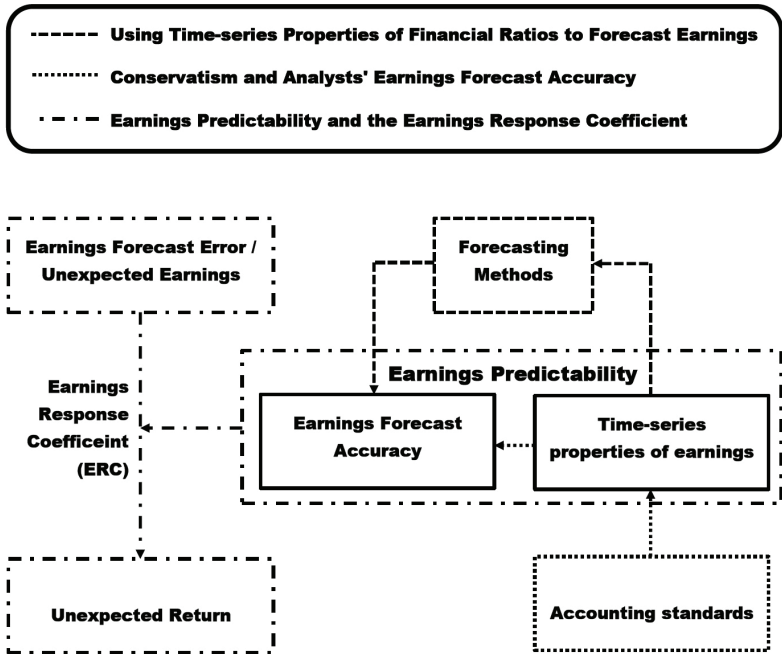
knowledge extends, no studies have focused on enhancing the forecasting accuracy of long-term (i.e. four or more years ahead), time-series-based earnings forecasting.

Another way to enhance the accuracy of earnings forecasts is to change the definition of earnings. Changing accounting standards is a way of redefining the definition of earnings. Mensah et al. (2004), Pae and Thornton (2010) and Sohn (2012) study how accounting standards (e.g. accounting conservatism) affects the accuracy of analysts' earnings forecasts. These studies assume that earnings volatility is exogenous. However, accounting conservatism probably changes the time-series properties of earnings, which again will affect the accuracy of analysts' earnings forecasts. Thus, earnings volatility should be treated as an endogenous variable.

The aim of this dissertation is to provide insight into how earnings predictability (i.e. forecast accuracy) can be enhanced and how this affects the market's reaction to earnings announcements. More specifically, the aim is to develop time-series based earnings forecasts that are more accurate than the existing time-series based earnings forecasting models; to analyze how accounting standards affect earnings predictability; and to analyze how earnings predictability moderates the relation between unexpected earnings and unexpected returns (also known as the Earnings Response Coefficient).

Figure 1 depicts the relations between the articles in the dissertation.

Figure 1: Article overview



The central concept of the dissertation, earnings predictability, is measured in different ways in the literature. The most widely used measure is the standard deviation of unexpected earnings, where unexpected earnings are defined as the forecast error (realized minus forecast value). For each firm, this measure can be estimated both cross-sectionally (i.e. based on analysts' forecasts)² and based on the time-series of earnings. The time-series properties of earnings (e.g. earnings volatility and persistence) is very closely related to the time-series standard deviation of unexpected earnings (Dichev and Tang (2009)). Thus, even though

²The standard deviation of unexpected earnings can also be estimated cross-sectionally based on time-series models. However this requires different time-series models, since a time-series model only generates a single forecast for each firm at a given point in time.

earnings volatility and persistence do not convey any information about forecasting accuracy (since no forecasting is required to estimate the earnings volatility and persistence), they can still be used as measures of earnings predictability.

In Article 1, I study whether the accuracy of time-series based earnings forecast can be enhanced by incorporating a well-known empirical long-run time-series property of earnings as well as well-known time-series properties of financial ratios: namely, the long-run growth in earnings and the mean-reversion in financial ratios. By modeling Return On Equity (ROE) and growth in book value of equity as two separate (but correlated) AR1 processes, I develop a time-series based model that generates mean-reversion forecasts for these financial ratios as well as forecasts where earnings grow in the long-run. Since this model incorporates well known empirical time-series properties, I hypothesize that its forecasting accuracy is better than that of the Random Walk (which does not incorporate long-run growth and mean-reversion of financial ratios in forecasts) and the Random Walk with drift (that does not incorporate mean-reversion of financial ratios in forecasts).

In Article 2, I study how accounting standards (e.g. accounting conservatism) affects the time-series properties of earnings and how this change in time-series properties affects the accuracy of analysts' earnings forecasts. Using the Penman and Zhang (2002) C-score (the estimated reserve) as a measure of accounting conservatism, I study how conservatism affects the accuracy of analysts' earnings forecasts, both directly and indirectly. The indirect effect is mediated through earnings volatility, because accounting conservatism decreases the match between revenue and expenses. This increases the volatility of earnings, which decreases the accuracy of analysts' forecasts (i.e. makes it more difficult to forecast). Thus,

in contrast to earlier research (Mensah et al. (2004), Pae and Thornton (2010) and Sohn (2012)) that treats earnings volatility as exogenous, I treat it as an endogenous variable.

In Article 3, I study how earnings predictability moderates the relation between unexpected earnings and unexpected returns (also known as the Earnings Response Coefficient (ERC)). I show how the most common empirical measures of earnings predictability are related, and how earnings predictability moderates the ERC without assuming a specific earnings expectation model, in contrast to earlier research that assumes specific earnings expectation models. Furthermore, using both a market based and two time-series based measures of earnings predictability, I estimate the relation between earnings predictability and the ERC.

2 Contributions

The three articles' abstracts are replicated below.

Article 1: Using Time-series Properties of Financial Ratios to Forecast Earnings

I forecast earnings from a model based on the time-series properties of financial ratios. This model captures two empirical patterns: mean reversion in financial ratios as well as long-run growth in earnings. I compare the accuracy of these earnings forecasts with the forecasts from a Random Walk model and analysts' forecasts based on a sample from 2001–2013. An analysis of the accuracy shows that the earnings forecast from the financial ratio based model are closer to having an equal frequency of optimistic and pessimistic forecasts than are those from the

Random Walk. However, in terms of forecasting accuracy and mean bias, the Random Walk model is the superior model.

Article 2: Conservatism and Analysts' Earnings Forecast Accuracy

Based on US data, I study the total effect that accounting conservatism has on the accuracy of analysts' earnings forecasts. I hypothesize that conservatism affects this accuracy directly and indirectly via the effect that conservatism has on the time-series properties of earnings. The results show that conservatism indirectly and positively affects the absolute forecast errors and dispersion, because conservatism increases earnings volatility. Furthermore, the results show that conservatism directly and positively influences the absolute forecast errors and dispersion, which indicates that either analysts do not correctly incorporate conservatism into their forecasts or there are other factors (besides earnings volatility) that mediate the relation between accounting conservatism and the accuracy of analysts' earnings forecasts. The findings suggest that regulators should not only consider the benefits of accounting conservatism, namely, protecting investors from future losses, but also the costs, in the form of higher earnings volatility and lower accuracy of earnings forecasts.

Article 3: Earnings Predictability and the Earnings Response Coefficient

One way to measure the informativeness of accounting information is the relation between unexpected stock returns and unexpected earnings (the Earnings Response Coefficient (ERC)). This paper analyzes how earnings predictability

affects the ERC. Earlier literature finds contradictory results about the relation between earnings predictability and the ERC, which might be explained by the earnings expectation model. I use three different measures of earnings predictability (earnings persistence, earnings volatility, and analyst forecast dispersion) and analytically show how they are related to each other and the ERC (without assuming a specific earnings expectation model). The analysis reveals that higher earnings volatility is associated with a higher analyst earnings forecast dispersion and lower earnings persistence. I provide evidence that a higher ERC is associated with a higher earnings predictability.

3 Data and research methods

The data used in the articles are all from large databases: Compustat, I/B/E/S and CRSP. The earnings forecasting accuracy (i.e. earnings predictability) measure in Article 1 is based on the “Street” earnings definition in the I/B/E/S database. The definition of “Street” earnings is a definition (used by financial analysts) that generally excludes nonrecurring items (Gu and Chen (2004), Abarbanell and Lehavy (2007)). I estimate the time-series model and study how earnings forecasting accuracy differs across this model, the Random Walk model and analyst forecasts. Estimation of the time-series properties on the individual firm-level implies small estimation samples. Under the assumption that the estimates of the time-series properties are consistent, increasing the sample size increases the probability of the estimates’ being close to the true value. To increase the sample size, I estimate the time-series properties of financial ratios grouped by industry, based on panel data. This, however, comes with a cost in terms of assuming that the time-series properties of the financial ratios are homogeneous across firms within an industry.

In Article 2, information from Compustat is used to estimate the conservative accounting factor (estimated reserve) as well as the earnings volatility and the I/B/E/S database is used to calculate the accuracy of analysts' forecasts (i.e. earnings predictability). The hypotheses in Article 2 were tested via path analysis using the PROC CALIS procedure in SAS.

In Article 3, the Earnings Response Coefficient (ERC) is estimated in the usual way (the ERC is the parameter estimate from regressing unexpected earnings on unexpected returns). The unexpected returns are estimated using stock returns from CRSP and the market model. The unexpected earnings are estimated from the I/B/E/S database as the difference between analysts' earnings forecasts and realized earnings. Estimating the earnings volatility and the earnings persistence (i.e. measures of earnings predictability) requires longitudinal data. Therefore I estimate the earnings volatility and earnings persistence based on earnings from Compustat, since estimating the earnings volatility and persistence from the I/B/E/S data would reduce the sample size significantly. Even though the definitions of earnings in I/B/E/S and Compustat differ, these measure are very probably highly correlated.

I test the hypotheses in Article 3 in the two step approach proposed by Cready et al. (2001): first I estimate individual firm ERCs; second, I regress the ERCs on earnings predictability and the market-to-book ratio.

4 Limitations and future research

Regarding Article 1, it is likely that the forecasting performance could have been enhanced by disaggregation of the (scaled) earnings into cash flow and accru-

als, since cash flows are more persistent than accruals (Sloan (1996)). Another possible disaggregation that might enhance the forecasting accuracy is splitting earnings into operating earnings and financial earnings. Thus, future research could study whether disaggregation can increase the forecasting accuracy of the proposed time-series model.

Article 2 only focuses on accounting conservatism from the cost side (i.e. expensing vs. capitalizing R&D and advertising costs). However, accounting conservatism can also arise on the revenue side by the choice of revenue recognition methods (i.e. completed-contract vs. percentage-of-completion method). Hence, a natural extension is to focus on unconditional conservatism from the revenue side.

In relation to Article 3, earlier studies (Sadka and Sadka (2009), Patatoukas (2014)) have made suggestions as to why the Earnings Response Coefficient (ERC) is negative when focusing on the aggregated level. Article 3 only focuses on the relation between earnings predictability and the ERC at the individual firm level. However, since the sign of the ERC is different depending on whether one looks at the individual firm level or the aggregated level, it is likely that the relation between earnings predictability and the ERC also depends on whether the focus is on the individual firm level or the aggregated level.

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Using Time-series Properties of Financial Ratios to Forecast Earnings

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Abstract

I forecast earnings from a model based on the time-series properties of financial ratios. This model captures two empirical patterns: mean reversion in financial ratios as well as long-run growth in earnings. I compare the accuracy of these earnings forecasts with the forecasts from a Random Walk model and analysts' forecasts based on a sample from 2001–2013. An analysis of the accuracy shows that the earnings forecast from the financial ratio based model are closer to having an equal frequency of optimistic and pessimistic forecasts than are those from the Random Walk. However, in terms of forecasting accuracy and mean bias, the Random Walk model is the superior model.

Keywords: Earnings forecasting, Time-series properties of earnings.

JEL classification: G17, C53.

1 Introduction

Earnings forecasts are used as inputs to estimate the intrinsic value of companies or infer the cost of capital of companies (also known as the implied cost of capital). In a practical setting, investors generate and use earnings forecasts when they assess the value of a company. Furthermore, in a scientific setting, earnings forecasts are used to estimate the implied cost of capital for firms, which is something used in financial and accounting research.

Empirically, financial ratios (such as scaled earnings) converge towards a long-run level (Nissim and Penman (2001) and Fama and French (2000)), e.g., Return On Equity (ROE) (and Return On Assets (ROA)) show signs of mean-reversion. These empirical findings are in line with economic theory, which suggests that competition drives the rate of return toward a constant level over time. Furthermore, Nissim and Penman (2001) show that sales growth (and growth in the book value of equity) converge to a positive constant level. Since revenue and costs are highly correlated, it is very likely that earnings growth will converge towards the same rate as sales growth¹. Positive long-run earnings growth is also supported by Myers (1999). He suggests that residual earnings follow a non-stationary (growing) time-series². Furthermore, positive long-run growth in earnings is a well known phenomenon at the macro-level (growth in GDP). Positive long-run GDP growth means that on average firms do have positive long-run earnings growth.

In practice, analyst earnings forecasts serve as input to investors for assessing

¹Under the assumption that a firm's profitability (profit margin) has converged to a constant level, earnings growth will equal sales growth

²Assuming that Return On Equity (ROE) is constant and different from the cost of equity capital, both residual earnings and earnings will grow at the same rate, namely the rate of growth in the book value of equity.

the value of a company. In the implied cost of capital literature, analyst earnings forecasts are the most widely used measure of the market's earnings expectations. However, Lambert et al. (2009) find that in the short run (one or two years ahead) analysts forecast EPS as if EPS follows a Random Walk (RW). This suggests that analysts use time-series based forecast models in the short run. Lambert et al. (2009) also find that analysts forecast the long-run earnings growth rate (five-year growth rate) based on fundamental analysis. However, others (e.g., Lacina et al. (2011) and Bradshaw et al. (2012)) show that over longer forecast horizons (five years), analyst forecasts are not superior to simple time-series based forecasts. Since analyst forecasts do not differ from RW forecasts in the short-run and perform worse than RW forecasts in the long-run, this suggests that enhancing time-series based forecasting accuracy can help analysts increase their forecast accuracy³. This might also lead to better stock recommendations generated by analysts, since Bradshaw (2004) find that analysts' recommendations are highly associated with the PEG (price/earnings growth) ratio and their estimates of the long-term growth (LTG) of earnings.

Simple time-series based models, such as the Random Walk (RW) model or the stationary Autoregressive of order 1 (AR1) model, do not forecast that earnings

³More accurate analyst earnings forecasts are not necessarily a better estimator of the market's earnings expectation, because the market's earnings expectations could be biased. Thus, enhancing the earnings forecast accuracy will not automatically lead to more efficient implied cost of capital estimates. Moreover, Francis et al. (2000, p. 46) shows empirically that (on average) the first five-year horizon represents only 7% (100%-72%-21%) of the firm value in the abnormal earnings model, whereas the terminal period accounts for 21% of the firm value. For the free cash flow (discounted dividend) model, the first five-year horizon equals 18% (35%) of firm value, compared to the terminal value that represents 82% (65%) of firm value. Thus the terminal period accounts for approximately three (two and five) times more of the firm value than the first five-year horizon. This means that, even though a more accurate earnings forecast would lead to more efficient implied cost of capital estimates, it is still conceivable that enhancing the accuracy of the analyst earnings forecasts over the first five-year forecast horizon will not lead to significantly more efficient implied cost of capital estimates, since the main part of firm value is generated in the terminal period.

grow in the long run. The non-stationary AR1 or time-series based models with (exponential) trend produce forecasts where the earnings grow exponentially over time. However, these time-series models of earnings do not impose a convergence structure on the financial ratios. For instance, if the long-run growth rate in earnings is not equal to the growth rate in book value of equity, this implies that the ROE does not converge to a constant value. So even the earnings growth convergence which is imposed by these time-series model does not imply that ROE and growth in book value of equity converge to constant values. To ensure the convergence of ROE and the growth rate of equity, these two processes have to be modeled separately. This has not been done in earlier time-series models. In this paper, I propose a time-series based earnings forecasting model that ensures long-run earnings growth and expected mean-reversion in ROE and the growth in book value of equity.

To ensure a) expected mean-reversion in ROE and growth in book value of equity, and b) long-run growth in earnings forecasts, I propose a time-series based earnings forecast model (which I will refer to as the Financial Ratio Autoregressive of order 1 (FRAR1) model) that assumes that the ROE and the (logarithm of) the growth in the book value of equity follow two different stationary AR1 processes. Furthermore, I will derive the implicit long-run expected (residual) earnings growth rate from the FRAR1⁴. To assess the accuracy of the earnings forecast, I compare the out-of-sample earnings forecasts from the FRAR1 model with the out-of-sample forecasts from an RW model of earnings and analysts' earnings forecasts. Based on data from I/B/E/S over the period 2001–2013, I estimate the FRAR1 model (there is nothing to estimate in an RW model).

⁴The model can be changed to a residual earnings model by changing the ROE process to an unexpected ROE process.

The analytical results show that earnings forecasts are a function of the current book value of equity, the future growth in the book value of equity, and future profitability (measured by the ROE). The analytical results further show that in the long run⁵ the growth in expected earnings will converge to a constant rate, which is equal to the growth rate in expected book value of equity. Assuming that the long-run growth in the expected book value of equity and the expected ROE is positive, long-run expected earnings will be higher than those of the long-run forecasts of an RW or an AR1 model, since expected long-run earnings from an RW or an AR1 model will converge to a constant. If implied cost of capital models assume no growth (or lower growth than the growth in book value of equity) in (residual) earnings, then their estimates will be lower than those from the earnings forecasts of the proposed models. The empirical results show that the accuracy and the mean bias of the proposed time-series model are worse than those of the RW model. However, if the bias size is ignored and one just focuses on the distribution between optimistic and pessimistic forecasts, the proposed model generates forecasts that are much closer to a binomial distribution with probability parameter of 0.5 (i.e., an equal number of optimistic and pessimistic forecasts) than do the RW model.

The rest of this paper is structured as follows. Section 2 reviews the literature. In Section 3, I describe the model and derive the earnings expectation based on the model's time-series parameters. In Section 4, I present the empirical research design. Sections 4.1 and 5 describe the sample and the results. Section 6 presents robustness tests. Section 7 concludes.

⁵This could be interpreted as the terminal period, even though a constant level of earnings growth is never reached. The process only converges toward a constant earnings growth level.

2 Related research

The earlier literature has analyzed whether analyst forecasts are better than forecasts based on statistics. These studies can mainly be divided into two lines of research. One line focuses on i) whether time-series based forecasts are superior to analyst forecasts; and another that ii) analyzes whether cross-sectional models (models that also include other information) perform better than analyst forecasts.

Regarding the first line of research, Bradshaw et al. (2012), Lacina et al. (2011) and Conroy and Harris (1987) have found that analyst earnings forecasts are not superior to a simple Random Walk (RW) model over longer forecast horizons (three to five years). These findings are in contrast with several earlier studies (see Bradshaw et al. (2012) for a review of these studies) that show that analyst earnings forecasts are superior to time-series based earnings forecasts. Bradshaw et al. (2012) conclude that the superiority of analyst earnings forecasts over time-series based forecasts is mainly driven by small sample sizes and a bias to large firms. Bradshaw et al. (2012) analyze a three-year forecasting period. They find that the superiority of analyst forecasts over RW forecasts declines as the forecast horizon increases and find that in the third year, the RW forecasts are superior to the analyst forecasts. This is in line with the findings of Conroy and Harris (1987) and Lacina et al. (2011) even though they looked at a five-year forecast horizon. They also find that the superiority of analyst forecasts over RW models declines over the forecast horizon. Conroy and Harris (1987) find that the RW is superior to analyst forecasts when forecasting earnings five years ahead. Lacina et al. (2011) do not find that the RW forecasts are superior to analyst forecasts when forecasting earnings five years ahead. However, when they use a RW with a growth rate, then they also find that it is superior to analyst forecasts when forecasting five

years ahead. Thus, over longer forecasting horizons, simple time-series models seem to perform better than (or just as good as) analyst forecasts. However, in the short run, analyst forecasts still seem to be superior to time-series based forecasts. This superiority is mainly due to timing and informational advantages.

With respect to the second line of research, Nissim and Ziv (2001), Fama and French (2006) and Hou et al. (2012) specify different cross-sectional earnings forecasting models. All these three models have high in-sample accuracy (R -squared around 60%–80% for all forecasting years)⁶. However, only Hou et al. (2012) studies the out-of-sample forecast performance. Hou et al. (2012) compares their proposed model's forecast with analyst forecasts. They conclude that analyst earnings forecasts are more accurate than their proposed cross-sectional model. However analyst earnings forecasts are more biased and produce lower Earning Response Coefficients (ERCs). Using a mixed-data sampling (MIDAS) regression⁷ Ball et al. (2014) reduce the timing and informational advantages that analysts have in the short run compared to time-series and cross-sectional based forecasts, and show that their statistical model outperforms analyst forecasts in terms of accuracy in the short run (one quarter ahead).

As mentioned above, the model proposed by Hou et al. (2012) outperforms analyst forecasts in terms of forecast bias and ERC, but is worse in terms of accuracy. On the other hand, Ball et al. (2014) show that their model is superior to analyst forecasts in terms of accuracy, but they do not report other performance measures. There are different dimensions along which to measure forecasting performance.

⁶The R -square from Fama and French (2006) range from 20% to 39%. This is much lower than the R -squares in Nissim and Ziv (2001) and Hou et al. (2012). However, this can be explained by the fact that the dependent variables in Fama and French (2006) are scaled by current book value.

⁷MIDAS regression allows the regressors to have a higher frequency than the regressand.

Forecasting performance could be measured a) directly, such as forecast bias and forecast accuracy (a discussion of direct forecast performance measures and scaling is provided in Section 4.2) and b) indirectly, such as the ERC and absolute valuation errors (Bach and Christensen (2013)).

3 The income process

In this paper, I forecast earnings by dividing earnings into a function of Return On Equity (ROE) and growth in book value (of equity). The future book value (of equity) at time T (BV_T) can be written as the product of the current book value (of equity) (BV_0) and the future growth rate in book value (of equity) (g_t^{BV}):

$$BV_T = BV_0 \prod_{t=1}^T (1 + g_t^{BV})$$

Going concerns are rarely insolvent, and therefore I assume that $1 + g_t^{BV} > 0$ for all t . Under this assumption, the future book value (of equity) can be written as

$$BV_T = BV_0 \underbrace{e^{\sum_{t=1}^T \ln(1 + g_t^{BV})}}_{G_T}$$

where G_T denotes the accumulated growth in book value (of equity) from time 0 to time T . Expressing the accumulated growth in book value (of equity) as the exponential of a sum instead of a product has a simple but huge advantage (under specific assumptions) when calculating expected values (and covariances). Assuming that $\ln(1 + g_t^{BV})$ is normally distributed, the expected value of growth in book value (of equity) is the expected value of the exponential of a normally distributed variable. The expected value of this follows easily from the moment generating function, whereas the expected value of a product of normally distributed variables is much more complex.

Earnings at time $T + 1$ are then equal to

$$INC_{T+1} = BV_T ROE_{T+1} = BV_0 G_T ROE_{T+1}$$

The earnings forecast at time $T + 1$, given the available information at time 0, Θ_0 , is therefore

$$\begin{aligned} E[INC_{T+1}|\Theta_0] &= E[BV_0 G_T ROE_{T+1}|\Theta_0] \\ &= BV_0 (E[G_T|\Theta_0]E[ROE_{T+1}|\Theta_0] + Cov[ROE_{T+1}, G_T|\Theta_0]) \quad (1) \end{aligned}$$

Thus the earnings forecasting model requires separate forecasts of the ROE and the accumulated growth in book value (of equity) and also an estimation of the covariance between the ROE and the accumulated growth in book value (of equity).

3.1 Expected value of Return On Equity (ROE)

I model the process of the ROE by an AR1 process, which means that

$$ROE_t = \gamma + \rho ROE_{t-1} + \omega_t$$

where $0 < \rho < 1$ and $\omega_t \sim N(0, \theta^2)$ and are mutually independent over time⁸.

This can be (using recursion) rewritten as

$$ROE_t = \underbrace{\frac{\gamma}{1-\rho} + \rho^t \left(ROE_0 - \frac{\gamma}{1-\rho} \right)}_{D_t} + \sum_{h=1}^t \rho^{t-h} \omega_h$$

⁸When the absolute value of the autoregressive parameter in an AR1 process is less than one (i.e. $|\rho| < 1$), the time-series is stationary and this will ensure that the expectation of the process will converge to a constant level in the long run. Furthermore, requiring the autoregressive parameter estimate to be positive (and still less than one) will imply that the expected convergence to a long-run constant level will be steady. If the parameter is negative (and smaller than one in absolute value), this will imply a oscillatory convergence pattern.

The expectation of ROE given the available information at time 0 is equal to

$$\begin{aligned} E [ROE_t | \Theta_0] &= E \left[\frac{\gamma}{1-\rho} + \rho^t \left(ROE_0 - \frac{\gamma}{1-\rho} \right) + \sum_{h=1}^t \rho^{t-h} \omega_h \middle| \Theta_0 \right] \\ &= \frac{\gamma}{1-\rho} + \rho^t \left(ROE_0 - \frac{\gamma}{1-\rho} \right) \end{aligned}$$

3.2 Expected value of the accumulated growth in book value of equity (G)

Like the process of ROE, I model the logarithm of one plus the growth in book value of equity by an AR1 process:

$$\ln (1 + g_t^{BV}) = \alpha + \beta \ln (1 + g_{t-1}^{BV}) + \epsilon_t$$

where $0 < \beta < 1$ and the $\epsilon_t \sim N(0, \sigma^2)$ are mutually independent over time.

Modeling the growth in book value of equity as an AR1 process might seem more appealing, because the structural relation between the ROE and the growth in book value of equity⁹ could be built into the model. However (as noted earlier) this would make the analysis a lot more complicated.

One way to still be able to model the growth in book value of equity as an AR1 process (instead of as the logarithm of one plus the growth in book value of equity) is to use a Taylor approximation. The first order Taylor approximation of $\ln (1 + g_t^{BV})$ around 0 is equal to g_t^{BV} . However, the errors of the Taylor approximation becomes larger the longer we move away from 0. Thus for values of $|g_t^{BV}|$ close to 0, the approximation is good. However if the values of g_t^{BV} lie

⁹Assuming the Clean Surplus Relation holds, then the growth in the book value of equity equals the ROE plus the net dividend ratio, defined as the net dividend divided by the initial book value of equity.

in the interval $[-50\%-50\%]$, the approximation of $\ln(1 + g_t^{BV}) \approx g_t^{BV}$ is a poor approximation for the whole interval. A growth in the book value of equity of about $-/+50\%$ is not that uncommon for firms. Therefore, it is $\ln(1 + g_t^{BV})$ that I model as an AR1 process.

In Appendix A, it is shown that the expected value of the accumulated growth in book value of equity equals

$$E \left[e^{\sum_{t=1}^T \ln(1+g_t^{BV})} \middle| \Theta_0 \right] = E[G_T | \Theta_0] = A_T e^{\frac{1}{2} H_T}$$

where

$$A_T = e^{\frac{\alpha}{1-\beta} T + \frac{\beta(1-\beta^T)}{1-\beta} (\ln(1+g_0^{BV}) - \frac{\alpha}{1-\beta})}$$

and

$$H_T = \sigma^2 \left(\frac{T - 2 \frac{\beta(1-\beta^{T+1})}{1-\beta} + \frac{\beta^2(1-\beta^{2(T+1)})}{1-\beta^2}}{(1-\beta)^2} \right)$$

3.3 Covariance between ROE and G

Assume that $X = \mu + \omega$ and that $\ln(Y) = \gamma + \epsilon$, where μ and γ are constants and where $\omega \sim \mathcal{N}(0, \theta^2)$ and $\epsilon \sim \mathcal{N}(0, \sigma^2)$. Then the covariance between X and Y equals

$$\begin{aligned} Cov[XY] &= Cov \left[X, e^{\ln(Y)} \right] = Cov \left[\mu + \omega, e^{\gamma + \epsilon} \right] \\ &= E[\mu e^{\gamma + \epsilon} + \omega e^{\gamma + \epsilon}] - E[\mu + \omega] E[e^{\gamma + \epsilon}] \\ &= E[\mu e^{\gamma + \epsilon}] + E[\omega e^{\gamma + \epsilon}] - \mu E[e^{\gamma + \epsilon}] = E[\omega e^{\gamma + \epsilon}] = e^{\gamma} E[\omega e^{\epsilon}] \end{aligned}$$

This means that

$$\begin{aligned}
& Cov[ROE_{T+1}, G_T | \Theta_0] \\
&= Cov \left[D_{T+1} + \sum_{i=1}^{T+1} \rho^{T+1-i} \omega_i, A_T e^{\sum_{t=1}^T \sum_{h=1}^t \beta^{t-h} \epsilon_h} \middle| \Theta_0 \right] \\
&= A_T Cov \left[\underbrace{\sum_{i=1}^{T+1} \rho^{T+1-i} \omega_i}_{v_{T+1}}, e^{\overbrace{\frac{1}{2} 2 \sum_{t=1}^T \sum_{h=1}^t \beta^{t-h} \epsilon_h}^{\eta_T}} \middle| \Theta_0 \right]
\end{aligned}$$

From Stein's Lemma, we then get that

$$\begin{aligned}
Cov[ROE_{T+1}, G_T | \Theta_0] &= A_T E \left[\frac{\partial e^{\frac{1}{2} \eta_T}}{\partial \eta_T} \right] Cov[v_{T+1}, \eta_T | \Theta_0] \\
&= \frac{1}{2} A_T E \left[e^{\frac{1}{2} \eta_T} \right] Cov[v_{T+1}, \eta_T | \Theta_0]
\end{aligned}$$

Furthermore (as noted in Appendix A), we get from the moment generating function that $E \left[e^{\frac{1}{2} \eta_T} \right] = e^{\frac{1}{8} Var[\eta_T | \Theta_0]}$. Thus

$$Cov[ROE_{T+1}, G_T | \Theta_0] = \frac{1}{2} A_T e^{\frac{1}{8} Var[\eta_T | \Theta_0]} Cov[v_{T+1}, \eta_T | \Theta_0]$$

where

$$A_T = e^{\frac{\alpha}{1-\beta} T + \frac{\beta(1-\beta^T)}{1-\beta}} (\ln(1+g_0^{\beta V}) - \frac{\alpha}{1-\beta})$$

as in Section 3.2, and expressions for the variance of v_{T+1} and η_T as well as their covariance are given in Appendix B.

Since $Var[\eta_T|\Theta_0] = 4H_T$, this means that

$$\begin{aligned} Cov[ROE_{T+1}, G_T|\Theta_0] &= \frac{1}{2}A_T e^{\frac{1}{2}H_T} Cov[v_{T+1}, \eta_T|\Theta_0] \\ &= \frac{1}{2}E[G_T|\Theta_0]Cov[v_{T+1}, \eta_T|\Theta_0] \end{aligned}$$

Inserting the expression for the expected value of ROE, the expected value of the accumulated growth in book value of equity, and the covariance between ROE and accumulated growth in book value of equity into Equation 1 implies that the forecast of period T earnings is

$$E[INC_T|\Theta_0] = BV_0 E[G_{T-1}|\Theta_0] \left(E[ROE_T|\Theta_0] + \frac{1}{2}Cov[v_T, \eta_{T-1}|\Theta_0] \right) \quad (2)$$

Using the FRAR1 model to estimate firms' intrinsic values (with the going concern assumption) or to estimate firms' implied cost of capital requires endless forecasts of earnings. Therefore it is interesting to analyze how the earnings process modeled by the FRAR1 model behaves in the long run (i.e., as T goes to infinity). It can be observed that the expectation of earnings in the long run is divergent. Therefore, focusing on the growth in expected earnings in the long run makes more sense. In Appendix C, I show that the growth in expected earnings is a function of the expected long-run growth (and volatility) of the book value of equity.

4 Empirical analysis

I compare the accuracy of out-of-sample earnings forecasts of the FRAR1 model with those of the Random Walk (RW) model and of analyst forecasts over a five-year forecasting period. When estimating the FRAR1 model, I allow the error terms in the two AR1 processes to be correlated, because ROE and growth in book value of equity are very likely to be positively correlated. Thus, the two AR1 processes can not be estimated separately. Therefore, I rewrite the model as a restricted VAR1 model and estimate it. The VAR1 model is

$$Y_t = A + BY_{t-1} + E_t$$

where

$$Y_t = \begin{bmatrix} ROE_t \\ \ln(1 + g_t^{BV}) \end{bmatrix}, \quad Y_{t-1} = \begin{bmatrix} ROE_{t-1} \\ \ln(1 + g_{t-1}^{BV}) \end{bmatrix}, \quad E_t = \begin{bmatrix} \omega_t \\ \epsilon_t \end{bmatrix}$$

and

$$A = \begin{bmatrix} \gamma \\ \alpha \end{bmatrix}, \quad B = \begin{bmatrix} \rho & 0 \\ 0 & \beta \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \theta^2 & \psi \\ \psi & \sigma^2 \end{bmatrix}$$

To generate the forecasts for years one to five from the FRAR1 model, I plug the estimated elements (i.e. γ , α , ρ , β , θ , σ and ψ) from the A, B and Σ matrices of the VAR1 model¹⁰ into Equation 2. By varying T from one to five I get the forecast for years one to five.

