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Brunke, L., 2024,
Forecasting Earnings Variance: Quantiles-Based Vs. Residuals-Based Approaches,
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Chapter 1

Introduction

Earnings are one of the most fundamental indicators for the financial performance of a company, especially, as the value of a company depends on the future earnings. Hence, accurate earnings forecasts are of immense importance for investors, analysts and firms themselves to obtain accurate information about the future financial situation of a company (e.g., Azevedo, Bielstein and Gerhart (2021) and Tian, Yim and Newton (2021)). Further, the entirety of higher moments of future earnings, i.e., earnings uncertainty, is important to any agent whose wealth directly or indirectly depends on earnings (Chang, Monahan, Ouazad and Vasvari (2021)). More specifically, both the value of debt and equity of a company is related to higher moments of future earnings (e.g., Konstantinidi and Pope (2016) and Chang, Monahan, Ouazad and Vasvari (2021)). Additionally, equity prices are a function, among other factors, of higher moments of future earnings (e.g. Merton (1987), Johnson (2004), Brunnermeier, Gollier and Parker (2007), Mitton and Vorkink (2007) and Barberis and Huang (2008)). Forecasts for the first moment of future earnings, i.e., mean earnings, typically come from either sell-side analysts or earnings forecast models. Whereas analyst earnings forecasts suffer from an inherent optimism bias (e.g., O'Brien (1988)) and insufficient coverage (e.g., La Porta (1996)), earnings forecast models overcome these disadvantages (e.g., Hou, Van Dijk and Zhang (2012), Li and Mohanram (2014), Evans, Njoroge and Yong (2017), Cao and You (2024), Tian, Yim and Newton (2021), Hansen and Thimsen (2021), Chen, Cho, Dou and Lev (2022), Hendriock (2022), Van Binsbergen, Han and Lopez-Lira (2023) and Campbell, Ham, Lu and Wood (2023)). Especially, cross-sectional models gained traction in that field of research as they do not exhibit as restrictive data requirements as time-series models do (e.g., Bradshaw, Drake, Myers and Myers (2012)). In contrast, approaches to accurately forecast higher moments of future earnings are sparse in this comparably novel stem of research (Monahan (2018)).

This thesis aims to contribute to the understanding of forecasting earnings by identifying factors associated with the accuracy and bias of both analyst and model-based earnings forecasts, namely accounting conservatism and earnings management (EM). Further, this study underlines the importance of incorporating information about a firm's degree of earnings management into earnings forecast models as this results in an increase in the predictive ability of the earnings forecast model and subsequently in an increase of the reliability of the implied cost of capital (ICC), which is based on earnings forecasts, as an expected return proxy. Finally, this study turns to higher moments of future earnings and aims to contribute to the literature by introducing a new earnings variance forecasting approach as well as new earnings variance forecast evaluation methods.

The first essay (Chapter 2) investigates the consequences of accounting conservatism on the accuracy and bias of both analyst as well as model-based earnings forecasts and the analyst forecast dispersion.[1] Accounting conservatism refers to the philosophy of "anticipate no profits and provide for all losses" (e.g., Bliss (1924)). The demand for such accounting philosophy mainly stems from debt market participants as they are faced with an asymmetric payoff, i.e., they do not gain an additional payoff from a strong financial situation, but face an increased default risk by a weak financial situation (e.g., Watts (2003), Ball, Robin and Sadka (2008) and Gigler, Kanodia, Sapra and Venugopalan (2009)). Although the demand for accounting conservatism mainly stems from debt market participants, it has influence on equity market participants, e.g., on the information environment of investors as it leads to biased financial statements (e.g., Ruch and Taylor (2015)). Accounting conservatism is usually divided into two categories, i.e., unconditional and conditional accounting conservatism (e.g., Chen, Folsom, Paek and Sami (2014) and Ruch and Taylor (2015)). Unconditional accounting conservatism refers to a constant under-

[1] This chapter is based on the working paper "Accounting Conservatism and the Reliability of Earnings Forecasts" (2024).

recognition of net assets, e.g., implementing a last-in first-out (LIFO) instead of a first-in first-out (FIFO) inventory (e.g., Penman and Zhang (2002)).[2] In this study, the degree of accounting conservatism is calculated as the difference between the skewness in earnings and cash flows as in Givoly and Hayn (2000) and Beatty, Weber and Yu (2008). On the other hand, conditional accounting conservatism is news-based, that is, it is characterized by an asymmetric recognition of positive and negative economic news (e.g., Ruch and Taylor (2015)). For example, if a company tests for long-lived asset impairments, any impairment loss has to be recognized immediately although there cannot be any upward revision (e.g., Penman and Zhang (2002)). Conditional accounting conservatism is calculated as the so called C-Score by Khan and Watts (2009), which itself is an extension of the accounting conservatism measure by Basu (1997). This study contributes to the ongoing discussion about the influences of accounting conservatism on equity market participants, more specifically, on the information environment of investors characterized by the earnings forecast reliability. The results of this study extend the findings by Mensah, Song and Ho (2004) and Louis, Lys and Sun (2014). That is, a higher degree of (un-)conditional accounting conservatism prior to the initial forecast is negatively related to the analyst as well as the model-based earnings forecast accuracy and the positively related to the analyst forecast dispersion for forecast horizons of up to three years. Further, the degree of (un-)conditional accounting conservatism prior to the initial forecast exhibits a negative relationship with the analyst forecast bias for forecast horizons of up to three years. That is, (un-)conditional accounting conservatism appears to increase the analyst optimism bias in the initial forecast. The same pattern is reported for model-based earnings forecast bias, although there appears to be no significant relationship between the degree of unconditional accounting conservatism and the two- and three years earnings forecast bias. The results also imply that the effect of conditional conservatism on the earnings forecast reliability is larger than the effect of unconditional conservatism. In addition, the findings of this study imply that analysts did not learn about accounting conservatism, i.e., also in recent years failed to incorporate the implications of (un-)conditional accounting conservatism into their forecasts. The presented results hold for the cross-section

[2]Note that although a LIFO inventory is prohibited under IFRS, it is indeed allowed under GAAP.

of firms. These findings serve as arguments for incorporating information about a firm's degree of (un-)conditional accounting conservatism into an earnings forecast model. However, adding a new predictor variable representing a firm's degree of (un-)conditional accounting conservatism to an earnings forecast model does not improve the forecast accuracy and only leads to a lower forecast bias when adding an unconditional accounting conservatism measure to the forecast model. This is at least partly due to a low persistence, i.e., fluctuations, in a firm's degree of (un-) conditional accounting conservatism from prior to the initial forecast to the period for which the forecast was made. In contrast to the results for the cross-section of all firms, for firms transitioning from a high to a low (low to a high) degree of (un-) conditional conservatism from prior to the initial forecast to the period for which the forecast was made, a decrease (increase) in the analyst forecast bias and an increase (decrease) in the model-based earnings forecast bias is reported. This has implications for analysts as they should not only incorporate information about a firm's degree of accounting conservatism prior to the initial forecast into their forecasts, but further anticipate changes in the degree of accounting conservatism. Likewise, it seems to be insufficient to simply incorporate information about the degree of accounting conservatism at the point of forecasting into earnings forecast models, but it is further important to incorporate information about anticipated changes in the firm-specific degree of accounting conservatism.

The second essay (Chapter 3) examines the relationship between a firm's extent of EM and the respective model-based earnings forecast accuracy.[3] This analysis is structured as follows. First, we examine the relationship between the firm's degree of EM and the model-based earnings forecast accuracy. We calculate discretionary accruals via the modified Jones (1991) model by Dechow, Sloan and Sweeney (1995) and use the absolute discretionary accruals as a measure for the firm's extent of EM (e.g., Frankel, Johnson and Nelson (2002), Klein (2002) and Bergstresser and Philippon (2006), among others). Further, we derive earnings forecasts based on the residual income (RI) earnings forecast model by Li and Mohanram (2014) for up to three years ahead and calculate the price-scaled absolute forecast error (PAFE), which we use as a measure for the respective earnings forecast accuracy. In a later

[3]This chapter is based on the working paper "The Relation Between Earnings Management and Model-Based Earnings Forecasts" (2022) co-authored by Dr. Tim Vater.

part of this study, we show that the results remain the same, if we use the earnings persistence (EP) model by Li and Mohanram (2014) or the earnings model by Hou, Van Dijk and Zhang (HVZ) (2012). Afterwards, we implement an annual cross-sectional regression of the earnings forecast accuracy on an intercept, the degree of EM and some control variables. We find a significant and positive relationship between the extent to which a firm engages in EM and the respective earnings forecast error for all forecast horizons. That is, the results imply that a higher degree of EM is significantly related to less accurate earnings forecasts. More specifically, for one-, two- and three-year ahead earnings forecasts, we find significantly positive average parameter estimates of 0.0204, 0.0189 and 0.018 for the degree of EM, respectively. In a second step, we annually rank firm into quintiles according to their extent of EM thus creating five dummy variables indicating the membership to a specific EM quintile. We then interact the earnings forecast model with the five dummy variables and generate earnings forecasts for forecast horizons of up to three years for the new, extended model. We find that the forecast error significantly decreases compared to the initial RI model underlying the importance of incorporating information about a firm's degree of earnings management into earnings forecast models. For example, the average median (mean) PAFE of the initial model is 3.72% (13.30%), whereas the extended model exhibits a value of 3.18% (11.76%). In the last step of this study we test whether this enhanced forecast accuracy translates to more reliable ICC estimates. For the cross-section of firms, we annually (i) regress realized future returns on the ICCs, and (ii) rank firms into deciles based on the firms' ICCs and implement a long-short-strategy, i.e., we compute the spread between the highest and lowest decile. The results show that the ICCs based on the extended model are more reliable as they exhibit a higher parameter estimate and higher R^2 values in the firm-level tests. Further, the long-short strategy based on the extended model leads to higher returns for holding periods of up to three years ahead. More specifically, for example, for one-year ahead forecasts, the initial model shows an average parameter estimate of 0.1904 and a buy-and-hold return of 10.63%, whereas the extended model exhibits values of 0.2176 and 12.32%, respectively. These findings contribute to the literature by first providing empirical evidence on a significantly negative relationship between a firm's extent of EM and the respective model-based forecast accuracy. Such relationship implies that managers' actions influence the predictability of earnings by an impaired quality of reported earnings. This adds to the debate on managers' incentives for EM and aligns with former research that finds that EM is performed for opportunistic reasons, i.e., to mislead stakeholders for personal gain (e.g., Perry and Williams (1994), Teoh and Wong (2002) and Bergstresser and Philippon (2006)) and not to increase the information content of accounting figures (Beneish (2001)). We further contribute by providing evidence that incorporating information about a firm's degree of earnings management prior to the initial forecast into an earnings forecast model does not only increase the accuracy of such forecasts, but further enhances the reliability of ICCs computed from these earnings forecasts leading to higher investment strategy returns.

The third essay (Chapter 4) compares different earnings variance forecasting approaches in terms of forecast accuracy.[4] First, a new earnings variance forecasting approach is introduced. This approach is based on a suggestion by Konstantinidi and Pope (2016) to regress the squared residuals from a mean earnings forecast model as a proxy for the variance of the respective observation onto some predictor variables and derive out-of-sample earnings variance forecasts. This approach is compared to two existing earnings variance forecasting approaches, which are based on quantile regressions, i.e., the two approaches by Konstantinidi and Pope (2016) and Chang, Monahan, Ouazad and Vasvari (2021). The resulting earnings variance forecasts are highly correlated with Spearman correlations ranging from 0.83 up to 0.96. Afterwards, these forecasts are evaluated via three different evaluation methods. As the realized firm-year earnings variance against which the forecasts can be benchmarked is not observable, all methods use different ways to circumvent this problem. The first evaluation method is motivated by Chang, Monahan, Ouazad and Vasvari (2021) and aggregates the firm-level earnings variance forecasts to industry-level variance forecasts via the law of total variances by Brillinger (1969). As realized industry-level earnings variances can be observed, the industry-level earnings variance forecasts are benchmarked against these by implementing Fama and MacBeth (1973) regressions. The results show that it is indeed possible to accurately forecast future earnings variance as the resulting R^2 values are comparably high ranging from 0.6379 up to 0.6584. More specifically, the newly introduced

[4] This chapter is based on the working paper "Forecasting Earnings Variance: Quantiles-Based Vs. Residuals-Based Approaches" (2024)

squared residuals approach outperforms both quantiles-based approaches, whereas the approach by Chang, Monahan, Ouazad and Vasvari (2021) still outperforms the approach by Konstantinidi and Pope (2016). Subsequently, this study introduces two new firm-level evaluation approaches which are not yet explored in this field. First, a realized firm-level earnings variance proxy is introduced and the accuracy of the firm-level earnings variance forecasts is evaluated by calculating the PAFE as well as the mean squared error (MSE). The results indicate that the quantiles-based approach by Konstantinidi and Pope (2016) leads to the most accurate firm-level earnings variance forecasts with values of 0.0177 and 0.1506, respectively. In order to make the results more robust and not dependent on an approximation of the realized earnings variance, a second firm-level evaluation method is implemented that draws on the idea of prediction intervals and uses these as an evaluation concept (e.g., Bollerslev (1986), Granger, White and Kamstra (1989), Chatfield (1993) and Tay and Wallis (2000)). The results confirm the findings from the first firm-level evaluation, i.e., that the earnings variance forecasts from the quantiles-based approach by Konstantinidi and Pope (2016) leads to the most accurate firm-level earnings variance forecasts. Further, the three evaluations emphasize the importance of the chosen level of aggregation when evaluating earnings variance forecasts. In conclusion, the residuals-based earnings variance forecasts lead to the most accurate forecasts on industry-level, whereas the forecasts based on the approach by Konstantinidi and Pope (2016) outperform the other two approaches on firm-level. Finally, in line with Chang, Monahan, Ouazad and Vasvari (2021), this study shows that all earnings variance forecasts are relevant to equity prices, i.e., equity prices are significantly negatively related to the earnings variance forecasts. That is, equity prices are increasing in the variance of future earnings.

In summary, Chapter 2 contributes by showing that not only the static degree of accounting conservatism of a firm prior to the initial forecast plays a crucial role for the earnings forecast reliability, but changes in the degree of accounting conservatism after the forecasting date as well. This calls for not only incorporating information about a firm's degree of accounting conservatism prior to the initial forecast into the analyst forecasts and earnings forecast models, but further for anticipating changes in the degree of a firm's accounting conservatism when making earnings forecasts.

Chapter 3 contributes by showing that EM prior to the initial forecast is negatively related to the respective forecast accuracy. Incorporating information about a firm's extent of EM into an earnings forecast model does not only increase the forecast accuracy, but further the reliability of the resulting ICCs. Chapter 4 contributes to forecasting the second moment of future earnings by (i) introducing a new earnings variance forecasting approach based on squared residuals and (ii) introducing two firm-level evaluation methods regarding the forecast accuracy of earnings variance forecasts, which were not yet explored in that field. Further, chapter 4 shows that a residuals-based earnings variance forecasting approach is best suited when forecasting industry-level earnings variance and the approach by Konstantinidi and Pope (2016) is best suited when forecasting firm-level earnings variance underlining the importance of the level of aggregation when evaluating earnings variance forecasts.

Chapter 2

Accounting Conservatism and the Reliability of Earnings Forecasts

2.1 Introduction

There is an ongoing debate about the benefits and disadvantages of accounting conservatism. The philosophy behind accounting conservatism is commonly stated as: "anticipate no profits and provide for all probable losses" (e.g., Bliss (1924)). Thus, accounting conservatism refers to accounting principles that keep book values of net assets relatively low (e.g., Penman and Zhang (2002)). There exist two forms of accounting conservatism, i.e., unconditional and conditional conservatism (e.g., Ruch and Taylor (2015) and Chen, Folsom, Paek and Sami (2014)). Unconditional conservatism refers to a constant under-recognition of accounting net assets (e.g., Ruch and Taylor (2015)). For example, implementing a LIFO inventory instead of a FIFO approach is considered to be a conservative accounting choice (e.g., Penman and Zhang (2002)). That is, under LIFO, the most recent inventory purchased is assumed to be sold first and the cost of goods sold (COGS) are calculated on the basis of the most recent inventory purchases, which, in a period of rising prices, are higher. Thus, LIFO is considered to be more conservative as the reported profit is lower due to higher COGS in times of rising prices in comparison to FIFO. Another example for unconditional conservatism are research & development ($R\&D$) expenditures. Whereas $R\&D$ usually lead to higher sales in future periods, no gain can be matched to the current $R\&D$ expenditures as it is prohibited to capitalize the $R\&D$ expenses. Conditional conservatism is characterized by the asymmetric recognition of positive and negative economic news (e.g., Ruch and Taylor (2015)). For example, if a company tests for impairment of a long-lived asset or goodwill, accounting conservatism requires any impairment loss to be recognized immediately, whereas there cannot be any upward revision.[1] Thus, the main difference between the two forms of accounting conservatism is that conditional conservatism depends on economic news (e.g., goodwill or long-lived asset impairment test), whereas unconditional conservatism does not (e.g., LIFO inventory or accelerated depreciation). In both cases, accounting conservatism creates "hidden reserves" by the deferral of gains to a later period (Penman and Zhang (2002)). In general, under unconditional accounting conservatism, a firm has the ability to actively create and release reserves, whereas the uncertainty paired with the news-based character of conditional accounting conservatism makes it more difficult for managers to rely on the accounting of news events in order to meet an earnings target (e.g., Ruch and Taylor (2015)).

The discussion about the consequences of accounting conservatism stems from opposing viewpoints of different stakeholders of a company. On the one hand, lenders to a company see the role of accounting from a "contracting perspective". The general notion in the literature is that the demand for accounting conservatism mainly stems from debt market participants (e.g., Watts (2003), Ball, Robin and Sadka (2008) and Gigler, Kanodia, Sapra and Venugopalan (2009)). Due to the asymmetric payoff, the lender is more concerned with a weak financial performance, which increases the risk of default, than with a strong financial performance, which in turn does not increase the payoff for the lender. Thus, the lender demands bad news to be reported in a timelier manner than good news (e.g., Watts (2003), Ball, Robin and Sadka (2008), Gigler, Kanodia, Sapra and Venugopalan (2009) and Ruch and Taylor (2015)). As a timelier recognition of losses results in an earlier violation of debt covenants and thus in an earlier opportunity for the debt holders to exercise their contractual rights, e.g., to restrict the actions of managers, it is argued that the efficiency of debt contracting is enhanced by conservative accounting practices (e.g., Gigler, Kanodia, Sapra and Venugopalan (2009) and Ruch and Taylor (2015)). Watts (2003) claims that conditional conservatism enhances the information quality for lenders as the asymmetric timeliness in the recognition of losses and gains pro-

[1] In this scenario, economic news refers to a test outcome where the assets' carrying value exceeds or is smaller than their recoverable amount.

vides lenders with more relevant information. Likewise, unconditional conservatism creates accounting numbers that reflect some "worst-case scenario" helping lenders to assess the risk of default. For example, Ahmed, Billings, Morton and Stanford-Harris (2002) find that unconditional as well as conditional conservatism reduces the bondholder–shareholder conflict and the cost of debt capital. Further, Zhang (2008) finds accounting conservatism to reduce the cost of debt capital and to enhance the identification of default risk. Wittenberg-Moerman (2008) find conditional conservatism to enhance debt trading efficiency by reducing information asymmetry. Further, Basu (1997) as well as Watts (2003) claim that even in a scenario where accounting is not be regulated, conservatism would arise as a natural consequence of an efficient contracting mechanism in order to reduce information asymmetry. However, Gigler, Kanodia, Sapra and Venugopalan (2009) claim that accounting conservatism has two opposing effects. That is, accounting conservatism decreases the probability of undue optimism, but increases the probability of a false alarm. Under those conditions, Gigler, Kanodia, Sapra and Venugopalan (2009) as well as Guay and Verrecchia (2006) find that conservatism leads to inefficient decision-making in contracting environments due to biased financial statements numbers.

On the other hand, investors see the role of accounting from a "valuation perspective" and require accounting numbers to reflect unbiased information that can be used to derive the market value of an investment and make investment decisions (Ruch and Taylor (2015)). For example, accounting conservatism is found to have a negative effect on earnings persistence and predictability (e.g., Basu (1997), Kim and Kross (2005), Dichev and Tang (2008), Bandyopadhyay, Chen, Huang and Jha (2010) and Chen, Folsom, Paek and Sami (2014)). Studies regarding the relationship of accounting conservatism and value relevance, i.e., the predictive power of accounting numbers for market returns, report mixed results. Some studies show that accounting conservatism reduces the value relevance of earnings as it results in biased financial statements (e.g., Collins, Maydew and Weiss (1997) and Lev and Zarowin (1999)), whereas other studies cannot find any evidence for such relationship (e.g., Francis and Schipper (1999) and Balachandran and Mohanram (2011)). Likewise, according to Feltham and Ohlson (1995) accounting policies do not alter the cash flows of the firm and thus should not affect its market value, whereas

Monahan (2005) states that the downward bias in accounting figures caused by conservative accounting practices leads to lower expectations for future earnings and thus a lower valuation. Similarly mixed is the evidence on the relationship between accounting conservatism and the cost of equity. That is, Francis, LaFond, Olsson and Schipper (2004) do not find any, Chan, Lin and Strong (2009) find a positive and García Lara, García Osma and Penalva (2011) a negative relationship between accounting conservatism and the cost of equity capital. Nevertheless, it is well documented that accounting conservatism increases the information asymmetry as information are withheld from investors (e.g., Francis, Hasan and Wu (2013), Kim, Li, Pan and Zuo (2013) and Ruch and Taylor (2015)). LaFond and Watts (2008) claim information asymmetry to induce conditional conservatism. Further, some studies document the relationship between accounting conservatism and analyst earnings forecasts. Pae and Thornton (2010) find that analysts fail to incorporate the implications of accounting conservatism into their forecasts and Helbok and Walker (2004) claim that the optimism bias in analyst forecasts results from analysts not anticipating accounting conservatism in between the initial forecast and the earnings announcement date. Mensah, Song and Ho (2004) find unconditional accounting conservatism to be negatively related to the analyst earnings forecast accuracy and positively related to the analyst earnings forecast dispersion. Their results regarding conditional conservatism are mixed. Louis, Lys and Sun (2014) find conditional accounting conservatism prior to the initial forecast to increase the optimism bias in analyst earnings forecasts. The focus of this study lies on the "valuation perspective" as it investigates the relationship between the firm-year degree of accounting conservatism and the information environment of investors, i.e., the earnings forecasts reliability of both analysts and models.[2] To the extent that analysts' or model-based earnings forecasts are economically relevant to the capital markets, any systematic relationship between the degree of accounting conservatism of a company and the respective earnings forecasts implies that accounting policies have economic relevance.

As a part of the information environment of investors, next to analyst forecasts, which suffer from optimism (O'Brien (1988)) and insufficient coverage (La Porta

[2] Earnings forecast reliability refers to the different characteristics of a forecast, such as accuracy, bias or analyst forecast dispersion.

(1996)), earnings forecast models gained a lot of popularity in the last decade. Most of the earnings forecast models employ a cross-sectional approach and thus, by design, are superior to analyst-based earnings forecasts in terms of coverage (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)). Extensive research has been conducted on forecasting future earnings (e.g., Hou, Van Dijk and Zhang (2012), Li and Mohanram (2014), Ohlson and Kim (2015), Konstantinidi and Pope (2016), Evans, Njoroge and Yong (2017), Cao and You (2024), Tian, Yim and Newton (2021), Chang, Monahan, Ouazad and Vasvari (2021), Hansen and Thimsen (2021), Chen, Cho, Dou and Lev (2022), Hendriock (2022), Van Binsbergen, Han and Lopez-Lira (2023) and Campbell, Ham, Lu and Wood (2023)). Traditional earnings forecast models use a large sample of current fundamentals data to predict future earnings via a linear cross-sectional approach (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)). Of these traditional mean earnings forecast models the RI model is typically found to perform best in terms of forecast accuracy (e.g., Li and Mohanram (2014)). Numerous methodological alternatives have been introduced: Evans, Njoroge and Yong (2017) as well as Tian, Yim and Newton (2021) implement a least absolute squares regression, i.e., a median regression and improve the model-based forecast performance. Konstantinidi and Pope (2016) and Chang, Monahan, Ouazad and Vasvari (2021) implement a quantile regression approach. Recently, machine learning techniques gained traction in the field of earnings forecast models as they are able to incorporate large numbers of predictor variables and are not restricted to a linear functional form (e.g., Cao and You (2024), Hansen and Thimsen (2021), Chen, Cho, Dou and Lev (2022), Hendriock (2022), Van Binsbergen, Han and Lopez-Lira (2023) and Campbell, Ham, Lu and Wood (2023)). However, the improvement of machine learning models compared to conventional linear forecast models is only moderate. For example, Hansen and Thimsen (2021) and Cao and You (2024) report only an average improvement of less than 7% in terms of forecast accuracy for one-year ahead forecasts.

This study aims aims to contribute to the ongoing discussion about the influences of accounting conservatism on equity market participants, more specifically, on the information environment of investors, characterized by the reliability of earnings forecasts, in three ways. Whereas Mensah, Song and Ho (2004) only investigate the effects of (un-)conditional accounting conservatism on the analyst forecast accuracy and the analyst forecast dispersion and Louis, Lys and Sun (2014) analyze the effects of conditional conservatism on the initial analyst forecast bias, this study aims to implement a more complete analysis. That is, first, the effect of both unconditional as well as conditional conservatism on the forecast accuracy and bias for both analyst and model-based earnings forecasts as well as on the analyst earnings forecast dispersion will be investigated and the analysis will be extended to forecasting periods up to three years ahead. Conditionally conservative earnings are found to be even less persistent and less predictable than unconditionally conservative earnings (Chen, Folsom, Paek and Sami (2014)). Further, the news-based character of conditional accounting conservatism induces a higher degree of uncertainty in comparison to the more long-term oriented accounting principles associated with unconditional conservatism. Thus, second, this study investigates whether unconditional or conditional conservatism affects the earnings forecast reliability stronger. Third, this study introduces a new viewpoint on the effects of accounting conservatism. That is, Mensah, Song and Ho (2004) and Louis, Lys and Sun (2014) analyze the effect of accounting conservatism prior to the initial forecast on the accuracy and bias of the forecast. However, this static analysis omits the effects of changes in the degree of accounting conservatism after the initial forecast was made. That is, not only the degree of accounting conservatism prior to the initial forecast has an influence on the forecast reliability, but changes in the degree of accounting conservatism after the initial forecast as well. A firm with a high degree of accounting conservatism prior to the initial forecast might build up even more hidden reserves through a continuously high degree of conservatism after the initial forecast or release hidden reserves through a lower degree of conservatism after the initial forecast. On the other hand, a firm with a low degree of accounting conservatism prior to the initial forecast might build up hidden reserves in the period for which the forecast was made, i.e., the firm might change from a low to a high degree of accounting conservatism. Such changes in the degree of accounting conservatism have an additional influence on the earnings forecast reliability and thus will be analyzed in addition to static the degree of accounting conservatism prior to the initial forecast.

First, the results of this study align with the findings by Mensah, Song and Ho (2004) as well as Louis, Lys and Sun (2014). In general, a higher degree of (un-)conditional accounting conservatism in the period prior to the initial forecast is negatively related to the analyst as well as the model-based earnings forecast accuracy and the positively related to the analyst forecast dispersion for forecasting periods up to three years ahead. Further, the degree of (un-)conditional accounting conservatism prior to the initial forecast exhibits a negative relationship with the analyst forecast bias for forecasting periods up to three years ahead. That is, (un-)conditional accounting conservatism appears to increase the analyst optimism bias in the initial forecast. The same pattern is reported for model-based earnings forecast bias, although there appears to be no significant relationship between the degree of unconditional accounting conservatism and the two- and three years earnings forecast bias. The results of this first analysis display a congruent pattern. Accounting conservatism leads to biased financial statements numbers (Ruch and Taylor (2015)) and creates hidden reserves which can be released in latter periods and cause a temporary distortion of operating performance which leads to less predictable earnings (Penman and Zhang (2002)). This is reflected in a negative relationship between the degree of (un-)conditional accounting conservatism and the earnings forecast accuracy for both models and analysts. If analysts do not only differ in their interpretation of the financial statements, but additionally in their anticipation of management's accounting principles, such additional interpretative dimension introduced by the presence of accounting conservatism leads to a higher forecast dispersion (Mensah, Song and Ho (2004)). Such relationship is found in the positive relationship between the degree of (un-)conditional accounting conservatism and the analyst forecast dispersion for forecasting periods up to three years ahead. If companies are growing, the earnings reducing effect of conservatism of the current period is likely to be larger than the reversal effect in the current period of the past conservatism, so that reported earnings are smaller than under neutral accounting. If information about accounting conservatism are not incorporated in the forecasts, the resulting forecasts are expected to be too large on average (Louis, Lys and Sun (2014)). Such a pattern is found in the negative relationship between the degree of (un-)conditional accounting conservatism and the earnings forecast bias, although the relationship between unconditional conservatism and two- and three year model-based forecasts is not significant. Thus, first, this study extends the existing analyses by Mensah, Song and Ho (2004) and Louis, Lys and Sun (2014) and finds their results to hold for both unconditional and conditional conservatism. This study is the first to analyze the effect of (un-)conditional accounting conservatism on model-based earnings forecasts and finds these forecasts to exhibit the same relationship with (un-)conditional accounting conservatism prior to the initial forecast as analyst earnings forecasts. Additionally, this study finds the effect of conditional conservatism to affect the earnings forecasts to a larger extent compared to unconditional conservatism. This aligns with Chen, Folsom, Paek and Sami (2014) who state that conditionally conservative earnings are even less persistent than unconditionally conservative earnings and thus more difficult to forecast. The results of a subsample analysis, i.e., of splitting the sample in three different ten year windows, imply that analysts did not learn about accounting conservatism, that is, did not start to incorporate information about accounting conservatism into their forecasts. These findings regarding the relationship between accounting conservatism and model-based earnings reliability measures serve as arguments for incorporating information about a firm's degree of (un-)conditional accounting conservatism into an earnings forecast model.[3] However, adding a new predictor variable representing a firm's degree of (un-)conditional accounting conservatism into an earnings forecast model at best only moderately improves the earnings forecast reliability. This is at least partly due to a low persistence, i.e., fluctuations, in a firm's degree of (un-) conditional accounting conservatism from prior to the initial forecast to the period for which the forecast was made.