¹⁰Note that the notation for the the covariance between the error terms in the VAR1 model is ψ , although it is denoted by $Cov[\omega_i, \epsilon_i]$ in the analytical derivation of the FRAR1 model.

For the empirical analysis, there are some issues related to the data. There are two main data issues: a) the length of the time-series of annual earnings and b) the definition of earnings. Regarding the first issue, the time-series of annual earnings are relatively short (normally around 10–15 years). So the seven parameter estimates (i.e. γ , α , ρ , β , θ , σ and ψ) will on average be based on only 10–15 observations when the FRAR1 model is estimated at the firm level. However, the FRAR1 model could be estimated for groups of firms. Estimating the parameters at the group level increases the size of the estimation sample (and thereby reduces the influence of outliers). On the other hand, a group level estimation assumes the homogeneity of the time-series parameters across the firms in the sample group. Now, the mean-reversion pattern as well as the long-run ROE are likely to be the same within an industry¹¹. Thus I estimate the time-series parameters of the VAR1 model at the industry level¹² using the least squares method. For AR (and VAR) models, the least squares estimate is biased because of a violation of the assumption of the independence of the regressor and the error term. To control for this estimation bias, different bias-correction methods have been proposed in the literature. Engsted and Pedersen (2014) show that for stationary series, the analytical bias-correction formula for VAR processes is just as good as more complicated correction procedures (such as bootstrap methods). Furthermore, they show that when the sample size is 200, the bias is very close to zero. Therefore, I require at least 200 observations per sample group.

Regarding the earnings definition issue, Compustat earnings and I/B/E/S earnings are defined differently. Compustat uses the US GAAP earnings definition,

¹¹The mean-reverting patterns in Nissim and Penman (2001) are also based on groups of firms. However, here the group formation is not based on industry, but on the level of the ratio.

¹²The industry is categorized according to the 2-digit SIC code.

whereas I/B/E/S use the so called “Street earnings” definition. Abarbanell and Lehavy (2007) describes how the I/B/E/S earnings measure excludes nonrecurring items, other special items, and non-operating items in the GAAP earnings measure. Also, they point out that the difference between I/B/E/S and GAAP earnings can never be traced back to raw data. The I/B/E/S database is less comprehensive than Compustat with respect to the historical period and the number of firms included, and thus will lead to a smaller estimation sample. Hou et al. (2012) deal with this problem by calculating the analyst forecast errors based on the realized I/B/E/S earnings and the forecasting errors from their proposed model on the realized US GAAP earnings. However, it is wrong to compare forecasting errors when they are based on different variables¹³. Thus, to ensure consistency in the definition of earnings, I estimate the FRAR1 model on data from the I/B/E/S database, even though I recognize the estimation sample will be smaller than when the FRAR1 model is estimated based on Compustat.

4.1 Sample Selection

The data sample used in the analysis is the intersection of the available forecasts from the FRAR1 model and the analysts. All observations with non-missing data (or data equal to zero) for the fiscal year of Book value of Equity Per Share (BPS) and of Earnings Per Share (EPS) are used. Firms with an SIC code in [4900–4999] or in [6000–6999] are excluded. These are regulated firms, such as utilities and financial institutions. To reduce the influence of outliers on the parameter estimates, I exclude observations where the common equity is negative, the absolute value of ROE is larger than one, or the absolute growth in book value of equity is

¹³Hou et al. (2012) also calculate the analyst and the model forecasting errors where both are based on the same earnings definition. This is also wrong since the analyst forecast earnings are I/B/E/S earnings and the model involves US GAAP earnings.

larger than one¹⁴. I Winsorize all independent and the dependent variables at the top and bottom 1% level. Table 1 shows the summary statistics of the variables used in the FRAR1 model. The table shows that the distribution of EPS and BPS is upper skewed, since the mean is much higher than the median.

Table 1: Descriptive Statistics

| Period | Variable | Mean | Median | No. Obs. |
|--------|---------------|---------|--------|----------|
| t+0 | BPS | 457.102 | 7.26 | 8983 |
| t+0 | Growth in BPS | 0.035 | 0.059 | 8968 |
| t+0 | ROE | 0.074 | 0.112 | 8400 |
| t+0 | EPS | 0.933 | 0.78 | 8414 |
| t+1 | BPS | 93.492 | 7.98 | 6673 |
| t+1 | Growth in BPS | 0.088 | 0.068 | 6651 |
| t+1 | ROE | 0.047 | 0.11 | 7262 |
| t+1 | EPS | 0.929 | 0.79 | 7286 |
| t+2 | BPS | 22.334 | 8.533 | 4937 |
| t+2 | Growth in BPS | 0.083 | 0.065 | 4708 |
| t+2 | ROE | 0.069 | 0.116 | 5271 |
| t+2 | EPS | 0.967 | 0.81 | 6018 |
| t+3 | BPS | 13.459 | 9.42 | 3565 |
| t+3 | Growth in BPS | 0.085 | 0.068 | 3332 |
| t+3 | ROE | 0.083 | 0.121 | 3935 |
| t+3 | EPS | 1.102 | 0.85 | 4971 |
| t+4 | BPS | 13.427 | 10.26 | 2621 |
| t+4 | Growth in BPS | 0.06 | 0.079 | 2377 |
| t+4 | ROE | 0.125 | 0.131 | 2858 |
| t+4 | EPS | 1.285 | 0.89 | 4075 |
| t+5 | BPS | 13.871 | 10.706 | 2046 |
| t+5 | Growth in BPS | 0.304 | 0.083 | 1810 |
| t+5 | ROE | 0.156 | 0.149 | 2036 |
| t+5 | EPS | 1.401 | 0.98 | 3330 |

Mean and median values of the variables and number of observations for each variable over the five-year forecasting period. Period $t + k$ indicates the j -year ahead forecast. Firm-year observations are pooled: thus the fiscal year for forecasting period $t + k$ could differ across firms (and also for a specific firm if forecasts are repeated for the same firm).

“BPS” is the Book Value of Equity Per Share. “Growth in BPS” is the growth-rate of Book Value of Equity Per Share. “ROE” is Return On Equity. “EPS” is Earnings Per Share.

¹⁴As shown in Section 3, the variance of the growth in BV increases with time due to persistence. This means that large variance estimates are extraordinarily inflated. So to deal with large variance estimates for the growth in book value of equity, I exclude observations where the growth in equity is larger than 1.

4.2 Measurement of the forecast bias and accuracy

The most common accuracy measures in the forecasting literature are the mean/median absolute error (MAE/MdAE), the mean/median absolute percentage error (MAPE/MdAPE), and the weighted mean absolute percentage error (wMAPE).

The forecast error is equal to the difference between the actual value and the forecast value. Let A_i denote the actual value for observation i , where i could indicate the time or the group or a combination of time and group. Then let F_i denote the forecast for observation i . The absolute error and absolute percentage error for observation i is defined as follows:

$$AE_i = |A_i - F_i|$$

$$APE_i = \left| \frac{A_i - F_i}{A_i} \right|$$

Let $\text{mean}(x)$ denote the mean of x and $\text{median}(x)$ its median. This means that, e.g., MAE and MAPE are defined by

$$\text{MAE} = \text{Mean}(\text{AE}) = \frac{1}{n} \sum_{i=1}^n |A_i - F_i|$$

$$\text{MAPE} = \text{Mean}(\text{APE}) = \frac{1}{n} \sum_{i=1}^n \left| \frac{A_i - F_i}{A_i} \right|$$

where n is the number of observations forecast.

The forecast error measures MAE (MdAE) are scale-dependent measures, which means that the error is dependent on the actual level. This means that since comparison is done on a wide sample of companies, including both very large companies and very small, a very high MAE (MdAE) could emerge even though the

model makes very accurate forecasts for small companies.

MAPE (MdAPE) are forecast error measures that are supposed to be not scale-dependent, since the forecast error is measured relatively to the actual value. However, in the earnings forecasting literature, the most widely used scale-independent measure is neither MAPE nor MdAPE: instead, a price-deflated measure is used. This price-deflated measure is defined as the absolute error deflated by the stock price¹⁵. However, as Jacob et al. (1999) notes, using the absolute price-deflated error (APDE) as a measure of forecast accuracy has drawbacks. Often there are large fluctuations in the APDE over the years. This stems from the fact that price-deflated absolute forecast errors could be rewritten as MAPE times the inverse price–earnings ratios¹⁶, which means that the APDE is a function of the forecast accuracy and a valuation multiple.

Hyndman and Koehler (2006) point out that these scale-independent measures have some other problems as well. When any actual value (stock price) is close to zero, the distribution of MAPE (APDE) is extremely skewed, since the MAPE (APDE) approaches infinity when the actual value (stock price) approaches zero. Forecast errors where the actual value (stock price) is close to zero will therefore be weighted much more highly than forecast errors for which the actual value (stock price) is higher.

To deal with this small denominator problem, Lacina et al. (2011) Winsorize the APE (and APDE) values above one. Another approach, which Gu and Wu (2003)

¹⁵The absolute error is deflated by the stock price when forecasting earnings per share. When forecasting earnings, it is deflated by the market value of the firm

¹⁶ $APDE = \frac{E_i - F_i}{P_i} = \frac{E_i - F_i}{E_i} \frac{E_i}{P_i} = MAPE_i \frac{E_i}{P_i}$

use, is to require that the demonimator (stock price) be at least three (dollars).

The accuracy measures presented here are linear loss functions (in contrast to, e.g., the mean squared error, which is a quadratic loss function). Assuming that analysts have quadratic loss functions, Basu and Markov (2004) show that analysts do not process public information efficiently. However, under the assumption that the analysts' loss function are instead linear, they show that analysts' forecasts are efficient. This suggests that analysts' loss functions are linear. Therefore accuracy measures with a linear loss function are appropriate when comparing forecasting accuracy that includes analysts' forecasts.

The main part of the literature (Lacina et al. (2011), Bradshaw et al. (2012), Hou et al. (2012)) on time-series/cross-sectional based earnings forecast accuracy versus analyst earnings forecast accuracy scale by the stock price (i.e. a price-deflated measure). I follow this line of the literature and use the mean/median absolute price-deflated error (MAPDE/MdAPDE) accuracy measure. To deal with the small denominator problem, I use the Winsorizing approach from Lacina et al. (2011).

Forecast bias measures could be defined analogously to the forecast accuracy measures by calculating the forecast error instead of the absolute value of the forecast error. Therefore I use the mean/median price-deflated error (MPDE/MdPDE) as a forecast bias measure.

5 Results

Table 2 shows the parameter estimates for the VAR(1) model. The table shows that all the industry–year sets of parameter estimates are stationary and will converge steadily to a long-run level (i.e. $0 < \rho < 1$ and $0 < \beta < 1$). Furthermore, as expected, the error terms from the two autoregressive processes are positively correlated (i.e. $\psi > 0$)¹⁷.

Table 2: Parameter Estimates

| SIC Code | Year | γ | ρ | α | β | θ | σ | ψ | No. Obs. |
|----------|------|----------|--------|----------|---------|----------|----------|--------|----------|
| 13 | 2007 | 0.10 | 0.45 | 0.08 | 0.42 | 0.12 | 0.24 | 0.02 | 222 |
| 13 | 2013 | 0.06 | 0.56 | 0.06 | 0.10 | 0.10 | 0.23 | -0.01 | 591 |
| 20 | 2013 | 0.03 | 0.85 | 0.07 | 0.05 | 0.08 | 0.20 | 0.01 | 273 |
| 28 | 2005 | -0.01 | 0.84 | -0.05 | 0.55 | 0.18 | 0.31 | 0.01 | 317 |
| 28 | 2013 | 0.03 | 0.77 | 0.03 | 0.18 | 0.16 | 0.28 | 0.01 | 636 |
| 35 | 2005 | 0.04 | 0.64 | 0.03 | 0.46 | 0.12 | 0.21 | 0.01 | 280 |
| 35 | 2013 | 0.06 | 0.68 | 0.07 | 0.11 | 0.11 | 0.22 | 0.01 | 607 |
| 36 | 2005 | 0.01 | 0.79 | -0.01 | 0.49 | 0.11 | 0.24 | 0.01 | 376 |
| 36 | 2014 | 0.05 | 0.66 | 0.04 | 0.14 | 0.10 | 0.25 | 0.01 | 273 |
| 37 | 2008 | 0.02 | 0.82 | -0.02 | 0.40 | 0.12 | 0.31 | 0.02 | 209 |
| 37 | 2013 | 0.06 | 0.68 | 0.04 | 0.25 | 0.11 | 0.24 | 0.01 | 300 |
| 38 | 2005 | 0.01 | 0.80 | -0.01 | 0.60 | 0.11 | 0.24 | 0.01 | 311 |
| 38 | 2013 | 0.03 | 0.77 | 0.07 | 0.15 | 0.09 | 0.18 | 0.01 | 537 |
| 48 | 2008 | 0.01 | 0.69 | -0.09 | 0.24 | 0.15 | 0.41 | 0.03 | 203 |
| 48 | 2013 | 0.04 | 0.59 | -0.04 | 0.15 | 0.16 | 0.34 | 0.02 | 292 |
| 50 | 2013 | 0.09 | 0.45 | 0.08 | 0.04 | 0.09 | 0.17 | 0.01 | 255 |
| 73 | 2005 | 0.04 | 0.63 | 0.03 | 0.36 | 0.11 | 0.25 | 0.01 | 490 |
| 73 | 2013 | 0.07 | 0.60 | 0.06 | 0.31 | 0.11 | 0.23 | 0.01 | 995 |

Parameter estimates for the VAR1 model by 2-digit SIC code and fiscal year. For clarity, only the first and last fiscal year for each 2-digit SIC code are shown. In total there are 62 sets of parameter estimates distributed over 10 2-digit SIC code industries.

Tables 3 and 4 present the mean and median price deflated forecast errors (MPDE and MdPE), also known as the mean and median bias.

¹⁷For clarity, only the first and last fiscal year for each 2-digit SIC code are shown in Table 2. In total there are 62 sets of parameter estimates distributed over 10 2-digit SIC code industries. The other 44 industry–year sets of parameter estimates that are untabulated are similar to the presented ones

Table 3: Forecast Bias—Mean Price Deflated Error

| Model | Period t+1 | | Period t+2 | | Period t+3 | | Period t+4 | | Period t+5 | |
|------------------|------------|----------|------------|----------|------------|----------|------------|----------|------------|----------|
| | MPDE | No. Obs. | MPDE | No. Obs. | MPDE | No. Obs. | MPDE | No. Obs. | MPDE | No. Obs. |
| FRAR1 | -0.013 | 5961 | -0.031 | 4406 | -0.024 | 2489 | -0.027 | 1889 | -0.023 | 1500 |
| Random Walk | 0 | 5961 | 0 | 4406 | 0.007 | 2489 | 0.013 | 1889 | 0.015 | 1500 |
| Analyst Forecast | -0.022 | 5961 | -0.044 | 4406 | -0.046 | 2489 | -0.063 | 1889 | -0.077 | 1500 |

Forecast bias measured by the Mean Price Deflated Error (MPDE) over the five-year forecasting period for the proposed model in the paper (FRAR1), the Random Walk, and Analyst Forecasts. Period $t + k$ indicates the j -year ahead forecast. Firm-year observations are pooled, thus the fiscal year for forecasting period $t + k$ could differ across firms (and also for a specific firm if forecasts are repeated for the same firm).

Table 3 shows that the FRAR1 model and the analyst forecasts are too optimistic (i.e., negative forecast bias) over the whole five-year forecasting period. The signs on the mean forecast bias for the RW model suggest that the RW model forecasts are unbiased in the first two years, whereas in the next three years they are too pessimistic (i.e., positive forecast bias). Furthermore, it shows that the RW model has the lowest (unsigned) mean forecast bias and that the analyst forecasts have the highest.

Table 4: Forecast Bias—Median Price Deflated Error

| Model | Period t+1 | | Period t+2 | | Period t+3 | | Period t+4 | | Period t+5 | |
|------------------|------------|----------|------------|----------|------------|----------|------------|----------|------------|----------|
| | MdPDE | No. Obs. | MdPDE | No. Obs. | MdPDE | No. Obs. | MdPDE | No. Obs. | MdPDE | No. Obs. |
| FRAR1 | 0.006 | 5961 | 0.006 | 4406 | 0.009 | 2489 | 0.011 | 1889 | 0.013 | 1500 |
| Random Walk | 0.004 | 5961 | 0.008 | 4406 | 0.012 | 2489 | 0.016 | 1889 | 0.018 | 1500 |
| Analyst Forecast | 0.003 | 5961 | -0.003 | 4406 | -0.004 | 2489 | -0.01 | 1889 | -0.017 | 1500 |

Forecast bias measured by the Median Price Deflated Error (MdPDE) over the five-year forecasting period for the proposed model in the paper (FRAR1), the Random Walk, and Analyst Forecasts. Period $t + k$ indicates the j -year ahead forecast. Firm-year observations are pooled, thus the fiscal year for forecasting period $t + k$ could differ across firms (and also for a specific firm if forecasts are repeated for the same firm).

However, Table 4 shows that the FRAR1 model has the lowest (unsigned) median forecast bias in forecasting in year five, whereas in years one to four, the analyst forecasts have the lowest. Furthermore, it shows that the RW model has

the highest (unsigned) median forecast bias in all years except year one, where the FRAR1 model have the highest. The signs of the median forecast bias show that the RW and FRAR1 model are too pessimistic, whereas the analyst forecasts are too optimistic (except for year one). Overall, the two tables do not clearly suggest which forecast has the lowest bias. On the other hand, Table 5 shows the percentage of forecasts where the forecast error is positive.

Table 5: Forecast Bias—Percentage of Positive Forecast Errors

| Model | Period t+1 | | Period t+2 | | Period t+3 | | Period t+4 | | Period t+5 | |
|------------------|------------|----------|------------|----------|------------|----------|------------|----------|------------|----------|
| | PPPE | No. Obs. | PPPE | No. Obs. | PPPE | No. Obs. | PPPE | No. Obs. | PPPE | No. Obs. |
| FRAR1 | 0.611 | 5961 | 0.569 | 4406 | 0.595 | 2489 | 0.608 | 1889 | 0.622 | 1500 |
| Random Walk | 0.618 | 5961 | 0.633 | 4406 | 0.681 | 2489 | 0.695 | 1889 | 0.722 | 1500 |
| Analyst Forecast | 0.558 | 5961 | 0.462 | 4406 | 0.442 | 2489 | 0.39 | 1889 | 0.322 | 1500 |

Forecast bias measured by the Percentage of Positive Forecast Errors (PPFE) over the five-year forecasting period for the proposed model in the paper (FRAR1), the Random Walk, and Analyst Forecasts. Period $t+k$ indicates the j -year ahead forecast. Firm-year observations are pooled, thus the fiscal year for forecasting period $t+k$ could differ across firms (and also for a specific firm if forecasts are repeated for the same firm).

This shows that the FRAR1 model produces forecasts that are a little more often pessimistic than optimistic (around 60% of the time) for the whole forecasting period. However, Table 5 further shows that the RW model produces forecasts that more often are pessimistic compared to the FRAR1 model. As the forecasting horizon increases, the frequency of pessimistic forecasts relative to optimistic forecasts increases as well for the RW model. At the five-year forecasting horizon, the RW model produces pessimistic forecasts approximately 70% of the time. With respect to analyst forecasts, the pattern is almost the same as the RW model except that the analyst forecasts are too optimistic. This forecast optimism bias in analyst forecasts is in line with findings in earlier research.

Tables 6 and 7 present the mean and median absolute price deflated forecast errors (MAPDE and MdAPDE).

Table 6: Forecast Accuracy—Mean Absolute Price Deflated Error

| Model | Period t+1 | | Period t+2 | | Period t+3 | | Period t+4 | | Period t+5 | |
|------------------|------------|----------|------------|----------|------------|----------|------------|----------|------------|----------|
| | MAPDE | No. Obs. | MAPDE | No. Obs. | MAPDE | No. Obs. | MAPDE | No. Obs. | MAPDE | No. Obs. |
| FRAR1 | 0.07 | 5961 | 0.08 | 4406 | 0.078 | 2489 | 0.082 | 1889 | 0.078 | 1500 |
| Random Walk | 0.068 | 5961 | 0.078 | 4406 | 0.076 | 2489 | 0.077 | 1889 | 0.072 | 1500 |
| Analyst Forecast | 0.077 | 5961 | 0.086 | 4406 | 0.085 | 2489 | 0.095 | 1889 | 0.102 | 1500 |

Forecast accuracy measured by the Mean Absolute Price Deflated Error (MAPDE) over the five-year forecasting period for the proposed model in the paper (FRAR1), the Random Walk, and Analyst Forecasts. Period $t + k$ indicates the j -year ahead forecast. Firm-year observations are pooled, thus the fiscal year for forecasting period $t + k$ could differ across firms (and also for a specific firm if forecasts are repeated for the same firm).

Table 7: Forecast Accuracy—Median Absolute Price Deflated Error

| Model | Period t+1 | | Period t+2 | | Period t+3 | | Period t+4 | | Period t+5 | |
|------------------|------------|----------|------------|----------|------------|----------|------------|----------|------------|----------|
| | MdAPDE | No. Obs. | MdAPDE | No. Obs. | MdAPDE | No. Obs. | MdAPDE | No. Obs. | MdAPDE | No. Obs. |
| FRAR1 | 0.019 | 5961 | 0.025 | 4406 | 0.028 | 2489 | 0.032 | 1889 | 0.034 | 1500 |
| Random Walk | 0.014 | 5961 | 0.021 | 4406 | 0.024 | 2489 | 0.027 | 1889 | 0.027 | 1500 |
| Analyst Forecast | 0.018 | 5961 | 0.022 | 4406 | 0.022 | 2489 | 0.026 | 1889 | 0.03 | 1500 |

Forecast accuracy measured by the Median Absolute Price Deflated Error (MdAPDE) over the five-year forecasting period for the proposed model in the paper (FRAR1), the Random Walk, and Analyst Forecasts. Period $t + k$ indicates the j -year ahead forecast. Firm-year observations are pooled, thus the fiscal year for forecasting period $t + k$ could differ across firms (and also for a specific firm if forecasts are repeated for the same firm).

Table 6 shows that the RW earnings forecasts are the most accurate in terms of MAPDE and that the analyst forecasts are the least accurate. In terms of MdAPDE, Table 7 shows that the FRAR1 model is the least accurate. This suggests that some of the analyst forecasts are much worse than the FRAR1 model, but analyst forecasts more often are more accurate than the FRAR1 model forecasts.

5.1 Enhancing the forecast performance of FRAR1

The poor accuracy of the FRAR1 model compared to the RW model could be driven by the model specification. In the following, I propose two different reasons for the poor forecasting performance of the FRAR1 model relative to the RW model. Furthermore, I propose possible solutions for enhancing the forecasting performance of the FRAR1 model, in terms of accuracy, for future research.

5.1.1 Non-constant convergence rate

Fama and French (2000) find that “mean reversion is faster when profitability is below its mean and when it is further from its mean in either direction.” Likewise Hayn (1995) and Basu (1997) show that, on average, losses are less persistent than profits. Thus, estimating the time-series parameters separately for firms that are above and below the long-run level could enhance the accuracy of FRAR1. There are two ways to do this: either the estimation sample data could be split into two parts or the time-series parameters could be estimated from one sample where an interaction term between the lagged earnings and an indicator variable (which should take the value of one when $ROE_0 > ROE_{LR}$ and zero otherwise) is included in the model. However, the latter method would lead to two different long-run levels, since the long-run level is equal to the constant divided by one

minus the autoregressive parameter.

Sloan (1996) find that there is a difference in persistence in the components of earnings, i.e., the cash flow component and the accruals component. Sloan (1996) find that cash flows are more persistent than accruals. Thus dividing earnings into cash flows and accruals might enhance the accuracy of forecasting from the FRAR1 model.

5.1.2 Segregation

The decomposition of financial ratios into a larger set of lower level ratios is widely used when analyzing financial statements, both in practice and in research. By segregating ROE (and/or the growth in book value of equity) into more components, forecasting accuracy can be enhanced. ROE can be decomposed (Nissim and Penman (2001)) into

$$ROE = RNOA + LEV(RNOA - NBC) \quad (3)$$

where RNOA is Return on Net Operating Assets, LEV is financial leverage, and NBC is net borrowing costs. Esplin et al. (2014) find that the forecasting accuracy of ROE can be enhanced by separately forecasting the components (the right hand side of Equation 3) of *ROE*. In addition, ROE could be decomposed even further by decomposing RNOA into profit margin (PM) and Asset Turnover (ATO). Fairfield and Yohn (2001) and Soliman (2008) find that the accuracy of forecasting the change in Return On Assets (ROA) can be enhanced by disaggregating the change in ROA into the change in PM and the change in ATO. Furthermore, Fairfield et al. (1996) decompose ROE additively in four steps: 1.) into nonrecurring and recurring items, 2.) separating special items from recurring items, 3.) separating operating earnings from recurring items without special items, 4.) a

full separation of line items (such as SGA expenses, depreciation, interest, tax). Fairfield et al. (1996) find that disaggregating ROE improves the forecasting accuracy and that the improvement increases with increasing disaggregation. Thus disaggregating ROE into lower level components could enhance the accuracy of forecasting from the FRAR1 model.

6 Robustness check

6.1 Industry definition

The definition of each industry probably influences the forecasting performance, since the “optimal” industry definition is the one that maximizes the homogeneity across firms of the time-series parameters for the ROE and growth in book value of equity. Homogeneity could be increased by increasing the number of industry segments. On the other hand, this would reduce the number of observations used to estimate the time-series parameters. Thus, choosing the “optimal” industry classification is a trade-off between homogeneity and sample size. The optimal industry classification is purely an empirical question. Using 2-digit NAICS codes as well as 1- and 2-digit SIC codes yield similar results.

6.2 Sample period

Time-series parameters can be highly influenced by a financial crisis. Including observations from the period of the financial crisis may lead to biased autoregressive parameters as well as positively biased volatility estimates. Using only observations before the financial crisis (2007) yields similar results.

6.3 Multiple forecasts for the same firm

The number of forecasts per firm (i.e. forecasts for the same firm at different points in time) varies across firms. However, one might expect the variation in the number of forecasts per firm to be low since most firms have existed over the whole period. However, for the forecast to be included in the accuracy analysis, it requires analyst forecasts, FRAR1 forecasts, as well as stock prices. These constraints increase the variation in the number of forecasts per firm. It is very likely that the forecast accuracy is correlated over time for the same firm. So if the accuracy of analyst forecasts is poor for firms with a higher number of forecasts, the results could be driven by a small number of firms. One way to deal with this is to only include one forecast per firm. Using the earliest (or the latest) forecast yield similar results.

7 Conclusion

This paper proposed an earnings forecasting model based on the time-series properties of financial ratios. The model captures two important earlier empirical findings: mean-reversion in financial ratios and long-run growth in earnings. I showed that the expected earnings growth in the long run for this model equals the expected long-run growth in book value of equity multiplied by a factor smaller than one. Thus, the expected earnings growth in the long run is smaller than the expected long-run growth in the book value of equity.

In addition, I analyzed the model's forecast accuracy in comparison to that of the Random Walk model and of analyst forecasts. The results showed that the RW model is superior to these two other forecasts in terms of accuracy and mean

bias. However, the earnings forecasts based on financial ratios seem to be superior in terms of equality in the number of forecasts that are too low with those that are too high over longer forecast horizons (four to five years ahead). The results show that the optimism (pessimism) in analyst (RW) forecasts increases with the forecast horizon, suggesting that analysts' expected earnings growth rates are too high and that the implied expectation of zero growth in earnings for the RW forecasts is too low (i.e. earnings grow on average over time). The results are not influenced by the sample period, industry definition, or auto-correlation of accuracy errors.

The earlier literature (e.g., Bansal et al. (2012)) has found that combination forecasts can generate more accurate forecasts than single forecasts. Thus further research should evaluate whether using combination forecasts of the FRAR1 model, the Random Walk, and other time-series models, can enhance the forecasting accuracy.

A Derivation of the expected value of the accumulated growth in book value of equity (G)

In the same way as with the process of the ROE, the (logarithm of one plus) growth in book value of equity can be rewritten as

$$\ln(1 + g_t^{BV}) = \frac{\alpha}{1 - \beta} + \beta^t \left(\ln(1 + g_0^{BV}) - \frac{\alpha}{1 - \beta} \right) + \sum_{h=1}^t \beta^{t-h} \epsilon_h$$

This means that the forecast of G_T at time 0 will be

$$\begin{aligned} E[G_T | \Theta_0] &= \left[e^{\sum_{j=1}^T \ln(1 + g_j^{BV})} \middle| \Theta_0 \right] \\ &= E \left[e^{\sum_{t=1}^T \left(\frac{\alpha}{1-\beta} + \beta^t \left(\ln(1 + g_0^{BV}) - \frac{\alpha}{1-\beta} \right) + \sum_{h=1}^t \beta^{t-h} \epsilon_h \right)} \middle| \Theta_0 \right] \\ &= E \left[e^{\sum_{t=1}^T \left(\frac{\alpha}{1-\beta} + \beta^t \left(\ln(1 + g_0^{BV}) - \frac{\alpha}{1-\beta} \right) \right)} e^{\sum_{h=1}^t \beta^{t-h} \epsilon_h} \middle| \Theta_0 \right] \\ &= e^{\sum_{t=1}^T \left(\frac{\alpha}{1-\beta} + \beta^t \left(\ln(1 + g_0^{BV}) - \frac{\alpha}{1-\beta} \right) \right)} E \left[e^{\sum_{t=1}^T \sum_{h=1}^t \beta^{t-h} \epsilon_h} \middle| \Theta_0 \right] \\ &= \underbrace{e^{\frac{\alpha}{1-\beta} T + \frac{\beta(1-\beta^T)}{1-\beta} \left(\ln(1 + g_0^{BV}) - \frac{\alpha}{1-\beta} \right)}}_{A_T} \underbrace{E \left[e^{\sum_{t=1}^T \sum_{h=1}^t \beta^{t-h} \epsilon_h} \middle| \Theta_0 \right]}_{B_T} \end{aligned}$$

Looking at the term B_T , we can rewrite this as

$$E \left[e^{\sum_{t=0}^{T-1} \beta^t \epsilon_1 + \sum_{t=0}^{T-2} \beta^t \epsilon_2 + \dots + \sum_{t=0}^0 \beta^t \epsilon_T} \middle| \Theta_0 \right] \quad (4)$$

Since the error terms ϵ_t are all mutually independent, we can split this into

$$E \left[e^{\sum_{t=0}^{T-1} \beta^t \epsilon_1} \middle| \Theta_0 \right] E \left[e^{\sum_{t=0}^{T-2} \beta^t \epsilon_2} \middle| \Theta_0 \right] \dots E \left[e^{\sum_{t=0}^0 \beta^t \epsilon_T} \middle| \Theta_0 \right] \quad (5)$$

We get from the moment generating function that $E[e^{tX}] = e^{t\mu_X + \frac{1}{2}t^2\sigma_X^2}$ if X is normally distributed with mean μ and variance σ . This means that

$$E \left[e^{\epsilon_i \sum_{t=0}^{T-i} \beta^t} \middle| \Theta_0 \right] = e^{\frac{1}{2}\sigma^2 \left(\frac{1-\beta^{T-i+1}}{1-\beta} \right)^2}$$

Putting all this together, we get that

$$E \left[e^{\sum_{t=1}^T \sum_{h=1}^t \beta^{t-h} \epsilon_h} \mid \Theta_0 \right] = e^{\frac{1}{2} \sigma^2 \sum_{i=0}^T \left(\frac{1-\beta^{T-i+1}}{1-\beta} \right)^2} = e^{\frac{1}{2} \sigma^2 \sum_{i=0}^T \left(\frac{1-\beta^{i+1}}{1-\beta} \right)^2}$$

which can be rewritten as

$$B_T = E \left[e^{\sum_{t=1}^T \sum_{h=1}^t \beta^{t-h} \epsilon_h} \mid \Theta_0 \right] = e^{\overbrace{\frac{1}{2} \sigma^2 \left(\frac{T - 2 \frac{\beta(1-\beta^{T+1})}{1-\beta} + \frac{\beta^2(1-\beta^{2(T+1)})}{1-\beta^2}}{(1-\beta)^2} \right)}^{H_T}}$$

We then have the following expression for the growth in book value of equity from time 0 to time t .

$$E[G_T | \Theta_0] = A_T e^{\frac{1}{2} H_T}$$

B Variance and covariance calculations

B.1 Variance of v_{T+1}

The variance of ω given the available information at time 0 is

$$\begin{aligned}
 Var[v_{T+1}|\Theta_0] &= Var\left[\sum_{h=1}^{T+1}\rho^{T+1-h}\omega_h\middle|\Theta_0\right] \\
 &= \sum_{h=1}^{T+1}\rho^{2(T+1-h)}Var[\omega_h|\Theta_0] + 2\sum_{k=1}^T\sum_{j=k+1}^{T+1}\rho^k\rho^j cov[\omega_k,\omega_j|\Theta_0] \\
 &= \sum_{h=1}^{T+1}\rho^{2(T+1-h)}\theta^2 = \frac{1-\rho^{2(T+1)}}{1-\rho^2}\theta^2
 \end{aligned}$$