In a second step, the influence of changes in the degree of accounting conservatism from the period prior to the initial forecast to the period for which the forecast was made, i.e., whether a firm releases or further creates hidden reserves,

[3]This study aims to demonstrate the importance of incorporating information about a firm's extent of (un-)conditional accounting conservatism into earnings forecast models by showing that doing so improves the forecast reliability. To do so, a simple OLS earnings forecast model, i.e., the RI model by Li and Mohanram (2014), instead of, for example, a more complex machine learning approach is used. However, if the information captured by the accounting conservatism variable are relevant for earnings forecast models, such variable might also be included in more complex forecasting models such as machine learning approaches. For example, Hess, Simon and Weibels (2024) use a large set of predictor variables to predict future earnings using machine learning techniques, but do not include information about a firm's extent of (un-)conditional accounting conservatism.

on the earnings forecast bias is investigated. The release (creation) of the hidden reserves created by accounting conservatism, i.e., represented by a transition from a high to a low (low to a high) degree of accounting conservatism, embodies a positive (negative) earnings surprise, if models and analysts do not anticipate changes in accounting conservatism.

The rationale behind that analysis reads as follows: According to the findings from the analysis by Louis, Lys and Sun (2014), a firm that exhibits a high degree of accounting conservatism is expected to exhibit an increased analyst optimism bias. However, taking changes in the degree of accounting conservatism after the initial forecast date into account, as analysts are overly optimistic, a release (creation) of hidden reserves after the initial forecast date, i.e., a positive (negative) earnings surprise, is actually expected to decrease (increase) the analyst optimism bias. In contrast, as models tend to underestimate future earnings, a release (creation) of hidden reserves after the initial forecast date, i.e., a positive (negative) earnings surprise, is actually expected to increase (decrease) the forecast bias. The opposite relationship is expected to hold for firms exhibiting a low degree of conservatism prior to the initial forecast, which then increase (decrease) their hidden reserves subsequently, i.e., exhibit an increased (decreased) degree of conservatism in their accounting. This study is the first to analyze the effects of such changes in the degree of accounting conservatism on the earnings forecast bias.

The results of this analysis imply that firms do indeed vary in their degree of (un-)conditional accounting conservatism. More specifically, around 27% of companies transition from a high to a low or a low to a high degree of conditional accounting conservatism from one period to the next, whereas around 16% of companies transition from a high to a low or a low to a high degree of unconditional accounting conservatism from one period to the next. As conditional conservatism is news-based and unconditional conservatism is related to general accounting principles in a firm, a higher fluctuation of firms regarding the degree of conditional conservatism compared to unconditional conservatism appears to be reasonable. Although the differences in the degree of accounting conservatism between industries are comparably small, according to the unconditional as well as conditional conservatism measure, the drugs industry is found to be the most conservative industry. With regard to the business model in the drugs industry, which is heavily conservative through research and development expenses being recognized much prior to the recognition of gains from selling the resulting drugs, the conservatism measures applied in this study seem to be able to reliably identify conservative accounting firms. Finally, in comparison to the full sample, for firms transitioning from a high to a low (low to a high) degree of (un-) conditional conservatism, a decrease (increase) in the analyst forecast bias and an increase (decrease) in the model-based earnings forecast bias is reported. Although the degree of accounting conservatism in the period for which the forecast is made is not observable at the time of forecasting, the results of this analysis add to the understanding of the consequences of accounting conservatism on analyst and model-based earnings forecasts, which form part of the investors' information environment. More specifically, for assessing the effect of accounting conservatism on the earnings forecast reliability, it is not only important to analyze the accounting conservatism prior, but further to anticipate changes in the degree of accounting conservatism after the initial forecast. Whereas accounting conservatism prior to the initial forecast has similar effects on earnings forecasts from both analysts and models, the forecast bias of analysts and models is affected differently by changes in the degree of accounting conservatism after the initial forecast date. Thus, the results of this study imply that it is additionally important to understand and anticipate the firm-specific variation of the degree of accounting conservatism in addition to the degree of accounting conservatism prior the initial forecast in order to evaluate the effects of accounting conservatism on the earnings forecast reliability of both analysts and models.

The remainder of this study is organized as follows. Section 2.2 explains the methodology, data is described in section 2.3, section 2.4 presents the empirical results and section 2.5 concludes.

2.2 Methodology

Mensah, Song and Ho (2004) were the first to relate accounting conservatism to the analyst forecast accuracy and dispersion. In addition, Louis, Lys and Sun (2014) investigate the relationship between a measure of conditional conservatism and the analyst forecast bias. This study extends the scope of both studies and assesses the relationship between (un-)conditional conservatism with both analyst and model-based earnings forecast accuracy and bias as well as the analyst forecast dispersion.

During the first step of this study, model-based firm-year earnings forecasts will be derived and the firm-year degree of (un-)conditional accounting conservatism is calculated. Afterwards, earnings forecast reliability measures such as both model-based and analyst forecast accuracy and bias as well as analyst dispersion will be calculated. Then the relationship between these measures and the firm-year degree of (un-)conditional accounting conservatism prior to the initial forecast will be analyzed. If such relationships are found to be statistically significant, they provide an argument for incorporating information about (un-)conditional accounting conservatism into an earnings forecast model, e.g., extending an earnings forecast model with an additional predictor variable representing the firm's degree of (un-)conditional accounting conservatism. A better earnings forecast reliability for such extended model underlines the importance of incorporating information about (un-)conditional accounting conservatism into an earnings forecast model. Afterwards, the magnitude in the influence of unconditional conservatism on earnings forecast reliability measures and conditional conservatism will be compared. Further, it will be studied whether analysts learned about accounting conservatism over the years and started to incorporate information about accounting conservatism into their forecasts. Finally, the persistence of a firm's degree of (un-)conditional accounting conservatism will be examined. Subsequently, the effects of changes in the degree of (un-)conditional accounting conservatism, i.e., the effect of firms transitioning from either a high to a low or a low to a high degree of accounting conservatism prior and after the initial forecast date, on the earnings forecast reliability will be studied.

2.2.1 Model-Based Earnings Forecasts

Model-based earnings forecasts for up to three periods ahead are derived via the RI model by Li and Mohanram (2014). There are more modern and sophisticated approaches to implement an earnings forecast model with techniques such as median regression, quantile regression or machine learning models being the latest improvement (e.g., Ohlson and Kim (2015), Konstantinidi and Pope (2016), Evans, Njoroge and Yong (2017), Cao and You (2024), Tian, Yim and Newton (2021), Chang, Monahan, Ouazad and Vasvari (2021), Cao and You (2024), Hansen and Thimsen (2021), Chen, Cho, Dou and Lev (2022), Hendriock (2022), Van Binsbergen, Han and Lopez-Lira (2023) and Campbell, Ham, Lu and Wood (2023)). However, Hess, Simon and Weibels (2024) show that even more sophisticated machine learning models are heavily based on earnings persistence, similar to the simple RI model by Li and Mohanram (2014). As this feature is the most crucial with regards to the chosen forecast model in this study, a simple ordinary least square (OLS) forecasting approach based on the RI model by Li and Mohanram (2014) is implemented, although the results should also hold for machine learning approaches. Thus, the following model is estimated via a rolling window OLS regression with a window length of ten years for $\tau = 1$ to 3:

$$\begin{aligned} Earn_{i,t+\tau} = \beta_0 + \beta_1 Earn_{i,t} + \beta_2 d^-_{i,t} + \beta_3 d^- Earn_{i,t} \\ + \beta_4 BkEq_{i,t} + \beta_5 TACC_{i,t} + \epsilon_{i,t+\tau}, \end{aligned} \tag{2.1}$$

where $Earn$ reflects earnings, d^- is an indicator variable equal to one if $Earn_{i,t} < 0$ and zero otherwise, $d^- Earn$ is an interaction term of the dummy variable d^- and $Earn$, $BkEq$ is the book-value of equity, $TACC$ reflects total accruals, t represents the time index, τ is a time constant and ϵ is the error term. In line with Li and Mohanram (2014), earnings are defined as earnings before extraordinary items minus special items. Further, if not stated otherwise, the analysis in this study is based on per-share measures for which all variables are scaled by common shares outstanding. A detailed explanation of the calculation of all variables used in this chapter follows in the appendix to chapter 2.

The main focus of this study lies on evaluating the effect of (un-)conditional accounting conservatism on earnings forecast reliability measures such as forecast accuracy, bias or analyst forecast dispersion. To evaluate the forecast accuracy of the above model as well as of analysts, the PAFE is calculated (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)):

$$PAFE_{i,t+\tau} = \left| \frac{Earn_{i,t+\tau} - \widehat{Earn}_{i,t+\tau}}{prc_{i,t}} \right|, \tag{2.2}$$

where $\widehat{Earn}$ is the respective earnings forecast and prc is the end-of-June stock price.

Further, the forecast bias is calculated as the price-scaled forecast error (PFE) (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)):

$$PFE_{i,t+\tau} = \frac{Earn_{i,t+\tau} - \widehat{Earn}_{i,t+\tau}}{prc_{i,t}}. \tag{2.3}$$

The last measure that will be related to the firms' degree of accounting conservatism is the analyst earnings forecast dispersion, which is calculated as the standard deviation of analysts' earnings forecasts scaled by the end-of-June stock price (Mensah, Song and Ho (2004)):

$$Disp_{i,t} = \frac{Std(\widehat{Earn}_{i,t+\tau})}{prc_{i,t}}. \tag{2.4}$$

2.2.2 Accounting Conservatism

In the following, the measure used to proxy the firms' degree of (un-)conditional accounting conservatism, will be explained. The degree of unconditional conservatism is proxied by the difference between the skewness of cash flows and earnings as suggested by Givoly and Hayn (2000) and Beatty, Weber and Yu (2008), whereas the so-called $C - Score$ by Khan and Watts (2009), which is based on the conservatism measure by Basu (1997), is used as the proxy for the degree of conditional conservatism. Chen, Folsom, Paek and Sami (2014) examine the effect of both conditional and unconditional accounting conservatism on earnings persistence and the stock market's valuation of earnings. They establish a consistent framework for the calculation of the conservatism measures based on the former independent studies by Basu (1997), Khan and Watts (2009), Givoly and Hayn (2000) and Beatty, Weber and Yu (2008). Thus, the calculation of the conservatism measures in this study follows Chen, Folsom, Paek and Sami (2014).[4] In this study, similar to Louis,

[4] The calculation of the unconditional conservatism measures by Givoly and Hayn (2000) and Beatty, Weber and Yu (2008) and the conditional conservatism measure by Khan and Watts (2009) is almost identical to the calculation used by Chen, Folsom, Paek and Sami (2014).

Lys and Sun (2014) and Chen, Folsom, Paek and Sami (2014), both conservatism measures are ranked annually into deciles.[5]

Conditional Conservatism

The most prominent measure for conditional accounting conservatism is the so-called $C - Score$ by Khan and Watts (2009), which is based on the conservatism measure by Basu (1997) (e.g., Ball, Kothari and Robin (2000), Pae, Thornton and Welker (2005), Ruddock, Taylor and Taylor (2006) and Ahmed and Duellman (2013)). Whereas the measure by Basu (1997) can only be calculated for an industry or a time-series of a firm, the changes made by Khan and Watts (2009) allow for a computation of a firm-year conservatism measure. Ball, Kothari and Nikolaev (2013) and Ettredge, Huang and Zhang (2012) argue that this measure is the best proxy for conditional conservatism. The measure is based on the idea that under conditionally conservative accounting practices bad news are recognized more timely than good news. It functions as an asymmetric earnings-timeliness measure by running a reverse regression of return on market equity on same-year annual stock returns. If earnings are conditionally conservative, a stronger relationship between the return on market equity and negative stock returns in comparison to positive stock returns is expected. In a first step the following regression is estimated annually:

$$\begin{aligned}
RoE^C_{i,t} = \alpha_0 &+ \alpha_1 DR^-_{i,t} \\
&+ R_{i,t}(\beta_0 + \beta_1 Size_{i,t} + \beta_2 MB_{i,t} + \beta_3 LEV_{i,t}) \\
&+ DR^-_{i,t} R_{i,t}(\chi_0 + \chi_1 Size_{i,t} + \chi_2 MB_{i,t} + \chi_3 LEV_{i,t}) \\
&+ (\delta_1 Size_{i,t} + \delta_2 MB_{i,t} + \delta_3 LEV_{i,t} \\
&+ \delta_4 DR_{i,t} Size_{i,t} + \delta_5 DR_{i,t} MB_{i,t} + \delta_6 DR_{i,t} LEV_{i,t}) \\
&+ \epsilon_{i,t},
\end{aligned} \tag{2.5}$$

and the conditional conservatism measure $CCon$ is the calculated as:

$$CCon_{i,t} = \chi_0 + \chi_1 Size_{i,t} + \chi_2 MB_{i,t} + \chi_3 LEV_{i,t}. \tag{2.6}$$

[5] In untabulated results, ranking the conservatism measures into percentiles or using the raw, but winsorized measures was tested. The results remain unchanged. As a comparison between the magnitude of the influence of conditional and unconditional conservatism on the earnings forecast reliability will be drawn throughout this study, a standardized version of the conservatism measures is beneficial. Thus, following Louis, Lys and Sun (2014) and Chen, Folsom, Paek and Sami (2014), annually decile-ranked accounting conservatism measures are applied.

RoE^C reflects earnings per share divided by the one-year lagged stock price, i.e., the return on market equity, R is the annual stock return compounded from monthly returns starting nine months before the end of fiscal year t and ending three months after, DR^- is a negative return dummy variable equal to one for firm-year observations with negative return R and zero otherwise, $Size$ is calculated as the natural logarithm of total assets, MB is the market-to-book ratio and LEV is the ratio of total liabilities to total assets. In line with Louis, Lys and Sun (2014) and Chen, Folsom, Paek and Sami (2014) the measure used for the following regression tests is the annually ranked decile ($RCCon$) of the firm's degree of conditional conservatism.

Unconditional Conservatism

Unconditional accounting conservatism is defined as a constant under-recognition of net assets (e.g., Chen, Folsom, Paek and Sami (2014) and Ruch and Taylor (2015)). In this study, the degree of a firm's unconditional accounting conservatism is proxied by the difference between the skewness of cash flows and earnings as suggested by Givoly and Hayn (2000) and Beatty, Weber and Yu (2008). The idea is that constant under-recognition of net assets would result in a negatively skewed earnings distribution, but not affect the cash flow skewness, so that larger differences between earnings and cash flow skewness imply a larger degree of unconditional accounting conservatism. For example, when inventory is purchased, the purchase price is directly paid and once it is sold, the selling price is collected. However, under LIFO inventory, the COGS are not necessarily equal to the purchase price, but equal the purchase price of the last item put on inventory, which in times of rising price is higher than the original purchasing price leading to lower reported profits. Thus, the LIFO method results in skewed earnings, but does not affect the skewness of the cash flow. In line with Beatty, Weber and Yu (2008), quarterly data is used to measure cash flow ($OCFQ$) and earnings ($EarnQ$) skewness. More specifically, a maximum of 20 and a minimum of 5 previous quarters is required to estimate the respective measure. The unconditional conservatism measure $UCon$ is then calculated as the difference between the cash flow and earnings skewness:

$$UCon_{i,t} = Skew(OCFQ_{i,t}) - Skew(EarnQ_{i,t}). \tag{2.7}$$

In line with Chen, Folsom, Paek and Sami (2014) and Louis, Lys and Sun (2014) the measure used for the following regression tests is the annually ranked decile ($RUCon$) of the firm's degree of unconditional conservatism.

2.2.3 The Relationship Between Accounting Conservatism and Earnings Forecast Reliability

After establishing measures that reflect the firm-year earnings forecast reliability and the degree of firm-year (un-)conditional accounting conservatism, in the following, the framework for investigating the relationship between these two concepts will be elaborated. Mensah, Song and Ho (2004) investigate the relationship between accounting conservatism prior to the initial forecast and analysts' earnings forecast accuracy and dispersion, whereas Louis, Lys and Sun (2014) analyze the relationship between conditional conservatism prior to the initial forecast and the analyst forecast bias. In this study a similar approach will be implemented. That is, the five forecast reliability measures ($FrcRel$) reflecting the forecast accuracy ($PAFE_M$ and $PAFE_A$) and bias (PFE_M and PFE_A) each for the RI model and analysts as well as the analyst forecast dispersion ($Disp_A$) in year $t+\tau$ will be independently regressed onto the two different conservatism concepts ($Conservatism$) and some control variables ($Control$) in year t.[6] That is, the following decile-rank regression as in Louis, Lys and Sun (2014) and Chen, Folsom, Paek and Sami (2014) is implemented for $\tau = 1$ to 3:

$$FrcRel_{i,t+\tau} = \beta_0 + \beta_1 Conservatism_{i,t} + \sum_n \beta_n Control_{n,i,t} + \epsilon_{i,t}. \qquad (2.8)$$

Chen, Folsom, Paek and Sami (2014) state that conditionally conservative earnings are even less persistent than unconditionally conservative earnings and thus more difficult to forecast. In a second analysis, the magnitude of the influence of conditional conservatism prior to the initial forecast will be compared to the magnitude of the influence of unconditional conservatism prior to the initial forecast.

[6] Using the estimated conservatism measures as independent variables potentially induces an "error-in-variables" bias. That is, the regression coefficient of the conservatism measure might be biased towards zero (Griliches and Ringstad (1970)). Hence, the empirical results might understate the true effect of conservatism on the earnings forecast reliability measures. However, an even higher true effect does not change the interpretation of the results.

Thus, the five different earnings reliability measures will be independently regressed onto an intercept, both conservatism rank measures and control variables leading to the following estimation equation, which will be estimated for $\tau = 1$ to 3:

$$FrcRel_{i,t+\tau} = \beta_0 + \beta_1 RCCon_{i,t} + \beta_2 RUCon_{i,t} + \sum_n \beta_n Control_{n,i,t} + \epsilon_{i,t}. \quad (2.9)$$

Afterwards, the parameter estimates for conditional as well as unconditional conservatism can be compared with each other.

Expectations

The expectations for the signs of the conservatism parameter estimate are the same for both unconditional as well as conditional conservatism. Accounting conservatism creates hidden reserves that can be released in later periods making earnings less persistent and less predictable (Penman and Zhang (2002)). Thus, a negative relationship of the degree of accounting conservatism prior to the initial forecast and the forecast accuracy for both analyst and model-based earnings forecasts is expected. Further, if analysts do not only differ in their interpretation of financial statements, but additionally in their anticipation of management's accounting principles, a higher analyst forecast dispersion for high conservatism firms is expected (Mensah, Song and Ho (2004)). If companies are growing, the earnings reducing effect of conservatism of the current period is likely to be larger than the reversal effect in the current period of the past conservatism, so that reported earnings are smaller than under neutral accounting. If information about accounting conservatism are not incorporated in the forecasts, the resulting forecasts are expected to be too large on average (Louis, Lys and Sun (2014)). Thus, a negative relationship between the degree of accounting conservatism prior to the initial forecast and the earnings forecast bias for both analyst and model-based forecasts is expected.

Chen, Folsom, Paek and Sami (2014) state that conditionally conservative earnings are even less persistent than unconditionally conservative earnings. This might translate to the earnings forecast reliability. Further, the higher uncertainty associated with the news-based character of conditional conservatism compared to unconditional conservatism further suggests a larger influence on the earnings forecast reliability. Thus, regarding the second analysis, i.e., the comparison between the magnitude of the influence of conditional and unconditional conservatism on earnings forecast reliability measures, a larger influence of conditional conservatism is expected.

2.2.4 Incorporating Accounting Conservatism Into Earnings Forecast Models

If the expectations regarding the relationship between the degree of (un-)conditional accounting conservatism and the model-based earnings forecast reliability measures are found to be statistically significant, such relationship provides an argument for incorporating information about the firm's degree of (un-)conditional accounting conservatism into the earnings forecast model. Thus, in the next step, the RI model by Li and Mohanram (2014) will be extended once with the measure $RCCon$ and once with the measure $RUCon$, both representing the degree of conditional and unconditional accounting conservatism prior to the initial forecast, respectively. That is, the following model will be estimated, out-of-sample forecasts will be computed and both forecast reliability measures PAFE and PFE will be derived. Afterwards, the measures for both extended models will be compared to the original RI model by Li and Mohanram (2014). Thus, the following model is estimated via a rolling window OLS regression with a window length of ten years for $\tau = 1$ to 3:

$$\begin{aligned} Earn_{i,t+\tau} = \beta_0 + \beta_1 Earn_{i,t} + \beta_2 d^-_{i,t} + \beta_3 d^- Earn_{i,t} \\ + \beta_4 BkEq_{i,t} + \beta_5 TACC_{i,t} + \beta_6 Conservatism_{i,t} + \epsilon_{i,t+\tau}, \end{aligned} \tag{2.10}$$

where $Conservatism$ is a placeholder for both measures $RCCon$ and $RUCon$, which will be added to the model independently.

2.2.5 The Relationship Between Changes In Accounting Conservatism and Earnings Forecast Reliability

Finally, this study introduces another dimension regarding which the influence of the firm-year degree of accounting conservatism on earnings forecast reliability is investigated. That is, instead of an isolated analysis of the degree of accounting conservatism prior to the initial forecast on the earnings bias, this study further analyzes the effects of firms changing from a high to a low degree of accounting conservatism and vice versa. That is, two subsamples are formed, i.e., one for firms transitioning from a high degree of accounting conservatism prior to the initial forecast to a low degree in the period for which the forecast was made and one for firms transitioning from a low degree of accounting conservatism prior to the initial forecast to a high degree in the period for which the forecast was made. Such a transition is used as an indicator for the release (high-to-low) or the additional creation (low-to-high) of hidden reserves.[7] This analysis focuses exclusively on the earnings forecast bias of both analyst and models as the release (creation) of hidden reserves leads to systematically higher (lower) reported future earnings. Such systematic increase or decrease and its effect on the forecast reliability is captured by the earnings forecast bias, whereas the forecast accuracy describes the entirety of deviations from the optimal forecast.

Expectations

Taking the changes in the degree of accounting conservatism after the initial forecast date into account changes the expectations for the subsample of firms transitioning from a high to a low or a low to a high degree of accounting conservatism compared to the former static analysis. That is, analysts are too optimistic (O'Brien (1988)). If a firm exhibits a high degree of accounting conservatism prior to the initial forecast, the expectation for that firm resulting from the former static analysis by Louis, Lys and Sun (2014) would be an increased optimism bias. However, if the firm transitions to a low degree of accounting conservatism in the year for which the forecast was made, this positive earnings surprise is expected to partly counter the optimism bias. On the other hand, a transition from a low to a high degree of accounting conservatism is expected to further enlarge the optimism bias. Earnings forecast models are heavily based on earnings persistence (Hess, Simon and Weibels (2024)). This feature of earnings forecast models leads to unbiased or even too pessimistic forecasts (e.g., Li and Mohanram (2014) and Hess and Wolf (2023)). If a

[7] A firm is considered to transition from a high to a low (a low to a high) degree of accounting conservatism if the rank of the (un-)conditional accounting conservatism measures was larger than 5 (smaller than 6) prior to the initial forecast and smaller than 6 (larger than 5) in the period for which the forecast was made. However, the results are similar if only transitions from the upper 30% to the lower 30% and vice versa are considered, although the amount of firms considered to be transitioning is then reduced. Refer to tables 2.4.10 and 2.4.9 for the amount of firms transitioning from one conservatism rank to another in subsequent year.

firm exhibits a high degree of accounting conservatism prior to the initial forecast, the expectation for that firm resulting from the former static analysis by Louis, Lys and Sun (2014) would be a more optimistic forecast. However, if the firm transitions to a low degree of accounting conservatism in the period for which the forecast was made, the resulting positive earnings surprise is expected to enhance the pessimistic bias of models even further. On the other hand, a transition from a low to a high degree of accounting conservatism, which results in a negative earnings surprise, is expected to reduce the model-based earnings forecast bias.

2.3 Data

The analysis includes all firms from the Compustat North America annual fundamentals file reporting in US Dollar during the period between 1988 and 2022. Stock market data is collected from the CRSP database and analyst forecasts as well as actuals are retrieved from IBES. To mitigate the effect of outliers, all relevant variables are winsorized at the 1^{st} and 99^{th} percentile. As financial companies are subject to different regulatory frameworks, they are excluded from the sample. That is, companies with a SIC code between 6000 and 6999 are excluded from the sample. All observations with missing entries for any of the variables used in the earnings forecasting model are excluded from the sample. Additionally, observations that correspond to a stock price that is smaller than one US dollar and/or zero common shares outstanding are excluded from the sample. The earnings definition used in this study corresponds to the “core earnings” definition by Li and Mohanram (2014) who define earnings as earnings per share excluding special items. Industries are assigned according to the Fama-French 49-Industries classification (FF49) based on the four-digit SIC code. A reporting lag of three months is implemented and the forecasts are made each year at the end of June. Table 2.3.1 shows summary statistics as well as cross-sectional correlations for the final sample of $115,778$ firm-year observations.

Table 2.3.1: Descriptive Statistics

Panel A: Summary Statistics

	N	Mean	Std	Min	P25	P50	P75	Max
$Earn$	115,778	0.91	2.34	-13.10	-0.15	0.56	1.63	32.99
d^-	115,778	0.30	0.46	0.00	0.00	0.00	1.00	1.00
d^-Earn	115,778	-0.29	0.83	-13.10	-0.15	0.00	0.00	0.00
$BkEq$	115,778	9.48	10.98	-12.02	2.46	6.29	12.70	115.26
$TACC$	115,778	-1.02	2.26	-29.17	-1.48	-0.47	-0.02	16.21

Panel B: Correlations

	$Earn$	d^-	d^-Earn	$BkEq$	$TACC$
$Earn$		-0.79***	0.81***	0.65***	-0.14***
d^-	-0.53***		-0.98***	-0.47***	0.03***
d^-Earn	0.54***	-0.54***		0.44***	0.01***
$BkEq$	0.61***	-0.32***	0.10***		-0.35***
$TACC$	-0.07***	-0.01**	0.29***	-0.36***	

Table 3.4.1 contains descriptive statistics for the pooled cross-section of firms from 1988 to 2022 for all variables of the RI forecast model after Li and Mohanram (2014). All values are on per-share level, i.e., scaled by common shares outstanding. Panel A displays summary statistics and Panel B presents the respective cross-correlations following Pearson (Spearman) above (below) the diagonal. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

2.4 Empirical Results

2.4.1 Model-Based Earnings Forecasts

Table 2.4.1 below shows the parameter estimates from running a rolling window OLS regression for the RI earnings forecast model by Li and Mohanram (2014).

The signs of all coefficients are identical to Li and Mohanram (2014) and the magnitude of the parameter estimates are comparable to the original study.

Table 2.4.2 reports the two forecast reliability measures accuracy ($PAFE$) and bias (PFE) each for model-based and analyst earnings forecasts for forecast horizons from one to three years.

Table 2.4.1: Parameter Estimates for the RI Mean Earnings Forecast Model

	Intercept	*Earn*	d^{-}	$d^{-}Earn$	*TACC*	*BkEq*
Par. Est.	**0.07****	**0.76*****	**-0.28*****	**-0.22*****	**-0.07*****	**0.01*****
	(0.0182)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0015)

Table 2.4.1 contains information regarding the time-series averages of the parameter estimates and the Newey and West (1987) p-values assuming a ten-year lag length from modelling the conditional first moment of future earnings, i.e. mean earnings by using the RI model by Li and Mohanram (2014). To obtain the parameter estimates, a rolling OLS regression approach with a window length of ten years in line with Li and Mohanram (2014) is implemented. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table 2.4.2: Forecast Evaluation

Panel A: Forecast Accuarcy			
	$PAFE_{t+1}$	$PAFE_{t+2}$	$PAFE_{t+3}$
Model	0.0239***	0.0316***	0.0358***
Analyst	0.0084***	0.0227***	0.0287***
Panel B: Forecast Bias			
	PFE_{t+1}	PFE_{t+2}	PFE_{t+3}
Model	0.0032***	0.0041**	0.0045**
Analyst	-0.0014**	-0.0125***	-0.0182***

Table 2.4.2 contains information about the Newey and West (1987) time-series averages of the median forecast accuracy ($PAFE$) in Panel A and bias (PFE) in Panel B for the entire sample, i.e. the pooled cross-section of firms from 1988 to 2022 for forecast horizons from one to three years independently for model-based and analyst earnings forecasts. Forecast accuracy is calculated as the End-of-June price-scaled absolute forecast error, whereas bias refers to the End-of-June price-scaled forecast error. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

The reported values are comparable to prior studies (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)). That is, analyst earnings forecasts are more accurate than model-based earnings forecasts with a $PAFE$ of 0.0084, 0.0227 and 0.0287 for one-, two- and three years forecasts compared to model-based $PAFE$ values of 0.0239, 0.0316 and 0.0358, respectively. Further, the results indicate that the analysts suffer from an optimism bias as described by O'Brien (1988), whereas the models generate too pessimistic forecasts. Further, forecast reliability for both models and analysts decreases with an increasing forecast horizon.

2.4.2 The Relationship Between Accounting Conservatism and Earnings Forecast Reliability

First, table 2.4.3 displays descriptive statistics for both conservatism measures on firm- and industry-level.

Table 2.4.3: Descriptive Statistics for the Conservatism Measures

Panel A: Firm-Level							
	Mean	Std	Min	P25	P50	P75	Max
$CCon$	0.13	4.68	-1056.7	0.08	0.12	0.19	329.25
$RCCon$	5.50	2.87	1.00	3.00	5.00	8.00	10.00
$UCon$	-0.26	1.77	-7.17	-1.42	-0.50	0.96	7.24
$RUCon$	5.50	2.87	1.00	3.00	5.00	8.00	10.00
Panel B: Industry-Level							
	Mean	Std	Min	P25	P50	P75	Max
$RCCon$	5.45	0.49	4.32	5.20	5.42	5.73	6.64
Industry			(Tobacco)				(Drugs)
$RUCon$	5.44	0.56	3.45	5.09	5.42	5.87	6.37
Industry			(Utilities)				(Drugs)

Table 2.4.3 contains summary statistics for the pooled cross-section of firms from 1988 to 2022 for the two raw conservatism measures $CCon$ after Khan and Watts (2009) and $UCon$ after Givoly and Hayn (2000) and Beatty, Weber and Yu (2008) and the respective annually decile-ranked measures $RCCon$ and $RUCon$ on firm-level (Panel A). Panel B presents the summary statistics for the average (un-) conditional conservatism decile rank per industry based on the Fama-French 49 industries classification.