B.2 Variance of η_T

It follows directly from the calculations in Section 3.2 that

$$\begin{aligned}
 Var[\eta_T|\Theta_0] &= Var\left[2\sum_{t=1}^T\sum_{h=1}^t\beta^{t-h}\epsilon_h\middle|\Theta_0\right] = 4Var\left[\sum_{t=1}^T\sum_{h=1}^t\beta^{t-h}\epsilon_h\middle|\Theta_0\right] \\
 &= 4H_T = 4\sigma^2\left(\frac{T-2\frac{\beta(1-\beta^{T+1})}{1-\beta}+\frac{\beta^2(1-\beta^{2(T+1)})}{1-\beta^2}}{(1-\beta)^2}\right)
 \end{aligned}$$

B.3 Covariance between v_{T+1} and η_T

$$\begin{aligned}
 Cov[v_{T+1},\eta_T|\Theta_0] &= Cov\left[\left(\sum_{i=1}^{T+1}\rho^{T+1-i}\omega_i\right)\left(2\sum_{t=1}^T\sum_{h=1}^t\beta^{t-h}\epsilon_h\right)\middle|\Theta_0\right] \\
 &= 2E\left[\left(\sum_{i=1}^{T+1}\rho^{T+1-i}\omega_i\right)\left(\sum_{t=1}^T\sum_{h=1}^t\beta^{t-h}\epsilon_h\right)\middle|\Theta_0\right]
 \end{aligned}$$

From Section 3.2, we see that

$$\sum_{t=1}^T \sum_{h=1}^t \beta^{t-h} \epsilon_h = \sum_{i=1}^T \epsilon_i \sum_{t=1}^{T-i} \beta^t = \sum_{i=1}^T \epsilon_i \left(\frac{1 - \beta^{T+1-i}}{1 - \beta} \right)$$

which means that

$$Cov[v_{T+1}, \eta_T | \Theta_0] = 2E \left[\left(\sum_{i=1}^{T+1} \rho^{T+1-i} \omega_i \right) \left(\sum_{i=1}^T \epsilon_i \left(\frac{1 - \beta^{T+1-i}}{1 - \beta} \right) \right) \middle| \Theta_0 \right]$$

Assuming that $Cov[\omega_i, \epsilon_j | \Theta_0] = 0$ for $i \neq j$ and that the covariance is stationary over time, so that $Cov[\omega_i, \epsilon_i | \Theta_0] = Cov[\omega_j, \epsilon_j | \Theta_0]$ for all i and j , we obtain

$$\begin{aligned} Cov[v_{T+1}, \eta_T | \Theta_0] &= \frac{2}{1 - \beta} Cov[\omega_i, \epsilon_i | \Theta_0] \sum_{i=1}^T \rho^{T+1-i} (1 - \beta^{T+1-i}) \\ &= \frac{2}{1 - \beta} Cov[\omega_i, \epsilon_i | \Theta_0] \left(\left(\sum_{i=1}^T \rho^{T+1-i} \right) - \sum_{i=1}^T (\rho\beta)^{T+1-i} \right) \\ &= \frac{2}{1 - \beta} Cov[\omega_i, \epsilon_i | \Theta_0] \left(\frac{1 - \rho^{T+1}}{1 - \rho} - \frac{1 - (\rho\beta)^{T+1}}{1 - \rho\beta} \right) \end{aligned}$$

C The growth in expected earnings in the long run

The growth in expected earnings in the long run (i.e. $\lim_{T \rightarrow \infty} \frac{E[INC_{T+1}|\Theta_0]}{E[INC_T|\Theta_0]}$) is equal to

$$\lim_{T \rightarrow \infty} \frac{BV_0 E[G_T|\Theta_0] \left(E[ROE_{T+1}|\Theta_0] + \frac{1}{2} \sqrt{Var[v_{T+1}|\Theta_0]} Cov[v_{T+1}, \eta_T|\Theta_0] \right)}{BV_0 E[G_{T-1}|\Theta_0] \left(E[ROE_T|\Theta_0] + \frac{1}{2} \sqrt{Var[v_T|\Theta_0]} Cov[v_T, \eta_{T-1}|\Theta_0] \right)}$$

Using the product rule for limits this can be rewritten as

$$\underbrace{\lim_{T \rightarrow \infty} \frac{E[G_T|\Theta_0]}{E[G_{T-1}|\Theta_0]}}_{X_T} \underbrace{\lim_{T \rightarrow \infty} \frac{E[ROE_{T+1}|\Theta_0] + \frac{1}{2} \sqrt{Var[v_{T+1}|\Theta_0]} Cov[v_{T+1}, \eta_T|\Theta_0]}{E[ROE_T|\Theta_0] + \frac{1}{2} \sqrt{Var[v_T|\Theta_0]} Cov[v_T, \eta_{T-1}|\Theta_0]}}_{Y_T}$$

The X_T term is equal to

$$\begin{aligned} X_T &= \lim_{T \rightarrow \infty} \frac{A_T e^{\frac{1}{2}H_T}}{A_{T-1} e^{\frac{1}{2}H_{T-1}}} \\ &= \lim_{T \rightarrow \infty} \frac{A_T}{A_{T-1}} \lim_{T \rightarrow \infty} e^{\frac{1}{2}(H_T - H_{T-1})} = e^{\frac{\alpha}{1-\beta}} e^{\frac{1}{2} \left(\frac{\sigma}{1-\beta} \right)^2} = e^{\frac{\alpha}{1-\beta} + \frac{1}{2} \left(\frac{\sigma}{1-\beta} \right)^2} \end{aligned}$$

When analyzing the Y_T term, let, for simplicity,

$$f(T+1) = E[ROE_{T+1}|\theta_0] + \frac{1}{2} \sqrt{Var[v_{T+1}|\Theta_0]} Cov[v_{T+1}, \eta_T|\Theta_0]$$

Using the division rule for limits, the Y_T term can be written as

$$Y_T = \lim_{T \rightarrow \infty} \frac{f(T)}{f(T)} = \frac{\lim_{T \rightarrow \infty} f(T+1)}{\lim_{T \rightarrow \infty} f(T)}$$

as long as both $\lim_{T \rightarrow \infty} f(T+1)$ and $\lim_{T \rightarrow \infty} f(T)$ exist.

To show that $\lim_{T \rightarrow \infty} f(T)$ exists, the addition rule and the product rule for limits

is needed. This gives

$$\begin{aligned}
& \lim_{T \rightarrow \infty} f(T) \\
&= \lim_{T \rightarrow \infty} \left(E[ROE_T | \Theta_0] + \frac{1}{2} \sqrt{\text{Var}[v_T | \Theta_0]} \text{Cov}[v_T, \eta_{T-1} | \Theta_0] \right) \\
&= \lim_{T \rightarrow \infty} E[ROE_T | \Theta_0] + \frac{1}{2} \lim_{T \rightarrow \infty} \sqrt{\text{Var}[v_T | \Theta_0]} \lim_{T \rightarrow \infty} \text{Cov}[v_T, \eta_{T-1} | \Theta_0]
\end{aligned}$$

The long-run expectation of ROE_T given the information available at time 0 is equal to

$$\lim_{T \rightarrow \infty} E[ROE_T | \Theta_0] = \lim_{T \rightarrow \infty} \left[\frac{\gamma}{1 - \rho} + \rho^T \left(ROE_0 - \frac{\gamma}{1 - \rho} \right) \right] = \frac{\gamma}{1 - \rho}$$

The long-run expectation of $\sqrt{\text{Var}[v_T | \Theta_0]}$ is equal to

$$\lim_{T \rightarrow \infty} \sqrt{\text{Var}[v_T | \Theta_0]} = \lim_{T \rightarrow \infty} \sqrt{\frac{1 - \rho^{2(T+1)}}{1 - \rho^2}} \theta = \sqrt{\frac{1}{1 - \rho^2}} \theta$$

The long-run expectation of $\text{Cov}[v_T, \eta_{T-1} | \Theta_0]$ is equal to

$$\begin{aligned}
& \lim_{T \rightarrow \infty} \text{Cov}[v_T, \eta_{T-1} | \Theta_0] \\
&= \lim_{T \rightarrow \infty} \frac{2}{1 - \beta} \text{Cov}[\omega_i, \epsilon_i | \Theta_0] \left(\frac{1 - \rho^{T+1}}{1 - \rho} - \frac{1 - (\rho\beta)^{T+1}}{1 - \rho\beta} \right) \\
&= \frac{2}{1 - \beta} \text{Cov}[\omega_i, \epsilon_i | \Theta_0] \left(\frac{1}{1 - \rho} - \frac{1}{1 - \rho\beta} \right)
\end{aligned}$$

So $\lim_{T \rightarrow \infty} f(T)$ exists. It can be seen that $\lim_{T \rightarrow \infty} f(T + 1)$ also exists and that $\lim_{T \rightarrow \infty} f(T) = \lim_{T \rightarrow \infty} f(T + 1)$, which means that $Y_T = 1$. Therefore

$$\lim_{T \rightarrow \infty} \frac{E[INC_{T+1} | \Theta_0]}{E[INC_T | \Theta_0]} = e^{\frac{\alpha}{1-\beta} + \frac{1}{2} \left(\frac{\sigma}{1-\beta} \right)^2}$$

Since $E [1 + g_T^{BV} | \Theta_0] = E [e^{\ln(1+g_T^{BV})} | \Theta_0]$ and $\lim_{T \rightarrow \infty} \ln (1 + g_T^{BV})$ is normally distributed with $\lim_{T \rightarrow \infty} E [\ln (1 + g_T^{BV}) | \Theta_0] = \frac{\alpha}{1-\beta}$ and $\lim_{T \rightarrow \infty} Var [\ln (1 + g_T^{BV}) | \Theta_0] = \frac{\sigma^2}{1-\beta^2}$, we get from the moment generating function that

$$E [1 + g_T^{BV} | \Theta_0] = e^{\frac{\alpha}{1-\beta} + \frac{1}{2} \frac{\sigma^2}{1-\beta^2}}$$

which means that

$$\begin{aligned} \lim_{T \rightarrow \infty} \frac{E[INC_{T+1} | \Theta_0]}{E[INC_T | \Theta_0]} &= E [1 + g_T^{BV} | \Theta_0] e^{\frac{1}{2} \sigma^2 \left(\frac{1}{(1-\beta)^2} - \frac{1}{1-\beta^2} \right)} \\ &= E [1 + g_T^{BV} | \Theta_0] e^{-\frac{1}{2} \sigma^2 \frac{2\beta(1+\beta)}{(1-\beta)^2(1-\beta^2)}} \end{aligned}$$

Thus the growth in expected earnings in the long run is equal to the expected long-run growth in book value of equity reduced by a factor (which is a function of the persistence and the volatility in the growth in book value).

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Conservatism and Analysts' Earnings Forecast Accuracy

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Abstract

Based on US data, I study the total effect that accounting conservatism has on the accuracy of analysts' earnings forecasts. I hypothesize that conservatism affects this accuracy directly and indirectly via the effect that conservatism has on the time-series properties of earnings. The results show that conservatism indirectly and positively affects the absolute forecast errors and dispersion, because conservatism increases earnings volatility. Furthermore, the results show that conservatism directly and positively influences the absolute forecast errors and dispersion, which indicates that either analysts do not correctly incorporate conservatism into their forecasts or there are other factors (besides earnings volatility) that mediate the relation between accounting conservatism and the accuracy of analysts' earnings forecasts. The findings suggest that regulators should not only consider the benefits of accounting conservatism, namely, protecting investors from future losses, but also the costs, in the form of higher earnings volatility and lower accuracy of earnings forecasts.

Keywords: Path analysis, Accounting conservatism, Earnings volatility, Analysts' earnings forecasts.

JEL classification: M41.

1 Introduction

This paper focuses on how the measurement of accounting earnings affects the accuracy of analysts' earnings forecasts. To analyze this relation, I address the question whether accounting conservatism impedes analysts' ability to accurately forecast earnings. Two things might affect this: first, analysts either take into account or fail to take into account conservatism when making their earnings forecasts; second, conservatism might change the time-series properties of earnings (earnings volatility). Although the earlier literature (Mensah et al. (2004), Pae and Thornton (2010) and Sohn (2012)) has studied the relation between conservatism and the accuracy of analysts' earnings forecasts, the findings have been inconsistent. Those studies analyze the relation by using multiple regression, controlling for, among other things, earnings volatility assuming that this is exogenous. This assumption fails to capture the total effect of conservatism on forecast accuracy, since conservatism might change the time-series characteristics of earnings.

Because financial analysts are intermediaries for investors in the financial market, what affects the accuracy of their forecasts is of great importance: more efficient analysts' earnings forecasts lead to a more efficient allocation of capital in society. If accounting principles systematically affect the accuracy of analysts' earnings forecasts, this means that policy decisions regarding accounting conservatism affect the allocation of capital in society. As far as my knowledge extends, no other study has looked at the total effect of conservatism on the accuracy of analysts' earnings forecasts.

To assess the total effect of conservatism on the accuracy of analysts' earnings forecasts, I estimate both the direct (analysts' ability to take into account conser-

vatism in their earnings forecasts¹) and indirect effect (the changes in earnings volatility because of conservatism). I hypothesize that conservatism increases earnings volatility, since conservatism decreases the match between revenue and expenses, which results in more volatile earnings. This is in contrast to earlier studies (Mensah et al. (2004), Pae and Thornton (2010) and Sohn (2012)), which assume that earnings volatility is exogenous (and as a result, only study the direct effect). I follow the literature by defining accounting conservatism as a relative understatement of book value (i.e. accounting conservatism exists when the market value of an asset is larger than the book value). Conservatism is referred to as unconditional (conditional) if it is independent (dependent) of the news (Beaver and Ryan 2005). An example of unconditional conservatism is the use of a depreciation scheme that is more accelerated than economic depreciation². In contrast, an asset write-down is an example of conditional conservatism, since it is dependent on the news about the market value of that particular asset. I only focus on unconditional conservatism, since analysts' earnings forecasts generally exclude the main part of the US GAAP transitory items (Gu and Chen 2004), which (in this case) are the market value adjustments (i.e. news).

The results show that the direct effect of unconditional conservatism on the accuracy of analysts' forecasts (measured by the mean absolute forecast error and the dispersion of analysts' forecasts) is negative, suggesting that analysts either over- or under-state conservatism in their forecasts. The results also show that the indirect effect on analyst forecast accuracy is negatively related to unconditional

¹Another conceivable explanation for a significant direct effect is that there are other mediating factors that are not modeled. Thus it is possible that a significant direct effect arises simply because the model is too simplified. However, in the rest of the paper I will refer to a significant direct effect as a sign of analysts' conservatism-adjustment failure.

²Depreciation of assets over a shorter period than the economically useful life of the assets normally also results in depreciation that is more accelerated than economic depreciation.

conservatism, because it increases earnings volatility. In sum, unconditional conservatism comes with a cost of decreased accuracy of analysts' forecasts, because of increased earnings volatility (indirect effect) and analysts' failure to adjust for conservatism (direct effect).

The rest of this paper is structured as follows. Section 2 reviews the literature. In Section 3, I discuss the difference between unconditional and conditional conservatism. I develop hypotheses in Section 4. In Section 5, I present the research design. Sections 5.3 and 6 describe the sample and the results. Section 7 concludes.

2 Related research

The literature on the relation between accounting standards and the accuracy of analysts' earnings forecasts³ can be divided into i) event studies and ii) level studies. Regarding the event studies, Brown (1983) and Elliott and Philbrick (1990) study the relation between accounting changes and the accuracy of analysts' earnings forecasts. Brown (1983) and Elliott and Philbrick (1990) analyze whether accounting changes lead to a change in the performance of analysts' earnings forecasts. Both Brown (1983) and Elliott and Philbrick (1990) find that the accuracy of analysts' earnings forecasts (accuracy measures b) and d)) worsen when accounting changes occur. However, as noted by Elliott and Philbrick (1990), when accounting changes take place, analysts should not only forecast the real value creation/destruction of the firm, but also the effect of the accounting changes. It

³Accuracy is measured in different ways in the literature. The four main measures of accuracy are: a) (Mean/Median) Forecast Error; b) Absolute (Mean/Median) Forecast Error; c) Mean Absolute Forecast Error; d) Standard Deviation of Forecast Error. Forecast error is the difference between the actual value and the forecast value. Measure a) is also known as "forecast bias". (For further details on forecast accuracy, see Section 5.2.1)

will be more difficult to forecast earnings when accounting changes have taken place, regardless of whether a company switches from a more or less conservative accounting method. Because of this, the findings of Brown (1983) and Elliott and Philbrick (1990) can not be used to make inferences about whether the accuracy of analysts' earnings forecasts increases or decreases with more conservative accounting methods.

The level studies follow two lines: one line of research studies the relation between earnings predictability and analysts' forecasts; the second investigates the relation between conservatism and analysts' forecasts. With respect to the relation between earnings predictability and analysts' forecasts, Das et al. (1998) find that lower earnings predictability leads to a more optimistic bias in analysts' forecasts (i.e. lower predictability decreases accuracy measure 'a'). Das et al. (1998) attribute this to how analysts deal with high uncertainty. The argument is that analysts issue optimistic forecasts to delight management and thereby get access to management's private information.

Earnings predictability (measured by the standard deviation of the residuals from an AR1 model of earnings) are also used as a measure of earnings quality (Ecker et al. (2006)), where a higher standard deviation of the residuals indicates a lower earnings predictability. Ecker et al. (2006) develop a return-based measure of earnings quality, which they refer to as "e-loading". In the same way as beta measures the sensitivity of individual firm return to market returns, "e-loading" measures the sensitivity of individual firm returns to market (or industry) earnings quality. Ecker et al. (2006) show that a higher e-loading (lower earnings quality) increases forecast inaccuracy (measured as the absolute value of analysts' forecasts bias and forecast dispersion), which is in line with the findings in Das et al.

(1998). Eames and Glover (2003) argue that the findings in Das et al. (1998) can be explained by the relation between earnings level and earnings predictability. Eames and Glover (2003) find that there does not exist a relation between earnings predictability and analysts' forecasts bias when the earnings level is used as a control variable. This suggests that the variations in earnings level are largely captured by the variation in earnings predictability and that the earnings level does affect analysts' forecasts bias, whereas earnings predictability does not.

The findings of Eames and Glover (2003) suggest there is no indirect (mediated) effect of conservatism on the accuracy of analysts' earnings forecasts, since earnings predictability does not result in analyst forecast bias. Nonetheless, even though earnings predictability offers no information about analysts' forecast bias when controlling for earnings level, it is still likely that it conveys information about the precision (accuracy measure c) or d)) of the forecasts. I discuss this further in Section 4.2.2 and discuss the differences between these measures of accuracy in Section 5.2.1.

Regarding the second line of research, Mensah et al. (2004), Pae and Thornton (2010) and Sohn (2012) study how conservatism affects the accuracy of analysts' earnings forecasts. Using the C-score of Penman and Zhang (2002) (the estimated reserve), Mensah et al. (2004) find that higher unconditional conservatism leads to higher absolute forecast errors and forecast dispersion⁴. In another study, Pae and Thornton (2010) look at unconditional and conditional conservatism simultaneously. Pae and Thornton (2010) find a positive correlation between unconditional

⁴They also use two other measures of conservatism, based on accruals, to test the robustness of their result. However, accrual based conservatism measures are also likely to capture conditional conservatism, since write-downs are a part of total accruals. So these two measures are not likely to capture the same constructs as the estimated reserve.

conservatism (measured by both the market-to-book value and the estimated reserve) and earnings forecast errors (bias). Since forecast error is the difference between the actual earnings and forecast earnings, this indicates that analysts are more optimistic about firms with low unconditional conservatism. However, when they control for other influential variables (including conditional conservatism⁵), the positive relation between unconditional conservatism and earnings forecast errors is no longer significant. Pae and Thornton (2010) use multiple linear regression and thereby assume that unconditional and conditional conservatism are independent. This might be an issue, since unconditional conservatism precedes conditional conservatism. In an additional study, Sohn (2012) uses six different measures of conservatism, where two of them, the market-to-book ratio and the change in the estimated reserve (the Penman and Zhang (2002) Q-score), capture unconditional conservatism. The study reveals that none of these widely used conservatism measures are highly correlated (See the discussion in Section 5.2.2). Sohn (2012) finds no statically significant difference in forecast errors between low and high conservatism firms, which is in line with Pae and Thornton (2010). This suggests that analysts incorporate conservatism into their forecasts, because (as Sohn (2012) points out) analysts' signed forecast errors (accuracy measure a)) are smaller for more conservative firms if earnings forecasts are not reduced by the same amount as conservatism reduces earnings. Sohn (2012) also analyzes the relation between the absolute forecast errors and conservatism and finds that lower conservatism leads to higher absolute forecast errors, contradicting the findings in Mensah et al. (2004) and the findings in the present paper.

The studies by Mensah et al. (2004), Pae and Thornton (2010) and Sohn (2012) have two things in common: they all use multiple regression in their analysis and

⁵Measured by Basu (1997)'s asymmetric timeliness measure

they all use earnings volatility as a control variable. Equation 1 show a representative model for these studies.

$$|FE| = \alpha + \beta_1 CONS + \beta_2 EARN_VOL + \sum_{i=1}^M \beta_{i+2} CONTROL_i \quad (1)$$

where $|FE|$ is the absolute value of the forecast error; $CONS$ is conservatism (the variable of interest); $EARN_VOL$ is earnings volatility (a control variable); and $CONTROL_1$ – $CONTROL_M$ are the control variables. If earnings volatility is not exogenous but endogenous (because conservatism may affect the volatility of earnings), these studies do not capture the full effect of conservatism on the accuracy of analysts' earnings forecasts. Actually, Mensah et al. (2004) question the exogeneity assumption about earnings predictability. In additional tests of this relation, Mensah et al. (2004) conclude that earnings predictability is not affected by conservatism. Nonetheless, Mensah et al. (2004) fail to treat earnings predictability as an exogenous variable, because the relation is tested by regressing earnings predictability on conservatism (and earnings volatility). Since the measures of earnings predictability and earnings volatility are closely dependent (the relation between these two measure are discussed in the Appendix A), Mensah et al. (2004) again treat earnings predictability as an exogenous variable.

Unlike Mensah et al. (2004), Pae and Thornton (2010) and Sohn (2012), I do not assume the exogeneity of earnings volatility. I hypothesize that earnings volatility is endogenously determined by unconditional conservatism. That is, the paper investigates both the direct effect of unconditional conservatism on the accuracy of analysts' forecasts (i.e. Mensah et al. (2004), Pae and Thornton (2010) and Sohn (2012)) and also the indirect effect that is mediated by earnings volatility.

3 Unconditional and Conditional Conservatism

It is not obvious how unconditional and conditional conservatism are linked to each other. In order to get further insight into how accounting conservatism (both unconditional and conditional) affects the accuracy of analysts' forecasts, a brief discussion of these two conservatism concepts follows.

Beaver and Ryan (2005) model the relation between unconditional conservatism and conditional conservatism. They show that unconditional conservatism affects conditional conservatism and that conditional conservatism affects future unconditional conservatism. The reason is that unconditional conservatism mitigates the magnitude and the likelihood of conditional conservatism. Expensing R&D and advertising is an example of "full" unconditional conservatism. This expensing eliminates any possibility of future conditional conservatism, since they are fully expensed and therefore can not be written down in the future.

Conditional conservatism affects future unconditional conservatism because it resets the cost bases of the net assets. When conditional conservatism events take place (e.g. an asset write-down to its market value), the subsequent unconditional conservatism for those assets is equal to zero because the book values now equal the market values of the assets. On a conceptual level, this is illustrated in Table 1, showing the relation between unconditional and conditional conservatism over time. The table shows how expensing (immediate writeoffs) of investments affects unconditional conservatism and hence the probability of future conditional conservatism events. It further shows how a conditional conservatism event affects future unconditional conservatism.

Table 1: The time-series link between unconditional and conditional conservatism

| Conditional Conservatism Event $(A_{t+\tau}^{MV} < A_t^{BV})$ | | |
|--|---|-------------------------------|
| $A_t^{BV} = I_t - \delta_t = A_t^{MV} - \delta_t$ | $A_{t+\tau}^{BV} = A_{t+\tau}^{MV}$ | $A_{t+1}^{BV} = A_{t+1}^{BV}$ |
| $UC_t = A_t^{MV} - A_t^{BV} = \delta_t$ | $UC_{t+\tau} = A_{t+\tau}^{MV} - A_{t+\tau}^{BV} = 0$ | $UC_{t+1} = 0$ |
| $WO_t = \delta_t$ | $WO_{t+\tau} = A_t^{BV} - A_{t+\tau}^{MV}$ | $WO_{t+1} = 0$ |

At time t , a firm invests I_t in an asset. The investment equals the market value at the time of purchase (A_t^{MV}). A part of the market value of the asset is immediately written off ($WO_t = \delta_t$). Therefore the book value of the asset (A_t^{BV}) equals $A_t^{MV} - \delta_t$. Unconditional conservatism at time t (UC_t) is therefore equal to δ_t , since unconditional conservatism equals the difference between the market value and the book value of the asset. In the period between time t and $t - 1$, the market value of the asset becomes lower than the book value (an unconditional conservatism event occurs) and, thus, the book value should be written down to the market value ($A_{t+\tau}^{BV} = A_{t+\tau}^{MV}$). That is, the difference between the market value and the book value of the asset equals 0. So, unconditional conservatism is 0 at time $t + \tau$. Following the conditional conservatism event, the unconditional conservatism is 0. If $\delta_t = A_t^{MV}$ (i.e. the asset is immediately fully written off such that $A_t^{BV} = 0$, resulting in $UC_t = A_t^{MV}$), the probability of a conditional conservatism event equals 0 because $P(A_{t+\tau}^{MV} < A_t^{BV}) = P(A_{t+\tau}^{MV} < 0) = 0$.

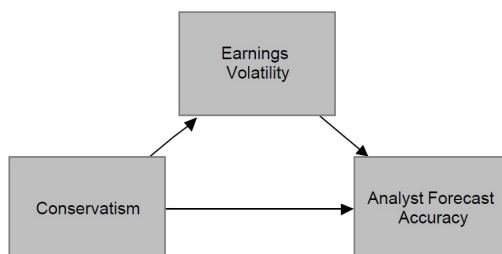
In a related study, Gu and Chen (2004) examine how analysts treat nonrecurring items (e.g. write-downs). Gu and Chen (2004) show that analysts are not consistent in which nonrecurring items they exclude or include. However, approximately 85% of the total nonrecurring items are, on average, excluded. This is in line with Abarbanell and Lehavy (2007), who show that I/B/E/S earnings (also known as “Street” earnings) generally exclude nonrecurring items (such as write-downs), other special items, and non-operating items from GAAP earnings. Since approximately 85% of the non-recurring items are excluded from the I/B/E/S earnings, analysts should only forecast around 15% of the non-recurring items. So analysts’ earnings forecasts should only take into account about 15% of the total conditional conservatism. Therefore I expect that the relation between conditional conservatism and analysts’ forecast accuracy is insignificant. For that reason, I only focus on unconditional conservatism in this paper.

4 Conservatism and the accuracy of analysts’ earnings forecasts

In this section I discuss and develop the hypotheses about how conservatism affects the accuracy of analysts’ earnings forecasts.

I hypothesize that unconditional conservatism affects analysts’ forecast accuracy both directly and indirectly. In Figure 1, the total effect of conservatism on the accuracy of analysts’ forecasts is the sum of the direct effect and indirect effect.

Figure 1: Path diagram showing the direct and indirect effects of conservatism on the accuracy of analysts' earnings forecasts.



Conservatism affects analysts' forecast accuracy directly and indirectly. The indirect effects is mediated by earnings volatility.

The affect of conservatism on analysts' forecast accuracy is partly mediated through earnings volatility. Now, I address the direct and indirect effects in turn.

4.1 Direct effect

If the direct effect is not different from zero, this suggests that analysts correctly incorporate conservatism into their earnings forecasts. As I do not focus on the direction of the bias, a positive direct effect suggests that analysts either understate or overstate the effect that conservatism has on earnings. If the direct effect is negative, this suggests that analysts are better at forecasting earnings for highly conservative firms, since the unsigned forecast errors are smaller for highly conservative firms. Sohn (2012) points out that unconditional conservatism decreases management's opportunity to manage earnings. Less earnings management is likely to decrease analysts' earnings forecast errors, implying a negative relation between unconditional conservatism and analysts' earnings forecast errors. Therefore, if the direct effect is negative, it is likely that earnings management (besides earnings volatility) mediates the effect of accounting conservatism on

analysts' earnings forecasts (see the discussion in Section 6.2.5). Thus I do not have ex ante expectations about whether conservatism directly increases or decreases the accuracy of analysts' forecasts.

4.2 Indirect effect

4.2.1 Conservatism and earnings volatility

As mentioned in Section 1, accounting conservatism is defined as the understatement of book value. Lev and Sougannis (1996) show that current R&D expenses generate revenues around five to eight years in the future. Likewise, advertising costs are also very likely to generate future revenue. Therefore, expensing R&D and advertising costs implies a poor match between revenue and costs. As a poor match increases the volatility of earnings (Dichev and Tang (2008)), I expect accounting conservatism to result in more volatile earnings. This leads to the following hypothesis:

H1: Accounting conservatism increases earnings volatility

4.2.2 Earnings volatility and the accuracy of analysts' forecasts

Independent of the accounting scheme adopted by the firm, analysts' earnings forecast errors should be equal to zero if there is no uncertainty about the inputs to the revenue and expense generating processes in the economy. However, in an economy without uncertainty, accounting is irrelevant (with no informational value). When uncertainty exists in the economy, accounting creates valuable information. Uncertainty arises from two sources: uncertainty about the future state of the economy and aggregation uncertainty. Aggregation uncertainty stems from the aggregation in the financial reports. For example, aggregation uncertainty is

induced in the forecasts of future depreciation/amortization expenses, since analysts do not have information about the book value of every single asset, estimated remaining life, scrap-value, and how it is depreciated.

Because aggregation uncertainty eliminates the possibility of generating single asset depreciation/amortization forecasts, I expect that analysts rely more strongly on aggregate time-series based forecasts of expenses. Since more volatile aggregate expenses are likely to lead to larger absolute errors in expense forecasts, I expect that more volatile aggregate expenses increase analysts' forecast errors.

So if the relation between earnings predictability and analyst forecast bias is insignificant (after controlling for the earnings level (Eames and Glover (2003))), I still expect a positive relation between earnings volatility and analyst forecast inaccuracy (measured by unsigned forecast bias and forecast dispersion). This expectation is in line with the empirical findings in Mensah et al. (2004), Ecker et al. (2006)⁶ and Sohn (2012). Mensah et al. (2004), Ecker et al. (2006) and Sohn (2012) find that earnings volatility increases absolute forecast error (and forecast dispersion). Thus, I hypothesize as follows:

H2: Earnings volatility increases the inaccuracy of analysts' forecasts

⁶Ecker et al. (2006) do not directly analyze the relation between earnings volatility and analyst forecast inaccuracy. They study the relation between e-loading (a measure of earnings quality) and analyst forecast inaccuracy. They show that higher e-loading increases analyst forecast inaccuracy. Furthermore, they show that e-loading is positively correlated with earnings predictability. They measure earnings predictability as the standard deviation of the residuals from an AR1 model of earnings, where a higher value indicates a lower earnings predictability. Because of its definition, this measure of earnings predictability is very highly positively correlated with earnings variance. Thus the findings in Ecker et al. (2006) suggest that higher earnings volatility increases analyst forecast inaccuracy.

5 Research design

5.1 Path analysis

To analyze the total effect of unconditional conservatism on the accuracy of analysts' earnings forecasts, I use path analysis. Path analysis is a special case of structural equation modeling (SEM). The difference between path analysis and SEM is that path analysis assumes that all variables are measured without error, whereas SEM allows latent variables, to account for measurement error. Path analysis (SEM) divides the total effect into direct and indirect paths. The indirect paths go through one or more mediating variables. For that reason, I use path analysis to deduce the total effect of conservatism on the accuracy of analysts' earnings forecasts.

5.2 Measures

Forecast accuracy, unconditional conservatism, and all the control variables (except firm size and analyst coverage) are scaled. I also scale earnings before estimating the earnings volatility. As the scaling variable, I use Net Operating Assets (NOA). Thus the measure of unconditional conservatism is defined as the Penman and Zhang (2002) C-score. All variables are logarithmically transformed to reduce the (right) skewness of the distribution.

5.2.1 Forecast accuracy

According to the International Organization for Standardization (ISO), accuracy is a 2-dimensional measure of trueness and precision. Trueness and precision are not interrelated constructs. Menditto et al. (2007) emphasize that trueness and precision are functions of systematic and random errors, respectively. Large

systematic errors mean low trueness, whereas large random errors imply low precision. A quantitative measure of trueness could be (absolute) bias. A quantitative measure of precision could be, e.g., the standard deviation.

Studies of the accuracy of analysts' earnings forecasts mainly rely on four measures:

- a) The mean of the (scaled) value of the earnings forecast error (MFE)

$$E[\epsilon] = \frac{1}{N} \sum_{j=1}^N \epsilon_j$$

- b) The absolute value of MFE (AMFE)

$$|E[\epsilon]| = \left| \frac{1}{N} \sum_{j=1}^N \epsilon_j \right|$$

- c) The mean of the absolute (scaled) value of earnings forecast errors (MAFE)

$$E[|\epsilon|] = \frac{1}{N} \sum_{j=1}^N |\epsilon_j|$$

- d) The standard deviation of the (scaled) earnings forecast errors (StdFE)

$$Std[\epsilon] = \sqrt{Var[\epsilon]} = \sqrt{\frac{1}{N} \sum_{j=1}^N \left(\epsilon_j - \frac{1}{N} \sum_{k=1}^N \epsilon_k \right)^2}$$

where ϵ_j denotes the forecast error for analyst j . The forecast error is the difference between the actual value and the forecast value. Note that the standard deviation of forecast errors is equal to the standard deviation of the forecasts (also known as the forecast dispersion), because the actual value is the same for all

analysts (the actual earnings are the same for all analysts). Further, note that measures a) and b) can be calculated when there is only one forecast⁷ and that the mean value is sometimes replaced by the median for these two measures in the literature.