Table 2.4.3 shows that especially the raw conservatism measure $CCon$, but to a lesser degree also the raw conservatism measure $UCon$, exhibit large outliers. Thus, using decile ranks of the respective measure appears to be reasonable in order to manage the effect of these outliers. The industry-level degree of (un-)conditional accounting conservatism indicates that accounting conservatism is less an industry- and more a firm-specific phenomenon. That is, the standard deviation of both decile rank degrees of accounting conservatism is comparably low and the measures exhibit similar values for the majority of the distribution. However, there seem to be some differences in between industries. Whereas the tobacco industry appears to be the least conservative industry according to the conditional accounting conservatism, the utilities industry exhibits the smallest industry-level degree of unconditional accounting conservatism. On the other hand, both measures identify the drugs industry to be the most conservative. That appears to be reasonable as the business model in the drugs industry is heavily based on *R&D* expenses occurring much prior to the collection of the matching gains from selling the developed drugs. In conclusion, accounting conservatism appears to be a firm-specific rather than an industry-specific characteristic and both measures seem to be able to identify conservative accounting firms. The decile ranking of firms according to their (un-) conditional accounting conservatism reduces the effect of outliers and makes both measures comparable in the remainder of this study.

In the following, the results from regressing one of the earnings forecast reliability measures ($PAFE_M$, $PAFE_A$, PFE_M, PFE_A, $Disp_A$) onto an intercept and the accounting conservatism measure (Panel A) and some control variables (Panel B) will be shown. This analysis will be run for unconditional as well as conditional accounting conservatism independently and for forecast horizons from one up to three years.

Conditional Conservatism

Table 2.4.4 below and tables A.1 and A.2 in the appendix to chapter 2 show the results for the conditional conservatism measure $RCCon$ after Khan and Watts (2009).

First, the results follow the expectations stated in section 2.2.3. That is, a negative relationship between the degree of conditional conservatism and the forecast accuracy for both models and analysts is documented. Similar results were already reported for the relationship between unconditional conservatism and the analyst forecast accuracy by Mensah, Song and Ho (2004). This aligns with the assertion that accounting conservatism makes earnings less persistent and less predictable (e.g., Basu (1997), Penman and Zhang (2002) and Dichev and Tang (2008)). Further, the results imply that a higher degree of conditional accounting conservatism is related to more optimistically biased earnings forecasts from both analysts and models. This aligns with the results by Louis, Lys and Sun (2014) and shows that

Table 2.4.4: The Relationship Between Conditional Accounting Conservatism and One-Year Earnings Forecasts

Panel A: Without Control Variables					
	$PAFE_{M,t+1}$	$PAFE_{A,t+1}$	$PFE_{M,t+1}$	$PFE_{A,t+1}$	$Disp_{A,t+1}$
$Intercept$	**0.0414*** **	**0.0023**	**-0.0054*** **	**0.0035** *	**0.0029*** **
	(0.0000)	(0.2563)	(0.0000)	(0.0805)	(0.0000)
$RCCon_{i,t}$	**0.0037*** **	**0.0070*** **	**-0.0005*** **	**-0.0049*** **	**0.0015*** **
	(0.0000)	(0.0000)	(0.0017)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0086**	**0.0053**	**0.0001**	**0.0026**	**0.0265**
Panel B: With Control Variables					
$Intercept$	**0.0209*** **	**-0.0038**	**-0.0054*** **	**0.0034**	**0.0003**
	(0.0000)	(0.1153)	(0.0000)	(0.1551)	(0.1967)
$RCCon_{i,t}$	**0.0047*** **	**0.0071*** **	**-0.0006*** **	**-0.0048*** **	**0.0015*** **
	(0.0000)	(0.0000)	(0.0010)	(0.0000)	(0.0000)
$TotalAssets_{i,t}$	**-0.0000*** **	**-0.0000*** **	**0.0000*** **	**0.0000**	**-0.0000*** **
	(0.0000)	(0.0069)	(0.0000)	(0.1226)	(0.0000)
$EarnVol_{i,t}$	**0.0279*** **	**0.0139*** **	**-0.0042*** **	**-0.0044*** **	**0.0048*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0015)	(0.0000)
$AnnRet_{i,t}$	**-0.0177*** **	**-0.0227*** **	**0.0186*** **	**0.0169*** **	**-0.0053*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0589**	**0.0107**	**0.0172**	**0.0050**	**0.0731**

Table 2.4.4 contains information about the relationship between the dependent variables $PAFE_{M,t+1}$, $PAFE_{A,t+1}$, $PFE_{M,t+1}$, $PFE_{A,t+1}$ and $Disp_{A,t+1}$ in year $t+1$ and the accounting conservatism measure $RCCon$ after Khan and Watts (2009) in year t. That is, the dependent variable is regressed onto an intercept and the conservatism measure $RCCon$ in Panel A and additionally onto some relevant control variables in Panel B using an OLS decile-rank regression approach. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

the already documented relationship for analysts additionally holds for model-based forecasts. Louis, Lys and Sun (2014) argue that a higher degree of conditional accounting conservatism prior to the initial forecasts leads to more optimistically biased earnings forecasts if companies are growing on average as the earnings reducing effect of conditional conservatism in the current period is larger than the reversal effect of the conditional conservatism from the prior period so that reported earnings are smaller than under neutral accounting. Finally, the results indicate a positive relationship between the degree of accounting conservatism prior to the initial forecast date and the analyst forecast dispersion. Such a relationship was already described for unconditional conservatism by Mensah, Song and Ho (2004) and seems to hold for conditional conservatism as well. As analysts, in the presence of conditional accounting conservatism, do not only differ in their interpretation of financial statements, but additionally in the anticipation of management's accounting choices, an increased analyst forecast dispersion can be observed (Mensah, Song and Ho (2004)). All results are stable for forecasting periods up to three years ahead.

Unconditional Conservatism

Table 2.4.5 below and tables A.3 and A.4 in the appendix to chapter 2 show the results for the unconditional conservatism measure $RUCon$ after Givoly and Hayn (2000) and Beatty, Weber and Yu (2008).

Again, the results follow the expectations stated in section 2.2.3 and align with the pattern already found for conditional conservatism. That is, a negative relationship between the degree of unconditional conservatism prior to the initial forecast date and the earnings forecast accuracy for both analysts and models is reported. Further, a positive relationship with the analyst dispersion is reported. Finally, a higher degree of unconditional conservatism is related to more optimistically biased earnings forecasts for both analysts and models, although the relationship with two- and three-years ahead model forecasts is not significant. Overall, the findings for the unconditional measure align with the results for the conditional measure and the relationship between the forecast reliability measures and the two conservatism measures follow the prior presented expectations. In conclusion, this study finds the same results as Mensah, Song and Ho (2004) and Louis, Lys and Sun (2014) and extends the scope of their analysis to both versions of accounting conservatism as well as to model-based earnings forecasts. The first finding of this study is that there exist consequences of (un-)conditional accounting conservatism on earnings forecasts and the influence of accounting conservatism prior to the initial forecast date has the same direction for both analyst and model-based earnings forecasts.

Conditional Vs. Unconditional Conservatism

Chen, Folsom, Paek and Sami (2014) state that conditionally conservative earnings are even less persistent than unconditionally conservative earnings and thus

Table 2.4.5: The Relationship Between Unconditional Accounting Conservatism and One-Year Earnings Forecasts

Panel A: Without Control Variables					
	$PAFE_{M,t+1}$	$PAFE_{A,t+1}$	$PFE_{M,t+1}$	$PFE_{A,t+1}$	$Disp_{A,t+1}$
$Intercept$	**0.0367*****	**0.0074*****	**-0.0028*****	**-0.0013**	**0.0024*****
	(0.0000)	(0.0000)	(0.0074)	(0.2874)	(0.0000)
$RUCon_{i,t}$	**0.0034*****	**0.0034*****	**-0.0004****	**-0.0018*****	**0.0010*****
	(0.0000)	(0.0000)	(0.0234)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0091**	**0.0064**	**0.0001**	**0.0020**	**0.0198**
Panel B: With Control Variables					
$Intercept$	**0.0251*****	**0.0052*****	**-0.0048*****	**-0.0029****	**0.0005****
	(0.0000)	(0.0001)	(0.0000)	(0.0276)	(0.0169)
$RUCon_{i,t}$	**0.0034*****	**0.0033*****	**-0.0003****	**-0.0018*****	**0.0010*****
	(0.0000)	(0.0000)	(0.0454)	(0.0000)	(0.0000)
$AssetsTotal_{i,t}$	**-0.0000*****	**-0.0000*****	**0.0000*****	**0.0000*****	**-0.0000*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$EarnVol_{i,t}$	**0.0223*****	**0.0090*****	**-0.0041*****	**-0.0018****	**0.0041*****
	(0.0000)	(0.0000)	(0.0000)	(0.0154)	(0.0000)
$AnnRet_{i,t}$	**-0.0186*****	**-0.0156*****	**0.0228*****	**0.0106*****	**-0.0047*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0511**	**0.0173**	**0.0224**	**0.0060**	**0.0687**

Table 2.4.5 contains information about the relationship between the dependent variables $PAFE_{M,t+1}$, $PAFE_{A,t+1}$, $PFE_{M,t+1}$, $PFE_{A,t+1}$ and $Disp_{A,t+1}$ in year $t+1$ and the accounting conservatism measure $RUCon$ after Givoly and Hayn (2000) and Beatty, Weber and Yu (2008) in year t. That is, the dependent variable is regressed onto an intercept and the conservatism measure $RUCon$ in Panel A and additionally onto some relevant control variables in Panel B using an OLS decile-rank regression approach. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

more difficult to forecast. Further, due to the news-based character of conditional conservatism a higher degree of uncertainty of conditionally conservative compared to unconditionally conservative earnings might affect the earnings forecast reliability stronger. Thus, in the following the influence of both types of conservatism on the earnings forecast reliability measures will be compared. Table 2.4.6 presents the results for forecasting periods of one, two and three years ahead. In order to conserve space, table 2.4.6 only reports the parameter estimates for the (un-)conditional conservatism measure as well as the respective statistical significance.

Table 2.4.6: Influence On Earnings Forecasts: Conditional vs. Unconditional Conservatism

	$PAFE_{M,t+\tau}$	$PAFE_{A,t+\tau}$	$PFE_{M,t+\tau}$	$PFE_{A,t+\tau}$	$Disp_{A,t+\tau}$
Panel A: One-Year Earnings Forecasts					
$RCCon_{i,t}$	0.0041***	0.0033***	-0.0005***	-0.0016***	0.0010***
$RUCon_{i,t}$	0.0030***	0.0029***	-0.0003*	-0.0016***	0.0009***
Panel B: Two-Years Earnings Forecasts					
$RCCon_{i,t}$	0.0045***	0.0049***	-0.0007***	-0.0022***	0.0017***
$RUCon_{i,t}$	0.0026***	0.0035***	0.0002	-0.0013***	0.0013***
Panel C: Three-Years Earnings Forecasts					
$RCCon_{i,t}$	0.0049***	0.0058***	-0.0012***	-0.0030***	0.0032***
$RUCon_{i,t}$	0.0020***	0.0041***	0.0002	-0.0016***	0.0019***

Table 2.4.6 contains information about the direct comparison of the effect of the two accounting conservatism measures $RUCon$ after Givoly and Hayn (2000) and Beatty, Weber and Yu (2008) and $RCCon$ after Khan and Watts (2009) in year t on the dependent variable ($PAFE_M$, $PAFE_A$, PFE_M, PFE_A or $Disp_A$) in year $t+1$, $t+2$ and $t+3$ in Panel A, B and C, respectively. That is, the dependent variable is regressed onto an intercept, both conservatism measures $RUCon$ and $RCCon$ and some relevant control variables using an OLS decile-rank regression approach. The parameter estimates for the intercept and the control variables are surpressed in order to conserve space. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

The results display a congruent pattern and follow the notion of the expectations described in section 2.2.3. That is, a larger influence of the degree of conditional conservatism prior to the initial forecast can be reported for all earnings forecast reliability measures as well as for all forecast horizons. The results imply that as conditionally conservative earnings are even less persistent than unconditionally conservative earnings (Chen, Folsom, Paek and Sami (2014)), the earnings forecast reliability is even more affected by conditional conservatism as it is by unconditional conservatism. The results further align with the higher uncertainty induced by the news-based character of conditional conservatism compared to unconditionally conservative earnings. As a result, the earnings forecast reliability is more affected by conditional than by unconditional accounting conservatism.

Did Analysts Learn About Accounting Conservatism?

In addition to Mensah, Song and Ho (2004) and Louis, Lys and Sun (2014), Pae and Thornton (2010) claim that analysts fail to incorporate information about accounting conservatism into their forecasts. This arises the question, whether in recent years analysts learned about (un-)conditional accounting conservatism and started incorporating its implications into their forecasts. In order to answer this question, the former analysis, i.e., regressing earnings forecast reliability measures onto an intercept, the conservatism measure and control variables, will be implemented for three subsamples of ten years (1993-2002, 2003-2012 and 2013-2022). If there still exists a significant relationship in the latest subsample between the degree of (un-)conditional accounting conservatism prior to the initial forecast and the analyst earnings forecast accuracy, bias or dispersion, it can be assumed that analysts did not learn about (un-)conditional accounting conservatism and still fail to incorporate its implications into their forecasts. In order to conserve space, table 2.4.7 only reports the parameter estimates for the (un-)conditional conservatism measure as well as the respective statistical significance.

Table 2.4.7 reports statistically significant parameter estimates for the (un-)conditional conservatism measure for all subsamples. That is, in all three time frames a negative relationship between the degree of (un-)conditional conservatism prior to the initial forecast and the analyst forecast accuracy is found. Further, a positive relationship between the degree of (un-)conditional conservatism prior to the initial forecast and the analyst forecast dispersion as well as the initial optimism bias is reported in all three time frames. In conclusion, the results suggest that analysts did not learn about accounting conservatism and still fail to incorporate the implications of (un-)conditional accounting conservatism into their forecasts. That is, the results by Mensah, Song and Ho (2004), Pae and Thornton (2010), Louis, Lys and Sun (2014) and this study still hold for more recent times.

Table 2.4.7: Subsample Analysis

Panel A: Conditional Conservatism			
	$PAFE_{A,t+1}$	$PFE_{A,t+1}$	$Disp_{A,t+1}$
2013 – 2022	0.0183***	-0.0134***	0.0031***
2003 – 2012	0.0023***	-0.0007***	0.0010***
1993 – 2002	0.0034***	-0.0024***	0.0010***
Panel B: Unconditional Conservatism			
	$PAFE_{A,t+1}$	$PFE_{A,t+1}$	$Disp_{A,t+1}$
2013 – 2022	0.0040***	-0.0022***	0.0010***
2003 – 2012	0.0030***	-0.0012***	0.0010***
1993 – 2002	0.0027***	-0.0020***	0.0008***

Table 2.4.7 displays results from the subsample analysis for the three time frames from 1993-2002, 2003-2012 and 2013-2022. Panel A reports the results for conditional conservatism ($RCCon$) after Khan and Watts (2009) and Panel B reports the results for unconditional conservatism ($RUCon$) after Givoly and Hayn (2000) and Beatty, Weber and Yu (2008). The reported values are the parameter estimates for the conservatism measure ($RCCon_t$ or $RUCon_t$) from regressing the dependent variable ($PAFE_{A,t+1}$, $PFE_{A,t+1}$ or $Disp_{A,t+1}$) onto the respective conservatism measure and some control variables via a decile-rank regression for each subsample. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

2.4.3 Incorporating Accounting Conservatism Into Earnings Forecast Models

In the next step, the RI model by Li and Mohanram (2014) will be extended by an additional predictor variable, i.e., a variable indicating a firm's degree of (un-) conditional accounting conservatism.[8] Afterwards, the earnings forecast reliability of both extended models will be compared to the original RI model for forecast horizons of up to three years. Table 2.4.8 shows the earnings forecast accuracy and bias for the initial as well as both extended models.

[8]As mentioned, the aim of this study is to demonstrate the importance of accounting conservatism for earnings forecast models and not to provide the most reliable earnings forecast model in existence. If the information captured by the accounting conservatism variable are relevant for the RI earnings forecast model by Li and Mohanram (2014), i.e. improve the earnings forecast reliability, such variable might also be included in more complex forecasting models such as machine learning approaches.

Table 2.4.8: Forecast Evaluation of the Extended RI Model

Panel A: Forecast Accuary			
	$PAFE_{t+1}$	$PAFE_{t+2}$	$PAFE_{t+3}$
RI Model	0.0225***	0.0303***	0.0347***
RI Model & $RCCon$	0.0224***	0.0303***	0.0346***
RI Model & $RUCon$	0.0221***	0.0301***	0.0349***
Panel B: Forecast Bias			
	PFE_{t+1}	PFE_{t+2}	PFE_{t+3}
RI Model	0.0049***	0.0066***	0.0078***
RI Model & $RCCon$	0.0046***	0.0059***	0.0071***
RI Model & $RUCon$	0.0023**	0.0025	0.0034

Table 2.4.8 contains information about the Newey and West (1987) time-series averages of the median forecast accuracy ($PAFE$) in Panel A and bias (PFE) in Panel B for the entire sample, i.e. the pooled cross-section of firms from 1988 to 2022 for forecast horizons from one to three years independently for earnings forecasts based on the traditional RI model by Li and Mohanram (2014) as well as the two extended models for which once the conditional ($RCCon$) and once the unconditional ($RUCon$) measure was added to the RI model as a predictor variable. Forecast accuracy is calculated as the End-of-June price-scaled absolute forecast error, whereas bias refers to the End-of-June price-scaled forecast error. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

The results indicate that there is no improvement in terms of forecast accuracy when incorporating information about the degree of accounting conservatism. That is, the values for the $PAFE$ measures for forecast horizons of up to three years are almost identical between the initial and the extended RI models. With regard to the PFE almost no improvement can be reported for the incorporation of the predictor variable $RCCon$, whereas incorporating the predictor variable $RUCon$ seems to decrease the bias and even leads to statistically not significant values for the two- and three-year forecast horizon. This is somewhat counterintuitive as no significant relationship between the degree of unconditional accounting conservatism prior to the initial forecast and the respective forecast bias was found in the former analysis. Overall, the improvement of incorporating information about the static degree of accounting conservatism prior to the initial forecast into an earnings forecast model appears to be at best only moderate. This might at least partly be due to a low persistence, i.e., fluctuations, in a firm's degree of (un-)conditional accounting conservatism from prior to the initial forecast to the period for which the forecast was made. As elaborated in section 2.2.5, not only the static degree of (un-)conditional accounting conservatism prior to the initial forecast has an influence on the respective forecast reliability, but changes in the degree of (un-)conditional accounting conservatism after the forecasting date are expected to additionally influence the reliability of earnings forecasts. Due to such potential relationship, it might be insufficient to simply incorporate information about the static degree of (un-)conditional accounting conservatism prior to the initial forecast into an earnings forecast model, which then leads to the reported weak results. Thus, the following analysis aims to investigate the consequences of changes in the degree of (un-)conditional accounting conservatism from prior to the initial forecast to the period for which the forecast was made on the earnings forecast reliability.

2.4.4 The Relationship Between Changes in Accounting Conservatism and the Earnings Forecast Bias

In the first part of this study, similar to Mensah, Song and Ho (2004) and Louis, Lys and Sun (2014), the effects of the degree of (un-)conditional accounting conservatism prior to the initial forecast on the earnings forecast reliability of both analysts and models were examined. As (un-)conditional accounting conservatism creates hidden reserves and results in biased financial statements (Penman and Zhang (2002)), (un-)conditional accounting conservatism has an influence on the earnings forecast reliability. However, this first analysis omits the effect of the degree of (un-)conditional accounting conservatism after the initial forecast, i.e., in the period for which the forecast was made. That is, it omits the fact that not only the degree of (un-)conditional accounting conservatism prior to the initial forecast, but also changes in the degree of (un-)conditional accounting conservatism from prior to the initial forecast to the period for which the forecast was made have an effect on the respective earnings forecast reliability. For example, if a firm exhibits a high degree of accounting conservatism prior to the initial forecast, it might continue to do so or exhibit a lower degree of accounting conservatism in the period for which the forecast was made. Such changes in the degree of accounting conservatism have an additional influence on the earnings forecast bias, so that in this section, the subsample of firms transitioning from a high to a low or a low to a high degree of (un-)conditional accounting conservatism will be examined.

First, the question whether there even exists a time-series variation in the degree of (un-)conditional accounting conservatism of a specific firm will be answered. Table 2.4.9 and 2.4.10 show the amount of firms that exhibit a specific degree of accounting conservatism in period t ($RCCon_t$ and $RUCon_t$) and the respective degree of accounting conservatism in period $t+1$ ($RCCon_{t+1}$ and $RUCon_{t+1}$), i.e., the amount of firms with changes in the degree of a firm's (un-)conditional accounting conservatism from one period to the next.

Table 2.4.9: Transition of the Conditional Conservatism Decile in t to $t+1$

$RCCon_t$ \ $RCCon_{t+1}$	1	2	3	4	5	6	7	8	9	10
1	5379	1286	371	337	291	225	225	302	575	1254
2	1339	3422	1706	716	459	426	456	564	696	437
3	490	1662	2597	1638	978	726	681	642	482	214
4	320	779	1703	2317	1762	1176	819	677	350	170
5	234	469	967	1768	2260	1898	1183	649	380	181
6	193	348	663	1205	1863	2239	1771	894	477	268
7	234	381	660	821	1131	1688	2124	1675	725	349
8	267	561	749	635	634	845	1425	2186	1701	533
9	477	823	463	363	348	403	749	1464	2600	1560
10	1313	429	181	183	172	255	323	530	1376	3781

Table 2.4.9 contains information about the number of firms that transition from a specific conditonal conservatism decile ($RCCon_t$) in year t to the respective conditional conservatism decile $RCCon_{t+1}$ in $t+1$.

Both tables show that there is indeed a strong time-series variation in the degree of (un-)conditional accounting conservatism from one period to the next. Further, table 2.4.11 shows the amount of firms transitioning from a high to a low degree of (un-)conditional conservatism and vice versa.

Table 2.4.11 shows that around 27% exhibit a high-to-low or a low-to-high transition with respect to their degree of conditional conservatism from one period to

Table 2.4.10: Transition of the Unconditional Conservatism Decile in t to $t+1$

$RUCon_t$ \ $RUCon_{t+1}$	1	2	3	4	5	6	7	8	9	10
1	3196	1146	345	213	140	148	127	127	102	88
2	777	2014	1464	578	257	171	128	108	116	104
3	371	1054	1709	1281	588	216	160	105	117	104
4	284	478	982	1617	1188	515	212	143	128	134
5	221	290	500	984	1621	1118	406	223	137	141
6	204	212	245	457	1035	1699	992	346	204	179
7	180	133	158	217	391	1040	1913	888	302	203
8	126	119	98	121	192	367	1062	2024	923	348
9	98	67	79	85	125	178	378	1190	2269	835
10	83	69	61	59	99	124	158	364	1044	3135

Table 2.4.10 contains information about the number of firms that transition from a specific unconditonal conservatism decile ($RUCon_t$) in year t to the respective unconditional conservatism decile $RUCon_{t+1}$ in $t+1$.

the next, whereas around 16% of firms change their degree of unconditional conservatism from one period to the next. Due to the less persistent, news-based character of conditional conservatism and the more constant character of unconditional accounting less fluctuations in the degree of unconditional conservatism appears to be reasonable. A high-to-low (low-to-high) transition will be used as an indicator for the release (creation) of hidden reserves.

In the following the the earnings forecast bias for both analyst and model-based forecasts for forecasting periods up to three years ahead will be displayed for the whole sample as well as for the two subsamples of firms that transition from a high to a low or a low to a high degree of (un-)conditional accounting conservatism. That is, if a firm exhibits a high degree of accounting conservatism prior to the initial forecast date and a low degree of accounting conservatism in the period for which the forecast was made, it forms part of the subsample $High - Low$. Transitions in the opposite direction form part of the subsample $Low - High$. Tables 2.4.12 and 2.4.13 display the results of the transition analysis for conditional and unconditional conservatism, respectively.

Table 2.4.11: Accounting Conservatism: High-Low (Low-High) Transitions

Panel A: Conditional Conservatism			
	$t+1$	$t+2$	$t+3$
High-Low	15,097	7,336	3,777
	(13.43%)	(6.53%)	(3.36%)
Low-High	15,388	8,350	5,260
	(13.69%)	(7.43%)	(4.68%)
Panel B: Unconditional Conservatism			
	$t+1$	$t+2$	$t+3$
High-Low	4,713	3,171	2,328
	(7.56%)	(5.08%)	(3.73%)
Low-High	5,078	3,536	2,602
	(8.14%)	(5.67%)	(4.17%)

Table 2.4.11 contains information about the number of firms that transition from a high degree of (un-)conditional conservatism ($RCCon_t > 5$ in Panel A and $RUCon_t > 5$ in Panel B) in year t to a low degree of (un-)conditional conservatism ($RCCon_{t+\tau} < 6$ in Panel A and $RUCon_{t+\tau} < 6$ in Panel B) in $t+\tau$ and vice versa. For reporting a transition from period t to period $t+2$ ($t+3$), it is required that the firm belonged to the same group in $t+1$ ($t+1$ and $t+2$) as in t. The percentage values refer to the number firm-years with a transition in relation to all firm-years for which $RCCon_t$ (Panel A) or $RUCon_t$ (Panel B) is not missing.

Before interpreting the results of tables 2.4.12 and 2.4.13, it is important to recall the findings from the former analysis that states the forecasts to be increasingly optimistically biased for a higher degree of (un-)conditional accounting conservatism prior to the initial forecast and vice versa. The results of the tables 2.4.12 and 2.4.13 challenge that claim for the subsample of firms transitioning from a high to a low or a low to a high degree of (un-)conditional accounting conservatism. Both tables display a congruent pattern. That is, for firms transitioning from a high to a low degree of (un-)conditional conservatism, i.e., firms that release hidden reserves and thus exhibit a positive earnings surprise in the period for which the forecast was made, a reduction in the analyst optimism bias is reported, whereas the pessimistic model-based earnings forecast bias increases. As analysts are too optimistic, the release of hidden reserves and thus the positive earnings surprise partly counters the

Table 2.4.12: Forecast Bias - Conditional Conservatism Transition Analysis

Panel A: Analyst Earnings Forecasts

	PFE_{t+1}	PFE_{t+2}	PFE_{t+3}
Full Sample	-0.0014**	-0.0125***	-0.0182***
High-Low	-0.0012*	-0.0106***	-0.0193***
Low-High	-0.0042***	-0.0192***	-0.0443***

Panel B: Model-Based Earnings Forecasts

	PFE_{t+1}	PFE_{t+2}	PFE_{t+3}
Full Sample	0.0032***	0.0041**	0.0045**
High-Low	0.0048***	0.0071***	0.0088**
Low-High	-0.0021	-0.0060**	-0.0096***

Table 2.4.12 contains information about the Newey and West (1987) time-series averages of the median forecast bias (PFE) for the entire sample, i.e. the pooled cross-section of firms from 1988 to 2022 for forecast horizons from one to three years for the analyst (Panel A) as well as the model-based (Panel B) earnings forecasts. Further, the same measures for the subsample of firms transitioning from a high degree of conditional accounting conservatism ($RCCon > 5$) in year t to a low degree of conditional accounting conservatism ($RCCon < 6$) in the years $t+1$, $t+2$ and $t+3$ (High-Low) and vice versa (Low-High) are reported. Forecast bias refers to the End-of-June price-scaled forecast error. Conditional accounting conservatism is calculated after the measure by Khan and Watts (2009). ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

optimism bias. On the other hand, it amplifies the forecast bias of earnings forecast models as their forecasts are already too small on average. This pattern reverses for firms transitioning from a low to a high degree of (un-)conditional accounting conservatism, i.e., for firms that increase their hidden reserves, which results in a negative earnings surprise. That is, the already existing optimism bias in analyst forecasts increases, whereas the too pessimistic model-based earnings forecasts is reduced.

The results of this analysis are diametrically opposed to the findings from the prior full sample analysis. Although it is not possible to incorporate information about future changes in the degree of accounting conservatism in the initial forecast, this study has implications for both analysts and earnings forecast models. According to the results in this study, in order to hand out more accurate and less

Table 2.4.13: Forecast Bias - Unconditional Conservatism Transition Analysis

Panel A: Analyst Earnings Forecasts			
	PFE_{t+1}	PFE_{t+2}	PFE_{t+3}
Full Sample	-0.0014**	-0.0125***	-0.0182***
High-Low	0.0008	-0.0050***	-0.0110***
Low-High	-0.0039***	-0.0182***	-0.0234***
Panel B: Model-Based Earnings Forecasts			
	PFE_{t+1}	PFE_{t+2}	PFE_{t+3}
Full Sample	0.0032***	0.0041**	0.0045**
High-Low	0.0085***	0.0138***	0.0173***
Low-High	-0.0028	-0.0039*	-0.0022

Table 2.4.13 contains information about the Newey and West (1987) time-series averages of the median forecast bias (PFE) for the entire sample, i.e. the pooled cross-section of firms from 1988 to 2022 for forecast horizons from one to three years for the analyst (Panel A) as well as the model-based (Panel B) earnings forecasts. Further, the same measures for the subsample of firms transitioning from a high degree of unconditional accounting conservatism ($RUCon > 5$) in year t to a low degree of unconditional accounting conservatism ($RUCon < 6$) in the years $t+1$, $t+2$ and $t+3$ (High-Low) and vice versa (Low-High) are reported. Forecast bias refers to the End-of-June price-scaled forecast error. Unconditional accounting conservatism is calculated after the measure by Givoly and Hayn (2000) and Beatty, Weber and Yu (2008). ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

biased forecasts, analysts should not only incorporate information about the degree of accounting conservatism prior to the forecasting date into their forecasts, but further anticipate firm-specific changes in the hidden reserves created by accounting conservatism. However, Helbok and Walker (2004) question whether analysts are even interested in incorporating the implications of conditional accounting conservatism into their forecasts as they argue that the initial forecast of analysts is more concerned with forecasting sustainable earnings to which earnings surprises from one-time news do not contribute. In contrast, analysts might be interested in incorporating information about unconditional accounting conservatism as the effects of accounting practices and changes in such have a more long-term effect on earnings. Further, it seems to be more promising to analyze and anticipate firm-specific characteristics of changes in the degree of unconditional accounting conservatism as conditional conservatism is news-based an thus associated with a higher degree of uncertainty. Thus, this study calls for analysts to incorporate information about the degree of unconditional accounting conservatism into their forecasts and further to anticipate firm-specific changes in the degree of unconditional accounting conservatism. If they should incorporate information about conditional conservatism or changes in such depends on whether the analyst aims to forecast sustainable or reported earnings.

Deriving suggestions for incorporating the results of this study into earnings forecast models is difficult. The degree of (un-)conditional accounting conservatism in the period for which the forecast was made is unknown at the time of forecasting and incorporating only information about the degree of accounting conservatism prior to the initial forecast into an earnings forecast model is shown to be insufficient. One could try to anticipate firm-specific changes in the degree of accounting conservatism by deriving measures capturing past firm-specific fluctuations in the degree of accounting conservatism, e.g., the standard deviation of a firm's degree of accounting conservatism over a specific time frame before the forecasting date. Nevertheless, incorporating firm-specific time-series characteristics into earnings forecast models diminishes the advantage of the cross-sectional approaches and might lead to a smaller coverage. Instead, one might be capable to identify predictors for the firm-specific measures anticipating future firm-specific fluctuations in the degree of accounting conservatism, e.g., an accounting conservatism reversal variable or an accounting conservatism momentum variable or even a model for the anticipation of the reversal of accounting conservatism in future periods. Especially machine learning algorithms that can identify relevant predictor variables from a large set of variables might identify relevant predictors for future changes in accounting conservatism, which can than be included in earnings forecast models. The identification and incorporation of such information will be left to future research. Again, the analyzing unconditional conservatism is potentially more promising as the news-based character of conditional conservatism is associated with a higher degree of uncertainty.

2.5 Conclusion

The demand for accounting conservatism stems mainly from debt market participants (e.g., Watts (2003), Ball, Robin and Sadka (2008) and Gigler, Kanodia, Sapra and Venugopalan (2009)). Nevertheless, accounting conservatism also affects equity market users. For example, it is documented that accounting conservatism increases the information asymmetry (e.g., Francis, Hasan and Wu (2013), Kim, Li, Pan and Zuo (2013) and Ruch and Taylor (2015)). Further, Mensah, Song and Ho (2004), Pae and Thornton (2010) and Louis, Lys and Sun (2014) show that analyst forecasts are affected by accounting conservatism prior to the initial forecast, that is, the forecast accuracy is decreasing and the analyst forecast dispersion as well as the optimism bias in analyst forecasts is increasing with a higher degree of accounting conservatism. This study extends the analysis of the effects of (un-)conditional accounting conservatism on the information environment of investors, i.e., on analyst as well as model-based earnings forecasts. The results show that both conditional as well as unconditional accounting conservatism prior to the initial forecast is related to a lower analyst forecast accuracy, a higher analyst forecast dispersion and an increase in the optimism bias of analysts. The results align with the studies by Mensah, Song and Ho (2004) and Louis, Lys and Sun (2014) and extend their analyses. Further, this study is the first to investigate the effects of (un-)conditional accounting conservatism on model-based earnings forecasts. The results suggest that (un-)conditional accounting conservatism prior to the initial forecast has the same influence on model-based earnings forecasts as on analyst forecasts. Additionally, this study shows that the effect of conditional conservatism on the earnings forecast reliability of both analysts and models is larger than the effect of unconditional accounting conservatism. This aligns with Chen, Folsom, Paek and Sami (2014) who claim conditionally conservative earnings to be even less persistent and predictable than unconditionally conservative earnings. The news-based character of conditional accounting seems to make it more difficult to incorporate its implications into earnings forecasts. This study also shows that analysts did not learn about accounting conservatism and even in more recent years failed to incorporate the implications of accounting conservatism prior to the initial forecast date into their forecasts. Further, this study aims to make use of the found relationship between the degree of (un-)conditional accounting conservatism and the earnings forecast reliability by incorporating such information into an earnings forecast model. That is, the RI model by Li and Mohanram (2014) is extended by a new predictor variable indicating the degree of (un-)conditional accounting conservatism prior to the initial forecast. However, such extension does only lead to at best a moderate improvement of the earnings forecast reliability. This is at least partly due to fluctuations in a firm's degree of (un-)conditional accounting conservatism from prior to the initial forecast to the period for which the forecast was made.

In addition to the static analysis of the effects of (un-)conditional accounting conservatism prior to the initial forecast on the earnings forecast reliability of both analysts and models, this study introduces a second dimension regarding which the effects of (un-)conditional accounting are investigated. That is, this study documents that there is a firm-specific time-series fluctuation in the degree of (un-) conditional accounting conservatism. Such fluctuations are used as an indicator for the change of the hidden reserves which are created by accounting conservatism (Penman and Zhang (2002)). Subsequently, this study independently analyzes the subsample of firms that exhibit a change in their degree of accounting conservatism from prior to the initial forecast to the period for which the forecast was made as such changes indicate the release or the creation of hidden reserves, i.e., a positive or negative earnings surprise. The results of such analysis differ in comparison to the first, isolated analysis of the effects of (un-)conditional accounting conservatism prior to the initial forecast date. That is, firms transitioning from a high to a low (low to a high) degree of accounting conservatism, i.e., reporting a positive (negative) earnings surprise, exhibit a smaller (larger) optimism bias in analyst forecasts and a larger (smaller) pessimistic bias in model-based earnings forecasts. Thus, this analysis of changes in the firm-specific degree of (un-)conditional accounting conservatism is an important extension of the former static analyses by Mensah, Song and Ho (2004) and Louis, Lys and Sun (2014). In conclusion, this study emphasizes that it is not sufficient to assess the degree of accounting conservatism of a firm at a single point in time, but further underlines the necessity of understanding firm-specific time-series variations in the degree of accounting conservatism.

According to the presented results, this study has implications for analysts as well as earnings forecast models. Analysts should not only incorporate information about the firm-specific degree of (un-)conditional accounting conservatism prior to the initial forecast date into their forecasts, but further anticipate changes in the firm-specific degree of (un-)conditional accounting conservatism after the initial forecast date. As Helbok and Walker (2004) claims that analysts are more concerned with forecasting sustainable earnings with their initial forecast, they might focus on the implications of unconditional conservatism. Incorporating such information in earnings forecast models is difficult. Whereas it is comparably easy to add a predictor variable indicating the degree of (un-)conditional accounting conservatism prior to the forecast date into an earnings forecast model, the analyses in this study point out that such information of the degree of accounting conservatism at a single point in time are not sufficient to capture the phenomenon of accounting conservatism. Incorporating a predictor variable that captures the change in accounting conservatism after the forecast date is also not feasible as such information are not available at the time of forecasting. Creating a predictor variable that captures the firm-specific variation of the degree of accounting conservatism, e.g., the standard deviation of a firm's degree of accounting conservatism, is theoretically possible, but diminishes the advantage of cross-sectional models in terms of coverage. Thus, future research might turn to other ways of capturing an anticipated firm-specific variation of the degree of accounting conservatism in an earnings forecast model. Again, the focus may be put on unconditional conservatism as the news-based character of conditional conservatism makes an anticipation of such difficult.

Chapter 3

The Relation Between Earnings Management and Model-Based Earnings Forecast Accuracy

3.1 Introduction

Earnings are a central measure of a firm's performance. Hence, it is of special interest for investors, analysts, and firms themselves to obtain accurate information about future earnings (Tian, Yim and Newton (2021)). For practitioners and academics alike, earnings forecasts are an important input for firm valuation, asset allocation, or cost of capital calculation (Azevedo, Bielstein and Gerhart (2021)). In recent years, research on cross-sectional model forecasts as an alternative to analysts' earnings forecasts emerged (e.g., Hou, Van Dijk and Zhang (2012), Li and Mohanram (2014), Ohlson and Kim (2015), Konstantinidi and Pope (2016), Evans, Njoroge and Yong (2017), Cao and You (2024), Tian, Yim and Newton (2021), Chang, Monahan, Ouazad and Vasvari (2021), Hansen and Thimsen (2021), Chen, Cho, Dou and Lev (2022), Hendriock (2022), Van Binsbergen, Han and Lopez-Lira (2023) and Campbell, Ham, Lu and Wood (2023)). Such model-based forecasts are typically used for the computation of the ICC, i.e., an expected return proxy, which is computed as the discount rate that equates expected future cash flows to current stock price. Several studies provide evidence that model-based ICCs are more reliable expected return proxies than analyst-based ICCs (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)).

A common denominator in most earnings forecast models is that last period's reported earnings are a key explanatory variable for future earnings (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)). This is unsurprising, as previous literature finds that earnings are highly persistent (e.g., Fama and French (2006) and Hou and Van Dijk (2019)). Thus, the reliability of the reported earnings figure is likely related to the predictive ability of the forecast models. However, among others, one factor affecting reported earnings, and thus earnings forecasts, has not been covered by research on model-based earnings forecasts, yet. This factor is the extent of a firm's earnings management (EM). A widely accepted definition of EM is the adjustment of financial reports in order to deceive certain stakeholders about a firm's economic performance or to affect contractual obligations that are based on reported financial numbers (e.g., Healy and Wahlen (1999), Dechow and Skinner (2000) and Lo (2008)). Hence, the occurrence of EM, i.e., intentionally modification earnings, should intuitively compromise the reliability of reported earnings. This assumption is further supported when looking at managers' incentives to manipulate earnings (Dechow, Sloan and Sweeney (1996) and Dechow and Schrand (2004)). For instance, managers use EM to increase stock prices before initial public offerings, to meet analysts' earnings targets or to maximize bonuses that are based on the respective earnings. Literature provides evidence for the occurrence of EM as a response to these incentives (e.g., Healy (1985), Perry and Williams (1994), Teoh, Welch and Wong (1998) and Doyle, Jennings and Soliman (2013)). Teoh and Wong (2002) provide evidence that discretionary accounting accruals are an important determinant for earnings surprises. These studies provide a first indication that EM reduces the reliability of reported earnings and in turn possibly negatively affect the accuracy of model-based earnings forecasts.

Consequently, with our paper, we aim to examine the relationship between EM and the predictability of future earnings. Higashikawa (2020) studies a similar relationship in his work, whereas he investigates the relationship between earnings quality measures, e.g., smoothness or persistence, and the respective earnings forecast accuracy. He finds that a higher earnings quality is associated with a better forecast accuracy, i.e., a lower earnings forecast error. However, there are two important differences between the study by Higashikawa (2020) and our study: First, compared to Higashikawa (2020) who uses the earnings forecast model by HVZ, we rely on the RI earnings forecast by Li and Mohanram (2014) model in our study.[1] To us, the use of the HVZ model appears somewhat counter-intuitive since former studies found the RI model to perform better in terms of forecasting accuracy (e.g., Li and Mohanram (2014)). Second, we do not incorporate earnings quality measures as Higashikawa (2020), which typically simply describe different features of earnings, but information about a firm's extent of EM, which aims to detect consequences of managers' manipulations.[2] In other words, behind the concept of earnings quality all choices made inside a firm are hidden, while EM specifically focuses on the choices made and actions taken by managers to modify earnings. Further, we seek to use the relation between a firm's extent of EM and the respective earnings forecast accuracy to improve the predictive ability of earnings forecasts models. That is, we incorporate information about firms' EM in the earnings forecast approach and furthermore evaluate if this results in more accurate forecasts and finally in more reliable ICC estimates.

For our primary analysis, we require measures of (i) earnings forecast accuracy and (ii) the extent of a firm's EM. To evaluate forecast accuracy, we first generate earnings forecasts for up to three years ahead using the RI model by Li and Mohanram (2014). Then, we calculate the PAFE. Firms manage earnings either through the manipulation of cash flows or accruals (Dechow and Schrand (2004)). In line with the bigger part of previous literature, we focus on the accruals component and use absolute discretionary accruals to measure the degree of firms' EM (e.g., Frankel, Johnson and Nelson (2002), Klein (2002), Bergstresser and Philippon (2006), among others). Discretionary accruals are defined as the residuals from the estimation of

[1]Our study aims to underline the importance of incorporating information about a firm's extent of EM into earnings forecast models by showing that doing so improves the forecast accuracy. In this study, we use a simple OLS earnings forecast model, i.e., the RI model by Li and Mohanram (2014), instead of, for example, a more complex machine learning approach. However, if the information captured by the EM variable are relevant for earnings forecast models, such variable might also be included in more complex forecasting models such as machine learning approaches. For example, Hess, Simon and Weibels (2024) use a large set of predictor variables to predict future earnings using machine learning techniques. If we find EM to be relevant for predicting future earnings, information about a firm's extent of EM can be added to their pool of predictor variables.

[2]Note that manipulation in this case is neither connoted in a good nor a bad way.

an accruals model. We use the modified Jones (1991) model by Dechow, Sloan and Sweeney (1995) for the estimation.[3]

The results of the empirical analysis support our assumption, i.e., we provide evidence for a negative relationship between the extent of a firm's EM and the ability to accurately forecast its respective earnings. When running annual cross-sectional regressions of the firm-year specific PAFE on the respective EM measure for one-, two-, and three-year ahead earnings forecasts, we find significantly positive average parameter estimates of 0.0204, 0.0189, and 0.0182, respectively. In other words, we provide empirical evidence that a higher level of EM corresponds to less accurate model-based earnings forecasts. Subsequently, we capitalize on this finding and use the relation between EM and the predictability of future earnings to improve forecast accuracy. We annually rank firms into quintiles based on the extent of a firm's EM and create five dummy variables that indicate a firm's respective quintile. We then interact the earnings forecast model with the EM quintile dummy variables. Again, we generate earnings forecasts for up to three years ahead and find that the forecasts of the interacted model show significantly lower PAFEs compared to the initial RI model. For instance, for one-year (two-year, three-year) ahead forecasts, the median PAFE of the RI model is 3.72% (4.88%, 6.41%), whereas the PAFE of the interacted model is 3.18% (4.58%, 5.64%). Further, analogous to the methodology used in previous studies (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)), we implement an ICC analysis and provide evidence that ICCs based on the interacted model are more reliable expected return proxies in comparison to ICCs based on the RI model. For the cross-section of firms, we annually regress realized future returns on ICCs. We show that ICCs based on the interacted model exhibit higher correlations to realized future returns. For example, for one-year ahead forecasts, the RI model shows an average parameter estimate of 0.1904 and an R^2 of 10.70%, while the interacted model shows values of 0.2176 and 12.80%, respectively. Moreover, we annually rank firms into deciles based on the ICCs and implement a long-short-strategy, i.e., we compute the spread between the highest and lowest decile. We find that this portfolio approach yields higher returns for holding periods of up to three years when using ICCs based on the interacted model

[3]We further elaborate on the selection of the earnings forecast model as well as on the selection of this specific accruals model in section 3.2.

compared to using ICC estimates based on the RI model (e.g., 12.32% vs. 10.63% for a one year holding period). Lastly, we ensure that our findings are robust to alternative underlying earnings forecast models. We rerun the previous tests and provide evidence that the tenor of results is unchanged when using the EP model by Li and Mohanram (2014) and the model by HVZ (2012).

Our findings contribute to the literature as follows. First, to our knowledge, we are the first to examine the relationship between the extent of a firm's EM and the possibility to accurately forecast its respective earnings figure. In line with our expectations, we provide evidence for a significantly negative relationship. That is, when the level of a firm's EM increases, the PAFE seems to increase as well. Our results suggest that a firm's extent of EM should be considered when generating model-based earnings forecasts. It leads to a higher forecast accuracy and results in more reliable ICCs that yield higher investment strategy returns. This is important as it supports previous research that identifies model-based earnings forecasts as a viable alternative to analysts' earnings forecasts (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)). Finally, our findings add to the debate on managers' incentives for EM. Beneish (2001) points out that there are potentially two perspectives on EM. On the one hand, the "informative perspective" suggests that managerial discretion is used to reveal private expectations about future cash flows to stakeholders. That is, EM could improve the information content of reported earnings and lead to more accurate earnings forecasts. However, there is no empirical evidence for this perspective, and our results do not support it either. On the other hand, the "opportunistic perspective" states that managers manipulate earnings to mislead investors with the intention of obtaining personal gain. This should impair the reliability of reported earnings, resulting in less accurate earnings forecasts. Our findings match this perspective, and therefore support the results of previous studies focusing on opportunistic managers' actions (e.g., Perry and Williams (1994), Teoh, Welch and Wong (1998), and Bergstresser and Philippon (2006)).

The remainder of this paper is structured as follows. Section 3.2 provides a brief overview of related literature. Section 3.3 outlines the methodology and section 3.4 describes the data we use for our empirical analysis. Section 3.5 covers the empirical results and section 3.6 concludes.

3.2 Related Literature

This section provides an overview regarding the literature related to our study. First, we present studies focusing on cross-sectional earnings forecasts and their relation to ICCs.[4] Second, we briefly discuss studies that implement models to estimate discretionary accruals as a measure for the extent of a firm's EM.

Model-Based Earnings Forecasts and Implied Cost of Capital

Information about the expected rate of return is crucial in various economic settings, e.g., to ensure an efficient allocation of scarce resources or capital budgeting (e.g., Botosan and Plumlee (2005) and Lee, So and Wang (2021)). There exists a vast amount of literature on different approaches for deriving an estimate of a firm's expected rate of return. It is well documented that using realized returns to proxy for expected returns bears a range of problems and leads to noisy and biased estimates (e.g., Fama and French (1997) and Easton and Monahan (2016)). Thus, in recent years, a stream of literature that approximates the expected rate of return with the ICC emerged (e.g., Gebhardt, Lee and Swaminathan (2001), Claus and Thomas (2001), Ohlson and Juettner-Nauroth (2005), and Easton (2004)). An advantage of the ICC estimation is that it does not rely on noisy realized returns to derive a proxy for expected returns (Lee, So and Wang (2010)). Although it is an important source of information for researchers and practitioners alike, the ICC of a firm itself is not observable. As mentioned before, it is defined as the internal rate of return that results from equating the current stock price to the present value of expected future cash flows. Whereas the current stock price is directly observable, information about future cash flows has to be approximated. In order to derive a reliable ICC estimate, this approximation relies heavily on the accuracy of the respective input factors, especially unobservable future cash flows (Botosan and Plumlee (2005)). While future cash flows are usually proxied by future earnings, future earnings itself are unobservable as well.

The literature provides two popular options to derive estimates of a firm's future earnings. On the one hand, for a subsample of firms, analyst forecasts of the

[4] Throughout this paper, we will use the terms "cross-sectional" and "model-based" earnings forecasts interchangeably.

respective firm's earnings are available. Easton and Monahan (2005) show that more reliable ICCs are the result of more accurate analysts' forecasts. Thus, they provide evidence for the necessity of accurate input factors for the ICC estimation. However, analyst earnings forecast suffer from an optimism bias (e.g., O'Brien (1988)) and insufficient coverage (e.g., La Porta (1996)). Thus, earnings forecast models gained a lot of popularity as they overcome both disadvantages (e.g., Hou, Van Dijk and Zhang (2012), Li and Mohanram (2014), Evans, Njoroge and Yong (2017), Cao and You (2024), Tian, Yim and Newton (2021), Hansen and Thimsen (2021), Chen, Cho, Dou and Lev (2022), Hendriock (2022), Van Binsbergen, Han and Lopez-Lira (2023) and Campbell, Ham, Lu and Wood (2023)). The majority of recent studies on model-based earnings forecasts implements a cross-sectional estimation approach. While the model-based forecasts show lower forecast accuracy, these forecasts beat analysts' earnings forecasts in terms of coverage, forecast bias and earnings response coefficient (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)). Further, ICCs based on cross-sectional earnings forecasts are more reliable expected return proxies than analyst-based ICC estimates. Thus, Hou, Van Dijk and Zhang (2012) provide evidence that suggests deriving ICC estimates from model-based earnings forecasts rather than from analyst forecasts. However, the puzzle why mechanical earnings forecast models result in less accurate forecasts compared to analyst earnings forecasts, but in more reliable ICC estimates, remains unanswered at this point (Hess, Meuter and Kaul (2019)). Additionally, Gerakos and Gramacy (2013) as well as Li and Mohanram (2014) note that the forecast errors resulting from the Hou, Van Dijk and Zhang (2012) model are quite similar to or even worse than those derived from a random walk model. They express doubt whether the forecasts from that model should be used at all. Thus, Li and Mohanram (2014) propose two new models to improve the approach of Hou, Van Dijk and Zhang (2012) by differentiating between the earnings persistence of profit and loss firms, adjusting the earnings metric for special items, and estimating earnings per share instead of firm-level earnings. They provide evidence that their models, i.e., the EP and RI model, outperform the model by Hou, Van Dijk and Zhang (2012) regarding forecast bias, accuracy, earnings response coefficient, and ICC reliability.

Evans, Njoroge and Yong (2017) and Tian, Yim and Newton (2021) show that using the least absolute deviation method, i.e., median regressions, further improves forecast performance. However, since our analysis is mainly concerned with the relation between EM and mean earnings forecast accuracy, we follow Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014) and employ the OLS method.[5]

In addition to forecasting mean or median earnings, Konstantinidi and Pope (2016) and Chang, Monahan, Ouazad and Vasvari (2021) use quantile regressions to estimate the distribution of expected earnings. Using these estimates, they compute the higher moments of future earnings. They argue that these moments are measures of uncertainty in future earnings and provide evidence that they are related to common risk measures such as credit risk ratings or corporate bond spreads. Although they also develop models to forecast future earnings, their work is mainly concerned with forecasting higher moments of future earnings and not with a mean forecast of earnings. Thus, in our study, we will not cover the models suggested by Konstantinidi and Pope (2016) and Chang, Monahan, Ouazad and Vasvari (2021) due to a deviating research focus. Additionally, both studies do not provide evidence that their models outperform established mean earnings forecast models in terms of forecasting accuracy.

More recently, machine learning approaches gained traction in the field of earnings forecasting as these models are able to incorporate a large number of predictor variables and are not restricted to a linear functional form (e.g., Cao and You (2024), Hansen and Thimsen (2021), Chen, Cho, Dou and Lev (2022), Hendriock (2022), Van Binsbergen, Han and Lopez-Lira (2023) and Campbell, Ham, Lu and Wood (2023)). However, the improvements of these machine learning models are only moderate. For example, Hansen and Thimsen (2021) and Cao and You (2024) report an average improvement of less than 7% in terms of forecast accuracy for one-year ahead forecasts. With this study we aim to emphasize the importance of incorporating information about a firm's extent of EM into earnings forecast models by showing that doing so increases the forecast accuracy. To do so, we use a simple OLS earnings forecast model, i.e., the RI model by Li and Mohanram (2014), instead of, for example, a more complex machine learning approach. In theory, in-

[5]Untabulated tests show that our results remain unchanged when median regressions are used.

formation about a firm's extent of EM, if relevant to earnings forecast models, can be added to any earnings forecast model regardless whether it is a simple OLS or a methodologically more advanced machine learning earnings forecast model.

Thus, throughout our empirical analysis, we focus on cross-sectional OLS models, more specifically, the RI model introduced by Li and Mohanram (2014), since previous studies find that it performs best in terms of forecast accuracy in that category. However, we will disclose the results based on the EP model by Li and Mohanram (2014) and the HVZ model by Hou, Van Dijk and Zhang (2012) in the appendix to chapter 3. Our main findings are robust to changes in the underlying earnings forecast model.

Estimation of the Earnings Management Measure

A widely accepted definition of EM in previous studies is the adjustment of financial reports in order to deceive certain stakeholders about a firm's economic performance or to affect contractual obligations that are based on reported financial numbers (e.g., Healy and Wahlen (1999) and Dechow and Skinner (2000)). However, this concept is difficult to measure directly, as it focuses on unobservable managerial intent (Dechow and Skinner (2000)). The most common approach to measure EM is isolating the discretionary part of accruals (Dechow, Hutton, Kim and Sloan (2012)). This part of accruals reflects distortions due to active EM, while the non-discretionary part captures adjustments based on fundamental performance (Dechow, Ge and Schrand (2010)). Estimates of discretionary accruals are obtained by directly modeling the accruals process. Widely used accruals models are developed by Jones (1991), Dechow, Sloan and Sweeney (1995), Dechow and Dichev (2002), McNichols (2002) and Dechow, Hutton, Kim and Sloan (2012)).

Jones (1991) analyzes whether firms use EM to decrease earnings during import relief investigations. Her model includes total accruals as dependent variable and change in revenues and property, plants and equipment as independent variables. The fitted value of the regression represents non-discretionary accruals and the residual represents discretionary accruals. Jones (1991) finds that managers actively decrease earnings to profit from import reliefs. Dechow, Sloan and Sweeney (1995) point out that the model by Jones (1991) implicitly assumes that revenues are non-discretionary. In consequence, if EM occurs through discretionary revenues, it is not accounted for in the discretionary accruals estimate. Dechow, Sloan and Sweeney (1995) propose a solution by modifying the model by Jones (1991). They use cash revenue instead of reported revenue, i.e., the change in revenues is adjusted for change in receivables. They provide empirical evidence that the modified model better detects EM compared to the initial model by Jones (1991). Dechow and Dichev (2002) suggest a new measure for accruals and earnings quality. While they do not explicitly intent to measure EM, their measure is based on the standard deviation of the residuals, i.e., discretionary accruals. Their model includes change in working capital as dependent variable and past, current and future cash flows as independent variables. They find that a larger standard deviation of discretionary accruals results in less persistent earnings, longer operating cycles and more volatile cash flows, accruals and earnings (Dechow, Ge and Schrand (2010)). McNichols (2002) links the approach of Jones (1991) to Dechow and Dichev (2002). She adds the variables of Jones (1991) to the model by Dechow and Dichev (2002) and shows that the explanatory power regarding working capital accruals increases. Moreover, Francis, LaFond, Olsson and Schipper (2005) use this model to compute the accruals quality measure proposed by Dechow and Dichev (2002). However, they further differentiate between accruals quality due to economic fundamentals and due to management choices. They find that lower accruals quality yields higher cost of debt, smaller price multiples on earnings and larger equity betas. Yet, they conclude that accruals quality driven by economic factors has a larger effect on cost of capital than accruals quality driven by management choices.

In this study, we use the modified Jones (1991) model by Dechow, Sloan and Sweeney (1995) to compute the EM measure for the following reasons: First, we exclude the original Jones (1991) model from the set of possibly applicable accruals models, because, as stated before, Dechow, Sloan and Sweeney (1995) show that their modified model better detects EM. Second, the accruals models by Dechow and Dichev (2002) and McNichols (2002) appear to be neither suitable for our specific research design since both models contain cash flows from period $t + 1$ as an explanatory variable for the discretionary accruals in period t. In other words, those two models incorporate information from a future period in order to model accruals in the current period. This induces a timing problem, because we aim to investigate the relationship between the firm's earnings management and the resulting earnings forecast error in the following period. A conceptual mismatch follows if we on the one hand calculate an earnings management measure for period t with information from period $t+1$ and at the same time pretend to not have information for period $t+1$ when forecasting earnings for that period. To prevent such a look-ahead-bias in our analysis, we would have to relate the forecast error of next period's earnings forecasts to last period's EM measure. However, we want to avoid such a timing lag between both measures. Additionally, Dechow and Dichev (2002) point out that their model is not specifically intended to estimate firms' EM. Based on those two arguments, we decided to also exclude the two accruals models by Dechow and Dichev (2002) and McNichols (2002) from our analysis. Third, the accruals quality measure of Francis, LaFond, Olsson and Schipper (2005) that is driven by management choices requires a seven-year time-series of firm-specific data. This potentially induces a survivorship bias that we intent to avoid. Finally, Dechow, Hutton, Kim and Sloan (2012) suggest caution when using their performance matching approach for detecting earnings management. They claim that this approach is in general only effective if knowledge about correlated omitted variables can be used to identify appropriate matched pairs. Since we do not have information about such, we refrain from implementing that approach. Additionally, according to Dechow, Hutton, Kim and Sloan (2012) performance matching entails a significant reduction in test power. This selection process leaves us with the modified Jones (1991) model as the best suited accruals model, which we thus in the following base our empirical analysis on.

To the best of our knowledge, we are the first to analyze the relationship between the extent of a firm's EM and model-based earnings forecast accuracy. Only the study by Higashikawa (2020) has a similar setup, since it investigates the relationship between earnings quality measures and earnings forecast accuracy. As elaborated before there are multiple important differences between the two studies. First, we study the influence of EM on earnings forecast accuracy not of earnings quality measures. This differentiation is important since both concepts cover different information. Whereas EM aims to specifically detect managers' earnings manipulation, earnings quality measures mainly describe earnings characteristics which are the result of all choices made within a firm. Second, somewhat counter-intuitive, Higashikawa (2020) uses the HVZ model instead of the in terms of forecast accuracy better performing RI model. Finally, Higashikawa (2020) does neither study the possibility of improving earnings forecast by incorporating insights about the studied relationship into earnings forecast models nor the implications of such improvements for the model-based ICC computation.

As noted in the previous section, model-based earnings forecasts are an important measure in practice as well as in academic studies. Thus, understanding the factors influencing their accuracy is worth investigating further. In the following, we present the methodology we applied to study such relationship.

3.3 Methodology

This section outlines the methodology we employ in this study. First, it shows how we generate earnings forecasts and the corresponding PAFEs. Second, it presents how we compute the EM measure, i.e., absolute discretionary accruals. Third, it depicts how we (i) examine the relation between the extent of a firm's EM and earnings forecast accuracy, (ii) use information about firms' EM to improve the predictive ability of earnings forecast models, and (iii) test if this information enhances ICC reliability.

Model-Based Earnings Forecasts

To forecast earnings, we use the RI model introduced by Li and Mohanram (2014). The model is defined as follows:

$$\begin{aligned} Earn_{i,t+\tau} = \beta_0 + \beta_1 Earn_{i,t} + \beta_2 NegE_{i,t} + \beta_3 NegExE_{i,t} \\ + \beta_4 BkEq_{i,t} + \beta_5 TACC_{i,t} + \epsilon_{i,t+\tau}, \end{aligned} \tag{3.1}$$

where $Earn$ reflects earnings, $NegE$ is a dummy variable that equals 1 for firms with negative earnings and 0 otherwise and $NegExE$ is an interaction term of the dummy variable and earnings. Further, $BkEq$ is the book value of equity, $TACC$ reflects total accruals, t represents the time index and τ is a time constant. If not stated differently, all variables in our analysis are scaled by the number of shares outstanding. We forecast earnings for up to five years ahead, i.e., for $\tau = 1 - 5$.[6] A detailed explanation of the calculation of all variables used in this chapter follows in the appendix to chapter 3.