In the ISO context, the first two measures relate to the trueness construct, whereas measures c) and d) capture the precision. In this paper, I use the unsigned bias (i.e. measure b)) as a measure of untrueness because I do not focus on whether the forecasts errors become higher or lower with more unconditional conservatism, but on whether the forecasts get closer to the actual value. As a measure of imprecision, I use the standard deviation of the (scaled) earnings forecast error (i.e. d)). I only include firm–year observations in the imprecision sample if it has forecasts from at least five different analysts.

In I/B/E/S, analysts make explicit earnings forecasts two to three years ahead and implicit forecasts about the average five-year earnings growth rate. In this paper, I only focus on the shortest forecast horizon (i.e. forecasts one year ahead), because the sample size decreases with the forecast horizon.

5.2.2 Unconditional Conservatism

Lara et al. (2009, p. 344) highlights the difficulties of measuring unconditional conservatism:

“Measuring unconditional conservatism is not a simple task. Recent research uses the market-to-book ratio (also a proxy for growth and risk), the C-Score proposed by Penman and Zhang (2002), the intercept of the Basu (1997)

⁷This can actually also be done for measure c). However, when there is only one forecast, measures b) and c) are the same.

regression, or the bias component developed by Beaver and Ryan (2000) as measures of unconditional conservatism.”

The use of the intercept from the Basu (1997) regression as a measure of unconditional conservatism is problematic in this paper as it does not yield yearly unconditional conservatism measures at the firm level. The firm-level fixed effects approach in Beaver and Ryan (2000) has the “same” problem.

Regarding the estimated reserve (C-score), the issue with this measure is that it only looks at conservatism in relation to inventory and intangible assets (R&D and advertising). However, unconditional conservatism also derives from the depreciation of tangible assets. The accounting depreciation expenses of tangible assets may be higher than the economic depreciation expenses, which is also a part of total unconditional conservatism. I refer to this part of unconditional conservatism as “depreciation conservatism”. McNichols et al. (2014) finds that the replacement costs of firms’ net assets is on average 1.865 (median 1.367) higher than the book value⁸. Thus the estimated reserve ignores depreciation conservatism. Thereby the estimated reserve implicitly (and wrongly) assumes that the depreciation schedule for assets chosen by the firm is equal to the economic depreciation of these assets. Thus, the C-score suffers from errors in measurement.

The market-to-book ratio includes depreciation conservatism. However, the market-to-book ratio has another issue. The problem is that the markets for the

⁸This relative understatement of assets derives from both tangible and intangible assets (including R&D and advertising expenses). However R&D and advertising only account for, on average, 23.4% (median 7.8%) of a firm’s total capital expenditures. Thus it is very likely that, on average, the accounting depreciation expenses of tangible assets are higher than the economic depreciation expenses

firms' net assets are incomplete. Empirically, some firms have market-to-book ratios below one, indicating incomplete markets. If the markets for the firms' net assets are complete, then the market-to-book value for each firm is not below one, since the accounting standards require a write-down of the assets to the market value (i.e. fair value) and (as a result) the market-to-book ratio equals one.

Following Penman and Zhang (2002), I calculate the estimated R&D reserve and advertising reserve by capitalizing the unamortized portion of the R&D and advertising expenses, using the industry amortization coefficients estimated (by Lev and Sougannis (1996)) for the R&D expenses and the sum-of-year's digits method over three years for the advertising expenses. In Section 6.2, I make robustness checks where I use different assumptions to calculate the estimated reserve.

Results (untabulated) show that the Pearson (Spearman) correlation between the Penman and Zhang (2002) estimated reserve and the market-to-book ratio is only 0.13 (0.17). However, these correlations are actually high compared to earlier studies (Pae and Thornton (2010) and Sohn (2012)⁹). The correlations suggest that the two conservatism measures, the estimated reserve and the market-to-book ratio, are not very closely related. This might be explained by the fact that the estimated reserve only reflects unconditional conservatism related to some operational activities whereas the market-to-book ratio reflects unconditional conservatism related to both operational and financial activities.

The unleveraged market-to-book ratio reflects only operational activities, as does

⁹The Pearson (Spearman), e.g., the correlations between the market-to-book ratio and the estimated reserve are 0.12 (0.002 and insignificant) in Pae and Thornton (2010). Sohn (2012) do not use the estimated reserve but the Penman and Zhang (2002) Q-score, which is equal to the change in the estimated reserve. Therefore the correlation in Sohn (2012) is even lower than in Pae and Thornton (2010).

the estimated reserve. For this reason, I expect the unleveraged market-to-book to be more highly correlated with the estimated reserve. Assuming that financial assets and financial liabilities are measured at their market values, the unleveraged market-to-book ratio is equal to

$$\frac{NOA^{MV}}{NOA^{BV}} = \frac{NFO^{MV} + E^{MV}}{NFO^{BV} + E^{BV}} \approx \frac{NFO^{BV} + E^{MV}}{NFO^{BV} + E^{BV}}$$

where NOA^{MV} , respectively, NOA^{BV} , denote the market, respectively, book value of Net Operating Assets. NFO^{MV} (NFO^{BV}) denotes the market (book) value of Net Financial Obligations and E^{MV} denotes the market value of equity. $NFO^{MV} \approx NFO^{BV}$ since most financial assets and liabilities are measured at fair value¹⁰. As expected, results (untabulated) show that the relation between the estimated reserve and the unleveraged market-to-book ratio is closer than that between the estimated reserve and the market-to-book ratio, yielding a Pearson (Spearman) correlation of 0.4 (0.3). Even though the correlation between the estimated reserve and the market-to-book ratio increases, because of the exclusion/adjustment of financial activities in the market-to-book ratio, the correlation still seems a little low if these two measures are to capture the same underlying construct.

McNichols et al. (2014) split the market-to-book ratio into a “future-to-book” factor and a “conservatism correction” factor. The conservatism correction factor comprises the replacement costs of the net assets deflated by their book value. Empirically, McNichols et al. (2014) find that the magnitude of the conservatism

¹⁰The unleveraged market-to-book is closely associated with the common practice estimate of Tobin’s Q (market value deflated by book value of the total assets). The only difference is that the unleveraged market-to-book focuses on Net Operating Assets, not on total assets

correction factor is about two-thirds of the overall market-to-book ratio¹¹.

Because one-third of the market-to-book ratio does not capture unconditional conservatism, I only use the estimated reserve (Penman and Zhang (2002)) as a measure of unconditional conservatism. The capitalization of R&D and advertising is the main part of the estimated reserve in the sample. The LIFO reserve accounts for only 9% of the estimated reserve¹². The capitalization of R&D and advertising is an estimate of the replacement costs of these assets deflated by the book value of the net operating assets¹³.

5.2.3 Earnings Volatility

Earnings volatility is measured as the earnings variance, over the past five years. Since the estimated level of unconditional conservatism is based on US GAAP information, I expect a stronger relation between unconditional conservatism and earnings volatility when earnings are measured using US GAAP than when using the I/B/E/S earnings. Since unconditional conservatism emerges from operational activities, I also expect a stronger effect of unconditional conservatism on earnings volatility when EBIT is used as the earnings measure, than when net income is used. EBIT is probably more closely related to I/B/E/S earnings than is net income, because earnings in I/B/E/S exclude nonrecurring items, other special items, and non-operating items from the GAAP earnings (Abarbanell and Lehavy (2007)). For this reason, I use EBIT as the measure of earnings in the estimation

¹¹McNichols et al. (2014) look at the adjusted market-to-book ratio. However, in this case, they only adjust for financial assets, not net financial assets, as I do.

¹²Ranging from 0% to 34% in the industries using the one-digit SIC.

¹³The estimated reserve plus 1 is equal to the replacement costs of the net operating assets deflated by their relative book values, assuming that the book values of net operating assets (excluding R&D and advertising costs) equal the replacement costs of the net operating assets (excluding R&D and advertising).

of the earnings volatility.

5.2.4 Controls

As mentioned in Section 2, Eames and Glover (2003) suggest that the effect of earnings predictability on analysts' forecast bias is captured by the earnings level. To ensure that the effect of earnings volatility on analysts' forecast accuracy is not fully mediated through the earnings level, I control for the absolute earnings level. I use the absolute level of earnings because the measure of analysts' forecast accuracy is an absolute measure as well. I therefore expect that higher absolute levels of earnings results in less accuracy in analysts' forecasts.

I control for market volatility to take into account changes in the macro-economic environment. Market volatility is expected to be negatively related to analysts' forecast accuracy.

Moreover, earlier literature (Mensah et al. (2004), Pae and Thornton (2010) and Sohn (2012)) about analysts' forecast bias/accuracy include firm size and the analysts' coverage as control variables. Following the literature, I measure firm size by the market capitalization and analysts' coverage as the number of analyst forecasts.

Lev (1983) analyzes the relation between earnings volatility (more specifically, the volatility in Return On Equity) and different economic factors: product type, entry barriers, firm size, and capital intensity. The product type is an indicator variable that equals one if the industry is classified as a "durable goods producing industry" according to the *Survey of Current Business*, and zero otherwise.

The findings in Lev (1983) suggest that firms in a non-durable goods producing industry have (on average) less volatile earnings. Lev (1983) attributes this to a smoother demand pattern for non-durable goods compared to that for durable goods. Furthermore, Lev (1983) expects that having higher entry barriers is negatively related to earnings volatility, because monopoly firms are less sensitive to shocks in the economic and technological environments. However, this relation is insignificant. With respect to firm size, Lev (1983) finds a negative association between firm size and earnings volatility. Lev (1983) argues that larger firms seem to have more stable growth patterns than do smaller firms. Lastly, Lev (1983) argues that capital intensity is positively related to earnings volatility. When capital intensity is high, revenue and costs are less correlated in capital intensive firms because capital intensity reflects the share of fixed to total costs. However, this relation is also empirically insignificant.

I include both firm size and capital intensity as controls for earnings volatility, even though Lev (1983) finds it to be insignificant, since theory suggests this relation. Capital intensity is likely to affect the level of unconditional conservatism, since capital intensive firms often have higher R&D and advertising expenses. Unconditional conservatism is also likely to be related to firm size, since larger firms are more willing to invest more in R&D and advertising than smaller firms. Therefore I also include capital intensity and firm size as a control variables for unconditional conservatism. I do not include product type and entry barriers, as these measures are industry specific; instead, I control for industry fixed effects. Furthermore, firm size and analysts' coverage are likely highly correlated, since larger firms are normally followed more closely. Hence I also include analysts' coverage as control for earnings volatility and unconditional conservatism. Finally, I include the earnings level as control for earnings volatility and uncondi-

tional conservatism, because, all else being equal, earnings volatility and the level of the estimated reserve (i.e. unconditional conservatism) are proportional to the earnings level.

5.3 Sample Selection and Descriptive Statistics

Analysts' earnings forecasts are collected from the I/B/E/S database and the (firm-level) accounting data from the Compustat database. The sample period is 1995–2012. The US sample begins in 1995 because Abarbanell and Lehavy (2007) show that a significant shift in the mean earnings took place in the early 1990s. I exclude regulated firms¹⁴ in the sample. To control for the influence of outliers, I Winzorize the dependent variable and all the independent variables at the 1st and 99th percentiles. Finally, for each year, I require five preceding years of information in order to calculate the earnings volatility.

Although all the variables are Winzorized at the 1st and 99th percentiles, the results can still be affected by extreme values in the dependent variable, due to the small denominator problem. Small forecast errors can be inflated (i.e. become extreme values) because the scaling variables can be close to zero (even though they are Winzorized). To deal with the small denominator problem, I follow the approach of Lacina et al. (2011), and Winzorize the values of the scaled forecast errors above one.

The sample size differs between the two measures of forecast accuracy (untrue-ness and imprecision), because only one analyst forecast is required to calcu-

¹⁴Regulated firms are utilities and financial institutions, which have SIC codes [4900–4999] and [6000–6999], respectively

late the Mean Absolute Forecast Error (MAFE), whereas to calculate the standard deviation of analysts' forecasts (STD), at least three analyst forecasts are required. Thus, using MAFE as the measure of forecast untruthfulness yields a sample of 18,432 firm–year observations, which is larger than the sample size of 15,566 firm–year observations obtained when STD is used as the measure of forecast imprecision. Table 2 presents the distribution of the unconditional conservatism, earnings volatility, analysts' forecast accuracy, and control variables, when MAFE is used as the forecast accuracy measure.

Table 2: Descriptive Statistics (FI (MAFE))

| Variable | Mean | Std Dev | 0% Min | 10% | 25% Q1 | 50% Median | 75% Q3 | 90% | 100% Max |
|-------------|--------|---------|--------|--------|--------|------------|--------|--------|----------|
| ABS_ST_EARN | 4.675 | 2.100 | -1.663 | 2.753 | 3.732 | 4.538 | 5.334 | 6.324 | 16.553 |
| CI | -2.230 | 0.659 | -3.894 | -2.974 | -2.630 | -2.276 | -1.897 | -1.451 | 0.565 |
| FI | 3.125 | 2.509 | -4.003 | 0.427 | 1.658 | 2.957 | 4.253 | 5.665 | 15.244 |
| SIZE | 6.567 | 1.914 | 1.725 | 4.152 | 5.231 | 6.444 | 7.832 | 9.145 | 11.886 |
| VAR_EARN | -5.002 | 2.569 | -10.40 | -7.914 | -6.778 | -5.341 | -3.609 | -1.774 | 5.284 |
| EST_RES | -2.029 | 1.712 | -7.002 | -4.307 | -3.071 | -1.917 | -0.861 | 0.025 | 2.815 |
| VOL_MARKET | 3.009 | 0.393 | 2.279 | 2.452 | 2.718 | 3.025 | 3.247 | 3.531 | 4.419 |
| NUM_ANALYST | 1.655 | 0.985 | 0.000 | 0.000 | 1.099 | 1.792 | 2.398 | 2.944 | 3.584 |

FI (MAFE) is the logarithm of the mean absolute forecast error. ABS_ST_EARN is the logarithm of the absolute value of the “Street” Earnings. CI is the logarithm of the depreciation expenses. SIZE is the logarithm of the market value of equity. VAR_EARN is the logarithm of the variance of the past five years of EBIT. EST_RES is the logarithm of the C-Score from Penman and Zhang (2002). VOL_MARKET is the logarithm of the Chicago Board Options Exchange Volatility Index of the market's expectation of 30-day volatility. NUM_ANALYST is the logarithm of the number of analysts covering the firm. All variables are scaled by Net Operating Assets (NOA) except SIZE and NUM_ANALYST, which are unscaled.

Since all variables take strictly positive values, it seems odd that the minimum values of the absolute value of the “Street” Earnings, capital intensity, forecast accuracy, earnings variance and the estimated reserve are negative. Nonetheless, a negative value simply indicates that the value is below one, since all the variables are logarithmically transformed to reduce skewness, as mentioned in Section 5.2.

Table 3 presents the distribution of the unconditional conservatism, earnings volatility, analysts' forecast accuracy, and control variables, for the sample where STD is used as the forecast accuracy measure.

Table 3: Descriptive Statistics (FI (STD))

| Variable | Mean | Std Dev | 0% Min | 10% | 25% Q1 | 50% Median | 75% Q3 | 90% | 100% Max |
|-------------|--------|---------|--------|--------|--------|------------|--------|--------|----------|
| ABS_ST_EARN | 4.674 | 2.009 | -1.663 | 2.835 | 3.789 | 4.557 | 5.319 | 6.225 | 17.099 |
| CI | -2.225 | 0.650 | -3.868 | -2.952 | -2.625 | -2.272 | -1.897 | -1.455 | 0.529 |
| SIZE | 6.929 | 1.807 | 2.402 | 4.680 | 5.679 | 6.788 | 8.105 | 9.351 | 11.926 |
| VAR_EARN | -5.073 | 2.576 | -10.55 | -7.990 | -6.853 | -5.408 | -3.687 | -1.835 | 5.343 |
| EST_RES | -2.033 | 1.711 | -7.002 | -4.308 | -3.082 | -1.910 | -0.864 | 0.003 | 2.522 |
| VOL_MARKET | 3.007 | 0.398 | 2.279 | 2.452 | 2.717 | 3.022 | 3.247 | 3.537 | 4.419 |
| NUM_ANALYST | 1.946 | 0.775 | 0.693 | 0.693 | 1.386 | 1.946 | 2.565 | 2.996 | 3.611 |
| FI | 12.792 | 2.539 | 3.614 | 10.054 | 11.240 | 12.592 | 14.063 | 15.559 | 27.373 |

FI (STD) is the logarithm of the standard deviation of the individual analysts' earnings forecasts. ABS_ST_EARN is the logarithm of the absolute value of the "Street" Earnings. CI is the logarithm of the depreciation expenses. SIZE is the logarithm of the market value of equity. VAR_EARN is the logarithm of the variance of the past five years of EBIT. EST_RES is the logarithm of the C-Score from Penman and Zhang (2002). VOL_MARKET is the logarithm of the Chicago Board Options Exchange Volatility Index of the market's expectation of 30-day volatility. NUM_ANALYST is the logarithm of the number of analysts covering the firm. All variables are scaled by Net Operating Assets (NOA) except SIZE and NUM_ANALYST, which are unscaled.

The sample distribution (over time) appears in Tables 4 and 5. Table 5 shows that the forecast imprecision sample has a higher average number of analysts who are following each firm (i.e. analysts' coverage), compared to the forecast untruthfulness sample (i.e. Table 4). This is because a larger number of analysts' forecasts are required to calculate the forecast imprecision than to calculate the forecast untruthfulness (as mentioned above). The higher average number of analysts following each firm is also reflected in a higher average firm size. The imprecision sample also has lower earnings volatility. This could be explained by the fact that larger firms are in the more mature part of the business lifecycle, where earnings are more constant. In contrast, smaller firms are more likely to be in a growth phase of the business cycle. Growth firms invest more, which can be observed in the

higher capital intensity in the precision sample. Over time, the samples do not show signs of large differences.

Table 4: Sample Characteristics over time (FI (MAFE))

| Year | No. Obs. | FI | ABS_ST_EARN | VOL_MARKET | SIZE | NUM_ANALYST | EST_RES | VAR_EARN | CI |
|-------|----------|-------|-------------|------------|-------|-------------|---------|----------|--------|
| 1995 | 1021 | 2.641 | 4.388 | 2.507 | 6.075 | 1.629 | -2.089 | -5.448 | -2.210 |
| 1996 | 1022 | 2.916 | 4.485 | 2.744 | 6.110 | 1.593 | -2.060 | -5.320 | -2.235 |
| 1997 | 1162 | 2.933 | 4.617 | 3.023 | 6.170 | 1.565 | -2.137 | -5.318 | -2.243 |
| 1998 | 1123 | 3.173 | 4.651 | 3.106 | 6.172 | 1.566 | -2.204 | -5.307 | -2.238 |
| 1999 | 1076 | 3.112 | 4.697 | 3.359 | 6.348 | 1.628 | -2.177 | -5.256 | -2.216 |
| 2000 | 1071 | 3.216 | 4.728 | 3.211 | 6.372 | 1.643 | -2.114 | -5.034 | -2.146 |
| 2001 | 1061 | 3.554 | 4.593 | 3.237 | 6.493 | 1.556 | -2.073 | -4.928 | -2.131 |
| 2002 | 1000 | 3.094 | 4.480 | 3.213 | 6.557 | 1.566 | -2.034 | -5.029 | -2.204 |
| 2003 | 1075 | 2.847 | 4.497 | 3.506 | 6.793 | 1.614 | -2.038 | -4.998 | -2.217 |
| 2004 | 1168 | 2.915 | 4.605 | 2.915 | 6.962 | 1.644 | -2.007 | -4.901 | -2.290 |
| 2005 | 1115 | 3.027 | 4.699 | 2.614 | 6.880 | 1.668 | -2.015 | -4.968 | -2.311 |
| 2006 | 1081 | 2.953 | 4.739 | 2.452 | 6.990 | 1.660 | -2.032 | -5.008 | -2.340 |
| 2007 | 1063 | 3.058 | 4.778 | 2.478 | 6.951 | 1.728 | -2.046 | -4.902 | -2.328 |
| 2008 | 1030 | 3.461 | 4.864 | 3.192 | 6.306 | 1.695 | -1.973 | -4.933 | -2.181 |
| 2009 | 900 | 3.626 | 4.744 | 3.701 | 6.639 | 1.675 | -1.805 | -4.704 | -2.130 |
| 2010 | 819 | 3.637 | 5.004 | 3.064 | 6.813 | 1.730 | -1.746 | -4.529 | -2.170 |
| 2011 | 807 | 3.221 | 4.849 | 2.974 | 6.790 | 1.850 | -1.876 | -4.509 | -2.265 |
| 2012 | 838 | 3.117 | 4.898 | 2.985 | 6.948 | 1.905 | -1.919 | -4.563 | -2.260 |
| Total | 18,432 | 3.125 | 4.675 | 3.009 | 6.567 | 1.655 | -2.029 | -5.002 | -2.230 |

FI (MAFE) is the logarithm of the mean absolute forecast error. ABS_ST_EARN is the logarithm of the absolute value of the “Street” Earnings. CI is the logarithm of the depreciation expenses. SIZE is the logarithm of the market value of equity. VAR_EARN is the logarithm of the variance of the past five years of EBIT. EST_RES is the logarithm of the C-Score from Penman and Zhang (2002). VOL_MARKET is the logarithm of the Chicago Board Options Exchange Volatility Index of the market’s expectation of 30-day volatility. NUM_ANALYST is the logarithm of the number of analysts covering the firm. All variables are scaled by Net Operating Assets (NOA) except SIZE and NUM_ANALYST, which are unscaled.

Table 5: Sample Characteristics over time (FI (STD))

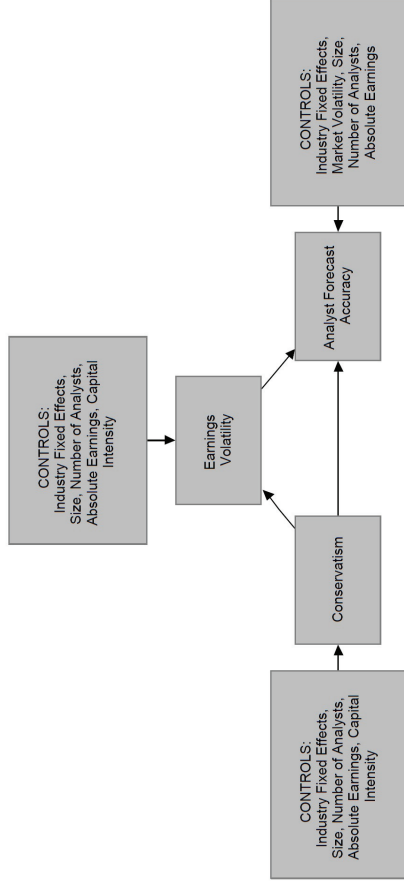
| Year | No. Obs. | FI | ABS_ST_EARN | VOL_MARKET | SIZE | NUM_ANALYST | EST_RES | VAR_EARN | CI |
|-------|----------|--------|-------------|------------|-------|-------------|---------|----------|--------|
| 1995 | 812 | 11.935 | 4.377 | 2.506 | 6.502 | 1.992 | -2.126 | -5.555 | -2.189 |
| 1996 | 815 | 12.024 | 4.385 | 2.747 | 6.529 | 1.944 | -2.081 | -5.442 | -2.231 |
| 1997 | 949 | 12.250 | 4.587 | 3.023 | 6.558 | 1.888 | -2.140 | -5.419 | -2.237 |
| 1998 | 908 | 12.342 | 4.643 | 3.103 | 6.590 | 1.883 | -2.236 | -5.464 | -2.230 |
| 1999 | 874 | 12.544 | 4.658 | 3.368 | 6.796 | 1.960 | -2.233 | -5.445 | -2.208 |
| 2000 | 869 | 12.531 | 4.646 | 3.210 | 6.840 | 1.962 | -2.174 | -5.193 | -2.161 |
| 2001 | 836 | 12.791 | 4.599 | 3.226 | 6.980 | 1.907 | -2.104 | -4.985 | -2.136 |
| 2002 | 821 | 13.006 | 4.490 | 3.215 | 6.983 | 1.890 | -2.048 | -5.072 | -2.194 |
| 2003 | 911 | 12.783 | 4.525 | 3.509 | 7.112 | 1.883 | -2.051 | -5.081 | -2.222 |
| 2004 | 989 | 12.753 | 4.562 | 2.914 | 7.304 | 1.949 | -2.017 | -4.989 | -2.272 |
| 2005 | 951 | 12.825 | 4.675 | 2.610 | 7.201 | 1.963 | -2.001 | -4.988 | -2.311 |
| 2006 | 959 | 12.883 | 4.748 | 2.455 | 7.272 | 1.904 | -1.997 | -5.043 | -2.329 |
| 2007 | 945 | 12.961 | 4.754 | 2.466 | 7.218 | 1.953 | -2.019 | -4.982 | -2.316 |
| 2008 | 913 | 13.116 | 4.818 | 3.196 | 6.613 | 1.930 | -1.967 | -5.004 | -2.167 |
| 2009 | 771 | 13.705 | 4.844 | 3.717 | 6.934 | 1.963 | -1.747 | -4.700 | -2.132 |
| 2010 | 722 | 13.506 | 5.091 | 3.066 | 7.076 | 1.972 | -1.762 | -4.582 | -2.175 |
| 2011 | 740 | 13.277 | 4.959 | 2.966 | 6.986 | 2.052 | -1.866 | -4.526 | -2.247 |
| 2012 | 781 | 13.317 | 4.878 | 2.987 | 7.160 | 2.083 | -1.916 | -4.626 | -2.244 |
| Total | 15,566 | 12.792 | 4.674 | 3.007 | 6.929 | 1.946 | -2.033 | -5.073 | -2.225 |

FI (STD) is the logarithm of the standard deviation of individual analysts' earnings forecasts. ABS_ST_EARN is the logarithm of the absolute value of the "Street" Earnings. CI is the logarithm of the depreciation expenses. SIZE is the logarithm of the market value of equity. VAR_EARN is the logarithm of the variance of the past five years of EBIT. EST_RES is the logarithm of the C-Score from Penman and Zhang (2002). VOL_MARKET is the logarithm of the Chicago Board Options Exchange Volatility Index of the market's expectation of 30-day volatility. NUM_ANALYST is the logarithm of the number of analysts covering the firm. All variables are scaled by Net Operating Assets (NOA) except SIZE and NUM_ANALYST, which are unscaled.

6 Results

I estimate the model using maximum likelihood estimation. As mentioned in Section 5.2.4, I include industry fixed effects (market volatility) to control for the cross-sectional (time-series) clustering of errors. The estimated model is depicted in figure 2.

Figure 2: Path diagram showing the direct and indirect effects of conservatism on the accuracy of analysts' earnings forecasts along with the control variables.



Conservatism affects analysts' forecast accuracy directly and indirectly. The indirect effects is mediated by earnings volatility.

6.1 Overall results

Table 6 shows the results of the effect of unconditional conservatism on analysts' forecast inaccuracy (measured by forecast untrueness and imprecision).

Table 6: Direct and indirect effects of unconditional conservatism on forecast untrueness and imprecision. Scaling variable: NOA

| Effect | Path from | Path to | Trueness (MAFE) | | Precision (STD) | |
|----------|-------------|----------|-----------------|-------------|-----------------|-------------|
| | | | Coefficient | t-statistic | Coefficient | t-statistic |
| Total | EST_RES | FI | 0.0771*** | 15.27 | 0.1117*** | 20.14 |
| Direct | EST_RES | FI | 0.0128** | 2.33 | 0.0435*** | 7.28 |
| Mediated | | | | . | | . |
| Direct | EST_RES | VAR_EARN | 0.4019*** | 60.12 | 0.3984*** | 54.25 |
| Direct | VAR_EARN | FI | 0.1601*** | 29.86 | 0.1712*** | 29.45 |
| Indirect | EST_RES | FI | 0.0644*** | 26.47 | 0.0682*** | 25.64 |
| Controls | | | | . | | . |
| Direct | ABS_ST_EARN | FI | 0.7092*** | 183.47 | 0.6454*** | 145.64 |
| Direct | VOL_MARKET | FI | 0.0375*** | 8.82 | 0.0527*** | 11.45 |
| Direct | NUM_ANALYST | FI | 0.0403*** | 6.23 | 0.1321*** | 19.47 |
| Direct | SIZE | FI | -0.2716*** | -40.57 | 0.2107*** | 30.29 |
| Direct | ABS_ST_EARN | EST_RES | 0.2077*** | 33.63 | 0.2135*** | 31.95 |
| Direct | CI | EST_RES | 0.2791*** | 45.07 | 0.2741*** | 40.95 |
| Direct | NUM_ANALYST | EST_RES | 0.0613*** | 6.64 | 0.0751*** | 7.81 |
| Direct | SIZE | EST_RES | -0.0242*** | -2.6 | -0.0357*** | -3.68 |
| Direct | ABS_ST_EARN | VAR_EARN | 0.1618*** | 26.59 | 0.1614*** | 24.27 |
| Direct | CI | VAR_EARN | 0.1583*** | 25.15 | 0.1676*** | 24.52 |
| Direct | NUM_ANALYST | VAR_EARN | 0.0557*** | 6.34 | 0.0559*** | 6.05 |
| Direct | SIZE | VAR_EARN | -0.2068*** | -23.47 | -0.2040*** | -22.06 |

*, **, and *** indicate significance at 0.10, 0.05 and 0.01, respectively. The table presents the direct, indirect and the total effect from unconditional conservatism on forecast inaccuracy. Furthermore the table presents the path coefficients for the control variables as well. All variables are scaled by Net Operating Assets (NOA) except SIZE and NUM_ANALYST, which are unscaled.

FI (MAFE) is the logarithm of the mean absolute forecast error. FI (STD) is the logarithm of the standard deviation of individual analysts' earnings forecasts. ABS_ST_EARN is the logarithm of the absolute value of the "Street" Earnings. CI is the logarithm of the depreciation expenses. SIZE is the logarithm of the market value of equity. VAR_EARN is the logarithm of the variance of the past five years of EBIT. EST_RES is the logarithm of the C-Score from Penman and Zhang (2002). VOL_MARKET is the logarithm of the Chicago Board Options Exchange Volatility Index of the market's expectation of 30-day volatility. NUM_ANALYST is the logarithm of the number of analysts covering the firm.

The total correlation is 0.08 (0.11) for forecast untruthfulness (imprecision). The total correlation is then divided into a direct effect and an indirect effect, where the latter is mediated through earnings volatility. The direct effect is positive (0.01 for forecast untruthfulness and 0.04 for forecast imprecision), indicating that analysts do not correctly incorporate conservatism into their forecasts. For more unconditionally conservative firms, analysts are either too optimistic or too pessimistic about future earnings. The effect of unconditional conservatism on earnings volatility is positive (0.40 for both forecast untruthfulness and imprecision), indicating that unconditional conservatism increases earnings volatility. The coefficient between the earnings volatility and the inaccuracy of the analysts' forecasts is also positive (0.16 for forecast untruthfulness and 0.17 for forecast imprecision), indicating that higher earnings volatility increases the inaccuracy. Overall, the total indirect effect (the relation between unconditional conservatism and analysts' forecast inaccuracy) is therefore also positive (0.06 for forecast untruthfulness and 0.07 for forecast imprecision). In short (and as expected/hypothesized), the results indicate that unconditional conservatism increases earnings volatility and (as a result) increases analysts' forecast inaccuracy. Furthermore, the results indicate that the indirect effect is the strongest. The indirect effect accounts for approximately 84% (61%) of the total correlation between unconditional conservatism and analysts' forecast untruthfulness (imprecision). However the *t*-statistics for all the other parameter estimates are high as well, which suggests there might still exist a clustering of the errors.

The path coefficients for the control variables in Table 6 have the expected signs except for the path from firm size to forecast inaccuracy, which is negative when forecast untruthfulness is used as the inaccuracy measure. This suggests that for larger firms, analysts' forecasts are closer to the actual value, but more imprecise

(analysts disagree more about their forecasts) than with smaller firms.

6.2 Additional analyses

6.2.1 Deflator

The variables in Table 6 were scaled by a book-value-based deflator (Net Operating Assets). I also estimate the model using a market-based deflator (Market Value of Equity). The path coefficient from estimating the model when variables are scaled by market value of equity is shown in Table 7.