In line with cross-sectional earnings forecast literature (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)), we use a rolling OLS regression approach with a ten-year window to generate the earnings forecasts.[7] First, at the end of June of each year of our sample period, data from year $t-9$ to year t is used to estimate the model parameters. Second, we multiply the computed parameters with the independent variables from year t to obtain firm-specific earnings estimates for year $t+\tau$. Out-of-sample earnings forecasts are available from 1979 onwards. To evaluate forecast accuracy, we use the PAFE (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)), which is defined as follows:

$$PAFE_{i,t+\tau} = \left| \frac{Earn_{t+\tau} - \widehat{Earn}_{t+\tau}}{prc_t} \right|, \tag{3.2}$$

where $\widehat{Earn}$ is the model-based earnings forecast and prc is the end-of-June stock price.

Earnings Management Measure

In line with previous literature (e.g., Frankel, Johnson and Nelson (2002), Klein (2002) and Bergstresser and Philippon (2006)), we use absolute discretionary accruals as a measure for the extent of a firm's EM. Discretionary accruals are defined as the residuals from the estimation of an accruals model. To compute non-discretionary accruals, we use the modified Jones (1991) model by Dechow, Sloan and Sweeney (1995):

$$TACC_{i,t} = \beta_0 + \beta_1(\Delta REV_{i,t} - \Delta REC_{i,t}) + \beta_2 PPE_{i,t} + \epsilon_{i,t}, \tag{3.3}$$

where ΔREV is the change in revenue, ΔREC is the change in receivables and PPE reflects property, plant and equipment. All variables are scaled by the number of

[6] For our analysis, we primarily use one-, two- and three-year ahead forecasts. Four- and five-year ahead forecasts are needed for the ICC computation in Section 3.5.3.

[7] To lower data requirements, we start with a five-year window at the beginning of the sample period and expand the window to ten years successively.

shares outstanding.[8] Further, as specified by Jones (1991) and Dechow, Sloan and Sweeney (1995), the intercept is also scaled, i.e., the true constant term is suppressed (Peasnell, Pope and Young (2000)).

Following more recent studies (e.g., Chung and Kallapur (2003), Francis, LaFond, Olsson and Schipper (2005) and Bergstresser and Philippon (2006) among others), we implement a cross-sectional approach instead of time-series analysis initially employed by Jones (1991). Comparing cross-sectional to time-series accruals models, Bartov, Gul and Tsui (2000) find that only cross-sectional models are constantly able to detect EM. Further, accruals models are frequently estimated at industry level (Dechow, Ge and Schrand (2010)). We follow this approach and employ the Fama and French 48 industry classification.[9]

Similar to the model-based earnings forecasts, we use rolling OLS regressions with a ten-year window to estimate the model.[10] First, model parameters are computed using data from year $t-9$ to year t. Second, the computed parameters are multiplied with the independent variables from year t to obtain an estimate of non-discretionary accruals for year t, which in the following is represented by $\widehat{TACC}$. Lastly, subtracting this estimate from respective actual total accruals $TACC$ provides an estimate for discretionary accruals. The absolute value of discretionary accruals serves as our measure for the extent of a firm's EM, depicted in the following by EM. This measure is available from 1975 onwards and defined as follows:

$$EM_{i,t} = \left| TACC_{i,t} - \widehat{TACC}_{i,t} \right|. \tag{3.4}$$

[8]We scale our variables by the number of shares outstanding to be consistent with the variable definition of the earnings forecast model. Thereby, we deviate from the variable definition of Jones (1991) and Dechow, Sloan and Sweeney (1995). They scale all variables by lagged total assets to reduce heteroscedasticity. Following the approach of Jones (1991), untabulated tests show that the error term of the unscaled accruals model is also highly correlated with the number of shares outstanding. This indicates that scaling by the number of shares outstanding is also reasonable.

[9]Untabulated tests show that the tenor of results is unchanged when we do not estimate the accruals model at industry level. However, we follow the approach which is dominantly used in the EM literature.

[10]Analogous to the earnings forecasts, we start with a five-year window at the beginning of the sample period and expand the window to ten years successively.

The Relationship Between EM and Earnings Forecast Errors

First, we test the relation between the extent of a firm's EM and model-based earnings forecast accuracy using the following regression equation:

$$PAFE_{i,t+\tau} = \beta_0 + \beta_1 EM_{i,t} + \beta_2 Size_{i,t} + \sum_{k=3}^{51} \beta_k Ind_{i,t,k} + \epsilon_{i,t+\tau}. \tag{3.5}$$

We explicitly control for firm size by including the logarithm of total assets ($Size$) and for industry by adding industry dummies (Ind) according to the Fama and French 48 industry classification.[11] We run annual cross-sectional OLS regressions for $\tau = 1 - 3$.[12]

Second, to examine whether the EM measure helps to improve the predictive ability of earnings forecast models, we use the following approach: We annually rank firms into quintiles based on the extent of a firm's EM and create five dummy variables that indicate a firm's respective quintile. Next, we interact the earnings forecast model with the EM quintile dummy variables, i.e., we run a separate regression for each quintile subsample:

$$\begin{aligned} Earn_{i,t+\tau} = \sum_{k=1}^{5} Q_k(&\beta_{0,k} + \beta_{1,k} Earn_{i,t} + \beta_{2,k} NegE_{i,t} + \beta_{3,k} NegExE_{i,t} \\ &+ \beta_{4,k} BkEq_{i,t} + \beta_{5,k} TACC_{i,t} + \epsilon_{i,t+\tau}) \end{aligned}. \tag{3.6}$$

The notation is analogous to equation 3.1 with the addition of the indicator variable Q representing the respective k^{th} EM quintile dummy variable. The variable is set to equal 1 if a firm belongs to the respective EM quintile and 0 otherwise. We rerun the analysis of the RI earnings forecast model and compare regression results and PAFEs of the initial RI model and our newly interacted model.

Third, we investigate if the earnings forecasts from the interacted model result in more reliable expected return proxies compared to the RI model. In line with

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[11] Ecker, Francis, Olsson and Schipper (2013) identify firm size as a potentially important correlated omitted variable in tests for EM.

[12] Using the estimated EM measure as independent variable potentially induces an "error-in-variables" bias. That is, the regression coefficient of the EM measure might be biased towards zero (Griliches and Ringstad (1970)). Hence, our empirical results might understate the true effect of EM on forecast accuracy. However, an even higher true effect does not change the interpretation of our results.

earnings forecast literature (e.g., Hou, Van Dijk and Zhang (2012), Li and Mohanram (2014), and Azevedo, Bielstein and Gerhart (2021)), we use ICCs as a proxy for expected returns. The forecasted earnings are used as future cash flow proxies. Hence, more accurate forecasts should yield more reliable expected return proxies. Prior research has developed various ICC estimation methods. To guarantee that our results are not affected by any particular method, we follow the earnings forecast literature and use a composite ICC. Our ICC measure is the average of the following five commonly used ICC metrics (e.g., Hou, Van Dijk and Zhang (2012), Li and Mohanram (2014) and Azevedo, Bielstein and Gerhart (2021)). We calculate one ICC measure based on a dividend discount model, i.e., the metric by Gordon and Gordon (1997), two ICCs based on a residual income model, i.e., the metrics by Gebhardt, Lee and Swaminathan (2001) and Claus and Thomas (2001), and two ICCs based on an abnormal earnings growth model, i.e., the metrics by Ohlson and Juettner-Nauroth (2005) and Easton (2004). We present a detailed description of the ICC metrics in the appendix to chapter 3. Following Hou, Van Dijk and Zhang (2012) and to increase coverage, we require only one ICC metric to be available to compute the composite ICC. We calculate the firm-specific composite ICC at the end of June of each year.

We analyze the relation of the composite ICC to future returns using two approaches commonly relied on in earnings forecast studies (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)). The first approach examines the relation at the firm-level using the following equation:

$$Ret_{i,t+1} = \beta_0 + \beta_1 ICC_{i,t} + \epsilon_{i,t+1}, \tag{3.7}$$

where Ret is the realized stock return at the end of June of the year $t+\tau$ and ICC is the one-year ahead composite ICC calculated at the end of June of the current year t for the end of June in year $t+\tau$. Using this equation, we run annual cross-sectional OLS regressions for $\tau = 1-3$. Values of β_1 closer to 1 imply a more reliable expected return proxy (Li and Mohanram (2014)).

The second approach evaluates the relation between the composite ICC and future returns on a portfolio level. In line with Hou, Van Dijk and Zhang (2012), we rank firms into decile portfolios based on the composite ICC at the end of June of each year. Next, we calculate the equally weighted buy-and-hold return for each decile portfolio for holding periods of up to three years. We mainly focus on the spread between the highest and lowest decile, i.e., implementing a long-short strategy (e.g., Hou, Van Dijk and Zhang (2012), Li and Mohanram (2014) and Azevedo, Bielstein and Gerhart (2021)). We test if this strategy results in significant returns and compare the realized returns based on the ICCs from the initial RI earnings forecast model to the ones retrieved from the interacted model. The idea behind this strategy is that more reliable ICCs result in a more accurate ranking of firms regarding their expected returns. Consequently, a more accurate ranking will yield higher returns from the long-short strategy.

3.4 Data

The sample we use for the empirical analysis consists of the intersection of the annual COMPUSTAT North American database and the monthly CRSP stock return file. It contains US American firms reporting in US dollar. The total sample period spans from 1971 to 2019. We implement a three-month reporting lag for firm fundamentals to become publicly available. Following previous literature (e.g., Dechow, Hutton, Kim and Sloan (2012)), we exclude financial firms (SIC codes 6,000 to 6,999) from our analysis as financial statements of these firms are subject to different regulatory frameworks.

The variables for the earnings forecast model are defined as follows. Earnings is income before extraordinary items (COMPUSTAT variable: IB) minus special items (SPI). Special items are set to zero if missing. Book equity is total common equity (CEQ). Total accruals are defined as income before extraordinary items (IB) minus cash flow from operations (OANCF). Since cash flow from operations is only available from 1988 onwards, we use the accruals definition of Richardson, Sloan, Soliman and Tuna (2005) in case of missing cash flow from operations (Li and Mohanram (2014)).[13] To compute the PAFE, we take the price from the monthly CRSP stock return file (PRC). To estimate the accruals model, we use the following variables. Total accruals are defined analogously to the earnings forecast model. The change in revenue is current period's total revenue (REVT) minus total revenue from

[13] The appendix to chapter 3 provides a detailed description of the accruals calculation.

the previous period. Likewise, the change in receivables is current period's total receivables (RECT) minus total receivables from the previous period. Property, plant, and equipment is total gross property, plant, and equipment (PPEGT). For all models, variables are scaled by the number of common shares outstanding (CSHO). We require all relevant variables to be non-missing. Further, to mitigate the effect of outliers, we winsorize all variables annually at the 1st and 99th percentile.

To compute the ICC metrics, we further use the following variables. Earnings are defined analogous to the earnings forecast model. Book equity is total common equity (CEQ), dividends are common dividends (DVC) and total assets are set to be equal to the total assets measure (AT). These variables are scaled by the number of common shares outstanding (CSHO), too. The one-year buy-and-hold return is computed by compounding returns from the monthly CRSP stock return file (RET).

Table 3.4.1 presents descriptive statistics for the variables included in the earnings forecast model and for the EM measure.

Panel A shows summary statistics (cross-sectional mean, median, standard deviation and selected percentiles for firm-years with complete data) and Panel B displays Pearson and Spearman correlations. Our sample contains 164,337 firm-year observations. Similar to former studies, our sample includes around 30% of firms with negative earnings (e.g., Hou, Van Dijk and Zhang (2012) and Hess, Meuter and Kaul (2019)). Focusing on the EM measure, Panel A reveals that it is skewed to the right, i.e., the cross-sectional mean (1.09) is approximately twice as large as the median (0.54). Further, Panel B shows that Pearson (Spearman) correlations between the EM measure and the variables included in the earnings forecast model range between -0.24 and 0.07 (-0.16 and 0.41). We report positive correlations between the EM variable and earnings itself. Unsurprisingly, the EM variable is negatively correlated with the negative earnings dummy, which appears reasonable due to the negative correlation between earnings and the negative earnings dummy.

Table 3.4.1: Descriptive Statistics

Panel A: Summary Statistics

	N	Mean	Std	P1	P25	P50	P75	P99
Earn	164,337	1.00	12.84	-3.55	-0.07	0.57	1.65	7.63
NegE	164,337	0.29	0.45	0.00	0.00	0.00	1.00	1.00
NegExE	164,337	-0.24	0.80	-3.55	-0.07	0.00	0.00	0.00
BkEq	164,337	10.11	109.78	-2.62	2.25	6.11	12.82	50.32
TACC	164,337	0.55	2.89	-6.70	-0.05	0.12	1.14	8.48
EM	164,337	1.09	1.62	0.01	0.21	0.54	1.25	8.73

Panel B: Correlations

	Earn	NegE	NegExE	BkEq	TACC	EM
Earn		-0.78***	0.80***	0.71***	0.37***	0.27***
NegE	-0.09***		-0.98***	-0.50***	-0.35***	-0.16***
NegExE	0.09***	-0.48***		0.47***	0.35***	0.12***
BkEq	0.75***	-0.04***	0.01***		0.28***	0.41***
TACC	0.07***	-0.17***	0.19***	0.04***		0.02***
EM	0.05***	-0.06***	-0.24***	0.07***	-0.03***	

Table 3.4.1 contains descriptive statistics for the pooled cross-section of firms from 1975 to 2019. Panel A displays summary statistics for the variables of the earnings forecast model and for the EM measure resulting from the accruals model by Dechow, Sloan and Sweeney (1995). Panel B presents the respective cross-correlations following Pearson (Spearman) below (above) the diagonal. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

3.5 Empirical Results

This section presents the empirical results. First, we provide evidence for a significant positive relation between the extent of a firm's EM and the respective model-based earnings forecast error. Second, we capitalize on this finding and use the EM measure to improve the predictive ability of earnings forecast models. Third, we show that the increased forecast accuracy results in more reliable expected return proxies. Lastly, we ensure that our findings are robust to different earnings forecast models.

3.5.1 The Relationship Between Earnings Management and Earnings Forecast Accuracy

First, we analyze the relation between the extent of a firm's EM and the accuracy of model-based earnings forecasts. We run annual cross-sectional regressions of PAFE on the EM measure while controlling for firm size and industry. Table 3.5.1 presents the results for forecast horizons of up to three years. It contains the time-series averages of the parameter estimates, Newey and West (1987) t-statistics and R^2 values.

Table 3.5.1: The Relationship Between EM and Earnings Forecast Accuracy

	PAFE_{t+1}	PAFE_{t+2}	PAFE_{t+3}
Coefficient	0.0204***	0.0189***	0.0182***
	(8.85)	(10.51)	(9.77)
R^2	0.1249	0.1334	0.1352
Controls	Yes	Yes	Yes

Table 3.5.1 depicts the relationship between EM and the RI model-based earnings forecast accuracy. It contains the time-series averages of the parameter estimates, Newey and West (1987) t-statistics and R^2 values from the annual regressions of PAFE on the EM measure. We control for firm size by including the logarithm of total assets and for industry by adding industry dummies according to the Fama and French 48 industry classification. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

In line with our expectations, the findings provide evidence for a significant positive relation between EM and forecast errors for all forecast horizons. That is, the higher the EM measure, the higher the PAFE, i.e., the lower the forecast accuracy. For one-, two-, and three-years ahead forecasts, the coefficient of the EM measure shows values of 0.0204, 0.0189, and 0.0182, respectively. Hence, the strength of the relation slightly decreases with an increasing forecast horizon. A possible explanation for such phenomenon includes two steps. First, the manipulation of earnings in the actual period negatively influences the earnings forecasts for the following periods, since those forecasts are made based on the modified earnings measure. Second, since forecasts tend to become less accurate with an increasing forecast horizon (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)), the proportion of the forecast error attributed to a management's modification of the earnings measure becomes less influential, which is reflected by the decreasing parameter estimates.

In general, the negative relation between EM and forecast accuracy we find indicates that managers' actions lower earnings' predictability. As pointed out in section 3.1, this could be related to an impaired quality of reported earnings due to opportunistic managerial discretion. Hence, our results are in line with previous studies finding that EM is performed with the intention of misleading stakeholders to obtain some personal gain (e.g., Perry and Williams (1994), Teoh and Wong (2002), and Bergstresser and Philippon (2006)), instead of aiming to increase the information content of reported earnings (Beneish (2001)).

Additionally, figure 3.5.1 plots the annual coefficients of the EM measure for one-, two-, and three-year ahead forecasts.

Figure 3.5.1: Relation Between Earnings Management and Earnings Forecast Accuracy Over Time

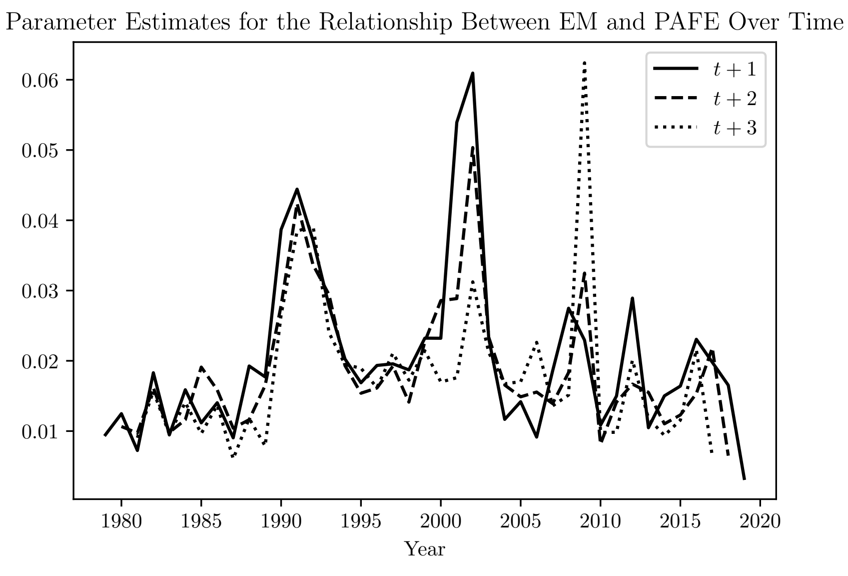


Figure 3.5.1 displays the influence of EM on model-based earnings forecast accuracy. It contains the annual parameter estimates from the regressions of PAFE on the EM measure for one-, two-, and three-year ahead forecasts. We further control for firm size and industry.

As can be seen, the coefficients approximately range between 0.01 and 0.06. Most importantly, figure 3.5.1 displays that the coefficients are entirely positive throughout the sample period, i.e., that the sign of the relation between EM and forecast accuracy is consistent. This further strengthens the significance of our findings. However, we add that it might bear interesting study opportunities to inspect the fluctuation of the coefficient's magnitude over time and leave that question for future research to be answered.

Although we tested and demonstrated a significant negative relationship between the firm's EM and the earnings forecast accuracy, future research might investigate the exact relationship in a more detailed way, i.e., the exact shape of such relationship. One could possibly as well find arguments for a U-shaped relationship. That is that firms in the extreme quantiles regarding their EM extent exhibit a lower earnings forecast accuracy compared to firms with a more moderate extent of EM. Thus, any extreme form of earnings management reduces the predictability of future earnings compared to a moderate earnings management. We leave testing this hypothesis or any other investigation of the exact form of the relationship between EM and forecast accuracy to future research.

3.5.2 The Importance of Incorporating Earnings Management into Earnings Forecast Models

In this section, we make use of the insights gained from the previous section, i.e., that a higher level of EM is significantly related to larger earnings forecast errors. Based on this finding, we assume that firms' EM characteristics contain information that is important for predicting future earnings. More specifically, that the parameter estimates of earnings forecast models are influenced by the extent of a firm's EM. As outlined in section 3.3, we interact the RI model by Li and Mohanram (2014) with five EM quintile dummy variables to account for information about firms' EM. By interacting the model with the dummy variables, we allow for an additional variation of coefficients across EM quintiles. Thus, we expect to obtain more accurate parameter estimates for each subsample. We assume this approach translates to lower forecast errors on average compared to the initial RI earnings forecast model.

Table 3.5.2 presents results for the rolling earnings regressions for one, two, and three years ahead. It contains the time-series averages of the parameter estimates, Newey and West (1987) t-statistics and R^2 values for the initial RI model as well as for each of the five quintiles of the interacted model.

The first column covers the initial RI earnings forecast model, whereas columns two to six report results for each EM quintile subsample. Looking at the individual parameter estimates for each EM quintile, it becomes evident that they differ across each subsample as well as compared to the parameter estimates of the RI model.[14] For example, for one-year ahead forecasts (Panel A), the RI model shows a lagged earnings parameter estimate of 0.79, whereas the EM quintiles exhibit larger coefficients ranging between 0.82 and 1. Similar patterns can be observed for two- and three-year ahead forecasts (Panel B and Panel C, respectively). For the negative earnings dummy, values for the EM quintiles are larger compared to the RI model, too. Values for the interaction term and for book equity vary, i.e., no clear pattern between the EM quintiles and the RI model is evident. Further, for all forecast horizons, the parameter estimate of total accruals is smaller for the EM quintiles in comparison to the RI model. This could be due to the fact that the EM measure is based on accruals, and thus, it already incorporates information about accruals into the model. To sum up, the findings support our assumption that the parameter estimates of earnings forecast models differ over the five subsamples characterized by the extent of a firm's EM. In other words, the relationship between the respective predictor variables and future earnings varies depending on the degree of EM a firm engages in.

Next, we assume that better fitting parameter estimates of the earnings forecast model for each EM quintile translates to lower forecast errors. Table 3.5.3 shows results of the forecasting performance of the RI model compared to the interacted model. We report mean and median PAFEs for earnings forecasts of up to three years ahead. Furthermore, we report the difference in PAFEs between both models and whether the difference is statistically significant.

[14]Nevertheless, the parameter estimates for the book-value of equity ($BkEq$) are almost identical among all five quintiles for each forecast horizon. This provides an argument for not running the model for each quintile individually, but to use all interacted variables in one model. In that case, the book-value of equity would not need to be interacted thus reducing the number of estimated parameter estimates. Such adjustment potentially leads to a better out-of-sample forecasting performance. However, this would only strengthen our results.

Table 3.5.2: Parameter Estimates from the Earnings Forecast Regression

Panel A: $t+1$						
	RI	EM Q1	EM Q2	EM Q3	EM Q4	EM Q5
Intercept	0.26***	0.15**	0.01	0.01	0.01	0.13*
	(2.92)	(2.40)	(0.72)	(0.84)	(0.35)	(1.70)
Earn	0.79***	0.82***	1.00***	0.96***	0.94***	0.84***
	(21.43)	(14.01)	(171.57)	(80.19)	(168.63)	(29.74)
NegE	-0.44***	-0.21***	-0.08***	-0.07***	-0.08***	-0.28***
	(-5.36)	(-3.76)	(-6.72)	(-5.72)	(-5.79)	(-4.67)
NegExE	-0.33***	-0.01	-0.30***	-0.22***	-0.29***	-0.41***
	(-9.00)	(-0.10)	(-5.27)	(-3.64)	(-14.52)	(-11.45)
BkEq	0.00	0.01***	0.01***	0.01***	0.01***	0.01*
	(0.28)	(6.42)	(3.73)	(4.84)	(3.83)	(1.97)
TACC	0.06***	0.02***	-0.01***	0.01***	0.01***	0.04***
	(3.53)	(4.14)	(-4.68)	(3.05)	(3.73)	(3.37)
R^2	0.69	0.77	0.71	0.69	0.63	0.66
Panel B: $t+2$						
Intercept	0.20***	0.13***	0.00	0.04*	0.07*	0.16*
	(3.72)	(3.09)	(0.13)	(1.83)	(1.99)	(1.88)
Earn	0.74***	0.86***	0.94***	0.93***	0.88***	0.72***
	(22.76)	(24.15)	(56.88)	(127.42)	(82.63)	(20.09)
NegE	-0.44***	-0.20***	-0.12***	-0.13***	-0.14***	-0.40***
	(-8.29)	(-5.74)	(-4.76)	(-7.36)	(-5.58)	(-5.70)
NegExE	-0.49***	-0.17**	-0.35***	-0.40***	-0.49***	-0.50***
	(-13.19)	(-2.07)	(-5.59)	(-9.32)	(-15.13)	(-10.44)
BkEq	0.03***	0.02***	0.03***	0.02***	0.02***	0.03***
	(5.13)	(4.55)	(6.26)	(10.14)	(5.46)	(4.97)
TACC	0.01	-0.00	-0.04***	-0.01	0.01	-0.01
	(0.76)	(-0.12)	(-4.51)	(-1.57)	(1.10)	(-0.63)
R^2	0.62	0.65	0.54	0.51	0.46	0.55
Panel C: $t+3$						
Intercept	0.20***	0.13***	0.00	0.04*	0.07*	0.16*
	(3.72)	(3.09)	(0.13)	(1.83)	(1.99)	(1.88)
Earn	0.74***	0.86***	0.94***	0.93***	0.88***	0.72***
	(22.76)	(24.15)	(56.88)	(127.42)	(82.63)	(20.09)
NegE	-0.44***	-0.20***	-0.12***	-0.13***	-0.14***	-0.40***
	(-8.29)	(-5.74)	(-4.76)	(-7.36)	(-5.58)	(-5.70)
NegExE	-0.49***	-0.17**	-0.35***	-0.40***	-0.49***	-0.50***
	(-13.19)	(-2.07)	(-5.59)	(-9.32)	(-15.13)	(-10.44)
BkEq	0.03***	0.02***	0.03***	0.02***	0.02***	0.03***
	(5.13)	(4.55)	(6.26)	(10.14)	(5.46)	(4.97)
TACC	0.01	-0.00	-0.04***	-0.01	0.01	-0.01
	(0.76)	(-0.12)	(-4.51)	(-1.57)	(1.10)	(-0.63)
R^2	0.62	0.65	0.54	0.51	0.46	0.55

Table 3.5.2 contains the time-series averages of the parameter estimates, Newey and West (1987) t-statistics and R^2 values from the annual earnings regressions. Results are displayed for the RI model and the model interacted with the earnings managemant quintiles. Further, we show results for one-, two-, and three-year ahead forecasts. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table 3.5.3: Earnings Forecast Error Comparison

	Median $PAFE_{t+1}$	Mean $PAFE_{t+1}$	Median $PAFE_{t+2}$	Mean $PAFE_{t+2}$	Median $PAFE_{t+3}$	Mean $PAFE_{t+3}$
RI	0.0372***	0.1330***	0.0488***	0.1437***	0.0641***	0.1690***
Model	(18.85)	(15.46)	(23.27)	(20.81)	(12.72)	(11.35)
Interacted	0.0318***	0.1176***	0.0458***	0.1335***	0.0564***	0.1470***
Model	(21.21)	(13.96)	(19.90)	(19.40)	(19.33)	(21.05)
Difference	-0.53***	-1.54***	-0.30***	-1.02***	-0.77*	-2.20*
	(−3.36)	(−4.34)	(−8.04)	(−6.15)	(−1.90)	(−1.97)

Table 3.5.3 compares time-series averages of median and mean PAFEs from the RI earnings forecast model and the model interacted with EM quintiles. One-, two-, and three-year ahead forecasts are analyzed. Further, we test if the difference in PAFE between both models (interacted model minus RI model) is statistically significant. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table 3.5.3 provides evidence that for both mean and median PAFEs, the interacted model significantly improves the predictive ability compared to the initial RI model. This finding holds for all forecast horizons. Forecasting one-year (two-year, three-year-) ahead leads to a median PAFE of 3.72% (4.88%, 6.41%) for the RI model compared to a significantly lower median PAFE of 3.18% (4.58%, 5.64%) for the interacted model. Results are similar when examining mean PAFE values, although mean PAFE values are generally higher than median PAFE values. Moreover, the differences in PAFEs between the RI and the interacted model are statistically significant at the 1% significance level for forecasts of up to two years ahead and at the 10% significance level for three-year ahead forecasts.

In conclusion, we provide evidence that incorporating information about the extent of a firm's EM into cross-sectional earnings forecast models leads to more accurate forecasts thus underlining the importance of incorporating information about a firm's degree of EM into earnings forecast models.

3.5.3 Evaluation of Implied Cost of Capital Estimates

The previous section provides evidence that adding information about a firm's degree of EM to an earnings forecast model is important as it improves forecast accuracy. In this section, we follow the literature (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)) and analyze if the increased forecast accuracy results in more reliable ICC estimates. In line with the academic literature on the ICC (e.g., Gebhardt, Lee and Swaminathan (2001) and Hou, Van Dijk and Zhang (2012)), we evaluate ICCs by assessing their predictive ability for future realized returns. First, we perform firm-level tests to evaluate the relation between the computed composite ICC and realized future returns. Second, we test the predictive power of the composite ICC for future realized returns on a portfolio level.

Table 3.5.4 on the next page presents the results of the firm level-tests, showing the relation between the composite ICC and buy-and-hold returns for one-, two-, and three-years ahead. We annually regress realized future returns on the composite ICC, for both the initial earnings forecast model and the interacted model. The table shows time-series averages of parameter estimates, Newey and West (1987) t-statistics and R^2 values. We expect a positive and significant coefficient if ICCs are able to predict future returns. Further, a coefficient closer to 1 represents an ICC estimate that is on average closer to realized returns.

Table 3.5.4 reveals that the coefficients of the interacted model are closer to 1 in comparison to the RI model. For one-year ahead forecasts, the coefficient of the RI model is 0.1904 compared to 0.2176 for the interacted model. For two-year and three-year ahead forecasts, the values are 0.1659 compared to 0.1947 and 0.1472 compared to 0.1896, respectively. Further, the coefficients of the interacted model show higher t-statistics and thus higher significance. Moreover, for all forecast horizons, R^2 increases when interacting the RI earnings forecast model with the EM quintile dummy variables. In total, Table 3.5.4 provides evidence that ICCs based the interacted model are closer related to realized future returns than ICCs based on the RI model.

Table 3.5.5 below illustrates the results of the portfolio tests for the RI earnings forecast model and the interacted model. We annually rank firms into decile

Table 3.5.4: ICC Firm-Level Test

Panel A: Ret$_{t+1}$			
	Intercept$_{t+1}$	ICC$_{t+1}$	R^2
RI Model	0.1099***	0.1904**	0.0107
	(3.91)	(2.62)	
Interacted Model	0.1058***	0.2176***	0.0128
	(3.78)	(2.77)	
Panel B: Ret$_{t+2}$			
	Intercept$_{t+2}$	ICC$_{t+2}$	R^2
RI Model	0.0484**	0.1659**	0.0129
	(2.48)	(2.69)	
Interacted Model	0.0437**	0.1947***	0.0149
	(2.26)	(2.91)	
Panel C: Ret$_{t+3}$			
	Intercept$_{t+3}$	ICC$_{t+3}$	R^2
RI Model	0.0408**	0.1472**	0.0146
	(2.69)	(2.61)	
Interacted Model	0.0355**	0.1896***	0.0164
	(2.41)	(3.13)	

Table 3.5.4 depicts the relation between the composite ICC and buy-and-hold returns for one-, two-, and three-years ahead. We compare the RI earnings forecast model with the interacted model. The table show the time-series averages of the parameter estimates, Newey and West (1987) t-statistics and R^2 values from the annual regressions of realized future returns on the composite ICC. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

portfolios based on the respective composite ICC. For each decile portfolio, we calculate annualized equally weighted buy-and-hold returns for holding periods of up to three years. Further, we implement a long-short strategy by calculating the spread between the highest and lowest decile. A positive and significant return spread illustrates that the composite ICC has significant predictive power for future realized returns.

Table 3.5.5: ICC Portfolio Test

	Decile	ICC	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}
RI Model	1	-0.0893	0.1022	0.0066	-0.0035
	2	-0.0200	0.1116	0.0437	0.0355
	3	0.0059	0.1130	0.0532	0.0471
	4	0.0259	0.1142	0.0540	0.0484
	5	0.0436	0.1217	0.0627	0.0575
	6	0.0615	0.1311	0.0748	0.0677
	7	0.0818	0.1363	0.0808	0.0716
	8	0.1095	0.1624	0.0917	0.0808
	9	0.1595	0.1747	0.0935	0.0807
	10	0.4834	0.2085	0.0786	0.0582
	H-L	**0.5727*** **	**0.1063*** **	**0.0720*** **	**0.0617*** **
		(13.74)	(3.24)	(3.19)	(3.20)
Interacted Model	1	-0.0948	0.0923	-0.0003	-0.0146
	2	-0.0246	0.1079	0.0365	0.0258
	3	0.0013	0.1128	0.0457	0.0435
	4	0.0209	0.1170	0.0524	0.0476
	5	0.0384	0.1251	0.0610	0.0551
	6	0.0554	0.1327	0.0803	0.0740
	7	0.0739	0.1441	0.0862	0.0757
	8	0.0975	0.1585	0.0970	0.0851
	9	0.1359	0.1698	0.0972	0.0863
	10	0.4461	0.2155	0.0835	0.0648
	H-L	**0.5410*** **	**0.1232*** **	**0.0838*** **	**0.0794*** **
		(11.10)	(3.48)	(3.50)	(3.94)

Table 3.5.5 reports time-series averages of annualized buy-and-hold returns of decile portfolios based on the composite ICC for one-, two-, and three-years ahead. We compare the RI earnings forecast model with the interacted model. For the high-minus-low (H-L) return spread, we further show Newey and West (1987) t-statistics. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table 3.5.5 reveals that for both models, annualized buy-and-hold returns for all holding periods increase almost monotonically from the first to last decile.[15] The

[15] With the exception of decile 10 for holding periods of two and three years.

corresponding high-minus-low return spreads are positive, statistically significant and economically meaningful for both models. However, the interacted model outperforms the RI model for all holding periods. For a one-year holding period, the buy-and-hold return spread for the RI model is 10.63%, while the interacted model yields a return spread of 12.32%. For a two-year (three-year) holding period, the return spread of the RI model is 7.20% (6.17%), whereas the interacted model shows a larger return spread of 8.38% (7.94%). Further, return spreads for the interacted model show larger t-statistics for all holding periods.

To summarize, Table 3.5.5 indicates that ICCs based on the interacted model have stronger predictive power for future realized returns on a portfolio level compared to ICCs based on the RI model. Combined with the results of Table 3.5.4, the findings provide evidence that the interacted model generates more reliable ICC estimates. Therefore, investors potentially benefit from using earnings forecasts that take information about the extent of a firm's EM into account. Furthermore, as the results from the previous section imply and in line with previous research, this gives additional arguments to establish earnings forecast models as an alternative to analysts' earnings forecasts (e.g., Hou, Van Dijk and Zhang (2012) and Hess, Meuter and Kaul (2019)).

3.5.4 Robustness Check: Alternative Earnings Forecast Models

The previous sections provide evidence that the extent of a firm's EM is significantly negatively related to earnings forecast accuracy. We show that it is important to incorporate information about EM into earnings forecast models as it leads to a higher forecast accuracy which then translates to more reliable ICCs. These findings are based on the RI earnings forecast model by Li and Mohanram (2014). To ensure that the findings are robust to alternative earnings forecast models, we further show results for the EP model by Li and Mohanram (2014) and the HVZ model by Hou, Van Dijk and Zhang (2012). The appendix to chapter 3 displays the results for the EP and HVZ model. As elaborated before, information about a firm's extent of EM, if relevant to earnings forecast models, can be added to any earnings forecast model regardless whether it is a simple OLS or a methodologically more advanced machine learning earnings forecast model. For example, Hess, Simon and Weibels (2024) use a large pool of predictor variables, but do not explicitly include EM.

First, tables A.5 and A.9 analyze the relation of the extent of a firm's EM to forecast accuracy analogously to table 3.5.1. For both models, findings are similar to the RI model, i.e., we document a positive and significant relation between EM and forecast accuracy for all forecast horizons. Second, table A.6 (A.10) compares forecast accuracy between the EP (HVZ) model and the EP (HVZ) model interacted with the EM quintile dummy variables. In line with our previous findings from Table 3.5.3, using the interacted models significantly improves forecast accuracy. Depending on the forecast horizon, the best performing model, i.e., RI, EP, or HVZ model, seems to vary. However, values for all models are rather close. Third, tables A.7 and A.11 show results for the firm-level ICC tests for the EP and the HVZ model, respectively, analogous to table 3.5.4. For both the EP and HVZ model, the interacted models show larger coefficients and t-statistics compared to the initial models. This confirms our previous findings. Further, while R^2 seems to be largest for the HVZ model, coefficients and t-statistics are largest for the RI model. Fourth, tables A.8 and A.12 display findings of the ICC portfolio tests. The results confirm our findings from Table 3.5.5, i.e., the interacted models yield larger return spreads for all holding periods. The only exception is the EP model for a one-year holding period. In general, return spreads for the RI and HVZ model seem rather similar, while the EP model performs worse.

In conclusion, the results in the appendix to chapter 3 provide evidence that our results are robust to alternative cross-sectional earnings forecast models. This further strengthens our findings as it implies that not only the RI model by Li and Mohanram (2014) profits from incorporating information about firms' EM, but cross-sectional earnings forecast models in general.

3.6 Conclusion

Having accurate earnings forecasts is crucial as they are an important input for firm valuation, asset allocation or ICC calculation. Intuitively, the occurrence of EM, i.e., intentionally modifying earnings, should negatively affect forecast accuracy.

Hence, the aim of this paper is to analyze the effect of firms' EM on model-based earnings forecast accuracy.

The analysis is structured as follows. First, we examine the general effect of EM on earnings forecast accuracy. We generate earnings forecasts for up to three years ahead with the RI model by Li and Mohanram (2014) and use the PAFE to evaluate forecast accuracy. Further, we compute the EM measure, i.e., absolute discretionary accruals, using the model of Dechow, Sloan and Sweeney (1995). We run annual cross-sectional regression of PAFE on the EM measure. In line with our expectations, we find a significantly positive relation between PAFE and EM for all forecast horizons. That is, with increasing EM, the PAFE increases, i.e., forecast accuracy decreases. Second, we capitalize on this finding and incorporate information about a firm's degree of EM into earnings forecast models. We rank firms annually into quintiles based on the level of EM and create five dummy variables indicating a firm's respective quintile. Next, we interact the earnings forecast model with the EM quintile dummy variables. Again, we generate earnings forecasts for up to three years ahead and find that the forecasts of the interacted model show significantly lower PAFEs compared to the initial RI model. Third, we provide evidence that ICCs based on the interacted model are more reliable expected return proxies in comparison to the initial RI model. Then, for the cross-section of firms, we annually regress realized future returns on the ICCs. We show that ICCs based on the interacted model exhibit higher correlations to realized future returns. Moreover, we annually rank firms into deciles based on the ICCs and implement a long-short-strategy, i.e., we compute the spread between the highest and lowest decile. We find that this portfolio approach yields higher returns for holding periods of up to three years when using ICCs based on the interacted model. Fourth, we ensure that the findings are robust to alternative earnings forecast models. We rerun the previous tests and provide evidence that the tenor of results is unchanged when using the EP model by Li and Mohanram (2014) or the HVZ model by Hou, Van Dijk and Zhang (2012).

We contribute to the literature by providing empirical evidence on the significantly negative relation between the extent of a firm's EM and the predictive ability of earnings forecast models. The negative relation indicates that managerial influence on earnings lowers earnings predictability. This is potentially related to an impaired quality of reported earnings due to opportunistic managerial discretion. Therefore, we support the findings of previous studies indicating that EM is performed for opportunistic reasons, i.e., with the intention of misleading stakeholders to obtain some personal gain (e.g., Perry and Williams (1994), Teoh and Wong (2002), and Bergstresser and Philippon (2006)), instead of aiming to increase the information content of reported earnings (Beneish (2001)). Further, we show that information about EM should be incorporated into earnings forecast models as it improves accuracy and results in more reliable ICCs that yield higher investment strategy returns. This supports previous research and further establishes cross-sectional earnings forecasts as a viable alternative to analysts' earnings forecasts (e.g., Hou, Van Dijk and Zhang (2012) and Hess, Meuter and Kaul (2019)). Additionally, the results of this study provide an argument for incorporating information about a firm's extent of EM into even methodologically more advanced machine learning earnings forecast model.

Future research on the relation between the extent of a firm's EM and forecast accuracy might focus on EM measures that are not based on accruals models. Some studies (e.g., Guay, Kothari and Watts (1996), McNichols (2000), and Thomas and Zhang (2000)) criticize the use of such EM measures as they argue that these models provide biased and noisy estimates of discretionary accruals. Alternatively, for instance, Stubben (2010) proposes to use revenue models instead of accruals models to estimate firms' EM or Dechow, Hutton, Kim and Sloan (2012) incorporate reversals of accruals accounting into their model. Further, we leave testing the hypothesis of a U-shaped or any other investigation of the exact form of the relationship between EM and forecast accuracy to future research as there are plausible arguments for a non-linear relationship as well. Finally, investigating the mechanism that leads to fluctuations in the magnitude of the relationship between the extent of EM and the respective forecast accuracy over time is a research question which due to focus limitations we did not touch on and thus as well leave for future researchers to answer.

To conclude, this study provides evidence that the extent of a firm's EM is significantly negatively related to the predictability of the respective firm's earnings.

We use this finding and show that incorporating information about firms' EM into earnings forecast models increases forecast accuracy and improves ICC reliability. Therefore, future studies on model-based earnings forecasts should account for firms' EM.

Chapter 4

Forecasting Earnings Variance: Quantiles-Based Vs. Residuals-Based Approaches

4.1 Introduction

Extensive research has been conducted on forecasting future mean earnings, i.e., the first moment of future earnings (e.g., Hou, Van Dijk and Zhang (2012), Li and Mohanram (2014), Evans, Njoroge and Yong (2017), Cao and You (2024), Tian, Yim and Newton (2021), Hansen and Thimsen (2021), Chen, Cho, Dou and Lev (2022), Hendriock (2022), Van Binsbergen, Han and Lopez-Lira (2023) and Campbell, Ham, Lu and Wood (2023)). Nevertheless, information about the higher moments of future earnings are important in various economic settings and to a range of economic agents, too, although methodological suggestions are sparse in this comparably novel stem of research.

In general, earnings uncertainty, i.e., the entirety of higher moments of future earnings, is relevant to any agent whose wealth is either directly or indirectly dependent on earnings (Chang, Monahan, Ouazad and Vasvari (2021), hereafter CH). More specifically, CH as well as Konstantinidi and Pope (2016), hereafter KP, show that both the value of debt and equity are related to higher moments of future earnings. Penman and Zhang (2002) as well as Dichev and Tang (2009) show that risk in earnings affects future growth persistence which then influences the predictability of earnings and subsequently a firm's valuation. According to Dichev and Tang (2009), these results fall in line with the findings by Graham, Harvey and Rajgopal (2005) who show that executives believe earnings predictability to be negatively related to earnings volatility. Further, research has shown that equity prices are a function of, inter alia, the higher moments of future earnings (e.g. Merton (1987), Johnson (2004), Brunnermeier, Gollier and Parker (2007), Mitton and Vorkink (2007) and Barberis and Huang (2008)). Donelson and Resutek (2015) find forward-looking earnings uncertainty to be able to predict future returns over 1-year horizons. They also find earnings uncertainty to be significantly related to equity analysts' and investors' overly optimistic expectations of future earnings. Thus, establishing a methodology to derive forecasts of earnings uncertainty or at least parts of earnings uncertainty, e.g., future earnings variance, appears to be reasonably useful in various economic settings. Despite the clear motivation to gain information on the higher moments of future earnings, it is a comparably novel area of research (Monahan (2018)). There exist two quantile-regression approaches using accounting data in a cross-sectional forecasting approach, e.g., KP and CH, to derive forecasts of higher moments of earnings such as variance, skewness and kurtosis. This study exclusively focusses on forecasting the second moment of future earnings, i.e., the variance, as different moments may demand distinct forecast models or at least different predictor variables. Focusing solely on one moment also streamlines the evaluation of forecasting methods as only one measure has to be evaluated at a time.[1]

This study contributes by introducing a new earnings variance forecasting approach based on using the squared residuals from a mean earnings forecast model as a proxy for the variance of the respective observation. This approach is motivated by a suggestion by KP who explicitly state that "*[...], one could capture conditional variance (dispersion) in future earnings by regressing the squared (or absolute) value of the residuals from an earnings forecasting model on predictor variables.*". Further, this study introduces two new evaluation methods for comparing different earnings variance forecasts on firm-level, which are yet not explored in the field of earnings variance forecasts as an alternative to the industry-level evaluation method by CH.

[1]In theory, the presented approaches are all suited to be applied to even higher moments of future earnings. Throughout the remainder of this paper the terms second moment of earnings and earnings variance are used interchangeably.

Traditionally, the variance of financial variables such as stock returns are predominantly forecasted via time-series approaches. Engle (1982) introduces the autoregressive conditional heteroskedastic (ARCH) model to forecast the conditional variance as a linear function of past squared residuals allowing the conditional variance to vary over time. Bollerslev (1986) developes the generalized autoregressive conditional heteroskedastic (GARCH) model that allows for past conditional variances in the current conditional variance equation, which helps capturing the persistence of volatility clustering in ARCH models by incorporating a moving average component. Subsequently, many have proposed the implementation of component volatility models, e.g., with a long- and short-run component (Engle and White (1999)) or other two-component volatility models (e.g., Ding and Granger (1996), Gallant, Hsu and Tauchen (1999), Alizadeh, Brandt and Diebold (2002), Chernov, Gallant, Ghysels and Tauchen (2003) and Adrian and Rosenberg (2008)). The more recent GARCH-MIDAS approach by Engle, Ghysels and Sohn (2013) allows to use data with different frequencies, e.g., daily stock market data and less frequent economic data, in one model. This improvement was inspired by Ghysels, Santa-Clara and Valkanov (2005) who used monthly return data while the variance was estimated using daily squared returns. In a literature review about the general forecasting of volatility in financial markets, Poon and Granger (2003) provide vast evidence that time-series forecasting methods based on historical volatility measures perform similarly well as more sophisticated models from the (G-)ARCH class or stochastic volatility forecast models. Time-series approaches to forecast equity risk usually rely on (G-)ARCH models and use daily (or even higher frequency) stock return data (e.g., KP). Although less common in practice, these time-series models can also include exogenous firm-specific or macroeconomic state variables (e.g., KP). For example, using a standard time-series approach with earnings data, Baginski and Wahlen (2003) estimate an abnormal return-on-equity beta, e.g., the systematic risk in residual income from a firm's time-series of residual return-on-equity. Sheng and Thevenot (2012) were the first to exploit the time-series of earnings data by applying GARCH-class time-series volatility models in order to forecast earnings volatility. Beaver, Kettler and Scholes (1970) find that accounting-based measures of risk are reflected in market-based measures of risk and claim that accounting-based risk measures are better suited to derive forecasts of market-based risk measures.

Baginski and Wahlen (2003) show that capital markets price the systematic risk in residual income. Following KP as well as CH, this study employs accounting data in contrast to market data. However, a time-series approach is not optimal when working with annual or quarterly earnings data due to three reasons: First, only if earnings are stable, past earnings volatility will proxy for future earnings uncertainty (Donelson and Resutek (2015)). Second, cross-sectional variation is not exploited (e.g., KP). Third, time-series analyses suffer from higher data requirements, which is a crucial disadvantage when working with annual or even quarterly earnings data (e.g., Bradshaw, Drake, Myers and Myers (2012)). The two studies by KP and CH tackle these issues and forecast higher moments of future earnings by applying cross-sectional quantile regression approaches. Thus, following KP and CH, this study uses a cross-sectional model for the new residuals-based earnings variance forecasting approach.

This new residuals-based earnings variance forecasting approach aims to serve as an alternative for the quantile-based approaches by KP and CH. The underlying idea of this new approach is based on using the squared residual from a mean earnings forecast model as a proxy for the variance of the respective observation. Such approximation has already been applied in other financial or economic settings and is now applied to earnings. For example, Granger and Ding (1995) employ this proxy in the context of analyzing asset returns and volatility. This approach stems from the idea of the aforementioned ARCH models that do not assume a constant variance, but allow the variance to conditionally vary (Engle (1982)) and translates this idea to a cross-sectional setting. More specifically, as mentioned above, KP suggest to regress the squared residuals from a mean earnings forecast model onto some predictor variables and subsequently derive firm-level earnings variance point-forecasts. According to Granger and Ding (1995), such a residuals-based variance approximation has great intuitive appeal due to its simplicity and thus is a viable alternative to forecasting the future earnings variance via time-series (G-)ARCH models. This new approach will then be benchmarked against the two quantiles-based approaches by KP and CH. KP use the difference between the forecasted 75^{th} and the 25^{th}, i.e., the interquartile range (IQR), as one of their earnings uncertainty measures and claim this measure to be proportional to the variance of future earnings. CH follow a similar approach as KP, but (a) construct their measures of higher moments differently and (b) include different predictor variables.[2] Further, in contrast to KP, CH model the return on equity and not earnings scaled by total assets. Similar to KP, CH implement a quantile regression approach, although they model 150 different quantiles between 0 and 1, which, in theory, helps covering the possibility of extreme outcomes. Based on the resulting 150 forecasted quantiles, they calculate different measures of earnings uncertainty.[3] The comparison between the two quantiles-based earnings variance forecasting approaches by KP and CH and the new residuals-based earnings variance forecasting approach based on the suggestion by KP will form the central part of this study.

In order to construct this residuals-based variance proxy, a mean model for the first moment of future earnings, from which the residuals will be retrieved, is needed. Traditional mean earnings forecast models employ a cross-sectional approach and thus, by design, are superior to analyst-based earnings forecasts in terms of coverage (e.g., Hou, Van Dijk and Zhang (2012) and Li and Mohanram (2014)). A popular earnings forecast model is the one developed by Hou, Van Dijk and Zhang (2012), hereafter HVZ. While their model beats analyst-based earnings forecasts in terms of coverage, forecast bias and earnings response coefficient, it performs worse with regard to the forecast accuracy. Additionally, Gerakos and Gramacy (2013) note that the HVZ model exhibits forecast errors similar to or even worse than a random walk model, questioning the suitability of the HVZ model. In response Li and Mohanram (2014) propose two new earnings forecast models, namely the EP model and the RI model. They provide evidence that both their models outperform the original HVZ model in terms of forecast bias, accuracy and earnings response coefficient. Of these mechanical mean earnings forecast models the RI model is typically found to perform best in terms of forecast accuracy (e.g., Li and Mohanram (2014)). Evans, Njoroge and Yong (2017) as well as Tian, Yim and Newton (2021) provide evidence that using the least absolute deviation method, i.e., median regressions, further improves the earnings forecast performance. More recently, forecasting earnings via

[2] A detailed explanation of the two approaches by KP and CH follows in the methodological part in section 4.2.2.

[3] A detailed explanation of the construction of the future second moment of earnings after CH follows in section 4.2.2.

machine learning approaches gained popularity although the studies in this field suggest only a mild improvement in forecast accuracy compared to the mechanical earnings forecast models (e.g., Cao and You (2024), Tian, Yim and Newton (2021), Hansen and Thimsen (2021), Chen, Cho, Dou and Lev (2022), Hendriock (2022), Van Binsbergen, Han and Lopez-Lira (2023) and Campbell, Ham, Lu and Wood (2023)). As the newly introduced variance proxy is based on residuals from modeling mean future earnings, other ways to gain information about future earnings, such as analyst forecasts and forecast models using a median regression or machine learning approaches, are not applicable for this approximation. Based on the presented findings from former studies, in this study the forecast model for the first moment of future earnings will be the RI model by Li and Mohanram (2014). As suggested by KP, the residuals from this mean earnings forecast model will be squared, used as a variance proxy for the respective observation and then themselves regressed onto some predictor variables in order to derive an out-of-sample firm-year earnings variance forecast.

Evaluating earnings variance firm-year point-forecasts is difficult as the realized variance of a single earnings realization is not directly observable. This study implements three different earnings variance forecast accuracy evaluation methods. The first evaluation method is based on the industry-level evaluation by CH. Their idea is to make use of the law of total variances described by Brillinger (1969) to calculate the forecasted industry-year variance from firm-year mean and variance forecasts, which can then be benchmarked against the realized and observable industry-year variance by implementing a Fama and MacBeth (1973) regression and comparing the resulting R^2. CH compare their quantiles-based forecasting approach with three other approaches, e.g., the approach used by KP, an extension of the historical matched-sample approach by Donelson and Resutek (2015) and an historical firm-level approach. They find their quantiles-based approach to outperform the other three approaches in this industry-level evaluation.

This study, in addition to the industry-level evaluation, introduces two different firm-level evaluations, which are not yet applied in the field of earnings variance forecasts evaluation. The first firm-level evaluation method is based on establishing a proxy for the realized firm-year variance as the squared difference between the forecast and the realized mean earnings against which the forecasted earnings variance can be benchmarked. Then two standard forecast evaluation metrics, i.e., the PAFE and MSE, are calculated in order to compare the forecast accuracy for the three different approaches. The second firm-level evaluation method is based on the idea of prediction intervals (e.g., Bollerslev (1986), Granger, White and Kamstra (1989), Chatfield (1993) and Tay and Wallis (2000)). That is, from a mean earnings forecast based on the RI model, the respective variance forecast and the Z-score for a chosen confidence-level, a prediction interval around the mean forecast is constructed. Then, the percentage of realized earnings falling into that prediction interval is reported. Percentage numbers closer to the chosen confidence-level imply a more accurate variance forecast.[4]

Finally, following KP and CH, this study investigates whether the earnings variance forecasts are relevant to equity prices. For example, KP assess the relation of the predicted IQR, skewness and kurtosis with equity and debt market measures and find that their forecasts of higher moments are related to equity and credit risk ratings, future return volatility, credit spreads and analyst based measures of earnings uncertainty and conclude that their forecasts possess incremental information. Similar to KP, CH also provide evidence for the relevance for equity prices of their quantiled-based predictions of the higher moments of future return on equity. They regress a number of equity-market and debt-market variables on their predictions and control variables and find that their predictions are related to both the equity- and the debt-market. More specifically, they provide evidence that equity prices are increasing (decreasing) in the standard deviation and skewness (kurtosis) of future return on equity and credit spreads are increasing (decreasing) in the standard deviation and kurtosis (skewness) of lead return on assets. Thus, such an analysis of the relevance for equity prices of the variance forecasts from the three forecasting approaches will be implemented in this study as well.

The results of this study show a clear pattern. First, the firm-level variance forecasts are all highly correlated with regard to the Spearman correlation indicating that all approaches assign similar variance forecast ranks to the same firm-years. However, due to comparably large maximal values for the variance forecasts from the

[4] A detailed explanation of the methodology of the evaluation methods follows in section 4.2.3.

quantiles-based approach by KP, the KP forecasts exhibit a lower Pearson correlation with the other forecasts. In general, the approach by KP leads to the smallest forecasts for the majority of the distribution, followed by the CH forecasts and the forecasts based on the squared residuals proxy, which exhibit the largest values for the majority of the distribution. These simple summary statistics are already able to explain the performance of the earnings variance forecasts in terms of forecast accuracy on industry- as well as firm-level.

In line with the findings by CH, the results of the industry-level evaluation confirm an outperformance of the quantiles-based variance forecasting approach by CH in comparison to the quantiles-based approach by KP. However, the residuals-based approach slightly outperforms both of these quantiles-based approaches in terms of industry variance forecast accuracy. The reason for that becomes evident in the summary statistics for both the firm- as well as the industry-level forecasts. As mentioned, the residuals-based firm-level variance forecasts are larger than their quantiles-based counterparts for the majority of the distribution, which translates to comparably larger industry-level forecasts as displayed in the summary statistics for the industry-level variance forecasts. As the realized industry variance is larger than the forecasted industry variances, not only in terms of the mean, but also for a large part of the distribution, larger industry-level variance forecasts translate to a higher forecast accuracy. That is, the industry-level variance forecasts from the residuals-based approach are larger compared to their quantiles-based counterparts, which translates to more accurate forecasts as the realized industry variance is larger than all forecasts. Nevertheless, the arguably more relevant level of aggregation for earnings variance forecasts from a practical perspective is the firm-level. The two firm-level evaluations show an opposing, but congruent pattern. The firm-level earnings variance forecasting approach by KP outperforms the approach by CH, whereas both of these quantiles-based approaches perform better than the residuals-based approach in terms of forecasting accuracy measured by the PAFE and the MSE. The results for the prediction interval evaluation follow that notion. The firm-level results as well as the firm-level summary statistics for the variance forecasts suggest that the approach by KP benefits from leading to comparably small firm-year earnings variance forecasts, which then translate to a higher forecast accuracy on firm-level. Overall, the results of this study suggest that the earnings variance forecasting approach by KP is suited best to derive firm-year earnings variance point-forecasts, whereas the squared-residuals approach leads to the most accurate forecasts on industry-level. Thus, the newly introduced earnings variance forecasting approach based on squared residuals serves as a viable alternative for the quantiles-based approaches when forecasting the industry-level earnings variance.

Finally, this study finds all earnings variance forecasts are relevant to equity prices. More specifically, the results of this study imply that information about future earnings variance derived from accounting data is priced in equity markets and that equity prices increase in the future earnings variance.

The remainder of this paper is structured as follows: Section 4.2 presents the methodology applied in this study. Section 4.3 describes the data, section 4.4 provides the results from the empirical analysis and discusses these. Section 4.5 concludes.

4.2 Methodology

The analysis is divided into three parts. First, section 4.2.1 and section 4.2.2 introduce the forecast models for the conditional first and second moment of future earnings. That is, in section 4.2.1, the conditional mean earnings forecast model by Li and Mohanram (2014) is presented. Section 4.2.2 then presents the two existing quantile-based approaches to derive forecasts for the conditional second moment of future earnings by KP and CH and subsequently the methodology for the residuals-based earnings variance forecasting approach. Second, section 4.2.3 presents the different evaluation techniques to compare the resulting forecasts of the future earnings variance. Following the industry-level evaluation after CH, the computation of the firm-level PAFE and MSE will be presented. Afterwards the firm-level evaluation via prediction intervals will be explained. Third, the methodology to assess the relevance of earnings variance forecasts for equity prices will be presented in section 4.2.4. That is, it will be examined whether the forecasted information are captured in equity prices.

4.2.1 Forecasting The First Moment of Future Earnings

Throughout the study, forecasts for the first moment of future earnings are needed for for the residuals-based earnings variance forecasting approach as well as for the evaluation methods. As elaborated in the introduction, the mean earnings forecasts in this study are derived from the RI model by Li and Mohanram (2014), which can be expressed by the following estimation equation:

$$\begin{aligned} Earn_{i,t+\tau} = \beta_0 + \beta_1 Earn_{i,t} + \beta_2 d^{-}_{i,t} + \beta_3 d^{-} Earn_{i,t} \\ + \beta_4 BkEq_{i,t} + \beta_5 TACC_{i,t} + \epsilon_{i,t+\tau}, \end{aligned} \tag{4.1}$$

where $Earn$ reflects earnings, d^{-} is an indicator variable equal to one if $Earn_{i,t} < 0$ and zero otherwise, $d^{-}Earn$ is an interaction term of the dummy variable d^{-} and $Earn$, $BkEq$ is the book-value of equity, $TACC$ reflects total accruals, t represents the time index, τ is a time constant and ϵ is the error term. In line with Li and Mohanram (2014), earnings are defined as earnings excluding special items and, if not stated otherwise, throughout the entire study per-share measures are applied, that is, all variables are scaled by the number of common shares outstanding. In that regard, this study differs to the studies by KP and CH. Whereas KP uses earnings scaled by total assets, CH analysis the return on equity calculated as earnings divided by common equity. A detailed explanation of the construction of all variables used in this chapter follows in the appendix to chapter 4. As in Li and Mohanram (2014), a cross-sectional rolling OLS regression approach with a window length of ten years in order to train the model is implemented. More specifically, for each window the annual data from year $t-9$ to year t is used to estimate the model's parameter estimates. To derive forecasts for the first moment of future earnings one year ahead, i.e., $\tau = 1$, the retrieved parameter estimates are multiplied with the realized data from year t in order to obtain firm-specific mean earnings estimates for year $t+\tau$.