Table 7: Direct and indirect effects of unconditional conservatism on forecast untruthfulness and imprecision. Scaling variable: MVE

| Effect | Path from | Path to | Trueness (MAFE) | | Precision (STD) | |
|----------|-------------|----------|-----------------|-------------|-----------------|-------------|
| | | | Coefficient | t-statistic | Coefficient | t-statistic |
| Total | EST_RES | FI | 0.0808*** | 16.19 | 0.1367*** | 23.72 |
| Direct | EST_RES | FI | 0.0650*** | 12.4 | 0.1167*** | 19.4 |
| Mediated | | | | . | | . |
| Direct | EST_RES | VAR_EARN | 0.1761*** | 27.32 | 0.1748*** | 24.71 |
| Direct | VAR_EARN | FI | 0.0897*** | 16.79 | 0.1144*** | 18.94 |
| Indirect | EST_RES | FI | 0.0158*** | 14.29 | 0.0200*** | 15.02 |
| Controls | | | | . | | . |
| Direct | ABS_ST_EARN | FI | 0.6849*** | 184.14 | 0.6897*** | 159.61 |
| Direct | VOL_MARKET | FI | 0.0357*** | 8.07 | 0.0521*** | 10.27 |
| Direct | NUM_ANALYST | FI | 0.0650*** | 9.51 | 0.1690*** | 22.38 |
| Direct | SIZE | FI | -0.2872*** | -39.98 | 0.2382*** | 30.2 |
| Direct | ABS_ST_EARN | EST_RES | 0.0285*** | 4.45 | 0.0276*** | 3.96 |
| Direct | CI | EST_RES | 0.4173*** | 63.62 | 0.4065*** | 56.56 |
| Direct | NUM_ANALYST | EST_RES | 0.0985*** | 10.25 | 0.1096*** | 10.89 |
| Direct | SIZE | EST_RES | -0.1787*** | -17.92 | -0.1807*** | -17.34 |
| Direct | ABS_ST_EARN | VAR_EARN | 0.0051 | 0.92 | 0.0086 | 1.42 |
| Direct | CI | VAR_EARN | 0.5020*** | 82.6 | 0.5137*** | 77.83 |
| Direct | NUM_ANALYST | VAR_EARN | -0.1164*** | -14 | -0.0971*** | -11.04 |
| Direct | SIZE | VAR_EARN | -0.1141*** | -13.12 | -0.1022*** | -11.14 |

*, **, and *** indicate significance at 0.10, 0.05 and 0.01, respectively. The table presents the direct, indirect and the total effect from unconditional conservatism on forecast inaccuracy. Furthermore the table presents the path coefficients for the control variables as well. All variables are scaled by Market Value of Equity (MVE) except SIZE and NUM_ANALYST, which are unscaled.

FI (MAFE) is the logarithm of the mean absolute forecast error. FI (STD) is the logarithm of the standard deviation of individual analysts' earnings forecasts. ABS_ST_EARN is the logarithm of the absolute value of the "Street" Earnings. CI is the logarithm of the depreciation expenses. SIZE is the logarithm of the market value of equity. VAR_EARN is the logarithm of the variance of the past five years of EBIT. EST_RES is the logarithm of the C-Score from Penman and Zhang (2002). VOL_MARKET is the logarithm of the Chicago Board Options Exchange Volatility Index of the market's expectation of 30-day volatility. NUM_ANALYST is the logarithm of the number of analysts covering the firm.

Scaling by market value of equity (Table 7) yields similar results as when the variables are scaled by net operating assets (Table 6), but differs slightly in two aspects. First, the relative importance of the direct and the indirect effects seems to change. In Table 7 the direct effect seem to be the strongest, whereas in Table 6 it seems to be the indirect effect. Second, in Table 7 the control variable "analysts' coverage" is negatively related to the estimated reserve (unconditional conservatism), whereas it is positive in Table 6.

6.2.2 Other estimation assumptions about the estimated reserve

I also estimate the R&D reserve assuming that the R&D asset life is five years and use two different amortization methods: linear amortization and sum-of-year's digits amortization. In addition, I calculate the estimated advertising reserve using linear amortization and sum-of-year's digits amortization, assuming a three year life period for advertising expenses. This gives four other estimates of the estimated reserve. These four new measures of the estimated reserve yield similar results.

6.2.3 R&D and advertising expenses

An alternative explanation of the findings in Table 6 are that the results are driven by companies that invest in R&D and/or advertising, since the estimated reserve primarily consists of capitalized R&D and/or advertising costs. Since compa-

nies that invest heavily in R&D or advertising are more difficult to forecast, it might not be conservatism but the difficulty in forecasting the revenue generation from R&D or advertising expenses that is driving the results. To test this alternative hypothesis, I exclude all firms that have R&D and/or advertising estimated reserves. The remaining firms either have no LIFO reserves (and hence no estimated reserves) or are firms that have LIFO reserves. Table 8 shows the effect of unconditional conservatism on analysts' forecast inaccuracy when firm-years with positive capitalized R&D and/or advertising costs are excluded. The results are similar to the results in Table 6 except that the direct effect now become insignificant.

Table 8: Direct and indirect effects of unconditional conservatism on forecast untruthfulness and imprecision when firm-years with positive capitalized R&D and/or advertising costs are excluded. Scaling variable: NOA

| Effect | Path from | Path to | Trueness (MAFE) | | Precision (STD) | |
|----------|-------------|----------|-----------------|-------------|-----------------|-------------|
| | | | Coefficient | t-statistic | Coefficient | t-statistic |
| Total | EST_RES | FI | 0.1008*** | 3.49 | 0.0864*** | 3.31 |
| Direct | EST_RES | FI | 0.0187 | 0.66 | 0.0130 | 0.51 |
| Mediated | | | | . | | . |
| Direct | EST_RES | VAR_EARN | 0.2686*** | 8.74 | 0.2692*** | 8.22 |
| Direct | VAR_EARN | FI | 0.3054*** | 11.26 | 0.2729*** | 10.69 |
| Indirect | EST_RES | FI | 0.0820*** | 6.8 | 0.0735*** | 6.41 |
| Controls | | | | . | | . |
| Direct | ABS_ST_EARN | FI | 0.4960*** | 20.47 | 0.4070*** | 17.03 |
| Direct | VOL_MARKET | FI | 0.0417 | 1.62 | 0.0802*** | 3.43 |
| Direct | NUM_ANALYST | FI | 0.1617*** | 4.39 | 0.1789*** | 5.39 |
| Direct | SIZE | FI | -0.2776*** | -7.56 | 0.3275*** | 9.91 |
| Direct | ABS_ST_EARN | EST_RES | 0.0302 | 0.95 | 0.0535 | 1.52 |
| Direct | CI | EST_RES | 0.0344 | 1.06 | 0.0467 | 1.3 |
| Direct | NUM_ANALYST | EST_RES | -0.1561*** | -3.57 | -0.0838* | -1.76 |
| Direct | SIZE | EST_RES | 0.0760* | 1.71 | 0.0542 | 1.12 |
| Direct | ABS_ST_EARN | VAR_EARN | 0.0705** | 2.31 | 0.0648* | 1.96 |
| Direct | CI | VAR_EARN | 0.1832*** | 5.9 | 0.1918*** | 5.72 |
| Direct | NUM_ANALYST | VAR_EARN | 0.1141*** | 2.68 | 0.2280*** | 5.12 |
| Direct | SIZE | VAR_EARN | -0.0834* | -1.94 | -0.1262*** | -2.76 |

*, **, and *** indicate significance at 0.10, 0.05 and 0.01, respectively. The table presents the direct, indirect and the total effect from unconditional conservatism on forecast inaccuracy when firm-years with positive capitalized R&D and/or advertising costs are excluded (i.e. positive unconditional conservatism can only stem from the LIFO reserve.). Furthermore the table presents the path coefficients for the control variables as well. All variables are scaled by Net Operating Assets (NOA) except SIZE and NUM_ANALYST, which are unscaled.

FI (MAFE) is the logarithm of the mean absolute forecast error. FI (STD) is the logarithm of the standard deviation of individual analysts' earnings forecasts. ABS_ST_EARN is the logarithm of the absolute value of the "Street" Earnings. CI is the logarithm of the depreciation expenses. SIZE is the logarithm of the market value of equity. VAR_EARN is the logarithm of the variance of the past five years of EBIT. EST_RES is the logarithm of the C-Score from Penman and Zhang (2002). VOL_MARKET is the logarithm of the Chicago Board Options Exchange Volatility Index of the market's expectation of 30-day volatility. NUM_ANALYST is the logarithm of the number of analysts covering the firm.

6.2.4 Bidirectional causality

Even though I argued that it is likely that unconditional conservatism affects earnings volatility (see section 4.2.1), it is also conceivable that earnings volatility affects unconditional conservatism (i.e. the causality direction might be reversed or bidirectional). This is because firms operating in a highly volatile business environment (and therefore having highly volatile earnings¹⁵) also have a high level of conservatism (i.e. high R&D and advertising costs).

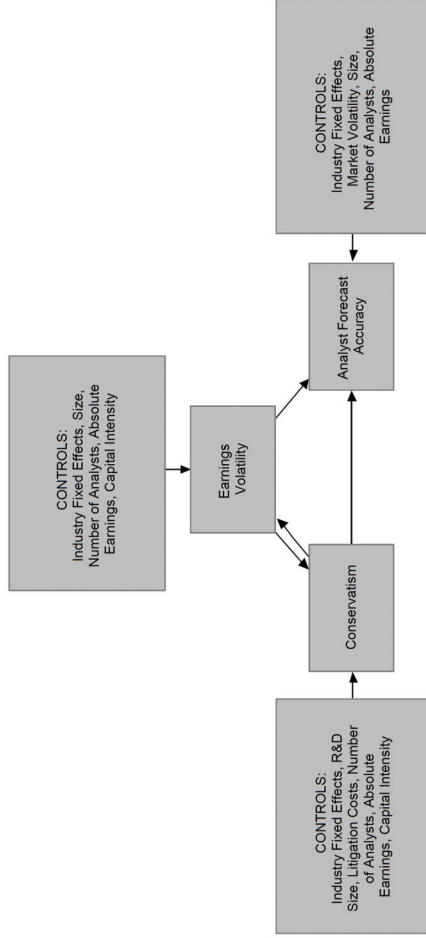
I test for simultaneity and bi-directional causality by reestimating the model depicted in figure 2 as a non-recursive model¹⁶. I do this by including an extra (or “reverse”) path from earnings volatility to conservatism. Thus, a bidirectional feedback loop now exists between conservatism and earnings volatility. The non-recursive model is illustrated in figure 3.

A non-recursive model, unlike a recursive model, is not always identified. Identification means that there exists a unique solution for the model parameters. One necessary (sufficient) condition for the model to be identified is that it satisfies the order (rank) condition. Since the model is block recursive (i.e. the effects from earnings and conservatism are direct effects on forecast accuracy), the order (rank) condition should be evaluated separately for each block (Kline (2011, pp. 135, 151–153)). Since recursive models are always identified, so is the recursive block. In order for the non-recursive block to fulfill the necessary condition for identification, the order condition says that earnings volatility must have at least one ($2-1=1$) explanatory variable that is not used as an explanatory variable for

¹⁵In a highly volatile business environment the revenue as well as the costs are highly volatile.

¹⁶A non-recursive model is a model that includes a feedback loop. A model that does not include one or more feedback loops is named a recursive model.

Figure 3: Path diagram showing the direct and indirect effects of conservatism on the accuracy of analysts' earnings forecasts along with the control variables and with a bidirectional relation between conservatism and earnings volatility.



Conservatism affects analysts' forecast accuracy directly and indirectly. The indirect effects is mediated by earnings volatility. However earnings volatility also affects conservatism.

conservatism and vice versa. Furthermore, when this holds, it is easily verified (using the approach from Kline (2011, pp. 151–153)) that the rank condition is satisfied, and hence the model is theoretically identified.

Empirical correlations (untabulated) show that, even though firm size seems to be significantly negatively correlated with both earnings volatility and conservatism, the correlation between firm size and conservatism is much lower (-0.02) compared to the correlation between firm size and earnings volatility (-0.17). Therefore, I exclude firm size as an explanatory variable for conservatism.

Qiang (2007) shows that higher litigation, regulation and tax costs increase unconditional conservatism¹⁷. Thus including either litigation, regulation or tax costs (or all of them) as explanatory variable(s) for conservatism would make the model theoretically identified since firm size is only used as explanatory variable for earnings volatility. However, Qiang (2007) assumes that the company has the opportunity to choose whether or not to understate the book value of the assets. With regard to the measure of unconditional conservatism used in this paper (i.e. the estimated reserve) the company does not have a choice whether or not to understate the value of the R&D and advertising assets since the accounting rules require these assets to be set to zero (i.e. the largest possible understatement). Even though the company can choose its inventory valuation method and there-

¹⁷Following Qiang (2007) I measure litigation costs as a binary variable that equals one if the company is audited by a big-four (earlier big-eight) company and zero otherwise. Regulation costs are measured as a binary variable that equals one if sales deflated by industry sales divided by the number of firms within the industry (based on a two-digit SIC code) is in the top quartile and zero otherwise. Taxation costs are measured as the parameter estimate for tax expense from a regression of tax expense minus deferred tax expense on tax expense (where all variables are deflated by lagged total assets). Qiang (2007) estimates the regression over the whole sample period, which generates a firm-specific estimate of taxation costs. I use a firm-year specific taxation costs estimate by only estimating over the same 5-year period as when estimating the earnings volatility.

fore has a choice about the last part of the estimated reserve (the LIFO reserve part), this part accounts for only 9% (see section 5.2.2) of the total estimated reserve. Thus the determinant factors of unconditional conservatism explored in Qiang (2007) will not likely be significant determinant factors of the estimated reserve. Empirical correlations (untabulated) show that taxation costs are not significantly correlated with the estimated reserve, but that litigation costs and regulation costs are. Nonetheless these correlations are low (0.02 for litigation costs and -0.03 for regulation costs¹⁸). Therefore, (because of these low correlations) if only litigation costs and regulation costs are included as explanatory variables, the model is likely not empirically identified. Because of that, I also include the level of R&D expenses¹⁹ (undeflated and logarithm transformed). To test that the model is empirically identified, I use different initial values and observe that the model converges to the same solution (Kline (2011, p. 233)). When estimating the model with R&D expenses, litigation costs and regulation costs as explanatory variables for conservatism the model is empirically unidentified. This is because regulation costs are highly correlated with firm size, and therefore the order and rank condition for earnings volatility is not empirically satisfied. Hence, I reestimate the model when only R&D expenses and litigation costs are included as explanatory variables for conservatism. The results are reported in table 9.

The table shows that there seems to be a bi-directional cause and effect from conservatism on earnings volatility. The effect from conservatism on earnings volatility is approximately 1.4 times larger than the effect from earnings volatility on conservatism.

¹⁸The correlation of -0.03 between regulation costs and conservatism contradicts the predictions and findings in Qiang (2007).

¹⁹The advertising expenses are not significantly correlated with the estimated reserve.

Table 9: Direct and indirect effects of unconditional conservatism on forecast untrueness and imprecision with bidirectional effects between unconditional conservatism and earnings volatility. Scaling variable: NOA

| Effect | Path from | Path to | Trueness (MAFE) | | Precision (STD) | |
|----------|-------------|----------|-----------------|-------------|-----------------|-------------|
| | | | Coefficient | t-statistic | Coefficient | t-statistic |
| Total | EST_RES | FI | 0.0529*** | 9.04 | 0.0869*** | 13.39 |
| Direct | EST_RES | FI | 0.0123** | 2.24 | 0.0430*** | 7.2 |
| Mediated | | | | . | | . |
| Direct | VAR_EARN | EST_RES | 0.1669*** | 13.05 | 0.1649*** | 11.59 |
| Direct | EST_RES | VAR_EARN | 0.2403*** | 15.81 | 0.2370*** | 13.95 |
| Direct | VAR_EARN | FI | 0.1600*** | 29.84 | 0.1705*** | 29.39 |
| Indirect | EST_RES | FI | 0.0406*** | 14.33 | 0.0438*** | 13.29 |
| Controls | | | | . | | . |
| Direct | ABS_ST_EARN | FI | 0.7098*** | 183.72 | 0.6453*** | 145.68 |
| Direct | VOL_MARKET | FI | 0.0375*** | 8.82 | 0.0527*** | 11.45 |
| Direct | NUM_ANALYST | FI | 0.0404*** | 6.24 | 0.1321*** | 19.53 |
| Direct | SIZE | FI | -0.2719*** | -40.48 | 0.2104*** | 30.2 |
| Direct | ABS_ST_EARN | EST_RES | 0.1575*** | 26.09 | 0.1622*** | 24.52 |
| Direct | CI | EST_RES | 0.1980*** | 30.98 | 0.1962*** | 27.74 |
| Direct | NUM_ANALYST | EST_RES | -0.0061 | -1.12 | 0.0051 | 0.87 |
| Direct | LIT_COSTS | EST_RES | 0.0138*** | 2.62 | 0.0023 | 0.4 |
| Direct | SIZE_R&D | EST_RES | 0.4643*** | 71.99 | 0.4570*** | 64.06 |
| Direct | ABS_ST_EARN | VAR_EARN | 0.1957*** | 29.06 | 0.1962*** | 26.44 |
| Direct | CI | VAR_EARN | 0.2047*** | 27.55 | 0.2133*** | 26.3 |
| Direct | NUM_ANALYST | VAR_EARN | 0.0659*** | 7.39 | 0.0683*** | 7.29 |
| Direct | SIZE | VAR_EARN | -0.2107*** | -23.42 | -0.2096*** | -22.21 |

*, **, and *** indicate significance at 0.10, 0.05 and 0.01, respectively. The table presents the direct, indirect and the total effect from unconditional conservatism on forecast inaccuracy. Furthermore the table presents the path coefficients for the control variables as well. All variables are scaled by Net Operating Assets (NOA) except SIZE, NUM_ANALYST, SIZE_R&D and LIT_COSTS, which are unscaled.

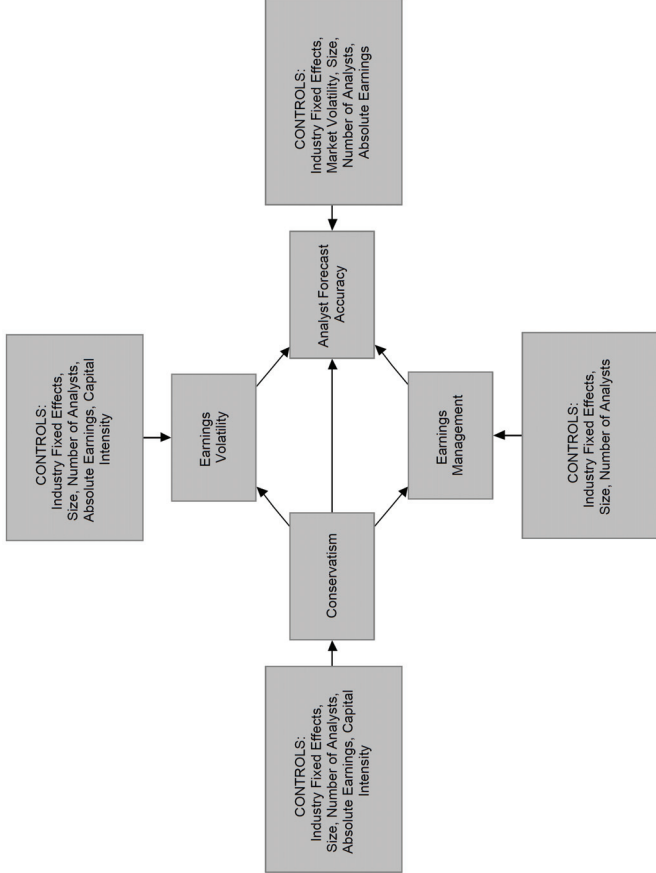
FI (MAFE) is the logarithm of the mean absolute forecast error. FI (STD) is the logarithm of the standard deviation of individual analysts' earnings forecasts. ABS_ST_EARN is the logarithm of the absolute value of the "Street" Earnings. CI is the logarithm of the depreciation expenses. SIZE is the logarithm of the market value of equity. VAR_EARN is the logarithm of the variance of the past five years of EBIT. EST_RES is the logarithm of the C-Score from Penman and Zhang (2002). VOL_MARKET is the logarithm of the Chicago Board Options Exchange Volatility Index of the market's expectation of 30-day volatility. NUM_ANALYST is the logarithm of the number of analysts covering the firm. LIT_COSTS is a binary variable that equals one if the company is audited by a big-four (earlier big-eight) company and zero otherwise. SIZE_R&D is the logarithm of the R&D expenses.

6.2.5 Earnings management

Burgsthaler and Eames (2006) find that earnings are managed to meet (or beat by a small amount) analysts' forecasts. Since unconditional conservatism decreases management's opportunity to manage earnings, it is likely that unconditional conservatism decreases analysts' earnings forecast errors through earnings management (as the mediator). However, "big bath" earnings management probably creates huge analysts' earnings forecast errors. Therefore it is not obvious whether the effect of conservatism on analysts' forecast accuracy is mediated through earnings management or not. Thus, I repeat the analysis by including earnings management in the estimation of the effect of conservatism on analysts' forecast accuracy. The model is depicted in Figure 4.

The level of earnings management is measured by the level of discretionary accruals (the modified Jones model (Dechow et al. (1995))). Since the (modified) Jones model estimates discretionary accruals scaled by total assets, I remove the scaling by multiplying by total assets. Then I rescale it according to the scaling used for the other variables. I include firm size and the analysts' coverage as control variables for earnings management, since larger and more closely covered firms are monitored more closely than smaller firms, which reduces the opportunity for engaging in earnings management. Table 10 shows that the inclusion of earnings management as a mediator does not change the overall results. However, the results reveal that the effect of unconditional conservatism on earnings management is positive, which contradicts the predictions. It also reveals that more earnings management is associated with a lower inaccuracy of analysts' forecasts.

Figure 4: Path diagram showing the direct and indirect effects of conservatism on the accuracy of analysts' earnings forecasts along with the control variables and with earnings management as an extra mediating variable.



Conservatism affects analysts' forecast accuracy directly and indirectly. The first indirect effect is mediated by earnings volatility. The second indirect effect is mediated through earnings management.

Table 10: Direct and indirect effects of unconditional conservatism on forecast untruthfulness and imprecision when earnings management is included as extra mediating variable. Scaling variable: NOA

| Effect | Path from | Path to | Truthfulness (MAFE) | | Precision (STD) | |
|----------|-------------|----------|---------------------|-------------|-----------------|-------------|
| | | | Coefficient | t-statistic | Coefficient | t-statistic |
| Total | EST_RES | FI | 0.0768*** | 15.16 | 0.1101*** | 19.77 |
| Direct | EST_RES | FI | 0.0150*** | 2.68 | 0.0468*** | 7.67 |
| Mediated | | | | | | |
| Direct | EST_RES | VAR_EARN | 0.3978*** | 58.93 | 0.3948*** | 53.24 |
| Direct | VAR_EARN | FI | 0.1592*** | 29.5 | 0.1692*** | 28.85 |
| Direct | EST_RES | ABS_DA | 0.2124*** | 29.39 | 0.2105*** | 26.24 |
| Direct | ABS_DA | FI | -0.0071 | -1.47 | -0.0165*** | -3.2 |
| Indirect | EST_RES | FI | 0.0619*** | 23.49 | 0.0633*** | 22.04 |
| Controls | | | | | | |
| Direct | ABS_ST_EARN | FI | 0.7128*** | 183.81 | 0.6519*** | 146.95 |
| Direct | VOL_MARKET | FI | 0.0365*** | 8.54 | 0.0517*** | 11.18 |
| Direct | NUM_ANALYST | FI | 0.0388*** | 5.97 | 0.1295*** | 18.99 |
| Direct | SIZE | FI | -0.2760*** | -39.53 | 0.1985*** | 27.38 |
| Direct | ABS_ST_EARN | EST_RES | 0.2020*** | 32.29 | 0.2101*** | 31.05 |
| Direct | CI | EST_RES | 0.2860*** | 45.72 | 0.2808*** | 41.52 |
| Direct | NUM_ANALYST | EST_RES | 0.0593*** | 6.35 | 0.0732*** | 7.53 |
| Direct | SIZE | EST_RES | -0.0165* | -1.75 | -0.0286*** | -2.92 |
| Direct | ABS_ST_EARN | VAR_EARN | 0.1581*** | 25.77 | 0.1589*** | 23.71 |
| Direct | CI | VAR_EARN | 0.1652*** | 25.97 | 0.1745*** | 25.29 |
| Direct | NUM_ANALYST | VAR_EARN | 0.0550*** | 6.21 | 0.0526*** | 5.66 |
| Direct | SIZE | VAR_EARN | -0.2046*** | -23.02 | -0.2007*** | -21.54 |
| Direct | NUM_ANALYST | ABS_DA | -0.0544*** | -5.42 | -0.0465*** | -4.36 |
| Direct | SIZE | ABS_DA | -0.3826*** | -39.13 | -0.3715*** | -35.79 |

*, **, and *** indicate significance at 0.10, 0.05 and 0.01, respectively. The table presents the direct, indirect and the total effect from unconditional conservatism on forecast inaccuracy when earnings management also mediates this effect. Furthermore the table presents the path coefficients for the control variables as well. All variables are scaled by Net Operating Assets (NOA) except SIZE and NUM_ANALYST, which are unscaled.

FI (MAFE) is the logarithm of the mean absolute forecast error. FI (STD) is the logarithm of the standard deviation of individual analysts' earnings forecasts. ABS_DA is the absolute abnormal accruals from the modified Jones model (rescaled by NOA). ABS_ST_EARN is the logarithm of the absolute value of the "Street" Earnings. CI is the logarithm of the depreciation expenses. SIZE is the logarithm of the market value of equity. VAR_EARN is the logarithm of the variance of the past five years of EBIT. EST_RES is the logarithm of the C-Score from Penman and Zhang (2002). VOL_MARKET is the logarithm of the Chicago Board Options Exchange Volatility Index of the market's expectation of 30-day volatility. NUM_ANALYST is the logarithm of the number of analysts covering the firm.

7 Conclusion

This paper has studied how the accuracy of analysts' earnings forecasts are affected by unconditional conservatism. I find that the accuracy of analysts' earnings forecasts is negatively related to unconditional conservatism. This relation derives from a direct negative effect of unconditional conservatism on the accuracy of analysts' earnings forecasts, suggesting that analysts do not correctly incorporate unconditional conservatism.

Further, I find that unconditional conservatism affects the accuracy of analysts' earnings forecasts indirectly, through earnings volatility. Unconditional conservatism increases earnings volatility, which decreases the accuracy of analysts' earnings forecasts.

Additional analyses reveal that the results are not explained by a high intensity of investment in R&D and advertising. Furthermore, these analyses document that earnings volatility also affects unconditional conservatism, but this effect is smaller than the effect from unconditional conservatism to earnings volatility. Finally, the additional analyses show that unconditional conservatism increases earnings management, and that earnings management increases the accuracy of analysts' earnings forecasts.

My findings have implications for regulators. Accounting conservatism has the benefits of protecting investors and creditors from losses. This study shows that accounting conservatism comes with a cost in the form of less predictable earnings (and as a result, lower forecast accuracy). In view of this, the present study suggests that regulators should consider the cost of accounting conservatism as

well when setting accounting standards. This study is, however, limited in a way, since it only focuses on conservatism from the cost side. Unconditional conservatism also derives from the revenue side, for example, the choice of revenue recognition method. Firms within, e.g., the construction industry, mainly use the completed-contract method or the percentage-of-completion method. Assuming that the contracts are profitable, the completed-contract method is more unconditionally conservative than the percentage-of-completion method. The reason for this is that the profit is recognized later using the completed-contract method than it is when using the percentage-of-completion method. Future research should therefore also focus on unconditional conservatism from the revenue side.

A Relation between earnings predictability and earnings volatility in Mensah et al. (2004)

In Mensah et al. (2004), earnings predictability is measured as the sum of the absolute forecast errors (seasonally adjusted quarterly earnings per share) over the past four quarters, deflated by the previous fiscal year-end stock price. The sum of the absolute forecast errors (SAFE) is very closely related to the standard deviation of the forecast errors (Std). The standard deviation of the forecast errors equals

$$Std[\epsilon] = \sqrt{\frac{1}{T} \sum_{\tau=1}^T \epsilon_{\tau}^2}$$

where ϵ_{τ} denotes the forecast error at time τ . Likewise the sum of the absolute forecast errors equals

$$SAFE[\epsilon] = \sum_{\tau=1}^T \sqrt{\epsilon_{\tau}^2}$$

Furthermore the standard deviation of the forecast error is very closely related to the standard deviation of the actual value, since

$$Std[\epsilon] = \sqrt{Var[\epsilon]} = \sqrt{Var[A] + Var[F] - 2Cov[A, F]}$$

where F denotes the forecast value and A denotes the actual value. Mensah et al. (2004) notes that they use a Random Walk earnings expectation model to calculate the SAFE. This means that the standard deviation of forecast errors is

$$\begin{aligned} Std[\epsilon_{\tau}] &= \sqrt{Var[A_{\tau}] + Var[A_{\tau-1}] - 2Cov[A_{\tau}, A_{\tau-1}]} \\ &= \sqrt{Var[A_{\tau}] + Var[A_{\tau-1}] - 2Corr[A_{\tau}, A_{\tau-1}] \sqrt{Var[A_{\tau}]} \sqrt{Var[A_{\tau-1}]}} \end{aligned}$$

Since $Var[A_\tau]$ and $Var[A_{\tau-1}]$ are very closely related, the standard deviation of forecast errors is approximately

$$Std[\epsilon_\tau] \approx \sqrt{2Var[A_\tau](1 - Corr[A_\tau, A_{\tau-1}])} = Std[A_\tau]\sqrt{2(1 - Corr[A_\tau, A_{\tau-1}])}$$

This means that the sum of the absolute forecast errors is very closely related to the standard deviation of the actual values. In Mensah et al. (2004) earnings predictability is measured as the sum of the absolute seasonally adjusted quarterly earnings per share, deflated by the previous fiscal year-end stock price; whereas earnings volatility is measured as the coefficient of variation (standard deviation divided by the mean) of the last five years' earnings before extraordinary items deflated by the absolute median. This difference in estimation period (four quarters rather than five years) along with the different scaling (previous fiscal year-end stock price rather than the absolute median) will of course weaken the relation between earnings predictability and earnings volatility. Table 8 in Mensah et al. (2004) shows the regression results of regressing earnings predictability on conservatism, earnings volatility, and other controls. It shows that the only variable that is significant (at the 0.05 level) in all four quarters (one regression for each quarter) is the coefficient of variation (this is significant at the 0.001 level). The adjusted R-squares are between 68% and 80% in the four quarters. This shows that even though the estimation period for earnings predictability and earnings volatility are different, they still seem to largely capture the same underlying construct.

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Earnings Predictability and the Earnings Response Coefficient

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Abstract

One way to measure the informativeness of accounting information is the relation between unexpected stock returns and unexpected earnings (the Earnings Response Coefficient (ERC)). This paper analyzes how earnings predictability affects the ERC. Earlier literature finds contradictory results about the relation between earnings predictability and the ERC, which might be explained by the earnings expectation model. I use three different measures of earnings predictability (earnings persistence, earnings volatility, and analyst forecast dispersion) and analytically show how they are related to each other and the ERC (without assuming a specific earnings expectation model). The analysis reveals that higher earnings volatility is associated with a higher analyst earnings forecast dispersion and lower earnings persistence. I provide evidence that a higher ERC is associated with a higher earnings predictability.

Keywords: Earnings response coefficient, Earnings predictability.

JEL classification: M41, G12, G14, G17.

1 Introduction

An unresolved issue in the accounting literature is how earnings predictability affects the returns–earnings relation, also known as the Earnings Response Coefficient (ERC). Earnings predictability refers to the ability of earnings forecasting models to forecast accurately. Researchers have looked at the relation between earnings predictability and the ERC in different ways, by assuming specific earnings expectation models (e.g., Lipe (1990) assumes that earnings expectations can be generated using an integrated autoregressive process of finite order as the earnings model). The reason why there is disagreement in the literature about whether higher earnings predictability is associated with a higher ERC (i.e. a positive relation) or associated with a lower ERC (i.e. a negative relation), could be the research approach or the difference in expectation models. As far as I know, no previous studies have analyzed analytically the relation between the ERC and earnings predictability without assuming a specific earnings expectation model.

In this paper I show that the ERC increases with earnings predictability (measured as earnings persistence, earnings volatility, or analyst forecast dispersion). The results do not rely on a specific earnings expectation model, but only on function approximations and the theory of probability. Using linear regression I empirically estimate the relation between the ERC and earnings predictability. Whether the relation between the ERC and earnings predictability is positive or negative is not obvious. Higher earnings predictability is likely to be reflected in a lower required return. Thus, (assuming that prices follow fundamental values) stock prices will react more strongly to an earnings surprise when predictability is higher. Likewise, one way of measuring earnings predictability is by earnings persistence, where a higher earnings predictability is associated with a higher

earnings persistence. Thus, an earnings surprise will be followed by a stronger price reaction when earnings have a higher predictability (Ohlson (1995)). This suggests that a higher earnings predictability is associated with a higher ERC. On the other hand, a higher earnings predictability indicates less uncertainty about future earnings. E.g., one measure of earnings predictability used in this paper is analyst earnings forecast dispersion, where a lower forecast dispersion indicates a higher earnings predictability. Lower forecast dispersion means that analysts agree more about future earnings than when the forecast dispersion is higher. When the agreement about future earnings is higher, it is likely that price reactions when earnings information is announced are smaller than the price reactions in the case of less agreement about future earnings. Thus it is not clear whether higher earnings predictability is related with a higher or a lower ERC.

If markets are perfect and complete, then the change in stock price would be equal to economic earnings. This means that if accounting earnings perfectly measured economic earnings, the ERC would be equal to one. If one takes the view that higher quality accounting earnings provide more information about the economic earnings, then it is important to study how different earnings quality measures are related to the ERC. Whether higher earnings predictability is associated with higher earnings quality is not obvious. Higher earnings predictability leads to less noise in the earnings signal, and could therefore be interpreted as being more trustworthy. However, if there is earnings smoothing going on, earnings become more predictable but not more trustworthy. If one uses the ERC as a measure of earnings quality, (see Dechow et al. (2010) for a review of the literature on earnings quality), greater earnings predictability is associated with higher earnings quality if it is positively related to the ERC.