Another option for deriving mean earnings forecasts would be to implement the different approaches by KP and CH to derive mean earnings forecasts. More specifically, CH compute mean earnings forecasts for their approach as the average of their 150 quantile forecasts. Further, CH calculate mean earnings forecasts for the approach by KP via a rolling window OLS regression with the model depicted in KP's study (equation 4.2). However, if the mean earnings forecasts throughout the evaluations differ in addition to the different variance forecasts, the presented evaluation methods do not independently assess the performance of the variance forecasts, but jointly evaluate the forecasts for the first and second moment. Table 4.2.1 demonstrates that the mean earnings forecasts from the CH and the KP approach do indeed differ in terms of accuracy and additionally exhibit different variances, which is an important disadvantage for the following industry-level evaluation.

Table 4.2.1: Mean Earnings Forecast Comparison

	RI	KP	CH
$PAFE$	0.0234***	0.0244***	0.0228***
Mean Forecast Variance	3.9657	3.6283	4.4177
$PAFE$ Difference		0.0016***	

Table 4.2.1 contains information about the Newey and West (1987) time-series averages of the median forecast accuracy ($PAFE$) and the variance of the mean forecasts for the entire sample, i.e. the pooled cross-section of firms from 1988 to 2022 for forecast horizons of one years for model-based mean earnings forecasts. KP mean earnings forecasts are derived via a rolling OLS regression version of the model for quantile forecasts depicted in equation 4.2. CH mean earnings forecasts are the calculated as the average over all 150 forecasted quantiles as elaborated in their study. Forecast accuracy is calculated as the End-of-June price-scaled absolute forecast error. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

In order to circumvent the problem of different mean earnings forecasts and in order to secure an isolated evaluation of the earnings variance forecasts, the mean earnings forecasts in this study are the same for all approaches, i.e., mean earnings forecasts retrieved from the RI forecast model by Li and Mohanram (2014).

4.2.2 Forecasting The Second Moment of Future Earnings

This section presents the methodology for deriving earnings variance forecasts based on the two-quantiles based approaches by KP and CH as well as the newly introduced residuals-based earnings variance forecasting approach. The predictor sets in the studies by KP and CH are not identical. Thus, in order to isolate the comparison between the quantiles- and the residuals-based approach from the suitability of the respective predictor set, the residuals-based forecasting approach will be implemented once with the predictor variables from the KP study and once with the predictor variables from the CH study.

The Earnings Variance Forecasting Approach by KP

The approach by KP is based on quantile regressions (Koenker and Bassett Jr. (1978)). First, the following estimation equation is applied for both the 25^{th} and the 75^{th} percentile, i.e., for $q = 0.25$ and $q = 0.75$:

$$\begin{aligned} Q_q(Earn_{i,t+\tau}|\cdot) = {} & \beta_0^q d_{i,t}^+ + \beta_1^q d_{i,t}^- + \beta_2^q d_{i,t}^+ TACC_{i,t} + \beta_3^q d_{i,t}^- TACC_{i,t} \\ & + \beta_4^q d_{i,t}^+ OCF_{i,t} + \beta_5^q d_{i,t}^- OCF_{i,t} + \beta_6^q d_{i,t}^+ SPI_{i,t} + \beta_7^q d_{i,t}^- SPI_{i,t} \\ & + \epsilon_{i,t+\tau}. \end{aligned} \tag{4.2}$$

where OCF is operating cash flow, SPI is special items and d^+ is an indicator variable equal to one if $Earn_{i,t} \geq 0$ and zero otherwise. Additionally, the model includes industry fixed effects according to the Fama-French 12-Industries classification (FF12).

The model is estimated on a rolling basis with window length of ten years, leading to a series of parameter estimates for the two quantiles. Afterwards, equal to the methodology for deriving forecasts for the first moment of future earnings, the parameter estimates are multiplied with the realized data from year t to derive out-of-sample quantile forecasts for the 25^{th} and the 75^{th} percentile for year $t + \tau$. Then, for each firm-year the difference between the 25^{th} and the 75^{th} percentile, i.e., the IQR, is calculated, which, according to KP, is assumed to be proportional to the variance of the respective observation (e.g., Koenker and Bassett Jr. (1982) and Angrist and Pischke (2009)). However, under the assumption of a normal distribution, in order to transform the IQR into a variance measure, the IQR has to be divided by 1.35 and the resulting measure has to be squared.[5] Doing so produces the firm-level out-of-sample earnings variance forecast, i.e., a forecast for the second moment of future earnings, which will be referred to as KP throughout the remainder of this study.

[5]This step is an important difference between the studies by KP and CH and this study. KP claim their IQR measure to be proportional to the variance if the conditional variance is linear in the predictor variables (e.g., Koenker and Bassett Jr. (1982) and Angrist and Pischke (2009)). However, KP do not explicitly claim to forecast future earnings standard deviation or variance, but the IQR. CH compare their forecast of the future standard deviation of earnings to the forecasted IQR by KP. However, they do not transform the IQR to a standard deviation and thus compare two slightly different concepts. In contrast, this study explicitly compares different earnings variance forecasts and thus implements a comparison of congruent concepts.

The Earnings Variance Forecasting Approach by CH

Similar to KP, the approach by CH is also based on quantile regressions (Koenker and Bassett Jr. (1978)). First, for a range of quantiles Q, i.e., 150 quantiles between 0.01 and 0.99 with equal increments, the following equation is estimated:

$$\begin{aligned} Q_q(Earn_{i,t+\tau}|\cdot) = \beta_0^q + \beta_1^q Earn_{i,t} + \beta_2^q d_{i,t}^- + \beta_3^q d_{i,t}^- Earn_{i,t} + \beta_4^q TACC_{i,t} \\ + \beta_5^q LEV_{i,t} + \beta_6^q PAYOUT_{i,t} + \beta_7^q PAYER_{i,t} + \epsilon_{i,t+\tau}, \end{aligned} \tag{4.3}$$

where LEV is the leverage ratio, $PAYOUT$ is dividends paid and $PAYER$ a dummy variable equal to 1 for dividend-paying firms. This model is estimated on a rolling basis with window length of ten years, leading to a series of 150 quantile parameter estimates for each year. Then the parameter estimates are multiplied with the realized data from year t to derive out-of-sample quantile forecasts for the 150 quantiles for each firm in year $t + \tau$. Afterwards, in line with CH, the quantile forecasts are rearranged using the approach by Chernozhukov, Fernández-Val and Galichon (2010), so that they do not cross, i.e., that the firm-year quantile forecasts are monotonically increasing with the quantiles. Then, to calculate the firm-level variance forecast, for each series of out-of-sample firm-year quantile forecasts, the squared mean of the firm-year quantile forecasts is subtracted from the mean of the squared quantile forecasts. This is the expected second moment of earnings according to CH, i.e.,:

$$\widehat{VAR}_{CH}(Earn_{i,t+\tau}) = \frac{1}{Q}\Sigma_{q=1}^{Q}(Q_q(Earn_{i,t+1}|\cdot))^2 - (\frac{1}{Q}\Sigma_{q=1}^{Q}(Q_q(Earn_{i,t+1}|\cdot)))^2. \tag{4.4}$$

The resulting earnings variance forecasts will be referred to as CH throughout the remainder of this study.

The Residuals-Based Earnings Variance Proxy

For the construction of the residuals-based earnings variance proxy an earnings forecast model is needed. Section 4.2.1 introduced the methodology applied to derive firm-year mean earnings forecasts by using the RI model by Li and Mohanram (2014). In a second step, the residuals from modeling the first moment of future earnings are retrieved, annually winsorized at the 1^{st} and 99^{th} percentile, squared and then used as a proxy for the variance of the respective observation, so that:

$$Var_{SR}(Earn_{i,t}) = (\epsilon_{i,t})^2. \tag{4.5}$$

To derive a forecast of the second moment of future earnings, the approach follows the suggestion by KP to regress the squared residuals from a mean earnings forecast model on predictor variables. In other words, the squared residuals are now themselves modeled. This translates to the following estimation equation:

$$\begin{aligned} Var_{SR}(Earn_{i,t+\tau}) = {} & \beta_0 d^+_{i,t} + \beta_1 d^-_{i,t} + \beta_2 d^+_{i,t} TACC_{i,t} + \beta_3 d^-_{i,t} TACC_{i,t} \\ & + \beta_4 d^+_{i,t} OCF_{i,t} + \beta_5 d^-_{i,t} OCF_{i,t} + \beta_6 d^+_{i,t} SPI_{i,t} + \beta_7 d^-_{i,t} SPI_{i,t} \\ & + \epsilon_{i,t+\tau}. \end{aligned} \tag{4.6}$$

Additionally, the model includes industry fixed effects according to the Fama-French 12 industry classification. As mentioned before, the same approach will also be implemented with the predictor variables from the study by CH as depicted in equation 4.3, which leads to the following model:

$$\begin{aligned} Var_{SR}(Earn_{i,t+\tau}) = {} & \beta_0 + \beta_1 Earn_{i,t} + \beta_2 d^-_{i,t} + \beta_3 d^-_{i,t} Earn_{i,t} + \beta_4 TACC_{i,t} \\ & + \beta_5 LEV_{i,t} + \beta_6 PAYOUT_{i,t} + \beta_7 PAYER_{i,t} + \epsilon_{i,t+\tau}. \end{aligned} \tag{4.7}$$

From modeling the variance of future earnings, the resulting parameter estimates are retrieved and then multiplied with the realized values from period t in order to obtain firm-specific earnings variance forecasts for year $t+\tau$.

Implementing the former three approaches to derive earnings variance forecasts leads to four different firm-year earnings variance forecasts from now on called SR_{KP}, SR_{CH}, KP and CH refering to the residuals-based variance forecasts once forecasted with the KP predictor variables and once with the CH predictor variables, the quantile-based variance forecast by KP and the quantile-based variance forecast by CH, respectively. The following section 4.2.3 presents the evaluation techniques used to compare the forecasts with each other.

4.2.3 Evaluation of the Earnings Variance Forecast Accuracy

The evaluation of firm-year earnings variance point-forecasts is not straightforward. That is, it is not possible to observe a realized variance in one point and thus it is not possible to evaluate the forecast in comparison to a realized value as it is, for example, possible when evaluating forecasts of the first moment of earnings for which a realized value as benchmark can actually be observed. Thus, three evaluation methods that all circumvent that problem are implemented in this study in order to make the results as robust as possible against the chosen evaluation method. First, the industry-level evaluation after CH, second, the computation of the firm-level PAFE and MSE and, third, the firm-level evaluation via prediction intervals will be presented.

Industry-Level Forecast Accuracy Evaluation

As it is possible to observe an industry-year realized variance, CH implement an industry-level evaluation approach. Although they implement their evaluation for the standard deviation forecasts, the same method can be applied to variance forecasts, which will be done in this study. That is, first, the forecasted industry-level earnings variance is calculated from firm-level mean and variance forecasts via the law of total variance as described by Brillinger (1969) for each year, which can then be evaluated against the realized industry earnings variance in the respective year. More specifically, the forecasted industry variance for each industry according to the Fama-French 49 industry classification is calculated as the sum of the variance of the industry's firm-level mean earnings forecasts ($VAR(\widehat{Earn}_{i,t+1}|\cdot)$), derived via the RI forecast model, and the industry mean of the forecasted variance ($\widehat{VAR}(Earn_{i,t+1}|\cdot)$):

$$\widehat{Var}(Earn_{IND,t+\tau}) = VAR(\widehat{Earn}_{i,t+1}|\cdot) + \widehat{VAR}(Earn_{i,t+1}|\cdot). \tag{4.8}$$

Afterwards, the realized industry variance is regressed on the predicted industry variance and an intercept, so that:

$$Var(Earn_{IND,t+\tau}) = \beta_0 + \beta_1 \widehat{Var}(Earn_{IND,t+\tau}) + \epsilon_{i,t+\tau}. \tag{4.9}$$

This approach implements the idea of a Fama and MacBeth (1973) regression on industry-level and the resulting out-of-sample R^2, representing the percentage of the variation in the realized variance captured by the variance forecast, for each of the four earnings variance forecasts can then be compared. A higher R^2 represents more accurate industry-level variance forecasts.

CH implement this evaluation approach in order to compare their earnings standard deviation to the approach by KP, among others. However, this study implements some improvements compared to the methodolgy for the industry-level evaluation approach by CH. First, CH use different mean earnings forecasts for the approximation of the industry earnings variance. As elaborated in section 4.2.1, this leads to conceptual problems and in order to circumvent the problem of different mean earnings forecasts, the mean earnings forecasts in this study are the same for all approaches, i.e., mean earnings forecasts retrieved from the RI forecast model by Li and Mohanram (2014). Further, CH explicitly forecast future earnings standard deviation, whereas KP derive a forecast for the IQR and claim this measure to be proportional to the variance if the conditional earnings variance is linear in the predictor variables (e.g., Koenker and Bassett Jr. (1982) and Angrist and Pischke (2009)). CH compare their standard deviation forecast to the IQR forecast by KP. However, there is a conceptual mismatch when comparing forecasts of the future earnings standard deviation with the future earnings IQR as the IQR has to be divided by 1.35 in order to be transformed to a standard deviation measure. This study addresses this problem and explicitly forecasts earnings variance so that all forecasts are conceptually comparable.

Firm-Level Earnings Variance Forecast Accuracy

As explained, a firm-year level evaluation is difficult when it comes to annual earnings variance forecasts. The former evaluation method evades the problem by evaluating the forecasts on industry level. This study presents two additional evaluation methods, which are not yet explored in the area of earnings variance forecasts that come closer to evaluating the forecasts on a firm-year level.

For the first of the two firm-level evaluation method similar to Hou, Van Dijk and Zhang (2012) or Li and Mohanram (2014), the PAFE as a measure of accuracy will be calculated. Additionally, the MSE, calculated as the average squared difference between the realized and the forecasted earnings variance for each forecasting approach, will be included in the analysis as a standard forecast evaluation metric. In order to compute both measures, information about the realized variance against which the forecasts can be benchmarked is needed. As the realized firm-year variance is not observable, a proxy will be introduced.[6] The intuition behind the realized variance proxy follows the idea of using the squared residuals from a mean earnings model as a proxy for the earnings variance. More specifically, the proxy aims to approximate the realized variance in one point as the squared difference between the forecasted earnings ($\widehat{Earn}_{i,t+\tau}$) from a mean earnings forecast model and the realized earnings value ($Earn_{i,t+\tau}$). In the following, this proxy for the realized variance in $t+\tau$ will be referred to as $Var^{real}(Earn_{i,t+\tau})$, so that:

$$Var^{real}(Earn_{i,t+\tau}) = ((\widehat{Earn}_{i,t+\tau}) - (Earn_{i,t+\tau}))^2. \tag{4.10}$$

Afterwards, the $PAFE$ can be calculated as:

$$PAFE_{i,t+\tau} = \left| \frac{Var^{real}(Earn_{i,t+\tau}) - Var(\widehat{Earn}_{i,t+\tau})}{prc_t} \right|, \tag{4.11}$$

whereas the MSE can be calculated as:

$$MSE_{i,t+\tau} = (Var^{real}(Earn_{i,t+\tau}) - \widehat{Var}(Earn_{i,t+\tau}))^2. \tag{4.12}$$

Forecast Accuracy Evaluation Using Predicted Intervals

The second of the two firm-level evaluation methods is based on the concept of prediction intervals. In contrast to point forecasts, density forecasts are able to provide a complete description of the uncertainty associated with a forecast. Prediction intervals are an intermediate form between these two and specify an interval in which the realized measure falls with a specified probability (e.g., Bollerslev (1986), Granger, White and Kamstra (1989), Chatfield (1993) and Tay and Wallis (2000)). Thus, a prediction interval consists of both an upper and lower boundery associated

[6] Although this proxy is economically justifiable and the best proxy at hand, it still might not perfectly capture the true variance. Thus, in the next section a second evaluation method that is independent from such approximation will be included.

with the chosen probability (Chatfield (1993)). For example, Granger, White and Kamstra (1989) combine different quantile forecasts to derive an interval forecast.[7]

In this study, the forecasts for the first and second moment of future earnings are combined to calculate a prediction interval for a chosen confidence-level. More specifically, similar to Chatfield (1993), a firm-year specific prediction interval assuming a normal distribution with a mean equal to the forecasted mean earnings ($\widehat{Earn}_{i,t+\tau}$), a standard deviation equal to the square-root of the forecasted earnings variance ($\widehat{Var(Earn)}_{i,t+\tau}$) and the respective Z-score (Z) for a given confidence-level (α) is calculated:

$$\text{Lower Bound} = \widehat{Earn}_{i,t+\tau} - (Z_\alpha \times \sqrt{\widehat{Var}(Earn_{i,t+\tau})}) \tag{4.13}$$

$$\text{Upper Bound} = \widehat{Earn}_{i,t+\tau} + (Z_\alpha \times \sqrt{\widehat{Var}(Earn_{i,t+\tau})}) \tag{4.14}$$

Afterwards, the percentage of realized mean earnings falling in the respective prediction interval, refered to as true coverage or interval score, will be calculated and compared to the chosen confidence-level, refered to as nominal coverage (e.g., Christoffersen (1998) and Baillie and Bollerslev (1992)). A true coverage closer to the nominal coverage implies better forecasts. That means, if, for example, a 80% confidence-level is chosen, 80% of the realized mean earnings values should fall in the respective range. As the mean forecast is the same for all four approaches, i.e., a mean earnings forecast based on the RI model by Li and Mohanram (2014), this evaluation approach isolates the performance of the earnings variance forecasts. This evaluation method does not rely on industry-level variances, but enables an evaluation on firm-year level. Additionally, it does not rely on a proxy for the realized firm-year variance as the prior evaluation method.

4.2.4 Evaluation of the Relevance for Equity Prices

Finally, this study investigates whether the variance forecasts bear relevance for equity prices. To assess the relevance for equity prices of the earnings variance forecasts, the evaluation method proposed by CH is applied. A similar analysis

[7] Note, that in this study the concept of prediction intervals is only applied as an evaluation method.

is also implemented by KP although the investigated variables are others. The central idea behind the approach is to regress different outcome variables on the variance forecasts and control variables. Two equity market variables are included in order to make the analysis robust to the chosen equity market metric.jo genau The chosen outcome variables are the book-to-market ratio (BP) and the earnings-to-price ratio (EP). A statistically significant parameter estimate for the variance forecast implies that the variance forecasts help to explain equity prices. Thus, the estimation equation 4.15 will be implemented for each variance forecast and both outcome variables. The outcome and the control variables are winsorized annually at the 1^{st} and 99^{th} percentile.

$$Outcome_i = \beta_0 + \beta_1 VarianceForecast_i + \sum_n \beta_n Control_{n,i} + \epsilon_i. \tag{4.15}$$

4.3 Data

This study's sample consists of the intersection between the databases COMPUSTAT and CRSP and includes annual data of US firms reporting in US Dollar during the period between 1988 and 2022. Financial statements data is retrieved from the COMPUSTAT database while stock price data is taken from the monthly CRSP file. The data preparation follows Li and Mohanram (2014). That is, a reporting lag of 3 months is implemented and each model is estimated at the end of June of the respective year. This requirement causes that financial information of firms with a fiscal year end between April and June in year $t-1$ are not available at the end of June, and thus for the estimation in year t data from April of year $t-1$ until March of year t is used. Further, all variables used in the forecasting models are scaled by the common shares outstanding, if not stated otherwise. All observations with missing entries for any of the variables used in any of the forecasting models are excluded from the sample. Additionally, observations that correspond to a stock price that is smaller than one US dollar and/or zero common shares outstanding are excluded from the sample. Then, financial firms (SIC codes 6,000 to 6,999) are excluded from the sample. In order to mitigate the effect of outliers, all variables are winsorized annually at the 1^{st} and 99^{th} percentile. The earnings definition used in this study corresponds to the "core earnings" definition by Li and Mohanram (2014) who define earnings as earnings per share excluding special items. Industries are assigned according to the FF12 based on the four-digit SIC code. Summary statistics for the resulting sample of 112,578 observations are displayed in table 4.3.1.

Table 4.3.1: Descriptive Statistics

Panel A: Summary Statistics

	N	Mean	Std	Min	P25	P50	P75	Max
$Earn$	112,578	0.88	2.16	-13.10	-0.14	0.56	1.61	29.74
d^-	112,578	0.30	0.46	0.00	0.00	0.00	1.00	1.00
d^+	112,578	0.70	0.46	0.00	0.00	1.00	1.00	1.00
d^-Earn	112,578	-0.28	0.81	-13.10	-0.14	0.00	0.00	0.00
$BkEq$	112,578	9.34	10.56	-11.88	2.46	6.28	12.60	103.41
$TACC$	112,578	-1.02	2.24	-30.54	-1.49	-0.48	-0.03	19.60
OCF	112,505	1.89	3.15	-13.02	0.02	1.03	2.84	34.88
SPI	112,578	-0.25	0.89	-16.17	-0.16	0.00	0.00	3.45
LEV	112,563	2.46	4.18	-35.47	1.37	1.92	2.89	47.70
$PAYOUT$	112,578	0.30	0.65	0.00	0.00	0.00	0.28	5.99
$PAYER$	112,578	0.40	0.49	0.00	0.00	0.00	1.00	1.00

Panel B: Correlations

	$Earn$	d^-	d^-Earn	$BkEq$	$TACC$
$Earn$		-0.79***	0.81***	0.65***	-0.14***
d^-	-0.55***		-0.98***	-0.47***	0.04***
d^-Earn	0.56***	-0.54***		0.44***	0.01*
$BkEq$	0.61***	-0.33***	0.10***		-0.36***
$TACC$	-0.07***	-0.01**	0.30***	-0.38***	

Table 3.4.1 contains descriptive statistics for the pooled cross-section of firms from 1988 to 2022 for all variables of the RI earnings forecast model after Li and Mohanram (2014), the model by Konstantinidi and Pope (2016) and the model by Chang, Monahan, Ouazad and Vasvari (2021). All values are on per-share level, i.e., scaled by common shares outstanding. Panel A displays summary statistics and Panel B presents the respective cross-correlations following Pearson (Spearman) above (below) the diagonal. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

4.4 Empirical Results

This section presents the empirical results. First, the regression results for the forecasting models for the first and second moment of future earnings will be presented in sections 4.4.1 and 4.4.2. Second, descriptive statistics for the resulting variance forecasts follow in section 4.4.3. Section 4.4.4 contains the empirical results from the three different evaluation methods concerned with the forecast accuracy of the variance forecasts. Third, section 4.4.5 presents the empirical evidence regarding the economic relevance of the forecasted variances.

4.4.1 Modeling the First Moment of Future Earnings

Table 4.4.1 presents the parameter estimates and the respective Newey and West (1987) p-values from the rolling window OLS regression using the RI model by Li and Mohanram (2014) for a forecasting horizon of one year.

Table 4.4.1: Parameter Estimates for the RI Mean Earnings Forecast Model For A One-Year Forecast Horizon

	$Intercept$	$Earn$	d^-	d^-Earn	$TACC$	$BkEq$
Par. Est.	**0.06****	**0.77*****	**-0.29*****	**-0.23*****	**-0.08*****	**0.01*****
	(0.0343)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0030)

Table 4.4.1 contains information regarding the time-series averages of the parameter estimates and the Newey and West (1987) p-values assuming a ten-year lag length from modelling the conditional first moment of future earnings, i.e. mean earnings by using the RI model by Li and Mohanram (2014). To obtain the parameter estimates, a rolling OLS regression approach with a window length of ten years in line with Li and Mohanram (2014) is implemented. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

As expected, all parameter estimates are statistically significant at the 1%-level, except the intercept which is only significant at the 5%-level. Most of signs of the explanatory variables align with the findings by Li and Mohanram (2014) and magnitude of the coefficients is comparable. Further, the resulting $PAFE$ is comparable to the study by Li and Mohanram (2014) as displayed in table 4.2.1. The forecasts resulting from this mean earnings forecast model will be used throughout the study.

4.4.2 Modeling the Second Moment of Future Earnings

In this section, the parameter estimates resulting from modeling the second moment of future earnings will be reported. The appendix to chapter 4 presents the average parameter estimates over all windows from a rolling regression approach for the different variance forecasting approaches that result in the earnings variance forecasts SR_{KP}, SR_{CH}, KP, CH. The parameter estimates for the 25^{th} and 75^{th} quantile from the forecasting approach by KP are represented by $KP25$ and $KP75$, respectively. Further, the functions of the parameter estimates for the 150 quantiles from the forecasting approach by CH are represented by CH in the graphs. Lastly, the parameter estimates from the squared residuals approach are marked as SR_{KP} and SR_{CH} in the graphs in the appendix to chapter 4.

As mentioned before, this study includes two different sets of predictor variables to forecast future earnings variance. That is, once the forecasting approach by KP is implemented with the respective predictor variables and once the forecasting approach by CH is implemented with the respective predictor variables. Further the squared-residuals approach is implemented twice, once with the predictor variables by KP and once with the predictor variables by CH. Since this study focusses on the forecast performance of the different approaches and less on the economic interpretation of the relationship between the predictor variables and the future earnings variance, for reasons of simplicity and not to extend the scope of this study, in the following only the sign of the coefficients from the OLS squared-residuals approach will be reported. The following patterns can be retrieved from the parameter estimates displayed in the appendix to chapter 4.

First, the predictor set from the study by KP will be analyzed, which is used to derive the two forecasts KP and SR_{KP}. The interpretation of the coefficients from squared-residuals approach is comparably simple as there is only one parameter estimate and thus one sign. The parameter estimates imply that non-loss firms have a smaller baseline future earnings variance compared to loss-firms. Further, for non-loss firms a positive relationship between the total accruals as well as the operating cash flow and the future earnings variance is reported, whereas the relationship for loss firms is the opposite. Finally, independently of whether a firm reports a loss or not, a negative relationship of special items with the future earnings variance is reported.

Second, the predictor set from the study by CH will be analyzed, which is used to derive the two forecasts CH and SR_{CH}. Again, interpretation of the squared-residuals approach is comparably simple as there is only one parameter estimate and thus one sign. That is, a positive sign is found for the relationship between the future earnings variance and earnings, the loss-firm dummy variable and leverage. A negative sign is found for the relationship between the future earnings variance and total accruals, the interaction term between earnings, dividends paid as well as the dummy for dividend-paying firms.

As the focus of this study lies on the predictive ability of the presented forecasting approaches and less on the economic interpretation of the relationships, the following part presents the results for the evaluation of the respective earnings variance forecast accuracy.

4.4.3 Descriptive Statistics for the Variance Forecasts

Table 4.4.2 provides descriptive statistics for the four earnings variance forecasts (SR_{KP}, SR_{CH}, KP, CH).

The summary statistics in Panel A show that for the majority of the distribution, i.e., the values between the 10^{th} and the 90^{th} percentile are relatively similar, although there are differences. That is, the approach by KP results in the lowest earnings variance forecasts, followed by variance forecasts from the approach by CH not only for the mean earnings variance forecast, but for the majority of the distribution as well. The two variance forecasts derived via the squared-residuals approach exhibit comparably large values. The values for the maximum exhibit the opposite pattern, which then translates to the standard deviation of the four variance forecasts. That is, the approach by KP results in extremely large maximal values compared to the other two approaches, whereas the approach by CH still produces larger maximums compared to the squared-residuals approach. Overall, the KP forecasts exhibit the largest standard deviation, but the lowest mean, whereas

Table 4.4.2: Descriptive Statistics of the Variance Forecasts

Panel A: Summary Statistics

	Mean	Std	Min	P10	P25	P50	P75	P90	Max
SR_{KP}	1.48	2.61	-21.7	0.27	0.45	0.78	1.53	3.20	54.57
SR_{CH}	1.53	2.80	-12.4	0.21	0.40	0.80	1.64	3.33	70.42
KP	0.96	3.97	0.00	0.07	0.13	0.28	0.69	1.74	288.31
CH	1.18	3.88	0.00	0.17	0.24	0.43	0.94	2.19	134.56

Panel B: Correlations

	SR_{KP}	SR_{CH}	KP	CH
SR_{KP}		0.92***	0.73***	0.81***
SR_{CH}	0.86***		0.66***	0.91***
KP	0.90***	0.89***		0.73***
CH	0.83***	0.96***	0.92***	

Table 4.4.2 contains descriptive statistics for the pooled cross-section of firm-year variance forecasts resulting from the four variance forecasting approaches. That is, the two quantile-based approaches by Konstantinidi and Pope (2016) represented by KP and Chang, Monahan, Ouazad and Vasvari (2021) represented by CH and the residuals-based approach which is implemented once with the predictor variables from Konstantinidi and Pope (2016) represented by SR_{KP} and once with the predictor variables from Chang, Monahan, Ouazad and Vasvari (2021) represented by SR_{CH}. Panel A displays summary statistics and Panel B presents the respective cross-correlations following Pearson (Spearman) above (below) the diagonal. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

the residuals-based forecasts exhibit the lowest standard deviation, but the highest mean.

This pattern is supported by the Pearson and Spearman correlations in Panel B. Table 4.4.2 shows that all variance forecasts exhibit high Spearman correlation with values ranging from 0.83 up to 0.96 implying that all approaches assign similar earnings variance forecast ranks to the same firms as the Spearman correlation is based on ranked values. However, according to the Pearson correlation, the forecasts from the KP approach are less correlated to the other approaches compared to the correlation of the three forecasts SR_{KP}, SR_{CH} and CH with each other. As the Pearson correlation is more sensitive to outliers, Panel B supports the findings from

Panel A that the quantiles-based approach by KP results in comparably large maximal values, but all approaches lead to relatively similar earnings variance forecasts for the majority of the distribution. The described patterns play a crucial role for interpreting the results of the following forecast accuracy evaluations.

4.4.4 Evaluation of the Earnings Variance Forecast Accuracy

Industry-Level Forecast Accuracy Evaluation

The evaluation approach by CH applies an industry-level test using Fama and MacBeth (1973) regressions for which the realized variance per industry is regressed onto the forecasted variance per industry and an intercept as described in the methodological part. Table 4.4.3 presents the resulting R^2s:

Table 4.4.3: Variance Forecast Accuracy Evaluation on Industry-Level

	SR_{KP}	SR_{CH}	KP	CH
R^2	0.6584	0.6569	0.6379	0.6563

Table 4.4.3 contains information about the forecast accuracy of the industry-level standard deviation forecast derived from the firm-level variance forecasts from the four approaches SR_{KP}, SR_{CH}, KP and CH via the law of total variances. More specifically, the resulting R^2 from regressing the realized industry standard deviation onto the predicted industry standard deviation is reported. This industry-level evaluation stems from Chang, Monahan, Ouazad and Vasvari (2021).