In order to get insight into the relation between the ERC and earnings predictability, I use the following definition of the ERC: it is defined as the covariance between unexpected returns and unexpected earnings divided by the variance of the unexpected earnings. By calculating the derivative of the ERC with respect to the earnings predictability, I analyze the relation between the ERC and earnings predictability. I measure earnings predictability in three different ways: as earnings persistence, earnings volatility, and analyst forecast dispersion. A greater earnings persistence indicates higher earnings predictability, whereas a higher earnings volatility together with a higher analyst forecast dispersion indicate a lower earnings predictability. The analytical analysis leads to the hypothesis that the ERC increases with any of the three measures of earnings predictability. The hypotheses are empirically tested using the two-stage approach from Cready et al. (2001). First, the individual firm's ERC is estimated. Then the estimated ERC from the earlier regression is regressed on the earnings predictability variables. I use the difference between realized earnings and analyst earnings forecasts as a measure of unexpected earnings because I expect analyst forecasts to be more closely related to market expectations than are time-series forecasts, since analysts are intermediaries for investors.

The findings show that the ERC is positively related to earnings persistence (i.e., the autocorrelation in the ROE), which is in line with earlier research (Kormendi and Lipe (1987), Easton and Zmijewski (1989), Collins and Kothari (1989), Lipe (1990) and Ohlson (1995)). The findings further show that the ERC decreases with unexpected earnings volatility (consistent with Teets and Wasley (1996)) and analyst forecast dispersion. Thus all three measures of earnings predictability show that the ERC is positively related to earnings predictability. These findings suggest that accounting earnings information is of higher quality for firms with

higher earnings predictability.

2 Related research

The cornerstones in accounting related capital market research are Ball and Brown (1968) and Beaver (1968). These event studies analyzed the stock price reactions to earnings announcements. The Earnings Response Coefficient (ERC) literature originated from these studies and the field is very well studied, with branches in other accounting literature as well. For example, current research uses the ERC as a measure of earnings quality because it relates earnings information to stock investment decisions, reflected in stock returns.

Beaver et al. (1980) suggested that not only do earnings convey information about prices, but prices also convey information about earnings, because in their view earnings and prices are jointly determined by an underlying state generating process. This idea led to another very closely related branch of the literature: the earnings recognition timeliness (ERT) literature. Whereas the ERC literature studied the return–earnings relation, the ERT literature focuses on the “reverse” relation: the earnings–return relation. Basu (1997) suggest that earnings are more sensitive to bad news (measured by the stock return), because the magnitude of the bad news is incorporated immediately in earnings, as opposed to good news, which is recognized over a longer period. Basu (1997) interpret this finding as a sign of conditional accounting conservatism¹.

The present paper focuses on the relation between earnings predictability and

¹Accounting conservatism is referred to as conditional conservatism if it is dependent on the news (Beaver and Ryan (2005))

the ERC. The earlier literature that has studied this relation has specified one or another specific earnings expectation model. The disagreement in the earlier literature about how the ERC is related to earnings predictability could, therefore, have arisen from the differences in earnings expectation models and the definitions of earnings predictability. Lipe (1990) assumes that earnings follow an integrated autoregressive process of finite order, and uses the variance of the residual from this model as a measure of earnings predictability: a lower residual variance means a higher earnings predictability. Theoretical and empirical studies find a positive relation between earnings predictability and the ERC. This is in line with the empirical findings in Teets and Wasley (1996) and Ecker et al. (2006). Using the difference between realized earnings and analyst earnings forecasts, Teets and Wasley (1996) show that the ERC and the variance of unexpected earnings are negatively related. By dividing the sample period from 1971–1990 into four subperiods with 20 quarters (five years) in each subperiod, Teets and Wasley (1996) obtain a sample of 6,300 firm–period observations. These firm–period observations are then randomly assigned to 84 equal-sized different portfolios (with 75 firm–period observations in each portfolio). Teets and Wasley (1996) estimate the ERC and the variance of unexpected earnings for each firm within the portfolio in order to estimate the correlation between the ERC and the variance of unexpected earnings for the portfolio. Teets and Wasley (1996) show that for all 84 portfolios the correlation is negative. Ecker et al. (2006) focus on earnings quality and finds that their proposed earnings quality measure (“e-loading”) is related with the ERC. They find that a higher e-loading (lower earnings quality) is associated with a lower ERC. Furthermore, they show that other widely used measures of earnings quality (among them, earnings predictability) are aligned with the e-loading measure of earnings quality. Thus the findings in Ecker et al. (2006) suggest that a higher earnings predictability should be associated with a higher ERC.

If one takes a different view of earnings predictability and measures it as earnings persistence (earnings autocorrelation), where a higher earnings autocorrelation means a higher earnings predictability, a positive relation between earnings predictability and the ERC is also shown in Kormendi and Lipe (1987), Collins and Kothari (1989), Easton and Zmijewski (1989), Lipe (1990), Ohlson (1995) and Ecker et al. (2006)².

On the other hand, Sadka and Sadka (2009) use a coefficient estimate and the *R*-square from a regression of lagged returns on earnings changes as measures of earnings predictability. These measures rely on the assumption that returns are a predictor of expected future earnings changes. By using an inverse regression and by using the realized value instead of the expected earnings changes, this creates a measurement error in the expected earnings changes. This measurement error biases the coefficient downwards and increases the residual error. When earnings predictability increases, the expected value is closer to the realized value³ which means that the measurement error is smaller. This means that the coefficient estimate from the regression and the *R*-square are increasing in earnings predictability. Sadka and Sadka (2009) then uses earnings changes as a measure of unexpected earnings and show that there is a negative relation between earnings predictability and the ERC, by dividing their dataset into portfolios and showing that more aggregated data (dividing the dataset into a lesser number of portfolios) increases earnings predictability and at the same time decreases the ERC.

²As mentioned above, Ecker et al. (2006) show that higher earnings quality is associated with a higher ERC and that the different earnings quality measures used in the literature (e.g., e-loading, earnings predictability, and earnings persistence) are aligned. Thus a higher earnings persistence is associated with a higher ERC.

³Put another way: When earnings predictability increases, the forecast error becomes smaller.

Earnings predictability (i.e., the inverse of the variance of the unexpected earnings) can also be viewed as an accounting based measure of risk. Beaver et al. (1970) analyze how accounting based risk measures relate to the market based risk measure, β . They find that earnings variability (the time-series standard deviation of earnings) and the accounting β^4 are positively related to the market β^5 . In line with this finding, Beaver et al. (1979) find a positive relation between the absolute value of unexpected earnings (forecast error) and the market β^6 . Thus cross-sectional differences in earnings variability might also capture cross-sectional differences in market β .

Other studies (Collins and Kothari (1989), Easton and Zmijewski (1989), Chambers et al. (2005)) analyze how market β affects the ERC. Collins and Kothari (1989) finds a negative relation between market β and the ERC. However, Cready et al. (2001) points to the fact that the sign of the parameter estimates from a reverse regression with multiple dual interactions (the estimation procedure used in Collins and Kothari (1989)) can not be directly interpreted (i.e., a negative parameter estimate for a reverse regression being interpreted as a positive relation in the direct regression and vice versa). Cready et al. (2001) furthermore follow a two-stage estimation approach on the sample from Collins and Kothari (1989) and

⁴The accounting β is defined analogously to the market β . Thus, the accounting β is the parameter estimate of β in the following regression:

$$E_i = \alpha + \beta E_M + \omega_i$$

⁵Among the seven accounting risk measures (payout ratio, asset growth, leverage, firm size, liquidity, and accounting beta) used in Beaver et al. (1970), earnings variability is the accounting based risk measure that has the highest (absolute) correlation with market β .

⁶Furthermore Beaver et al. (1979) studies the relation between unexpected earnings and unexpected returns (the residuals from the market model). Beaver et al. (1979) refer to the unexpected returns as unsystematic returns. They find this relation to be positive (i.e., a positive ERC).

show that the relation between market β and the ERC actually is positive. Easton and Zmijewski (1989) and Chambers et al. (2005)⁷ find no significant (0.05 level) relation between market β and ERC. Thus, the risk view of earnings predictability provides little evidence of a relation between earnings predictability and the ERC. Basu (2005) suggest that the different findings in the literature regarding the association between risk and ERC could be explained by the differences in return measurement intervals, the differences in returns specifications, the differences in the unexpected earnings measures, and/or the differences in test periods.

3 The relation between the ERC and earnings predictability

As mentioned in Section 1, the Earnings Response Coefficient (ERC) is defined as the covariance between the unexpected returns and the unexpected earnings divided by the variance of the unexpected returns, which is equal to θ in the following regression:

$$UR_t = \alpha + \theta UX_t + \epsilon_t$$

where UR_t is the unexpected return at time t , UX_t is the unexpected earnings at time t , and ϵ_t is an error term.

The ERC is a measure of the relation between (unexpected) earnings and (unexpected) price changes. Since R_t is the price change scaled by the beginning price, it is natural to scale X_t by the beginning price as well. However, in the literature, different scaling variables are used. Nonetheless, I show (in Appendix

⁷However, Chambers et al. (2005) find a positive relation between the total risk (stock price variance) and the ERC.

A) that scaling only affects the ERC in a proportional way, where the proportionality constants are deterministic. Thus the relation between the ERC and earnings predictability is not affected by the scaling variable.

To analytically analyze how the ERC is related to earnings predictability, I calculate the derivative of the ERC with respect to the earnings predictability (denoted by Ψ). Ψ could in principle be any variable, but in relation to the interests of this paper, Ψ would be the earnings predictability. Taking the derivative of the ERC with respect to Ψ gives

$$\begin{aligned}
 \frac{\partial ERC_t}{\partial \Psi} &= \frac{\partial \frac{Cov[UR_t, UX_t]}{Var[UX_t]}}{\partial \Psi} \\
 &= \frac{\frac{\partial Cov[UR_t, UX_t]}{\partial \Psi} Var[UX_t] - Cov[UR_t, UX_t] \frac{\partial Var[UX_t]}{\partial \Psi}}{Var[UX_t]^2} \\
 &= \frac{1}{Var[UX_t]} \left(\frac{\partial Cov[UR_t, UX_t]}{\partial \Psi} - ERC_t \frac{\partial Var[UX_t]}{\partial \Psi} \right) \quad (1)
 \end{aligned}$$

So in order to determine whether the ERC is positively or negatively related to earnings predictability, we need to determine the sign of $\frac{\partial Cov_{t-1}[UR_t, UX_t]}{\partial \Psi}$ and $\frac{\partial Var_{t-1}[UX_t]}{\partial \Psi}$. To analyze whether $\frac{\partial Cov_{t-1}[UR_t, UX_t]}{\partial \Psi}$ is positive or negative I assume that log returns are conditionally normally distributed. Thus we have that the unexpected returns equals

$$UR_t = R_t = E_{t-1}[R_t] = e^{\ln(1+R_t)} - e^{E_{t-1}[\ln(1+R_t)] + \frac{1}{2}Var_{t-1}[\ln(1+R_t)]}$$

This implies that the covariance between the unexpected returns and the unexpected earnings is

$$\begin{aligned}
 Cov[UR_t, UX_t] &= Cov \left[e^{\ln(1+R_t)}, UX_t \right] \\
 &\quad - Cov \left[e^{E_{t-1}[\ln(1+R_t)] + \frac{1}{2}Var_{t-1}[\ln(1+R_t)]}, UX_t \right]
 \end{aligned}$$

Furthermore, I assume that UX_t and $E_{t-1}[\ln(1+R_t)]$ are normally distributed and that $Var_{t-1}[\ln(1+R_t)]$ is truncated normally distributed. Thus we have (using Stein's Lemma) that

$$\begin{aligned}
Cov[UR_t, UX_t] &= E \left[e^{\ln(1+R_t)} \right] Cov[\ln(1+R_t), UX_t] \\
&\quad - E \left[e^{E_{t-1}[\ln(1+R_t)] + \frac{1}{2}Var_{t-1}[\ln(1+R_t)]} \right] \\
&\quad \cdot Cov \left[E_{t-1}[\ln(1+R_t)] + \frac{1}{2}Var_{t-1}[\ln(1+R_t)], UX_t \right] \\
&= E[1+R_t] Cov[\ln(1+R_t), UX_t] - E[E_{t-1}[1+R_t]] \\
&\quad \cdot Cov \left[E_{t-1}[\ln(1+R_t)] + \frac{1}{2}Var_{t-1}[\ln(1+R_t)], UX_t \right] \\
&= E[1+R_t] Cov[\Delta E_t[\ln(1+R_t)], \Delta E_t[X_t]] \\
&\quad + E[1+R_t] \frac{1}{2} Cov[Var_{t-1}[\ln(1+R_t)], \Delta E_t[X_t]]
\end{aligned}$$

The variance of the log returns and the unexpected earnings are assumed to be independent. Thus the covariance between the unexpected returns and the unexpected earnings is

$$Cov[UR_t, UX_t] = E[1+R_t] Cov[\Delta E_t[\ln(1+R_t)], \Delta E_t[X_t]]$$

The derivative of $Cov[UR_t, UX_t]$ with respect to Ψ is

$$\begin{aligned}
\frac{\partial Cov[UR_t, UX_t]}{\partial \Psi} &= \frac{\partial E[1+R_t]}{\partial \Psi} Cov[\Delta E_t[\ln(1+R_t)], \Delta E_t[X_t]] \\
&\quad + E[1+R_t] \frac{Cov[\Delta E_t[\ln(1+R_t)], \Delta E_t[X_t]]}{\partial \Psi} \quad (2)
\end{aligned}$$

Substituting Equation 2 into Equation 1 gives

$$\begin{aligned}
\frac{\partial ERC_t}{\partial \Psi} &= \frac{1}{Var[UX_t]} \frac{\partial E[1+R_t]}{\partial \Psi} Cov[\Delta E_t[\ln(1+R_t)], \Delta E_t[X_t]] \\
&\quad + \frac{1}{Var[UX_t]} E[1+R_t] \frac{Cov[\Delta E_t[\ln(1+R_t)], \Delta E_t[X_t]]}{\partial \Psi} \\
&\quad - \frac{1}{Var[UX_t]} ERC_t \frac{\partial Var[UX_t]}{\partial \Psi} \quad (3)
\end{aligned}$$

In order to further analyze the relation between the ERC and earnings predictability, I need to define a measure for the construct (i.e., make the construct measurable). I measure earnings predictability three different ways: as earnings persistence, earnings volatility (variance), and analyst forecast dispersion. I choose the two first measures in order to be in line with the main definitions of earnings predictability used in earlier research. Even though earlier studies do not refer to earnings persistence as a measure of earnings predictability (Kormendi and Lipe (1987) and Collins and Kothari (1989)), it can be viewed as such, since higher earnings persistence implies that current earnings are more informative about future earnings and thereby future earnings are easier to predict.

Lipe (1990) and Dichev and Tang (2009) refer to earnings predictability as the variance of the residuals from an expectations model. Using this definition, earnings variance and earnings predictability are very closely related⁸. Since there are an unlimited number of time-series based models, I instead use earnings volatility since it does not require a specific expectations model in order to be estimated. The third earnings predictability measure (analyst forecast dispersion) is in line with the definition of earnings predictability as being the variance of the residuals from an expectations model (Lipe (1990) and Dichev and Tang (2009)). In this relation, analyst forecasts are the expectations. Since the realized value is the same for all analysts (for a given firm at a given point in time), the variance of the residuals from the analysts' forecasts is the same as the variance of the analysts' forecasts. Thus analyst forecast dispersion can be viewed as a market-based version of the definitions of earnings predictability in Lipe (1990) and Dichev and Tang (2009).

⁸Using an AR1 expectation model. Untabulated results show that the correlation is above 0.9

Starting with earnings persistence, I argue (in Appendix B) that the term $\frac{\partial E[(1+R_t)]}{\partial \Psi}$ in Equation 3 is positive. Based on Vuolteenaho (2002), I further argue (in Appendix C) that the term $Cov[\Delta E_t[\ln(1 + R_t)], \Delta E_t[X_t]]$ and the term $\frac{Cov[\Delta E_t[\ln(1+R_t)], \Delta E_t[X_t]]}{\partial \Psi}$ in Equation 3 are also positive. Furthermore, since $\ln(1 + R_t)$ is assumed to be normally distributed, then $1 + R_t > 0$. Thus the term $E[1 + R_t]$ in Equation 3 is positive. Additionally, in Appendix D, I show (under reasonable assumptions) that $\frac{\partial Var_{t-1}[X_t]}{\partial \Psi} < 0$. Furthermore, in Appendix E, I show that $\frac{\partial Var_{t-1}[UX_t]}{\partial Var_{t-1}[X_t]} > 0$. Thus, from the chain rule, it follows that $\frac{\partial Var_{t-1}[UX_t]}{\partial \Psi} = \frac{\partial Var_{t-1}[X_t]}{\partial \Psi} \frac{\partial Var_{t-1}[UX_t]}{\partial Var_{t-1}[X_t]} < 0$. So the term $\frac{\partial Var_{t-1}[UX_t]}{\partial \Psi}$ in Equation 3 is negative. This is also in line with findings in the earlier literature (Dichev and Tang (2008), Dichev and Tang (2009) and Li (2011)). Thus (assuming that the ERC is positive and the other assumptions hold), based on Equation 3, I conclude that earnings persistence is positively related to the ERC. Therefore, my first hypothesis is that

H1: Earnings persistence is positively related to the ERC

This hypothesis is in line with Collins and Kothari (1989). Using the assumptions that the dividend discount model correctly predicts stock prices and that future expected dividends are linearly related to current earnings, Collins and Kothari (1989) argues that the ERC is positively related to earnings persistence. The argument is that a higher earnings persistence increases the linear relation between current earnings and future expected dividends, which implies that the strength of the relation between current earnings and price increases. Thereby, an earnings shock will create a larger return shock (i.e., the ERC will be higher) when earnings persistence is higher.

Using the chain rule, the relation between any other variable and the ERC can be studied by studying the relation between that variable (Φ) and the earnings

persistence (ρ). The chain rule yields

$$\frac{\partial ERC_t}{\partial \Phi} = \frac{\partial ERC_t}{\partial \rho} \frac{\partial \rho}{\partial \Phi}$$

Thus, since earnings persistence and volatility are negatively related (as shown in Appendix D) and I expect earnings persistence to be positively related to the ERC (see H1 above), this leads to my next hypothesis:

H2: Earnings volatility is negatively related to the ERC

In Appendix E, I show that the time-series variance (i.e. volatility) of unexpected earnings and realized earnings are positively related. Furthermore, in Appendix F, I show that the time-series variance of unexpected earnings and analyst forecast dispersion is positively related. Thus (by using the chain rule) I further hypothesize that

H3: Earnings forecast dispersion is negatively related to the ERC

4 Empirical analysis and measures

I estimate the empirical relation between the Earnings Response Coefficient (ERC) and earnings predictability (whether measured by earnings persistence, earnings volatility, or earnings forecast dispersion) using a two-stage approach as in Cready et al. (2001): first, the individual firm's ERC is estimated; second, the ERC is regressed on the variables of interest. If analyzing cross-sectional ERC differences is of interest, then the ERC should be estimated using time-series data, which generates individual firm-specific ERC estimates. But, if time-series ERC differences are of interest, then the ERC should be estimated using cross-sectional data for each year, which will generate one time-series of ERC estimates. Since this paper analyzes the relation between the ERC and earnings predictability, I estimated the

individual firm's ERC using time-series data. Likewise, the measures of earnings predictability are estimated using time-series data. The three different measures of earnings predictability are measured as follows. The volatility of unexpected earnings (*EARN_VOL*) is estimated as the time-series variance of unexpected earnings over the same estimation period as the ERC. Persistence in unexpected earnings (*PERSIST*) is estimated as the autocorrelation of unexpected earnings over the same period as the ERC. As proved in Section F, the time-series variance of unexpected earnings is a function of the mean over time of the earnings forecast dispersion across analysts. Thus the earnings forecast dispersion is estimated as the time-series mean of the analyst earnings forecast dispersion over the estimation period of the ERC. To reduce the skewness of the two variables (volatility in unexpected earnings and earnings forecast dispersion), I transform these variables by the natural logarithm.

Estimate of the unexpected returns and unexpected earnings are needed in order to estimate the ERC. The unexpected returns are estimated as the difference between the stock returns and the expected returns (estimated by the market model). Unexpected earnings are estimated as the difference between announced actual earnings minus the latest announced earnings forecast (scaled by price). Thus the unexpected returns window should begin when the latest earnings forecast are announced and end when earnings are announced, so that the unexpected earnings and the unexpected returns correspond to each other. This is because if the market receives new earnings information (at some point in time in the period between the latest announced earnings forecast and the earnings announcement) this will lead to a revised earnings expectation by the market, which will result in an immediately change in the stock's price (assuming that the market is efficient). Thus the movement of the stock price that occurs when earnings are announced is now

instead based on the revised earnings expectation, which is unobservable. This is illustrated in Table 1.

However, in order to be certain that the new earnings information (that emerges because of the earnings announcement) is incorporated in the stock price, I expand the return window so that it ends two days after the earnings announcement. The magnitude of the unexpected return is proportional to the return window length. Thus I need to normalize the unexpected return, since the length of the return period differs between firms (and over time). I normalize the unexpected returns to the daily returns by calculating the daily geometric mean return. The unexpected returns are estimated as the residual from the regression of firm returns on value-weighted market returns.

The estimation approach from Cready et al. (2001) starts with estimating the following regression

$$UR_{i,t} = \alpha_i + \theta_i UX_{i,t} + \epsilon_{i,t}. \quad (4)$$

Then, the estimate of θ_i , which is denoted by $\hat{\theta}_i$, is used as the dependent variable in the second-stage regression

$$\hat{\theta}_i = \alpha + \beta_1 EARN_PRED_i + \beta_2 MTB_i + \xi_i \quad (5)$$

where UR , UX , $EARN_PRED$ and MTB are, respectively, the return, unexpected earnings, earnings predictability, and the market-to-book ratio. The indices i and t denote firm i and time t .

Table 1: Return window length

| Announced Earnings Forecast | New Earnings Expectation (Unobservable) | Earnings Announcement |
|--------------------------------|---|--|
| $E[X_T \Theta_t]$ | $E[X_T \Theta_{t+\tau}]$ | $E[X_T \Theta_T] = X_T$ |
| P_t | $ERR_{t+\tau} = E[X_T \Theta_{t+\tau}] - E[X_T \Theta_t]$ | $ERR_T = X_T - E[X_T \Theta_{t+\tau}]$ |
| | $P_{t+\tau}$ | P_T |

At time t , an analyst-consensus earnings forecast is announced by $I/B/E/S$. This forecast is denoted by $E[X_T|\Theta_t]$ and is assumed to be equal to the earnings expectation of the market. The stock price at this point in time is denoted by P_t . At time $t + \tau$, the market changes its earnings expectation, because of some new information. This new earnings expectation by the market is denoted by $E[X_T|\Theta_{t+\tau}]$. Thus the earnings expectation revision ($ERR_{t+\tau}$) is equal to the difference between the updated earnings forecast ($E[X_T|\Theta_{t+\tau}]$) and the earlier earnings forecast ($E[X_T|\Theta_t]$). In an efficient market, this earnings revision leads to a stock price reaction from P_t to $P_{t+\tau}$. Earnings are then announced at time T , equal to $E[X_T|\Theta_T] = X_T$. This leads to an earnings expectation revision (ERR_T) at time T of $X_T - E[X_T|\Theta_{t+\tau}]$. However, as the updated earnings expectation at time $t + \tau$ ($E[X_T|\Theta_{t+\tau}]$) is unobservable, the unexpected earnings (ERR_T) are also. Since the observable unexpected earnings is equal to $X_T - E[X_T|\Theta_t]$, this is the same as the sum of the two earnings revisions (i.e. $X_T - E[X_T|\Theta_t] = E[X_T|\Theta_{t+\tau}] - E[X_T|\Theta_t] + X_T - E[X_T|\Theta_{t+\tau}] = ERR_{t+\tau} + ERR_T$). Thus, in order to estimate how stock price changes react to earnings announcements (and thereby unexpected earnings), the return window needs to start before the unobservable change in earnings expectation ($ERR_{t+\tau}$) occurs. Since the change in earnings expectation ($ERR_{t+\tau}$) is unobservable, one cannot know when the return window should begin. Thus the return window should start at time t when the latest earnings forecast ($E[X_T|\Theta_t]$) is announced, since all information is incorporated in this forecast.

A fixed return window that begins at an arbitrary point in time (i.e. in the time interval $[t; t + \tau]$) only corresponds to the observable unexpected earnings if no new earnings information arises in this period.

However, since the ERC (θ_i) and earnings predictability ($EARN_PRED_i$) are both estimated variables, they are measured with error. Because the parameter estimates (and the standard errors of the parameter estimates) are biased and can not be corrected for analytically, statistical inference should not be based on the direct regression presented above (Equation 5). Even though analytical bias correction formulas exist (as shown in Appendix G) the analytical bias correction can not be done in practice because the variance of the measurement error is unknown and can not be estimated.

Cready et al. (2001) propose an approach for creating bounds for the parameter estimates using a reverse regression technique. According to their approach, if all the variables are measured with error, the second-stage regression should not be a single regression, but the following regression system:

$$ERC = \alpha_0 + \alpha_1 EARN_PRED + \alpha_2 MTB \quad (6)$$

$$EARN_PRED = \beta_0 + \beta_1 ERC + \beta_2 MTB \quad (7)$$

$$MTB = \lambda_0 + \lambda_1 EARN_PRED + \lambda_2 ERC \quad (8)$$

Rearranging the two reverse regressions gives

$$ERC = -\frac{\beta_0}{\beta_1} + \frac{1}{\beta_1} EARN_PRED - \frac{\beta_2}{\beta_1} MTB \quad (9)$$

$$ERC = -\frac{\lambda_0}{\lambda_2} - \frac{\lambda_1}{\lambda_2} EARN_PRED + \frac{1}{\lambda_2} MTB \quad (10)$$

Thus the two reverse regressions (i.e. (7) and (8)) give implicit coefficient estimates (shown in Equations (9) and (10)) for the direct regression (6). “In order to unconditionally bound the direct model’s coefficient estimates (i.e., place ranges on their magnitude) all the normalized coefficient estimates (except the intercept) derived from each reverse regression must possess the same sign as the coefficient estimates from the direct model. The extreme high and low estimates for

each coefficient then serve as its maximum likelihood bounds. If, however, any normalized coefficient estimate differs in sign from its direct model estimate then not only is that coefficient estimate unbounded, but the coefficient estimates for all the variables are also unbounded.” (Cready et al. (2001, p. 230)). Thus if

$$\text{sign}(\alpha_1) = \text{sign}\left(\frac{1}{\beta_1}\right) = \text{sign}\left(\frac{\lambda_1}{\lambda_2}\right)$$

and

$$\text{sign}(\alpha_2) = \text{sign}\left(\frac{\beta_2}{\beta_1}\right) = \text{sign}\left(\frac{1}{\lambda_2}\right)$$

the coefficient estimates for *EARN_PRED* and *MTB* are bounded between

$$\left[\min\left(\alpha_1, \frac{1}{\beta_1}, \frac{\lambda_1}{\lambda_2}\right); \max\left(\alpha_1, \frac{1}{\beta_1}, \frac{\lambda_1}{\lambda_2}\right) \right]$$

and

$$\left[\min\left(\alpha_2, \frac{\beta_2}{\beta_1}, \frac{1}{\lambda_2}\right); \max\left(\alpha_2, \frac{\beta_2}{\beta_1}, \frac{1}{\lambda_2}\right) \right],$$

respectively. These bounds consistently bound the true regression coefficients (Klepper and Leamer (1984, p. 164)).

Since the market-to-book ratio in this relation simply captures the scaling factor difference between the book-value of equity deflated ERC and the price-deflated ERC (and not as a measure of growth opportunities as in Cready et al. (2001)), the

market-to-book ratio is, in relation to the analysis in this paper, measured without error. Thus, according to Cready et al. (2001) (and Klepper and Leamer (1984)), the regression where the market-to-book ratio is the independent variable can be removed from the regression system and sign differences in the market-to-book ratio do not create unboundedness (Cready et al. (2001, p. 230)). Thus, in this paper, the regression system becomes

$$ERC = \alpha_0 + \alpha_1 EARN_PRED + \alpha_2 MTB \quad (11)$$

$$EARN_PRED = \beta_0 + \beta_1 ERC + \beta_2 MTB \quad (12)$$

Since the measure of unexpected earnings might be measured with error, the estimates of the ERCs (i.e. θ_i from Equation 4) might be biased toward zero. To strengthen the results, the analysis is therefore also carried out where the ERCs are estimated using the reverse regression, which gives implied ERC estimates that are upward biased.

EARN_PRED and *MTB* are highly correlated when *EARN_PRED* is measured as earnings volatility (or forecast dispersion). To deal with this multicollinearity issue, I use Principal Component Regression (PCR). Basically, PCR uses Principal Component Analysis (PCA) to reduce the set of variables by generating principal components. These principal components are linear transformations of the observed variables. The principal components that account for the highest amount of variance in the observed variables are then used as independent variables in the regression instead of the observed variables. Since the principal components are linear transformations of the observed variables, the parameter estimates for the principal components can be easily transformed into parameter estimates for the observed variables.

4.1 Data-related issues

The estimation procedure raises some issues related to the data. First, the two stage approach proposed by Cready et al. (2001) poses the problem of how to divide the data between the two estimation stages. Second, because of the definition of the ERC, there are some potential sample selection biases.

4.1.1 Division of data between the two estimation stages

ERCs could be estimates for the individual firm or for a group of firms (e.g. an industry level). Estimating individual ERCs for each firm in the first stage gives a larger sample for the second stage regression(s) than when ERCs are estimated at the group level. However, the estimates of individual firms' ERCs might be unstable because of the short length of the time-series. On the other hand, when estimating ERCs at the group level, the firms within a group should be homogeneous. Reducing the heterogeneity across observations in a group also reduces the sample size for the second stage regression(s).

4.1.2 Potential sample selection biases

Since the definition of the ERC requires that firms are listed, the sample consist of larger, more mature firms. Thus the sample suffers from a "large-firm" selection bias. For smaller (and newer) firms with high uncertainty, earnings predictability is probably lower than for larger firms. For these smaller firms, earnings information might be very informative to investors and hence the ERC might be higher. Thus for smaller firms, one can expect the opposite relation. However it is impossible to estimate the ERC when firms are not listed. Yet the sample of noted firms can be divided into smaller and larger firms. So (even though this does not deal with the issue of firms' not being listed), one way to deal with the "large-firm

bias” is to use propensity score matching (PSM). In short, PSM splits the sample into two samples (i.e. large firms and small firms), where each observation from one of the groups is matched with one observation from the other group. Each pair of observations is matched based on propensity scores, which is simply the probability of the observation’s belonging to the first group (i.e. the sample of large firms). The predictor variables used to estimate the probability of being in the first group should also be associated with the dependent variable of interest (i.e. the ERC).

Thus (in this case), the sample should be split into two: one of large firms and the other of small firms. Sorting on firm size and using the median firm as a threshold could be used to divide the sample into two samples. Then a probit or a logistic regression with the dependent variable being one if the firm belongs to the large firm sample and zero otherwise should be estimated. The predictor variable(s) used should be earnings predictability, but could also include, e.g. bid–ask spreads or stock price volatility, since both these variables are expected to be associated with firm size and the ERC.

The sample suffers not only from a “large-firm” selection bias, but also from another selection bias: survivorship bias. This is because the firm ERCs are estimated from individual firm time-series. Thus, firms need to survive over a time period in order to estimate individual firm ERCs. Firms that go bankrupt and firms that are acquired and then delisted during the estimation period are therefore excluded from the sample. To deal with survivorship bias, the Heckman correction approach can be used. The Heckman correction approach is described in Baltagi (2001, pp. 383–409). The following model was presented in Baltagi (2001, p.

385)

$$y^* = x\beta + u \quad \text{and} \quad I^* = z\gamma - \epsilon$$

where u and ϵ are regression errors and I^* is an indicator variable that equals one if y^* is observed and zero otherwise. Thus, in relation to the case in this paper, y^* would be the ERC, x would be a vector with earnings predictability and the market-to-book ratio as elements, I^* would be an indicator variable that equals one if the firm has the required minimum time-series observations for unexpected returns and unexpected earnings, and z would be a vector whose elements are predictors for the firm's being acquired or going bankrupt over the estimation period.

Baltagi (2001, p. 386) explain a two-stage method to deal practically with this: "In the first stage, γ is estimated by the probit maximum likelihood method. The least squares method can then be applied to estimate β and $\sigma_{1\epsilon}$ in

$$y = x\beta + \sigma_{1\epsilon} \left(-\frac{\phi(z\hat{\gamma})}{\Phi(z\hat{\gamma})} \right) + \tilde{\eta}$$

with the observed subsample corresponding to $I = 1$, where $\hat{\gamma}$ is the probit maximum likelihood estimate of γ ."

4.2 Sample selection

My sample includes firms from Compustat and firms where a one-year ahead earnings forecast is available from I/B/E/S. I use the sample period 1995–2012, since Abarbanell and Lehavy (2007) show that a significant shift in mean earnings took place in the early 1990s. To control for outliers, I exclude firms where the absolute ROE or absolute returns are larger than 1, and Winsorize all variables at the 1st and 99th percentiles. Firms with SIC codes in the intervals [4900–4999]

or [6000–6999] are utilities and financial institutions. Since these types of firms are regulated, they are excluded from the sample as well.

4.3 Descriptive statistics and results

Unexpected returns and unexpected earnings are used to estimate the individual firms’ ERCs. The descriptive statistics in Table 2 show the distribution of unexpected returns and unexpected earnings. The mean (median) of the price-deflated unexpected earnings is -0.9% (0.0%), which indicates that analysts’ forecasts are close to being unbiased. The mean (median) unexpected stock return is 0.0% (0.0%). That the mean unexpected stock return is 0.0% is not surprising since the unexpected stock returns are the residual from the market model regression. In an OLS regression, the mean of the residual is always zero.

Table 2: Descriptive Statistics for returns and unexpected earnings

| Variable | N | Mean | Std Dev | 0% Min | 10% | 25% Q1 | 50% Median | 75% Q3 | 90% | 100% Max |
|------------|--------|--------|---------|--------|--------|--------|------------|--------|-------|----------|
| UNEXP_EARN | 49,836 | -0.009 | 0.072 | -1.203 | -0.014 | -0.002 | 0.000 | 0.002 | 0.007 | 0.295 |
| UNEXP_RET | 49,836 | -0.000 | 0.007 | -0.054 | -0.008 | -0.003 | -0.000 | 0.003 | 0.007 | 0.072 |

Distribution of the data used to estimate the firm specific Earnings Response Coefficient (ERC). UNEXP_RET is the unexpected return of the stock (measured as the difference between realized return and the expected return, where expected return is estimated using the market model). UNEXP_EARN is the firm’s unexpected earnings (measured as the difference between realized earnings and the mean value of analyst earning forecasts deflated by stock price at the beginning of the year).

Table 3 shows that the mean (median) ERC estimated from a direct regression is 0.251 (0.027), whereas the mean (median) ERC estimated from a reverse regression is 4.024 (0.484). This indicates that the distribution of the ERC estimates are right skewed.

Table 3: Descriptive Statistics for the Earnings Response Coefficient (ERC), volatility of earnings, forecast dispersion, and persistence of unexpected earnings

| Variable | N | Mean | Std Dev | 0% Min | 10% | 25% Q1 | 50% Median | 75% Q3 | 90% | 100% Max |
|------------------|-------|--------|---------|--------|--------|--------|------------|--------|--------|----------|
| ERC.D | 4,982 | 0.251 | 1.123 | -3.414 | -0.313 | -0.035 | 0.027 | 0.285 | 1.101 | 6.380 |
| ERC.R | 4,570 | 4.024 | 36.249 | -153.7 | -7.918 | -0.660 | 0.484 | 4.278 | 18.720 | 227.66 |
| LN_FORECAST_DISP | 2,729 | -10.50 | 2.584 | -15.56 | -13.62 | -12.34 | -10.72 | -8.825 | -7.180 | -3.236 |
| LN_VOL_EARN | 3,970 | -6.777 | 2.293 | -12.83 | -9.287 | -8.190 | -7.078 | -5.505 | -3.762 | -0.037 |
| MTB | 4,981 | 2.470 | 1.768 | 0.007 | 0.761 | 1.311 | 2.037 | 3.161 | 4.752 | 9.460 |
| PERSIST_EARN | 3,889 | 0.313 | 0.560 | -1.000 | -0.551 | -0.017 | 0.440 | 0.768 | 0.931 | 1.000 |

Distribution of the estimated Earnings Response Coefficient (ERC) as well as the expected determinants of the ERC. ERC.D and ERC.R are the ERC estimated using direct regression and reverse regression, respectively. PERSIST_EARN is the first-order autocorrelation of unexpected earnings (scaled by price). LN_VOL_EARN is the logarithm of unexpected earnings volatility (which is the standard deviation of unexpected earnings) LN_FORECAST_DISP is the logarithm of the standard deviation of analyst earnings forecasts. MTB is the market-to-book ratio.

Table 4 presents the correlations between the ERC, earnings persistence, earnings volatility, earnings forecast dispersion, and the market-to-book ratio. It shows that earnings persistence and the ERC are positively correlated. Furthermore, it shows that earnings volatility (forecast dispersion) and the ERC are negatively correlated. These correlations are in line with the theoretical predictions from Section 3. Lastly, Table 4 shows that earnings volatility and forecast dispersion are positively correlated. This is in line with the theoretical findings in Appendix F.

Table 4: Correlation matrix

| | ERC_D | ERC_R | LN_VOL_EARN | LN_FORECAST_DISP | PERSIST_EARN | MTB |
|------------------|------------|------------|-------------|------------------|--------------|------------|
| ERC_D | | 0.8208*** | -0.1801*** | -0.1770*** | 0.0825*** | 0.1100*** |
| ERC_R | 0.2924*** | | -0.1703*** | -0.1736*** | 0.0928*** | 0.1229*** |
| LN_VOL_EARN | -0.1717*** | -0.0543*** | | 0.6344*** | -0.0646*** | -0.1420*** |
| LN_FORECAST_DISP | -0.1896*** | -0.0495** | 0.6718*** | | -0.2964*** | -0.2926*** |
| PERSIST_EARN | 0.0632*** | 0.0385** | -0.0282* | -0.2521*** | | 0.1521*** |
| MTB | 0.1100*** | 0.0402*** | -0.0987*** | -0.2455*** | 0.1283*** | |

*, **, and *** indicate significance at the 0.10, 0.05 and 0.01 levels. Correlation coefficients below (above) the diagonal are the Pearson (Spearman) correlation. ERC_D and ERC_R are the ERC estimated using direct regression and reverse regression, respectively. PERSIST_EARN is the first-order autocorrelation of unexpected earnings (scaled by price). LN_VOL_EARN is the logarithm of unexpected earnings volatility (which is the standard deviation of unexpected earnings) LN_FORECAST_DISP is the logarithm of the standard deviation of analyst earnings forecasts. MTB is the market-to-book ratio.

Table 5 presents the results from the regression of ERC on earnings persistence and the market-to-book ratio. In Table 5.A the first row presents the direct regression of ERC on the variables PERSIST_EARN and MTB, whereas the second row presents the implied coefficient estimates from a reverse regression of PERSIST_EARN on ERC and MTB. The coefficient estimate for MTB changes from positive to negative in 5.A, which would have implied unboundness for both the coefficient estimates for PERSIST_EARN and MTB. However, since MTB is measured without error this does not create unboundness (as noted in Section 4).

Table 5: Regression of Earnings Response Coefficient (ERC) on earnings persistence and MTB ratio

Table 5.A Parameter estimates

| Dependent Variable | PERSIST_EARN | MTB |
|--------------------|--------------|--------|
| ERC_D | 0.087 | 0.104 |
| PERSIST_EARN | 45.498 | -1.876 |

Table 5.B Maximum R-Squared

| R^{*2} | | 0.027 | 0.04 | 0.053 | 0.066 | 0.078 |
|--------------|------|-------|-------|-------|-------|-------|
| PERSIST_EARN | Min. | 0.087 | 0.087 | 0.087 | 0.087 | 0.087 |
| PERSIST_EARN | Max. | 0.087 | 0.684 | 1.281 | 1.879 | 2.476 |
| MTB | Min. | 0.104 | 0.078 | 0.052 | 0.026 | 0 |
| MTB | Max. | 0.104 | 0.104 | 0.104 | 0.104 | 0.104 |

Table 5.C Minimum Correlation

| ρ^2 | | 0.2 | 0.4 | 0.6 | 0.8 | 1 |
|--------------|------|-------|--------|--------|-------|-------|
| PERSIST_EARN | Min. | -1.2 | -0.177 | -0.015 | 0.051 | 0.087 |
| PERSIST_EARN | Max. | 0.628 | 0.331 | 0.204 | 0.132 | 0.087 |
| MTB | Min. | 0.083 | 0.097 | 0.101 | 0.103 | 0.104 |
| MTB | Max. | 0.705 | 0.27 | 0.176 | 0.131 | 0.104 |

Table 5.D Parameter estimates

| Dependent Variable | PERSIST_EARN | MTB |
|--------------------|--------------|---------|
| ERC_R | 2.234 | 1.081 |
| PERSIST_EARN | 2128.074 | -89.935 |

Table 5.E Maximum R-Squared

| R^{*2} | | 0.004 | 0.007 | 0.01 | 0.012 | 0.015 |
|--------------|------|-------|-------|--------|--------|--------|
| PERSIST_EARN | Min. | 2.234 | 2.234 | 2.234 | 2.234 | 2.234 |
| PERSIST_EARN | Max. | 2.234 | 8.548 | 14.861 | 21.174 | 27.487 |
| MTB | Min. | 1.081 | 0.811 | 0.541 | 0.27 | 0 |
| MTB | Max. | 1.081 | 1.081 | 1.081 | 1.081 | 1.081 |

Table 5.F Minimum Correlation

| ρ^2 | | 0.2 | 0.4 | 0.6 | 0.8 | 1 |
|--------------|------|--------|-------|-------|-------|-------|
| PERSIST_EARN | Min. | -6.054 | 0.313 | 1.47 | 1.961 | 2.234 |
| PERSIST_EARN | Max. | 12.022 | 6.205 | 4.091 | 2.951 | 2.234 |
| MTB | Min. | 0.015 | 0.782 | 0.958 | 1.036 | 1.081 |
| MTB | Max. | 6.151 | 2.782 | 1.848 | 1.372 | 1.081 |

Coefficient estimates (and implied coefficient estimates) along with coefficient bounds for regressing ERC on PERSIST_EARN and MTB. Panel A–(D–F) is based on the direct (reverse regression) ERC estimate. The first row in Table 5.A (5.D) presents the direct regression of ERC on PERSIST_EARN and MTB. The second presents the implied regression coefficient for PERSIST_EARN and MTB when regressing PERSIST_EARN on ERC and MTB. To deal with the multicollinearity between PERSIST_EARN and MTB, Principal Component Regression (PCR) is used. Table 5.B (5.E) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum value of the coefficient estimate) as a function of R^{*2} . R^{*2} denotes the maximum value of the squared multiple correlation (R^2), if there were no measurement error in the explanatory variables. Table 5.C (5.F) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum coefficient values) as a function of ρ^2 . ρ^2 denotes the minimum squared correlation between the true construct and the variable used to measure that construct. ERC_D and ERC_R are the ERC estimated using direct regression and reverse regression, respectively. PERSIST_EARN is the first-order autocorrelation of earnings (scaled by price). MTB is the market-to-book ratio.

So, in line with expectations, a higher market-to-book ratio and persistence of unexpected earnings is associated with a higher ERC.

As noted in Collins and Kothari (1989), the market-to-book ratio also captures persistence and growth. Thus the model may suffer from “omitted-variable bias” because the model does not include a measure for growth. Because the market-to-book ratio is correlated with the growth (the omitted variable), this creates the same issue as when the market-to-book ratio has measurement error (i.e. the market-to-book ratio is correlated with the error term). Hence the change in the sign of the estimate of the coefficient for the market-to-book ratio in Table 5.A may generate unboundness for the coefficient estimates for PERSIST_EARN on ERC and MTB. Klepper and Leamer (1984) deals with this issue by imposing a condition that creates lower and upper bounds for the coefficient estimates.

Klepper and Leamer (1984) show that if one can conclude that the squared multiple correlation (R^2) does not exceed a given level (R^{*2}) if there were no measurement error in the explanatory variables, then lower and upper bounds for the coefficient estimates can be calculated. Table 5.B presents statistics about this condition. The third column presents the direct regression estimates (where there is measurement error in the independent variables) and shows that the R-Square for the direct regression is 2.7%⁹. The table shows that if the measurement error in the variables were removed and this would not imply that R-Squared increased to more than 7.8%, then both the coefficient estimates would be positively

⁹At first the R-Square of 2.7% for the direct regression might seem low. However earlier studies (Collins and Kothari (1989) and Basu (1997)) in this field also have low R-Squares, but are not directly comparable because they do not use the two-stage regression method. Collins and Kothari (1989) report R-Squares between 12% and 20%. However, those are pooled regressions with fixed year effects. Basu (1997) also use pooled regressions and report R-Squares between 8% and 13%

bounded (i.e., PERSIST_EARN and MTB would lie in the interval [0.087;2.476] and [0;0.104], respectively).

Besides generating bounds for the coefficient estimates as a function of the squared multiple correlation, Klepper and Leamer (1984) also show that coefficient bounds can be created if one can conclude that the correlation between the true construct and the variable used to measure the construct is larger than a given level (ρ_{*}^2). Table 5.C presents a coefficient bound based on this condition. The correlation values are shown for five different correlations, where the highest possible correlation of course is one and the lowest correlation shown is the value where the coefficient estimates still are bounded (i.e. if the correlation value is lower than 0.2, then the coefficient estimates are unbounded). In the last column (where the correlation equals one), the bound becomes a single point and these coefficients equal the direct regression coefficients. However, the table also shows that the correlation between the true construct (earnings predictability) and the measurable variable (earnings persistence) should be high (at least 0.8) to bound the coefficient for earnings persistence to a positive value (i.e., PERSIST_EARN would then lie in the interval [0.051;0.132]). Based on these three tables, the empirical analysis suggests (in line with expectations) that both the persistence of unexpected earnings and the market-to-book ratio are positively related to the ERC.

Tables 5.A, 5.B and 5.C are based on ERCs that are estimated from a direct regression. Similar to these tables are Tables 5.D, 5.E and 5.F. The only difference is that these last are based on ERCs estimated from a reverse regression.

In Table 6, the earnings predictability measure used is earnings volatility. Since the earnings persistence and earnings volatility are negatively related, a negative

Table 6: Regression of Earnings Response Coefficient (ERC) on earnings volatility and MTB ratio

Table 6.A Parameter estimates

| Dependent Variable | LN_VOL_EARN | MTB |
|--------------------|-------------|--------|
| ERC_D | -0.076 | 0.097 |
| LN_VOL_EARN | -3.021 | -0.309 |

Table 6.D Parameter estimates

| Dependent Variable | LN_VOL_EARN | MTB |
|--------------------|-------------|---------|
| ERC_R | -0.829 | 1.079 |
| LN_VOL_EARN | -337.447 | -44.617 |

Table 6.B Maximum R-Squared

| R^2 | | 0.05 | 0.107 | 0.164 | 0.22 | 0.277 |
|-------------|------|--------|--------|--------|--------|--------|
| LN_VOL_EARN | Min. | -0.076 | -0.252 | -0.427 | -0.603 | -0.779 |
| LN_VOL_EARN | Max. | -0.076 | -0.076 | -0.076 | -0.076 | -0.076 |
| MTB | Min. | 0.097 | 0.073 | 0.048 | 0.024 | 0 |
| MTB | Max. | 0.097 | 0.097 | 0.097 | 0.097 | 0.097 |

Table 6.E Maximum R-Squared

| R^2 | | 0.005 | 0.011 | 0.017 | 0.023 | 0.029 |
|-------------|------|--------|--------|--------|--------|--------|
| LN_VOL_EARN | Min. | -0.829 | -2.816 | -4.803 | -6.79 | -8.777 |
| LN_VOL_EARN | Max. | -0.829 | -0.829 | -0.829 | -0.829 | -0.829 |
| MTB | Min. | 1.079 | 0.809 | 0.54 | 0.27 | 0 |
| MTB | Max. | 1.079 | 1.079 | 1.079 | 1.079 | 1.079 |

Table 6.C Minimum Correlation

| ρ^2 | | 0.1 | 0.325 | 0.55 | 0.775 | 1 |
|-------------|------|----------|--------|--------|--------|--------|
| LN_VOL_EARN | Min. | -8.493 | -0.245 | -0.146 | -0.101 | -0.076 |
| LN_VOL_EARN | Max. | 1.539 | -0.034 | -0.061 | -0.071 | -0.076 |
| MTB | Min. | -1.1.104 | 0.024 | 0.071 | 0.088 | 0.097 |
| MTB | Max. | 2.792 | 0.317 | 0.188 | 0.13 | 0.097 |

Table 6.F Minimum Correlation

| ρ^2 | | 0.1 | 0.325 | 0.55 | 0.775 | 1 |
|-------------|------|---------|--------|--------|--------|--------|
| LN_VOL_EARN | Min. | -29.808 | -2.668 | -1.583 | -1.103 | -0.829 |
| LN_VOL_EARN | Max. | 12.939 | -0.346 | -0.657 | -0.77 | -0.829 |
| MTB | Min. | -33.972 | 0.309 | 0.808 | 0.987 | 1.079 |
| MTB | Max. | 25.193 | 3.523 | 2.089 | 1.447 | 1.079 |

Coefficient estimates (and implied coefficient estimates) along with coefficient bounds for regressing ERC on LN_VOL_EARN and MTB. Panel A–C (D–F) is based on the direct (reverse regression) ERC estimate. The first row in Table 6.A (6.D) presents the direct regression of ERC on LN_VOL_EARN and MTB. The second presents the implied regression coefficient for LN_VOL_EARN and MTB when regressing LN_VOL_EARN on ERC and MTB. To deal with the multicollinearity between LN_VOL_EARN and MTB, Principal Component Regression (PCR) is used. Table 6.B (6.E) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum value of the coefficient estimate) as a function of R^2 . R^{*2} denotes the maximum value of the squared multiple correlation (R^2) if there were no measurement error in the explanatory variables. Table 6.C (6.F) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum coefficient values) as a function of ρ^2 . ρ^2 denotes the minimum squared correlation between the true construct and the variable used to measure that construct. ERC_D and ERC_R are the ERC estimated using direct regression and reverse regression, respectively. LN_VOL_EARN is the logarithm of earnings volatility (which is the standard deviation of earnings). MTB is the market-to-book ratio.

relation between the ERC and earnings volatility is expected (as mentioned in Section 3). The table shows (in line with expectations) that the ERC and earnings volatility are negatively related.

Likewise, Table 7 shows the results when analyst forecast dispersion is used as the measure of earnings predictability. A negative relation between analyst forecast dispersion and ERC is observed, which is in line with expectations. Since higher (lower) earnings persistence (earnings volatility and forecast dispersion) indicates higher earnings predictability, a positive (negative) relation between the ERC and earnings persistence (earnings volatility and forecast dispersion) indicates that higher earnings predictability increases the ERC.

Table 7: Regression of Earnings Response Coefficient (ERC) on analyst earnings forecast dispersion and MTB ratio

Table 7.A Parameter estimates

| Dependent Variable | LN_FORECAST_DISP | MTB |
|--------------------|------------------|--------|
| ERC_D | -0.080 | 0.074 |
| LN_FORECAST_DISP | -3.080 | -1.038 |

Table 7.D Parameter estimates

| Dependent Variable | LN_FORECAST_DISP | MTB |
|--------------------|------------------|----------|
| ERC_R | -0.697 | 0.782 |
| LN_FORECAST_DISP | -423.974 | -158.974 |

Table 7.B Maximum R-Squared

| | | | | | | |
|------------------|------|-------|-------|-------|-------|-------|
| R^{*2} | | 0.045 | 0.061 | 0.077 | 0.093 | 0.109 |
| LN_FORECAST_DISP | Min. | -0.08 | -0.13 | -0.18 | -0.23 | -0.28 |
| LN_FORECAST_DISP | Max. | -0.08 | -0.08 | -0.08 | -0.08 | -0.08 |
| MTB | Min. | 0.074 | 0.056 | 0.037 | 0.019 | 0 |
| MTB | Max. | 0.074 | 0.074 | 0.074 | 0.074 | 0.074 |

Table 7.E Maximum R-Squared

| | | | | | | |
|------------------|------|--------|--------|--------|--------|--------|
| R^{*2} | | 0.003 | 0.005 | 0.006 | 0.007 | 0.008 |
| LN_FORECAST_DISP | Min. | -0.697 | -1.216 | -1.734 | -2.252 | -2.77 |
| LN_FORECAST_DISP | Max. | -0.697 | -0.697 | -0.697 | -0.697 | -0.697 |
| MTB | Min. | 0.782 | 0.587 | 0.391 | 0.196 | 0 |
| MTB | Max. | 0.782 | 0.782 | 0.782 | 0.782 | 0.782 |

Table 7.C Minimum Correlation

| | | | | | | |
|------------------|------|--------|--------|--------|--------|-------|
| ρ^2_* | | 0.3 | 0.475 | 0.65 | 0.825 | 1 |
| LN_FORECAST_DISP | Min. | -0.424 | -0.184 | -0.128 | -0.099 | -0.08 |
| LN_FORECAST_DISP | Max. | -0.02 | -0.06 | -0.071 | -0.077 | -0.08 |
| MTB | Min. | -0.32 | -0.011 | 0.04 | 0.062 | 0.074 |
| MTB | Max. | 0.29 | 0.176 | 0.126 | 0.095 | 0.074 |

Table 7.F Minimum Correlation

| | | | | | | |
|------------------|------|--------|--------|--------|--------|--------|
| ρ^2_* | | 0.3 | 0.475 | 0.65 | 0.825 | 1 |
| LN_FORECAST_DISP | Min. | -3.488 | -1.587 | -1.116 | -0.862 | -0.697 |
| LN_FORECAST_DISP | Max. | 0.082 | -0.459 | -0.595 | -0.66 | -0.697 |
| MTB | Min. | -2.284 | 0.098 | 0.506 | 0.682 | 0.782 |
| MTB | Max. | 3.144 | 1.813 | 1.297 | 0.99 | 0.782 |

Coefficient estimates (and implied coefficient estimates) along with coefficient bounds for regressing ERC on LN_FORECAST_DISP and MTB. Panel A-C (D-F) is based on the direct (reverse regression) ERC estimate. The first row in Table 7.A (7.D) presents the direct regression of ERC on LN_FORECAST_DISP and MTB. The second presents the implied regression coefficient for LN_FORECAST_DISP and MTB when regressing LN_FORECAST_DISP on ERC and MTB. To deal with the multicollinearity between LN_FORECAST_DISP and MTB, Principal Component Regression (PCR) is used. Table 7.B (7.E) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum value of the coefficient estimate) as a function of R^{*2} . R^{*2} denotes the maximum value of the squared multiple correlation (R^2) if there were no measurement error in the explanatory variables. Table 7.C (7.F) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum coefficient values) as a function of ρ^2_* . ρ^2_* denotes the minimum squared correlation between the true construct and the variable used to measure that construct. ERC_D and ERC_R are the ERC estimated using direct regression and reverse regression, respectively. LN_FORECAST_DISP is the logarithm of the standard deviation of analyst earnings forecast. MTB is the market-to-book ratio.

4.4 Additional analyses

4.4.1 Other measures for unexpected returns

As noted in Section 4, unexpected returns were estimated using the market model with value weighted returns. Estimating unexpected returns using the market model with with equal weighted returns or by estimating it as the difference between the realized firm returns and the realized returns on a beta matched portfolio yield similar results.

4.4.2 Transformation of earnings volatility and forecast dispersion

As mentioned in Section 4.2, earnings volatility and forecast dispersion are logarithmically transformed so as to reduce the skewness of the variables. Using the untransformed variables yields similar results.

4.4.3 The definition of earnings

Realized earnings in the I/B/E/S database is defined differently than in Compustat. Generally, I/B/E/S earnings exclude nonrecurring items (such as write-downs), other special items, and non-operating items from GAAP earnings (Abarbanell and Lehavy (2007)). To test whether the difference in definition of the earnings seems to be important, I also use the EBIT earnings definition.

Untabulated results show that the Pearson (Spearman) correlation between earnings and EBIT persistence is 0.3320 (0.3092) and is statistically significant at a 0.01 level. Likewise, the Pearson (Spearman) correlation between earnings volatility and EBIT volatility is -0.0149 (0.4490). In this case, the Pearson correlation is insignificant at the 0.1 level, whereas the Spearman correlation is significant at the 0.01 level. This suggests that earnings volatility and EBIT volatility

are positively related, but not linearly related.

Table 8 presents the results from the regression of ERC on EBIT persistence and the market-to-book ratio. The table shows ambiguous results. EBIT persistence is negatively related to the ERC when the ERCs are estimated from a direct regression. On the other hand, EBIT persistence and ERC are positively related when the ERCs are estimated from a reverse regression. Thus the relation between EBIT persistence and the ERC is unclear, since it depends on how the ERCs are estimated.

Table 9 presents the results from the regression of ERC on EBIT volatility and the market-to-book ratio. The results show that EBIT volatility and the ERC are negatively related.

Table 8: Regression of Earnings Response Coefficient (ERC) on EBIT persistence and MTB ratio

Table 8.A Parameter estimates

| Dependent Variable | PERSIST_EBIT | MTB |
|--------------------|--------------|-------|
| ERC_D | -0.016 | 0.078 |
| PERSIST_EBIT | -324.354 | 5.800 |

Table 8.B Maximum R-Squared

| R^{*2} | | 0.013 | 0.26 | 0.507 | 0.753 | 1 |
|--------------|------|--------|--------|----------|---------|----------|
| PERSIST_EBIT | Min. | -0.016 | -81.1 | -162.185 | -243.27 | -324.354 |
| PERSIST_EBIT | Max. | -0.016 | -0.016 | -0.016 | -0.016 | -0.016 |
| MTB | Min. | 0.078 | 0.078 | 0.078 | 0.078 | 0.078 |
| MTB | Max. | 0.078 | 1.508 | 2.939 | 4.369 | 5.8 |

Table 8.D Parameter estimates

| Dependent Variable | PERSIST_EBIT | MTB |
|--------------------|--------------|----------|
| ERC_R | 0.662 | 0.833 |
| PERSIST_EBIT | 7654.946 | -121.348 |

Table 8.E Maximum R-Squared

| R^{*2} | | 0.002 | 0.003 | 0.005 | 0.007 | 0.009 |
|--------------|------|-------|--------|--------|--------|--------|
| PERSIST_EBIT | Min. | 0.662 | 0.662 | 0.662 | 0.662 | 0.662 |
| PERSIST_EBIT | Max. | 0.662 | 13.712 | 26.762 | 39.813 | 52.863 |
| MTB | Min. | 0.833 | 0.625 | 0.417 | 0.208 | 0 |
| MTB | Max. | 0.833 | 0.833 | 0.833 | 0.833 | 0.833 |

Table 8.C Minimum Correlation

| ρ^2 | | 0.1 | 0.325 | 0.55 | 0.775 | 1 |
|--------------|------|--------|--------|--------|--------|--------|
| PERSIST_EBIT | Min. | -3.094 | -0.369 | -0.143 | -0.059 | -0.016 |
| PERSIST_EBIT | Max. | 0.68 | 0.201 | 0.075 | 0.017 | -0.016 |
| MTB | Min. | 0.078 | 0.078 | 0.078 | 0.078 | 0.078 |
| MTB | Max. | 1.199 | 0.247 | 0.143 | 0.101 | 0.078 |

Table 8.F Minimum Correlation

| ρ^2 | | 0.1 | 0.325 | 0.55 | 0.775 | 1 |
|--------------|------|---------|--------|--------|-------|-------|
| PERSIST_EBIT | Min. | -2.1069 | -2.151 | -0.366 | 0.308 | 0.662 |
| PERSIST_EBIT | Max. | 11.433 | 3.888 | 2.008 | 1.152 | 0.662 |
| MTB | Min. | 0.657 | 0.796 | 0.819 | 0.828 | 0.833 |
| MTB | Max. | 10.258 | 2.58 | 1.52 | 1.077 | 0.833 |

Coefficient estimates (and implied coefficient estimates) along with coefficient bounds for regressing ERC on PERSIST_EBIT and MTB. Panel A–C (D–F) is based on the direct (reverse regression) ERC estimate. The first row in Table 8.A (8.D) presents the direct regression of ERC on PERSIST_EBIT and MTB. The second presents the implied regression coefficient for PERSIST_EBIT and MTB when regressing PERSIST_EBIT on ERC and MTB. To deal with the multicollinearity between PERSIST_EBIT and MTB, Principal Component Regression (PCR) is used. Table 8.B (8.E) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum value of the coefficient estimate) as a function of R^{*2} . R^{*2} denotes the maximum value of the squared multiple correlation (R^2) if there were no measurement error in the explanatory variables. Table 8.C (8.F) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum coefficient values) as a function of ρ^2 . ρ^2 denotes the minimum squared correlation between the true construct and the variable used to measure that construct. ERC_D and ERC_R are the ERC estimated using direct regression and reverse regression, respectively. PERSIST_EBIT is the first-order autocorrelation of EBIT (scaled by price). MTB is the market-to-book ratio.

Table 9: Regression of Earnings Response Coefficient (ERC) on EBIT volatility and MTB ratio

Table 9.A Parameter estimates

| Dependent Variable | LN_VOL_EBIT | MTB |
|--------------------|-------------|--------|
| ERC.D | -0.050 | 0.050 |
| LN_VOL_EBIT | -6.704 | -3.580 |

Table 9.D Parameter estimates

| Dependent Variable | LN_VOL_EBIT | MTB |
|--------------------|-------------|----------|
| ERC.R | -0.447 | 0.600 |
| LN_VOL_EBIT | -739.988 | -402.640 |

Table 9.B Maximum R-Squared

| R^2 | | 0.021 | 0.024 | 0.027 | 0.031 | 0.034 |
|-------------|------|-------|--------|--------|--------|--------|
| LN_VOL_EBIT | Min. | -0.05 | -0.073 | -0.096 | -0.119 | -0.142 |
| LN_VOL_EBIT | Max. | -0.05 | -0.05 | -0.05 | -0.05 | -0.05 |
| MTB | Min. | 0.05 | 0.037 | 0.025 | 0.012 | 0 |
| MTB | Max. | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |

Table 9.E Maximum R-Squared

| R^2 | | 0.002 | 0.003 | 0.003 | 0.003 | 0.004 |
|-------------|------|--------|--------|--------|--------|--------|
| LN_VOL_EBIT | Min. | -0.447 | -0.722 | -0.997 | -1.272 | -1.548 |
| LN_VOL_EBIT | Max. | -0.447 | -0.447 | -0.447 | -0.447 | -0.447 |
| MTB | Min. | 0.6 | 0.45 | 0.3 | 0.15 | 0 |
| MTB | Max. | 0.6 | 0.6 | 0.6 | 0.6 | 0.6 |

Table 9.C Minimum Correlation

| ρ^* | | 0.5 | 0.625 | 0.75 | 0.875 | 1 |
|-------------|------|--------|--------|--------|--------|-------|
| LN_VOL_EBIT | Min. | -0.152 | -0.094 | -0.072 | -0.059 | -0.05 |
| LN_VOL_EBIT | Max. | -0.01 | -0.033 | -0.042 | -0.047 | -0.05 |
| MTB | Min. | -0.05 | 0.014 | 0.034 | 0.044 | 0.05 |
| MTB | Max. | 0.132 | 0.092 | 0.073 | 0.06 | 0.05 |

Table 9.F Minimum Correlation

| ρ^* | | 0.5 | 0.625 | 0.75 | 0.875 | 1 |
|-------------|------|--------|--------|--------|--------|--------|
| LN_VOL_EBIT | Min. | -1.238 | -0.826 | -0.646 | -0.53 | -0.447 |
| LN_VOL_EBIT | Max. | 0.176 | -0.209 | -0.336 | -0.404 | -0.447 |
| MTB | Min. | -0.094 | 0.325 | 0.471 | 0.55 | 0.6 |
| MTB | Max. | 1.712 | 1.112 | 0.866 | 0.711 | 0.6 |

Coefficient estimates (and implied coefficient estimates) along with coefficient bounds for regressing ERC on LN_VOL_EBIT and MTB. Panel A–C (D–F) is based on the direct (reverse regression) ERC estimate. The first row in Table 9.A (9.D) presents the direct regression of ERC on LN_VOL_EBIT and MTB. The second presents the implied regression coefficient for LN_VOL_EBIT and MTB when regressing LN_VOL_EBIT on ERC and MTB. To deal with the multicollinearity between LN_VOL_EBIT and MTB, Principal Component Regression (PCR) is used. Table 9.B (9.E) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum value of the coefficient estimate) as a function of R^{*2} . R^{*2} denotes the maximum value of the squared multiple correlation (R^2) if there were no measurement error in the explanatory variables. Table 9.C (9.F) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum coefficient values) as a function of ρ^* . ρ^* denotes the minimum squared correlation between the true construct and the variable used to measure that construct. ERC.D and ERC.R are the ERC estimated using direct regression and reverse regression, respectively. LN_VOL_EBIT is the logarithm of EBIT volatility (which is the standard deviation of earnings). MTB is the market-to-book ratio.

4.4.4 Unexpected vs. realized earnings variance and persistence

In Appendix E it is shown that the time-series variance of unexpected earnings is positively related with the time-series variance of realized earnings. Furthermore, in Appendix D, it is shown that the relation between the time-series variance of a given variable and its time-series persistence does not depend on how the variable is defined. Thus, (from the chain rule we have that) the persistence of unexpected earnings¹⁰ also is positively related with the persistence of realized earnings. Untabulated results show that the Pearson (Spearman) correlation between earnings persistence and the persistence of unexpected earnings is 0.1796 (0.1752) and is statistically significant at the 0.01 level. Likewise, the Pearson (Spearman) correlation between earnings volatility and the volatility of unexpected earnings is 0.6352 (0.6808) and is statistically significant at the 0.01 level.

Even though realized earnings persistence (volatility) and the persistence (volatility) of unexpected earnings seem to be highly positively correlated, it is still possible that the relation between the persistence (volatility) of unexpected earnings and the ERC is different from the relation between realized earnings persistence (volatility) and the ERC. To test whether the relation (positive or negative) between the persistence (volatility) of unexpected earnings and the ERC is the same as the relation between realized earnings persistence (volatility) and the ERC, I ran the second stage of the two-stage regression using the volatility (persistence) of unexpected earnings instead of realized earnings variance (persistence).

¹⁰Earlier research had argued that because analyst forecast errors (i.e. unexpected earnings) are predictable, then analysts are irrational in their forecasts, because since the forecast errors are predictable they should control for this in their forecasts. Markov and Tamayo (2006) propose another interpretation of this. They argue and empirically show that the autocorrelation in analysts' forecast errors can be present when analysts do not know the underlying time-series process or parameters of the earning series. So if there is a persistence in unexpected earnings, this does not necessarily mean that the analysts are irrational.

The results from the regression of ERC on the persistence of unexpected earnings and the market-to-book ratio are shown in Table 10. Like Table 8 (where earnings predictability is defined as EBIT persistence), the results are ambiguous because they depend on the estimation of the ERC.

Table 11 presents the results from the regression of ERC on the volatility of unexpected earnings and the market-to-book ratio. The results are similar to the results studying the relation between realized earnings volatility and the market-to-book ratio.

Table 10: Regression of Earnings Response Coefficient (ERC) on persistence of unexpected earnings and MTB ratio

Table 10.A Direct ERC regression

| Dependent Variable | PERSIST_UNEXP_EARN | MTB |
|--------------------|--------------------|--------|
| ERC_D | 0.022 | 0.102 |
| PERSIST_UNEXP_EARN | 203.860 | -0.832 |

Table 10.B Maximum R-Squared

| R^2 | | 0.024 | 0.05 | 0.077 | 0.104 | 0.13 |
|--------------------|------|-------|-------|--------|--------|-------|
| PERSIST_UNEXP_EARN | Min. | 0.022 | 0.022 | 0.022 | 0.022 | 0.022 |
| PERSIST_UNEXP_EARN | Max. | 0.022 | 5.577 | 11.131 | 16.685 | 22.24 |
| MTB | Min. | 0.102 | 0.076 | 0.051 | 0.025 | 0 |
| MTB | Max. | 0.102 | 0.102 | 0.102 | 0.102 | 0.102 |

Table 10.C Minimum Correlation

| ρ^2 | | 0.1 | 0.325 | 0.55 | 0.775 | 1 |
|--------------------|------|--------|--------|--------|--------|-------|
| PERSIST_UNEXP_EARN | Min. | -1.624 | -0.316 | -0.109 | -0.024 | 0.022 |
| PERSIST_UNEXP_EARN | Max. | 1.416 | 0.376 | 0.164 | 0.073 | 0.022 |
| MTB | Min. | 0.1 | 0.101 | 0.102 | 0.102 | 0.102 |
| MTB | Max. | 1.031 | 0.313 | 0.185 | 0.131 | 0.102 |

Coefficient estimates (and implied coefficient estimates) along with coefficient bounds for regressing ERC on PERSIST_UNEXP_EARN and MTB. Panel A-C (D-F) is based on the direct (reverse regression) ERC estimate. The first row in Table 10.A (10.D) presents the direct regression of ERC on PERSIST_UNEXP_EARN and MTB. The second presents the implied regression coefficient for PERSIST_UNEXP_EARN and MTB when regressing PERSIST_UNEXP_EARN on ERC and MTB. Table 10.B (10.E) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum value of the coefficient estimate) as a function of R^2 . R^2 denotes the maximum value of the squared multiple correlation (R^2); if there were no measurement error in the explanatory variables. Table 10.C (10.F) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum coefficient values) as a function of ρ^2 . ρ^2 denotes the minimum squared correlation between the true construct and the variable used to measure that construct. ERC_D and ERC_R are the ERC estimated using direct regression and reverse regression, respectively. PERSIST_UNEXP_EARN is the first-order autocorrelation of unexpected earnings (scaled by price). MTB is the market-to-book ratio.

Table 10.D Reverse ERC regression

| Dependent Variable | PERSIST_UNEXP_EARN | MTB |
|--------------------|--------------------|--------|
| ERC_R | -0.776 | 0.971 |
| PERSIST_UNEXP_EARN | -7045.605 | 30.100 |

Table 10.E Maximum R-Squared

| R^2 | | 0.002 | 0.251 | 0.501 | 0.75 | 1 |
|--------------------|------|--------|-----------|----------|-----------|-----------|
| PERSIST_UNEXP_EARN | Min. | -0.776 | -1761.983 | -3523.19 | -5284.397 | -7045.605 |
| PERSIST_UNEXP_EARN | Max. | -0.776 | -0.776 | -0.776 | -0.776 | -0.776 |
| MTB | Min. | 0.971 | 0.971 | 0.971 | 0.971 | 0.971 |
| MTB | Max. | 0.971 | 8.253 | 15.536 | 22.818 | 30.1 |

Table 10.F Minimum Correlation

| ρ^2 | | 0.1 | 0.325 | 0.55 | 0.775 | 1 |
|--------------------|------|---------|--------|--------|--------|--------|
| PERSIST_UNEXP_EARN | Min. | -21.695 | -5.142 | -2.467 | -1.372 | -0.776 |
| PERSIST_UNEXP_EARN | Max. | 9.095 | 1.701 | 0.215 | -0.422 | -0.776 |
| MTB | Min. | 0.859 | 0.945 | 0.961 | 0.967 | 0.971 |
| MTB | Max. | 10.278 | 3.038 | 1.781 | 1.258 | 0.971 |

Table 11: Regression of Earnings Response Coefficient (ERC) on volatility of unexpected earnings and MTB ratio

Table 11.A Direct ERC regression

| Dependent Variable | LN_VOL_UNEXP_EARN | MTB |
|--------------------|-------------------|--------|
| ERC.D | -0.086 | 0.059 |
| LN_VOL_UNEXP_EARN | -1.449 | -0.638 |

Table 11.D Reverse ERC regression

| Dependent Variable | LN_VOL_UNEXP_EARN | MTB |
|--------------------|-------------------|---------|
| ERC.R | -1.243 | 0.336 |
| LN_VOL_UNEXP_EARN | -118.817 | -59.473 |

Table 11.B Maximum R-Squared

| | | | | | | |
|-------------------|------|--------|--------|--------|--------|--------|
| R^2 | | 0.081 | 0.101 | 0.12 | 0.139 | 0.159 |
| LN_VOL_UNEXP_EARN | Min. | -0.086 | -0.114 | -0.143 | -0.172 | -0.2 |
| LN_VOL_UNEXP_EARN | Max. | -0.086 | -0.086 | -0.086 | -0.086 | -0.086 |
| MTB | Min. | 0.059 | 0.044 | 0.029 | 0.015 | 0 |
| MTB | Max. | 0.059 | 0.059 | 0.059 | 0.059 | 0.059 |

Table 11.E Maximum R-Squared

| | | | | | | |
|-------------------|------|--------|--------|--------|--------|--------|
| R^2 | | 0.012 | 0.014 | 0.015 | 0.016 | 0.018 |
| LN_VOL_UNEXP_EARN | Min. | -1.243 | -1.408 | -1.574 | -1.739 | -1.904 |
| LN_VOL_UNEXP_EARN | Max. | -1.243 | -1.243 | -1.243 | -1.243 | -1.243 |
| MTB | Min. | 0.336 | 0.252 | 0.168 | 0.084 | 0 |
| MTB | Max. | 0.336 | 0.336 | 0.336 | 0.336 | 0.336 |

Table 11.C Minimum Correlation

| | | | | | | |
|-------------------|------|--------|--------|--------|--------|--------|
| ρ^2 | | 0.3 | 0.475 | 0.65 | 0.825 | 1 |
| LN_VOL_UNEXP_EARN | Min. | -0.73 | -0.207 | -0.138 | -0.106 | -0.086 |
| LN_VOL_UNEXP_EARN | Max. | -0.057 | -0.075 | -0.081 | -0.084 | -0.086 |
| MTB | Min. | -1.048 | -0.096 | 0 | 0.038 | 0.059 |
| MTB | Max. | 0.253 | 0.16 | 0.111 | 0.08 | 0.059 |

Table 11.F Minimum Correlation

| | | | | | | |
|-------------------|------|---------|--------|--------|--------|--------|
| ρ^2 | | 0.3 | 0.475 | 0.65 | 0.825 | 1 |
| LN_VOL_UNEXP_EARN | Min. | -12.562 | -3.137 | -2.028 | -1.535 | -1.243 |
| LN_VOL_UNEXP_EARN | Max. | -1.1 | -1.18 | -1.213 | -1.231 | -1.243 |
| MTB | Min. | -19.803 | -2.346 | -0.655 | -0.007 | 0.336 |
| MTB | Max. | 2.31 | 1.43 | 0.918 | 0.579 | 0.336 |

Coefficient estimates (and implied coefficient estimates) along with coefficient bounds for regressing ERC on LN_VOL_UNEXP_EARN and MTB. Panel A-C (D-F) is based on the direct (reverse regression) ERC estimate. The first row in Table 11.A (11.D) presents the direct regression of ERC on LN_VOL_UNEXP_EARN and MTB. The second presents the implied regression coefficient for LN_VOL_UNEXP_EARN and MTB when regressing LN_VOL_UNEXP_EARN on ERC and MTB. To deal with the multicollinearity between LN_VOL_UNEXP_EARN and MTB, Principal Component Regression (PCR) is used. Table 11.B (11.E) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum value of the coefficient estimate) as a function of R^2 . R^{*2} denotes the maximum value of the squared multiple correlation (R^2) if there were no measurement error in the explanatory variables. Table 11.C (11.F) presents the lower and upper bounds for the coefficient estimates (i.e. the minimum and maximum coefficient values) as a function of ρ^2 . ρ^2 denotes the minimum squared correlation between the true construct and the variable used to measure that construct. ERC.D and ERC.R are the ERC estimated using direct regression and reverse regression, respectively. LN_VOL_UNEXP_EARN is the logarithm of unexpected earnings volatility (which is the standard deviation of unexpected earnings).

5 Conclusion

This paper has studied the relation between earnings predictability and the Earnings Response Coefficient (ERC). It shows that the ERC is a function of earnings predictability and how different measures of earnings predictability—earnings (and unexpected earnings) persistence, earnings (and unexpected earnings) volatility, and analyst forecast dispersion—are related. The empirical findings show that the ERC is negatively related to earnings (and unexpected earnings) volatility and analyst forecast dispersion. With regard to the persistence measure of earnings predictability, the results are ambiguous. The results show that when the ERCs are estimated using direct regression, unexpected earnings persistence (EBIT persistence) is positively (negatively) related to the ERC, but when ERCs are estimated using reverse regression the relation is negative (positive). However when focusing on earnings persistence, the results show that earnings persistence is positively related to the ERC. Overall, these results suggest that more predictable earnings have higher value-relevance for investors (i.e. a higher earnings predictability is associated with a higher ERC).

The earnings quality literature suggests different ways to measure earnings quality (Dechow et al. (2010)): among them are earnings persistence (measured as the auto-covariance), earnings smoothness (earnings volatility deflated by cash flow volatility), and the ERC. The literature suggests that a higher earnings quality is associated with higher levels of the earnings persistence and the ERC, but lower levels of earnings smoothness (i.e. higher levels of earnings volatility). However, Dechow et al. (2010) notes that accounting quality is context-specific. The findings in this paper support this context-specific view of accounting quality, since the ERC and earnings volatility are negatively related.

A Scaling

In the literature, unexpected earnings is deflated by the lagged book value of equity, the lagged price, or lagged nominal earnings. Let UX_t , X_t , BVE_t , P_t , and ROE_t denote the scaled unexpected earnings, nominal earnings, the book value of equity, the stock price, and Return on Equity at time t , respectively.

In case the unexpected earnings are scaled by the lagged book value of equity, it is equal to the unexpected ROE, since

$$\begin{aligned} UX_t &= \frac{UX_t}{BVE_{t-1}} = \frac{X_t}{BVE_{t-1}} - \frac{E_{t-1}[X_t]}{BVE_{t-1}} \\ &= ROE_t - E_{t-1} \left[\frac{X_t}{BVE_{t-1}} \right] = ROE_t - E_{t-1} [ROE_t] \end{aligned}$$

If, instead, the scaling variable for unexpected earnings is the lagged price or lagged nominal earnings, then the scaled unexpected earnings can be rewritten so as to again become a function of unexpected ROE. In the case where it is scaled by the lagged price, it is equal to

$$\begin{aligned} UX_t &= \frac{UX_t}{P_{t-1}} = \frac{X_t}{P_{t-1}} - \frac{E_{t-1}[X_t]}{P_{t-1}} \\ &= \frac{X_t}{BVE_{t-1}} \frac{BVE_{t-1}}{P_{t-1}} - E_{t-1} \left[\frac{X_t}{BVE_{t-1}} \right] \frac{BVE_{t-1}}{P_{t-1}} \\ &= \frac{BVE_{t-1}}{P_{t-1}} (ROE_t - E_{t-1} [ROE_t]) \end{aligned}$$

In this case, it is equal to the unexpected ROE times the inverse lagged market-to-book ratio.

When it is scaled by lagged earnings, it is equal to

$$\begin{aligned}
 UX_t &= \frac{UX_t}{X_{t-1}} = \frac{X_t}{X_{t-1}} - \frac{E_{t-1}[X_t]}{X_{t-1}} \\
 &= \frac{X_t}{BVE_{t-1}} \frac{BVE_{t-1}}{X_{t-1}} - E_{t-1} \left[\frac{X_t}{BVE_{t-1}} \right] \frac{BVE_{t-1}}{X_{t-1}} \\
 &= \frac{BVE_{t-2}}{X_{t-1}} (1 + g_{t-1}^{BVE}) (ROE_t - E_{t-1} [ROE_t]) \\
 &= \frac{1 + g_{t-1}^{BVE}}{ROE_{t-1}} (ROE_t - E_{t-1} [ROE_t])
 \end{aligned}$$

where g_{t-1}^{BVE} denotes the growth in book value of the equity at time $t - 1$.

Since we condition on information at time $t - 1$, unexpected earnings are proportional to the unexpected ROE for the three scaling factors mentioned above: lagged book value of equity, lagged price, or lagged nominal earnings. This means that the Earnings Response Coefficient (ERC) is only proportionally different for the three different scaling factors. The proportional differences are equal to

$$\begin{aligned}
 \theta_{BVE} &= \frac{Cov_{t-1}[UR_t, ROE_t - E_{t-1} [ROE_t]]}{Var_{t-1}[ROE_t - E_{t-1} [ROE_t]]} \\
 &= \frac{BVE_{t-1}}{P_{t-1}} \frac{BVE_{t-1}}{P_{t-1}} \frac{Cov_{t-1}[UR_t, ROE_t - E_{t-1} [ROE_t]]}{\left(\frac{BVE_{t-1}}{P_{t-1}}\right)^2 Var_{t-1}[ROE_t - E_{t-1} [ROE_t]]} \\
 &= \frac{BVE_{t-1}}{P_{t-1}} \theta_P = \theta_X \frac{ROE_{t-1}}{1 + g_{t-1}^{BVE}}
 \end{aligned}$$

where θ_{BVE} is the ERC where unexpected earnings are deflated by the book value of equity, θ_P is that where they are deflated by price, and θ_X is when they are deflated by earnings.

B Derivations

$$\begin{aligned} \frac{\partial E[1 + R_t]}{\partial \Psi} &= E \left[\frac{\partial e^{\ln(1+R_t)}}{\partial \Psi} \right] = E \left[e^{\ln(1+R_t)} \frac{\ln(1 + R_t)}{\partial \Psi} \right] \\ &= E \left[(1 + R_t) \left(\sum_{j=0}^{\infty} \vartheta^j \frac{\ln(1 + ROE_{t+j})}{\partial \Psi} - \sum_{j=1}^{\infty} \vartheta^j \frac{\ln(1 + R_{t+j})}{\partial \Psi} + \frac{\theta_{t-1}}{\partial \Psi} \right) \right] \end{aligned}$$

where θ_{t-1} denotes the log of the market-to-book ratio $\left(\ln \left(\frac{P_{t-1}}{B_{t-1}} \right) \right)$ at time $t - 1$.

For most firms, $ROE_t > 0$, thus, when Ψ denotes earnings persistence, I assume that $\frac{\ln(1+ROE_{t+j})}{\partial \Psi} > 0$. Furthermore, since earnings persistence is more closely related to future earnings than to future returns, I assume that

$\frac{\ln(1+ROE_{t+j})}{\partial \Psi} > \frac{\ln(1+R_{t+j})}{\partial \Psi}$. Thus¹¹

$$\frac{\partial E[1 + R_t]}{\partial \Psi} > 0$$

¹¹ $\frac{\theta_{t-1}}{\partial \Psi}$ is ignored. However, for most firms, the current market-to-book ratio is positively related to earnings persistence, thus $\frac{\theta_{t-1}}{\partial \Psi} > 0$

C Decomposition of the expected returns

Vuolteenaho (2002) shows that

$$r_t - E_{t-1}[r_t] = \Delta E_t \left[\sum_{j=0}^{\infty} \vartheta^j (e_{t+j} - f_{t+j}) \right] - \Delta E_t \left[\sum_{j=1}^{\infty} \vartheta^j r_{t+j} \right] + \kappa_t$$

where e_t denotes the logarithm of one plus the Return On Equity, f_t denotes the logarithm of one plus the interest rate, r_t is the excess log stock return¹² and κ_t is an approximation error. This can easily be rewritten as

$$\begin{aligned} \Delta E_t[\tilde{r}_t] &= \tilde{r}_t - E_{t-1}[\tilde{r}_t] = r_t + f_t - E_{t-1}[r_t + f_t] \\ &= \Delta E_t \left[\sum_{j=0}^{\infty} \vartheta^j e_{t+j} \right] - \Delta E_t \left[\sum_{j=1}^{\infty} \vartheta^j (r_{t+j} + f_{t+j}) \right] + \kappa_t \\ &= \Delta E_t \left[\sum_{j=0}^{\infty} \vartheta^j e_{t+j} \right] - \Delta E_t \left[\sum_{j=1}^{\infty} \vartheta^j r_{t+j} \right] + \kappa_t \end{aligned}$$

where \tilde{r}_t denotes the logarithm of one plus the stock return.

The covariance between the log of the unexpected stock returns and the unexpected earnings ($Cov[\Delta E_t[\ln(1 + R_t)], \Delta E_t[X_t]]$) must be positive (if X_t denotes ROE¹³), since a positive change in the expectation of the ROE is likely to change the expectation of the future ROE in a positive direction as well. Likewise, the term $\frac{\partial Cov[\Delta E_t[\ln(1 + R_t)], \Delta E_t[X_t]]}{\partial \Psi}$ must also be positive if Ψ denotes earnings persistence, because higher earnings persistence will lead to a larger revision of future ROE for a given earnings shock.

¹²Vuolteenaho (2002) defines the excess log stock return as the logarithm of one plus the stock return minus the logarithm of one plus the interest rate.

¹³As mentioned in Appendix A the scaling factor for earnings only affects the scaling of the ERC by a deterministic scaling factor

D Relation between variance and first-order autocorrelation

Let ΔX_t denote the change in X_t from period $t - 1$ to t (i.e. $\Delta X_t = X_t - X_{t-1}$). This means that the first order auto-covariance and variance can be rewritten as

$$Cov[X_t, X_{t-1}] = Cov[X_t, X_t - \Delta X_t] = Var[X_t] - Cov[X_t, \Delta X_t]$$

and

$$Var[X_{t-1}] = Var[X_t - \Delta X_t] = Var[X_t] + Var[\Delta X_t] - 2Cov[X_t, \Delta X_t]$$

Assuming variance stationarity (i.e. $Var[X_t] = Var[X_{t-1}]$) means that

$$\begin{aligned} Var[X_{t-1}] &= Var[X_t] + Var[\Delta X_t] - 2Cov[X_t, \Delta X_t] \\ &\Updownarrow \\ Cov[X_t, \Delta X_t] &= \frac{1}{2}Var[\Delta X_t] \end{aligned}$$

and that the first-order autocorrelation equals

$$\begin{aligned} \rho &= \frac{Cov[X_t, X_{t-1}]}{Std[X_t]Std[X_{t-1}]} = \frac{Cov[X_t, X_{t-1}]}{Var[X_t]} \\ &= 1 - \frac{Cov[X_t, \Delta X_t]}{Var[X_t]} = 1 - \frac{1}{2} \frac{Var[\Delta X_t]}{Var[X_t]} \end{aligned}$$

The relation between the variance and the first-order autocorrelation can be analyzed by calculating the derivative of the first-order autocorrelation with respect to the variance. Thus

$$\begin{aligned} \frac{\partial \rho}{\partial Var[X_t]} &= -\frac{1}{2} \frac{\frac{\partial Var[\Delta X_t]}{\partial Var[X_t]} Var[X_t] - Var[\Delta X_t]}{Var[X_t]^2} \\ &= -\frac{1}{2} \frac{1}{Var[X_t]} \frac{\partial Var[\Delta X_t]}{\partial Var[X_t]} + \frac{1}{Var[X_t]} (1 - \rho) \end{aligned} \quad (13)$$

where

$$\begin{aligned}
 \frac{\partial Var[\Delta X_t]}{\partial Var[X_t]} &= \frac{\partial Var[X_t] - Cov[X_t, X_{t-1}]}{\partial Var[X_t]} \\
 &= 1 - \frac{\partial Cov[X_t, X_{t-1}]}{\partial Var[X_t]} = 1 - \frac{\partial \rho Var[X_t]}{\partial Var[X_t]} \\
 &= 1 - \left(\frac{\partial \rho}{\partial Var[X_t]} \frac{1}{Var[X_t]} + \rho \frac{1}{Var[X_t]^2} \right) \quad (14)
 \end{aligned}$$

Substituting Equation 14 into Equation 13 and solving for $\frac{\partial \rho}{\partial Var[X_t]}$ yields

$$\begin{aligned}
 \frac{\partial \rho}{\partial Var[X_t]} &= \frac{\rho + Var[X_t]^2 - 2\rho Var[X_t]^2}{Var[X_t](2Var[X_t]^2 - 1)} \\
 &= \frac{-\rho(2Var[X_t]^2 - 1) + Var[X_t]^2}{Var[X_t](2Var[X_t]^2 - 1)} \\
 &= -\frac{\rho}{Var[X_t]} + \frac{Var[X_t]}{2Var[X_t]^2 - 1}
 \end{aligned}$$

Thus the variance and the first-order autocorrelation are negatively related if

$$2Var[X_t]^2 - 1 < 0 \Leftrightarrow Var[X_t] < \frac{1}{\sqrt{2}}$$

So, the variance and the first-order autocorrelation are negatively related under the assumption that the earnings variance is bounded and the variance is stationary. In the context of this paper, the X_t are the scaled earnings (Return On Equity). If $|ROE| < \frac{1}{\sqrt{2}}$ then $Var[X_t] < \frac{1}{\sqrt{2}}$. Since the absolute value of ROE mainly is below $\frac{1}{\sqrt{2}} \approx 70.5\%$, it seems reasonable to assume that $Var[X_t] < \frac{1}{\sqrt{2}}$. Thus, for most of the firms, the ROE time-series variance is negatively related to the first-order autocorrelation of the ROE.

E Relation between time-series variance of unexpected earnings and realized earnings

Let $Var[UX]$, respectively, $Var[X]$ denote the time-series variance of unexpected earnings, respectively, the time-series variance of realized earnings. Since

$$\begin{aligned}
 Var[UX] &= Var[X - \hat{X}] \\
 &= Var[X] + Var[\hat{X}] - 2Corr[X, \hat{X}]\sqrt{Var[X]}\sqrt{Var[\hat{X}]} \\
 &= \left(\sqrt{Var[X]} - \sqrt{Var[\hat{X}]}\right)^2 \\
 &\quad + 2\sqrt{Var[X]}\sqrt{Var[\hat{X}]}(1 - Corr[X, \hat{X}]) \\
 &= \left(1 - \sqrt{\frac{Var[\hat{X}]}{Var[X]}}\right)^2 Var[X] \\
 &\quad + 2\sqrt{\frac{Var[\hat{X}]}{Var[X]}}(1 - Corr[X, \hat{X}]) Var[X]
 \end{aligned}$$

where X denotes realized earnings and \hat{X} denotes the expected value (forecasts) of earnings. Thus the time-series variance of unexpected earnings (i.e. $Var[UX]$) is positively related with the time-series variance of realized earnings. The correlation between the realized value and the forecast value (i.e. $Corr[X, \hat{X}]$) expresses a form of forecast accuracy. Thus a higher forecast accuracy decreases the relation between the variance of unexpected earnings (i.e. $Var[UX]$) and the variance of realized earnings (i.e. $Var[X]$).

F Relation between time-series variance of unexpected earnings and forecast dispersion

When an individual firm's Earnings Response Coefficient (ERC) is estimated, this is based on time-series data from the current and T previous periods. Let $UX_{t,j}$ be the unexpected earnings at time t for analyst j . Suppose there are M analysts and T periods. The mean unexpected earnings at time t over all analysts is

$$E_{\Omega}[UX_t] = \frac{1}{M} \sum_{j=1}^M UX_{t,j}$$

Likewise, the mean unexpected earnings for analyst j over the ERC estimation period is

$$E_{\tau}[UX_j] = \frac{1}{T} \sum_{u=1}^T UX_{t+1-u,j}$$

where Ω denotes the set of analysts and τ the set of time periods. The variances $Var_{\Omega}[UX_t]$ and $Var_{\tau}[UX_j]$ are defined analogously.

The time-series variance of unexpected earnings can also be written as

$$\begin{aligned} Var[UX_t] &= Var_{\tau}[E_{\Omega}[UX_t]] \\ &= \frac{1}{M} \left(\frac{1}{M} \sum_{j=1}^M Var_{\tau}[UX_j] + \frac{2}{M} \sum_{j=2}^M \sum_{i=1}^{j-1} Cov_{\tau}[UX_i, UX_j] \right) \quad (15) \end{aligned}$$

So the time-series variance of the unexpected earnings is equal to the mean of the individual analysts' time-series variances of the unexpected earnings plus two times the mean of the time-series covariance of unexpected earnings between two analysts.

The mean of the individual analysts' time-series variances of the unexpected earnings can be rewritten as

$$\begin{aligned}
\frac{1}{M} \sum_{j=1}^M Var_{\tau}[UX_j] &= \frac{1}{M} \sum_{j=1}^M \frac{1}{T} \sum_{u=1}^T UX_{t+1-u,j}^2 - \frac{1}{M} \sum_{j=1}^M E_{\tau}[UX_j]^2 \\
&= \frac{1}{T} \sum_{u=1}^T (Var_{\Omega}[UX_{t+1-u}] + E_{\Omega}[UX_{t+1-u}]^2) - \frac{1}{M} \sum_{j=1}^M E_{\tau}[UX_j]^2 \\
&= \frac{1}{T} \sum_{u=1}^T Var_{\Omega}[UX_{t+1-u}] \\
&\quad + \frac{1}{T} \sum_{u=1}^T E_{\Omega}[UX_{t+1-u}]^2 - \frac{1}{M} \sum_{j=1}^M E_{\tau}[UX_j]^2 \tag{16}
\end{aligned}$$

So the first term in this mean is equal to the mean over time of the variance in the analyst forecasts. The second term is equal to

$$\begin{aligned}
\frac{1}{T} \sum_{u=1}^T E_{\Omega}[UX_{t+1-u}]^2 &= Var[UX_t] + \left(\frac{1}{T} \sum_{u=1}^T E_{\Omega}[UX_{t+1-u}] \right)^2 \\
&= Var[UX_t] + \left(\frac{1}{M} \sum_{j=1}^M E_{\tau}[UX_j] \right)^2 \tag{17}
\end{aligned}$$

and the last term equals

$$\frac{1}{M} \sum_{j=1}^M E_{\tau}[UX_j]^2 = Var_{\Omega}[E_{\tau}[UX_j]] + \left(\frac{1}{M} \sum_{j=1}^M E_{\tau}[UX_j] \right)^2 \tag{18}$$

Inserting Equations 17 and 18 into Equation 16 gives

$$\begin{aligned}
\frac{1}{M} \sum_{j=1}^M Var_{\tau}[UX_j] &= \frac{1}{T} \sum_{u=1}^T Var_{\Omega}[UX_{t+1-u}] + Var[UX_t] - Var_{\Omega}[E_{\tau}[UX_j]] \tag{19}
\end{aligned}$$

The last term of Equation 19 ($Var_{\Omega}[E_{\tau}[UX_j]]$) equals

$$\frac{1}{T} \left(\frac{1}{T} \sum_{u=1}^T Var_{\Omega}[UX_{t+1-u}] + \frac{2}{T} \sum_{u=2}^T \sum_{s=1}^{u-1} Cov_{\Omega}[UX_{t+1-s}, UX_{t+1-u}] \right) \quad (20)$$

Substituting Equation 19 and 20 into Equation 15 and rearranging yields

$$\begin{aligned} Var[UX_t] &= \frac{1}{M-1} \frac{T-1}{T^2} \sum_{u=1}^T Var_{\Omega}[UX_{t+1-u}] \\ &\quad + \frac{1}{M-1} \frac{2}{M} \sum_{j=2}^M \sum_{i=1}^{j-1} Cov_{\tau}[UX_i, UX_j] \\ &\quad - \frac{1}{M-1} \frac{2}{T^2} \sum_{u=2}^T \sum_{s=1}^{u-1} Cov_{\Omega}[UX_{t+1-s}, UX_{t+1-u}] \end{aligned}$$

Since actual earnings are the same for all analysts, the variance of unexpected earnings across analysts equals the variance of forecasts across analysts

(i.e. $Var_{\Omega}[UX_{t+1-u}] = Var_{\Omega}[F_{t+1-u}]$), where F denotes the analyst forecast. So the time-series variance of the unexpected earnings in the ERC is positively related to the mean over time of the analyst forecast variance. The time-series covariance between the unexpected earnings for two analysts is equal to

$$\begin{aligned} Cov_{\tau}[UX_i, UX_j] &= Cov_{\tau}[X - F_i, X - F_j] \\ &= Var_{\tau}[X] + Cov_{\tau}[F_i, F_j] - Cov_{\tau}[X, F_i] - Cov_{\tau}[X, F_j] \end{aligned}$$

where F_j denotes the earnings forecast for analyst j and X denotes realized earnings. So the time-series variance of the unexpected earnings in the ERC is also positively related to the time-series variance of the actual earnings and the time-series covariance between the earnings forecasts for two analysts. Likewise, the covariance between the unexpected earnings for two different points in time but involving the same analyst equals

$$\begin{aligned} Cov_{\Omega}[UX_{t+1-s}, UX_{t+1-u}] &= Cov_{\tau}[X_{t+1-s}, X_{t+1-u}] + Cov_{\tau}[F_{t+1-s}, F_{t+1-u}] \\ &\quad - Cov_{\tau}[X_{t+1-s}, F_{t+1-u}] - Cov_{\tau}[X_{t+1-u}, F_{t+1-s}] \end{aligned}$$

This implies that the time-series variance of the unexpected earnings in the ERC is negatively related to the auto-covariance (persistence) in earnings and in the earnings forecasts.

G Bias of the parameter estimate and the t -score when variables are measured with error

Maddala (1992, pp. 451–454) show the bias of a parameter coefficient in a model where one of the two explanatory variables and the dependent variable are measured with error. The model from Maddala (1992, pp. 451–454) is

$$y = \beta_1 x_1 + \beta_2 x_2 + e$$

The observed variables are

$$Y = y + v \quad X_1 = x_1 + u \quad X_2 = x_2$$

where u , v and e are mutually uncorrelated and also uncorrelated with y , x_1 and x_2 . Then the regression based on the observable variables is

$$Y = \beta_1 X_1 + \beta_2 X_2 + w$$

where

$$w = e + v - \beta_1 u$$

Then it is shown that

$$\begin{aligned} \text{plim } \hat{\beta}_1 &= \beta_1 \left(1 - \frac{\lambda}{1 - \rho} \right) \\ \text{plim } \hat{\beta}_2 &= \beta_2 + \frac{\beta_1 \lambda \rho}{1 - \rho^2} \end{aligned}$$

where $\lambda = \frac{\text{Var}[u]}{\text{Var}[X_1]}$ and $\rho = \text{Cov}[X_1, X_2]$. So for β_1 the bias is multiplicative, whereas for β_2 it is additive.

To make a t -test, one needs to estimate the standard deviation of the parameter estimate. This is equal to

$$SE_{\hat{\beta}_1} = \frac{1}{\sqrt{n-2}} \frac{Var[e] + Var[v] + \beta_1^2 Var[u]}{Var[x_1] + Var[u]}$$

$$SE_{\hat{\beta}_2} = \frac{1}{\sqrt{n-2}} \frac{Var[e] + Var[v] + \beta_1^2 Var[u]}{Var[x_2]}$$

Because

$$t_{\text{score}} = \frac{\hat{\beta} - \beta_0}{SE_{\hat{\beta}}}$$

the t -statistic is also biased. Since $Var[u]$ is unknown and can not be estimated, one can not analytically correct either the bias of the estimate or the standard error of the parameter estimate. As a consequence, the t -statistics and significance conclusions for the parameters are not appropriate when the variables are measured with error.

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