First, the results show quite high R^2 values for all four approaches implying that it is indeed possible to forecast the earnings variance on industry-level.[8] This is in line with the summary statistics and the correlations for the earnings variance forecasts displayed in table 4.4.2. Nevertheless, the residuals-based approaches perform slightly better than the quantiles-based approaches with a R^2 of 0.6584 and 0.06569 for the two forecasts SR_{KP} and SR_{CH}, respectively. The result for the comparison between the two quantiles-based approaches is in line with the study by

[8]Note, that the R^2 values are not comparable to the study by CH as they (a) use industry standard deviation instead of variance forecasts in their study, (b) investigate the standard deviation of the return on equity and not earnings per share, (c) have different mean forecasts for each approach, whereas in this study all mean forecasts are the same RI model-based mean earnings forecasts and (d) compare their approach for forecasting the standard deviation with the IQR forecast from the KP approach without transforming the IQR to a standard deviation.

CH, who also find their variance forecasting approach to perform better with a R^2 of 0.6583 than the approach by KP with a R^2 of 0.6379 in the industry-level test.

The outperformance of the residuals-based industry-level variance forecasts can be explained by the summary statistics for the realized and the forecasted industry earnings variance as display in table 4.4.4 below.

Table 4.4.4: Descriptive Statistics of the Industry Variance Forecasts

	Mean	Std	Min	P10	P25	P50	P75	P90	Max
$real.Var_{IND}$	6.51	10.05	0.04	1.29	1.97	3.62	7.00	13.80	157.79
SR_{KP}	5.21	5.61	0.57	1.49	2.10	3.43	5.97	10.41	60.79
SR_{CH}	5.21	5.66	0.46	1.47	2.09	3.44	5.93	10.32	65.40
KP	4.69	5.52	0.22	1.14	1.75	2.93	5.28	9.49	56.95
CH	4.86	5.77	0.32	1.23	1.81	3.02	5.51	9.94	70.15

Table 4.4.4 contains descriptive statistics for the pooled cross-section of industry-year variance forecasts resulting from the aggregation of the four firm-level variance forecasting approaches and the mean earnings forecasts from the RI model by Li and Mohanram (2014) to industry-level variance forecasts via the law of total variance after Brillinger (1969). That is, the two quantile-based approaches by Konstantinidi and Pope (2016) represented by KP and Chang, Monahan, Ouazad and Vasvari (2021) represented by CH and the residuals-based approach which is implemented once with the predictor variables from Konstantinidi and Pope (2016) represented by SR_{KP} and once with the predictor variables from Chang, Monahan, Ouazad and Vasvari (2021) represented by SR_{CH}. $real.Var_{IND}$ refers to the realized industry variance.

Table 4.4.2 showed that the residuals-based firm-level earnings variance forecasts are larger than their quantiles-based counterparts for the majority of the distribution. This leads to comparably larger industry-level forecasts as displayed in table 4.4.4. As the realized industry variance is larger than the forecasted industry variances, not only in terms of the mean, but also for a large part of the distribution, larger industry-level variance forecasts translate to a higher industry-level forecast accuracy. This pattern is reflected in the results for the industry evaluation in table 4.4.3.

Finally, although the results of this industry-level evaluation are in line with the findings by CH, the results of this study are conceptually more robust. That is, CH use different mean forecasts for calculating the industry earnings variance forecast via the law of total variance by Brillinger (1969). In this study, all mean earnings forecasts are the same so that the evaluation isolates the performance of the variance forecasts and does not jointly evaluate mean and variance forecasts.

However, this evaluation method is concerned with industry-level earnings variance forecasts, although the firm-level earnings variance forecasts are arguably more relevant from a practical point of view. In contrast to the industry variance, it is not possible to observe the realized firm-year earnings variance, so that the industry evaluation after CH cannot simply be applied to firm-level earnings variance forecasts. Thus, this study implements two firm-level evaluation approaches, which are yet not explored in the field of earnings variance forecasting. The results of these two tests will be presented in the following. Both firm-level evaluations are based on different concepts so that the results are robust to the chosen evaluation method.

Firm-Level Forecast Accuracy Evaluation

Table 4.4.5 presents the earnings variance forecast accuracy measured by the PAFE and MSE.

Table 4.4.5: Variance Forecast Accuracy Evaluation on Firm-Level

	SR_{KP}	SR_{CH}	KP	CH
$PAFE$	0.0474***	0.0451***	0.0177***	0.0262***
MSE	1.0839***	1.1065**	0.1506**	0.2767***

Table 4.4.5 contains information about the Newey and West (1987) time-series averages of the median forecast accuracy ($PAFE$ and MSE) for the entire sample, i.e. the pooled cross-section of variance forecasts of the four variance forecasting approaches SR_{KP}, SR_{CH}, KP and CH. $PAFE$ is calculated as the End-of-June price-scaled absolute forecast error and MSE is calculated as the squared difference between the realized and the forecasted earnings variance. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

The pattern resulting from this firm-level evaluation is different to the industry-level evaluation, but aligns with the findings from the descriptive statistics for the firm-level variance forecasts. First, it can be seen that the highest forecast accuracy is achieved via the quantiles-based approach by KP with a $PAFE$ of 0.0177, followed by the quantiles-based approach by CH $PAFE$ of 0.0262, which both perform better than both residuals-based approaches with $PAFE$ values of 0.0474 and 0.0451. This ranking of the forecast accuracy aligns with the ranking of the magnitude of the earnings variance forecasts for the majority of the distribution. More specifically, smaller firm-level variance forecasts seem to translate to a higher forecast accuracy. Second, the results exhibit a similar pattern when using the MSE as a forecast accuracy measure. That is, the quantiles-based approach by KP performs best with a MSE of 0.1506, followed by the quantiles-based approach by CH with a MSE of 0.2767, which both perform better than both residuals-based approaches with MSE values of 1.0839 and 1.1065.

The results of the firm-level forecast accuracy evalution imply that the KP forecasts are the most accurate on firm-level. It seems that lower level of variance forecast values for the majority of the distribution as displayed in the firm-level summary statistics in table 4.4.2 translate to more accurate firm-level earnings variance forecasts. The higher level of the CH earnings variance forecasts for the majority of the distribution seems to lead to a performance worse than the KP forecasts on firm-level. The comparably high level for the squared-residuals earnings variance forecast values does translate to even less accurate firm-level earnings variance forecasts. However, at this point it remains unanswered whether the true earnings variance distribution has an even lower level than the KP forecasts so that the KP forecasts are the most accurate or whether the true earnings variance distribution lies somehwere inbetween the KP and the CH forecast distribution, but closer to the KP forecast distribution so that KP forecasts perform best. The following evaluation aims to answer that question. Additionally, this second firm-level evaluation that does not use a realized variance proxy in order to make the findings more robust.

Forecast Accuracy Evaluation Using Prediction Intervals

The third evaluation method is based on prediction intervals as elaborated in section 4.2.3. As the mean forecast is the same in all cases, this method evaluates the variance forecasts independently. Table 4.4.6 presents the results from that evaluation.

The results in table 4.4.6 confirm the results from the first firm-level evaluation using the $PAFE$ and the MSE as evaluation measures. The second firm-level evaluation method which applies prediction intervals and does not rely on a realized variance proxy shows a similar pattern. That is, for seven of the eight confidence-

Table 4.4.6: Forecast Accuracy Evaluation Using Prediction Intervals

Confidence-Level	SR_{KP}	SR_{CH}	KP	CH
1%	0.0157	0.0151	0.0092	0.0124
5%	0.0776	0.0750	0.0456	0.0594
10%	0.1550	0.1505	0.0922	0.1201
20%	0.3016	0.2943	0.1867	0.2392
30%	0.4349	0.4249	0.2794	0.3527
40%	0.5455	0.5372	0.3745	0.4602
60%	0.7158	0.7122	0.5573	0.6472
80%	0.8312	0.8305	0.7240	0.7941

Table 4.4.6 contains information about the forecast accuracy of the four conditional variance forecasting approaches SR_{KP}, SR_{CH}, KP and CH. That is, the percentage of realized mean earnings of the forecasted period falling in the prediction interval constructed by using the forecasted mean earnings value, the square-root of the forecasted variance and the Z-value to determine the range of a specific prediction interval in which the respective percentage number of realized mean earnings should fall is reported. That means, if, for example, a 40% confidence level is chosen, 40% of the realized mean earnings values should fall in the respective prediction interval.

levels, the KP variance forecasts perform best, followed by the CH variance forecasts and the two residuals-based variance forecasts. More specifically, the percentage of realized mean earnings figures falling in the prediction interval constructed with the forecasted mean and variance of earnings and the Z-score comes closest to the chosen confidence-level for the KP variance forecasts. In detail, the results confirm the findings from the former analyses that the residuals-based earnings variance forecasts are on average too large resulting in too large prediction intervals. That also holds for the CH earnings variance forecasts although they perform better than the residuals-based forecasts. Further, the results from the prediction interval evaluation suggest that the firm-level earnings variance forecasts from the quantiles-based approach by KP are too small resulting in too narrow prediction intervals. However, the approach by KP still comes closest to the correct prediction intervals. The only deviation from the described pattern is the 80% confidence-level. For this chosen level the CH variance forecasts are the most accurate. This aligns with the former findings regarding the pattern of the forecasted variances. It seems that the quantiles-based earnings variance forecasting approach by KP results in comparably low variance forecasts. This translates to a better forecasting accuracy on firm-level as the above tests show. However, it seems that the prediction intervals based on the approach by KP are too small, especially in comparison to the other three approaches for which the resulting prediction intervals are too big. This advantage seems to fade when the level of the forecasted variance increases. Thus, it can be concluded that the realized earnings variance distribution lies somewhere inbetween the KP and the CH forecasts on firm-level, although the results imply that for the majority of the distribution, the KP forecasts come closer to the realized variance than the CH forecasts and the forecasts based on the squared-residuals approach.

In conclusion, the three evaluation methods show a congruent pattern. That is, the variance forecasts based on the quantiles-approach by KP exhibit the smallest values for the majority of the distribution, whereas the residuals-based variance forecasts are relatively large. This translates to the following forecast accuracy characteristics: First, on industry-level the squared-residuals approach seems to benefit from the larger firm-level earnings variance forecasts and thus performs best. On firm-level the earnings variance forecasts from the approach by KP leads to the most accurate earnings variance forecasts. Thus, this study contributes in two ways. First, it compares an earnings variance forecasting approach based on squared-residuals to the two quantiles-based earnings variance forecasting approaches by KP and CH. The study concludes that the squared-residuals approach is a viable option to the quantiles-based approaches and is best suited when the goal is to derive accurate industry earnings variance forecasts, whereas the quantiles-based approach by KP is best suited when concerned with firm-level earnings variance forecasts. Further, this study emphasizes the importance of the chosen level of aggregation when evaluating earnings variance forecasts. Finally, this study contributes by introducing two firm-level evaluation methods to the field of earnings variance forecasts which pose viable alternatives to the industry-level evaluation by CH.

4.4.5 Evaluation of the Relevance for Equity Prices

After analyzing the forecast accuracy of the different variance forecasts, this section deals with the relevance for equity prices of these forecasts. Thus, two different outcome variables, i.e., the book-to-market and the earnings-to-price ratio, are regressed on the variance forecasts and some control variables.[9] A significant relationship between the outcome variable and the variance forecast implies that the forecast contains information that help explain the respective outcome variable. Such regression analysis is implemented for each of the four earnings variance forecasts (SR_{KP}, SR_{CH}, KP, CH) and is inspired by CH who perform the same test. A similar test is also included in the study by KP although they use different outcome variables.

Outcome Variable: Book-to-Market Ratio

The first outcome variable analyzed is the book-to-market ratio. Table 4.4.7 presents the results from the respective regression.

First, it appears that future earnings variance is negatively associated with the book-to-market ratio, that is, equity prices are increasing in the variance of future earnings. This result is in line CH who report the same relationship. The relationships are significant for all firm-level earnings variance forecasts. Overall, in line with CH, the findings suggest that the earnings variance forecasts are relevant for equity prices, i.e., their information is priced. Further, the variable $HflStd$, representing a simple time-series earnings standard deviation forecast, is highly significant for all approaches, implying that the earnings variance forecasts obtained via the cross-sectional approaches in this study contain information beyond the information captured in a time-series approach. That gives another argument for the application of cross-sectional approaches in the field of earnings variance forecasting so that it is possible to exploit cross-sectional differences. Additionally, this evaluation provides another argument for the validity of these earnings variance forecasting concepts. In the following the same analysis for the earnings-to-price ratio is implemented in order to make the result more robust.

[9] The variable $HflStd$ is a forecast for the future firm-level standard deviation based on the the historical firm-level standard deviation in order to account for the prominence of time-series approaches. Thus, the test reveals whether the forecasts contain information beyond the ones captured in this time-series measure. The results remain the same if not a time-series standard deviation forecast, but a time-series variance forecast is included.

Table 4.4.7: Evaluation of Economic Relevance: BP

	SR_{KP}	SR_{CH}	KP	CH
$Intercept$	**0.8056*** **	**0.8073*** **	**0.8007*** **	**0.8006*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$VarianceForecast_{i,t+1}$	**-0.0056*** **	**-0.0105*** **	**-0.0030** **	**-0.0065*** **
	(0.0057)	(0.0000)	(0.0406)	(0.0001)
$HflStd_{i,t+1}$	**0.0502*** **	**0.0567*** **	**0.0483*** **	**0.0545*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Size_{i,t}$	**-0.0000*** **	**-0.0000*** **	**-0.0000*** **	**-0.0000*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Beta_{i,t}$	**-0.2390*** **	**-0.2384*** **	**-0.2397*** **	**-0.2401*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$AnnRet_{i,t}$	**-0.1598*** **	**-0.1595*** **	**-0.1605*** **	**-0.1603*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$RetStd_{i,t}$	**0.5947*** **	**0.5887*** **	**0.6103*** **	**0.6057*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R^2	**0.0793**	**0.0800**	**0.0792**	**0.0797**

Table 4.4.7 contains information about the relevance of the conditional variance forecast for equity prices. That is, the parameter estimates and the p-values as well as the R^2 resulting from regressing the outcome variable BP on the forecasted variance and control variables for the four variance forecasting approaches SR_{KP}, SR_{CH}, KP and CH is reported. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Outcome Variable: Earnings-to-Price Ratio

Table 4.4.8 below presents the results from the regression of the outcome variable EP on the variance forecasts and control variables.

Table 4.4.8 confirms the results from the first analysis of the relevance for equity prices. That is, future earnings variance is negatively related to the earnings-to-price ratio, i.e., equity prices are increasing in the variance of future earnings. Again, the relationship is significant for all firm-level earnings variance forecasts.

In conclusion, the analysis of the economic relevance finds strong evidence that equity markets price information about future earnings variance and equity prices are increasing in future earnings variance.

Table 4.4.8: Evaluation of Economic Relevance: EP

	SR_{KP}	SR_{CH}	KP	CH
$Intercept$	**0.1206*** **	**0.1221*** **	**0.1147*** **	**0.1175*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$VarianceForecast_{i,t+1}$	**-0.0032*** **	**-0.0072*** **	**-0.0075*** **	**-0.0042*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$HflStd_{i,t+1}$	**-0.0078*** **	**-0.0027* **	**-0.0008**	**-0.0047*** **
	(0.0000)	(0.0681)	(0.5819)	(0.0014)
$Size_{i,t}$	**0.0000*** **	**0.0000*** **	**0.0000*** **	**0.0000*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Beta_{i,t}$	**-0.0076*** **	**-0.0071*** **	**-0.0079*** **	**-0.0082*** **
	(0.0006)	(0.0013)	(0.0003)	(0.0002)
$AnnRet_{i,t}$	**0.0493*** **	**0.0496*** **	**0.0492*** **	**0.0491*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$RetStd_{i,t}$	**-0.8068*** **	**-0.8122*** **	**-0.7932*** **	**-0.8003*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
R^2	**0.1071**	**0.1109**	**0.1151**	**0.1092**

Table 4.4.8 contains information about the relevance of the conditional variance forecast for equity prices. That is, the parameter estimates and the p-values as well as the R^2 resulting from regressing the outcome variable EP on the forecasted variance and control variables for the four variance forecasting approaches SR_{KP}, SR_{CH}, KP and CH is reported. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

4.5 Conclusion

Information about the future second moment of earnings, i.e., the variance of future earnings, is crucial in various economic settings. This study contributes to the understanding of future earnings variance forecasting approaches in two ways. First, a residuals-based earnings variance proxy is presented and benchmarked against the two existing quantiles-based variance forecasting approaches by KP and CH. Second, this study introduces two firm-level evaluation approaches that pose viable alternatives to the industry-level evaluation by CH.

The results from all three evaluations imply that it is generally possible to accurately forecast earnings variance, which aligns with the findings by KP and CH. With regard to the industry-level evaluation, this study confirms the outperformance of the approach CH in comparison to the approach by KP, which CH document in their study. However, the new residuals-based approach is able to outperform both quantiles-based approaches on industry-level. This is due to the fact that the realized industry-level variance is larger than all industry-level variance forecasts. As the squared-residuals approach results in larger forecast in comparison to the other approaches, the squared-residuals approach exhibits a better forecast accuracy. Thus, this study finds that the squared residuals approach is not only a viable alternative to the quantiles-based approaches by KP and CH, but even performs best in terms of industry-level forecasting accuracy.

This pattern changes when looking at the results for the firm-level tests, stressing out the importance of the level of aggregation when evaluating forecasts. This study introduces two new firm-level evaluation approaches to the field of earnings variance forecasting. The first evaluation is based on approximating the realized variance on firm-level. Such approximation may not be perfect, although it seems to be the best one at hand. The second evaluation does not rely on any proxy for the realized variance, but instead applies prediction intervals in order to evaluate the forecast accuracy on firm-level. The results are robust to the chosen firm-level evaluation method and suggest that the quantiles-based approach by KP performs best in terms of forecast accuracy on firm-level. Additionally, the prediction interval evaluation implies that the true firm-level realized variance distribution lies inbetween the distribution of the KP and the CH forecasts and is closer to the KP forecasts for the majority of the distribution, resulting in a higher forecast accuracy for the KP forecasts. Future research might explore alternative evaluation approaches as well as alternative proxies for the realized earnings variance against which the firm-level forecasts can be benchmarked. Although not tested in this study, in theory both quantiles-based approaches as well as the residuals-based approach can be applied to forecast even higher moments of future earnings, i.e., skewness or kurtosis. Future research might additionally turn to an in-depth analysis of the respective forecasting approaches for skewness and kurtosis independently. In that setting the approach by CH possibly benefits from estimating the extreme quantiles which are potentially more relevant to higher moments such as skewness and kurtosis.

Finally, in line with CH, this study finds that information about future earnings variance is priced in equity markets. More specifically, equity prices are increasing in the variance of future earnings.

Appendix to Chapter 2

Variable Definitions

Panel A: Earnings Forecasts		
Variable	Description	COMPUSTAT/CRSP Variable
$Earn$	Earnings divided by number of shares outstanding.	(IB-SPI)/CSHO
d^-	Indicator variable that equals 1 for firms with negative earnings and 0 otherwise.	
d^-Earn	Interaction term of $Earn$ and d^-.	
$BkEq$	Book value of equity divided by number of shares outstanding.	CEQ/CSHO
OCF	Cashflow divided by number of shares outstanding. XIDOC set to 0, if missing.	(OANCF-XIDOC)/CSHO
$TACC$	$Earn$ minus OCF. Set to 0, if missing.	
prc	End-of-June CRSP stock price	PRC
$Std_t(\widehat{Earn}_{t+\tau})$	IBES analysts' consensus earnings forecast standard deviation.	STDEV

Panel B: Conservatism Measure		
Variable	Description	COMPUSTAT/CRSP Variable
$OCFQ$	Quarterly cash flow calculated as the difference between two subsequent year-to-date cash flow observations.	OANCFY(t)-OANCF(t-1)
$EarnQ$	Quarterly earnings.	IBQ
RoE^C	Return on market equity used for the calculation of conditional conservatism according to Chen, Folsom, Paek and Sami (2014).	((IB-SPI)/CSHO)/PRCCF(t-1)

R	Annual stock return compounded from monthly returns from the CRSP monthly file starting nine months before fiscal year end and ending three months after.	RET
DR	Negative return dummy variable for return R. Set to 1 for negative return firm-year observations and 0 otherwise.	
$Size$	Natural logarithm of total assets.	AT
MB	Market-to-book ratio.	(PRCCF*CSHO)/CEQ
LEV	Leverage ratio as ratio of total liabilities to total assets.	(DLC+DLTT)/AT

Panel C: Other Variables

Variable	Description	COMPUSTAT/CRSP Variable
$AssetsTotal$	Total assets.	AT
$EarnVol$	Earnings volatility calculated as the standard deviation of earnings over the last five years requiring at least 3 observations.	IB
$AnnRet$	Annual stock return compounded from monthly returns from the CRSP monthly file starting nine months before fiscal year end and ending three months after.	RET

The Relationship Between Conditional Conservatism and Earnings Forecast Reliability

Table A.1: The Relationship Between Conditional Accounting Conservatism and Two-Years Earnings Forecasts

	$PAFE_{M,t+2}$	$PAFE_{A,t+2}$	$PFE_{M,t+2}$	$PFE_{A,t+2}$	$Disp_{A,t+2}$
Panel A: Without Control Variables					
$Intercept$	**0.0504*****	**0.0168*****	**0.0042*****	**-0.0035***	**0.0038*****
	(0.0000)	(0.0000)	(0.0001)	(0.0614)	(0.0000)
$RCCon_{i,t}$	**0.0037*****	**0.0085*****	**-0.0010*****	**-0.0058*****	**0.0025*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0081**	**0.0095**	**0.0005**	**0.0047**	**0.0355**
Panel B: With Control Variables					
$Intercept$	**0.0305*****	**0.0055*****	**-0.0008**	**-0.0085*****	**-0.0001**
	(0.0000)	(0.0009)	(0.5323)	(0.0000)	(0.8081)
$RCCon_{i,t}$	**0.0047*****	**0.0084*****	**-0.0006*****	**-0.0049*****	**0.0026*****
	(0.0000)	(0.0000)	(0.0015)	(0.0000)	(0.0000)
$TotalAssets_{i,t}$	**-0.0000*****	**-0.0000*****	**0.0000*****	**0.0000*****	**-0.0000*****
	(0.0000)	(0.0000)	(0.0006)	(0.0019)	(0.0000)
$EarnVol_{i,t}$	**0.0283*****	**0.0222*****	**0.0031*****	**0.0022****	**0.0069*****
	(0.0000)	(0.0000)	(0.0000)	(0.0180)	(0.0000)
$AnnRet_{i,t}$	**-0.0158*****	**-0.0176*****	**0.0082*****	**0.0058*****	**-0.0074*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0483**	**0.0306**	**0.0038**	**0.0094**	**0.0818**

Table A.1 contains information about the relationship between the dependent variables $PAFE_{M,t+2}$, $PAFE_{A,t+2}$, $PFE_{M,t+2}$, $PFE_{A,t+2}$ and $Disp_{A,t+2}$ in year $t+2$ and the accounting conservatism measure $RCCon$ after Khan and Watts (2009) in year t. That is, the dependent variable is regressed onto an intercept and the conservatism measure $RCCon$ in Panel A and additionally onto some relevant control variables in Panel B using an OLS decile-rank regression approach. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table A.2: The Relationship Between Conditional Accounting Conservatism and Three-Years Earnings Forecasts

Panel A: Without Control Variables					
	$PAFE_{M,t+3}$	$PAFE_{A,t+3}$	$PFE_{M,t+3}$	$PFE_{A,t+3}$	$Disp_{A,t+3}$
$Intercept$	**0.0560*****	**0.0249*****	**0.0129*****	**-0.0020**	**0.0014****
	(0.0000)	(0.0000)	(0.0000)	(0.2771)	(0.0191)
$RCCon_{i,t}$	**0.0039*****	**0.0104*****	**-0.0018*****	**-0.0075*****	**0.0055*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0078**	**0.0205**	**0.0014**	**0.0134**	**0.0791**
Panel B: With Control Variables					
$Intercept$	**0.0377*****	**0.0150*****	**0.0050*****	**-0.0134*****	**-0.0012***
	(0.0000)	(0.0000)	(0.0010)	(0.0000)	(0.0729)
$RCCon_{i,t}$	**0.0049*****	**0.0104*****	**-0.0013*****	**-0.0065*****	**0.0053*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$TotalAssets_{i,t}$	**-0.0000*****	**-0.0000*****	**0.0000****	**0.0000***	**-0.0000*****
	(0.0000)	(0.0000)	(0.0133)	(0.0504)	(0.0000)
$EarnVol_{i,t}$	**0.0276*****	**0.0231*****	**0.0089*****	**0.0090*****	**0.0060*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$AnnRet_{i,t}$	**-0.0213*****	**-0.0425*****	**0.0021****	**0.0074*****	**-0.0113*****
	(0.0000)	(0.0000)	(0.0154)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0443**	**0.0440**	**0.0037**	**0.0145**	**0.1068**

Table A.2 contains information about the relationship between the dependent variables $PAFE_{M,t+3}$, $PAFE_{A,t+3}$, $PFE_{M,t+3}$, $PFE_{A,t+3}$ and $Disp_{A,t+3}$ in year $t+3$ and the accounting conservatism measure $RCCon$ after Khan and Watts (2009) in year t. That is, the dependent variable is regressed onto an intercept and the conservatism measure $RCCon$ in Panel A and additionally onto some relevant control variables in Panel B using an OLS decile-rank regression approach. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

The Relationship Between Unconditional Conservatism and Earnings Forecast Reliability

Table A.3: The Relationship Between Unconditional Accounting Conservatism and Two-Years Earnings Forecasts

Panel A: Without Control Variables					
	$PAFE_{M,t+2}$	$PAFE_{A,t+2}$	$PFE_{M,t+2}$	$PFE_{A,t+2}$	$Disp_{A,t+2}$
$Intercept$	**0.0483*****	**0.0238*****	**0.0030****	**-0.0119*****	**0.0043*****
	(0.0000)	(0.0000)	(0.0120)	(0.0000)	(0.0000)
$RUCon_{i,t}$	**0.0031*****	**0.0041*****	**0.0001**	**-0.0016*****	**0.0015*****
	(0.0000)	(0.0000)	(0.6937)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0065**	**0.0095**	**-0.0000**	**0.0017**	**0.0235**
Panel B: With Control Variables					
$Intercept$	**0.0363*****	**0.0164*****	**-0.0008**	**-0.0157*****	**0.0016*****
	(0.0000)	(0.0000)	(0.5696)	(0.0000)	(0.0000)
$RUCon_{i,t}$	**0.0031*****	**0.0040*****	**0.0001**	**-0.0015*****	**0.0015*****
	(0.0000)	(0.0000)	(0.5020)	(0.0000)	(0.0000)
$AssetsTotal_{i,t}$	**-0.0000*****	**-0.0000*****	**0.0000*****	**0.0000*****	**-0.0000*****
	(0.0000)	(0.0000)	(0.0009)	(0.0000)	(0.0000)
$EarnVol_{i,t}$	**0.0239*****	**0.0178*****	**0.0017****	**0.0021*****	**0.0059*****
	(0.0000)	(0.0000)	(0.0366)	(0.0071)	(0.0000)
$AnnRet_{i,t}$	**-0.0170*****	**-0.0164*****	**0.0094*****	**0.0047*****	**-0.0065*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0414**	**0.0294**	**0.0035**	**0.0037**	**0.0748**

Table A.3 contains information about the relationship between the dependent variables $PAFE_{M,t+2}$, $PAFE_{A,t+2}$, $PFE_{M,t+2}$, $PFE_{A,t+2}$ and $Disp_{A,t+2}$ in year $t+2$ and the accounting conservatism measure $RUCon$ after Givoly and Hayn (2000) and Beatty, Weber and Yu (2008) in year t. That is, the dependent variable is regressed onto an intercept and the conservatism measure $RUCon$ in Panel A and additionally onto some relevant control variables in Panel B using an OLS decile-rankregression approach. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table A.4: The Relationship Between Unconditional Accounting Conservatism and Three-Years Earnings Forecasts

Panel A: Without Control Variables					
	$PAFE_{M,t+3}$	$PAFE_{A,t+3}$	$PFE_{M,t+3}$	$PFE_{A,t+3}$	$Disp_{A,t+3}$
$Intercept$	**0.0578***	**0.0304***	**0.0087***	**-0.0118***	**0.0051***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$RUCon_{i,t}$	**0.0026***	**0.0049***	**-0.0000**	**-0.0021***	**0.0023***
	(0.0000)	(0.0000)	(0.9441)	(0.0000)	(0.0000)
$Adj.R^2$	**0.0038**	**0.0082**	**-0.0000**	**0.0019**	**0.0280**
Panel B: With Control Variables					
$Intercept$	**0.0462***	**0.0235***	**0.0026***	**-0.0177***	**0.0031***
	(0.0000)	(0.0000)	(0.0961)	(0.0000)	(0.0000)
$RUCon_{i,t}$	**0.0025***	**0.0048***	**0.0001**	**-0.0020***	**0.0023***
	(0.0000)	(0.0000)	(0.7877)	(0.0000)	(0.0000)
$AssetsTotal_{i,t}$	**-0.0000***	**-0.0000***	**0.0000***	**0.0000***	**-0.0000***
	(0.0000)	(0.0000)	(0.0028)	(0.0001)	(0.0000)
$EarnVol_{i,t}$	**0.0246***	**0.0200***	**0.0067***	**0.0054***	**0.0052***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$AnnRet_{i,t}$	**-0.0221***	**-0.0338***	**0.0025****	**-0.0023**	**-0.0091***
	(0.0000)	(0.0000)	(0.0181)	(0.1773)	(0.0000)
$Adj.R^2$	**0.0382**	**0.0347**	**0.0018**	**0.0037**	**0.0664**

Table A.4 contains information about the relationship between the dependent variables $PAFE_{M,t+3}$, $PAFE_{A,t+3}$, $PFE_{M,t+3}$, $PFE_{A,t+3}$ and $Disp_{A,t+3}$ in year $t+3$ and the accounting conservatism measure $RUCon$ after Givoly and Hayn (2000) and Beatty, Weber and Yu (2008) in year t. That is, the dependent variable is regressed onto an intercept and the conservatism measure $RUCon$ in Panel A and additionally onto some relevant control variables in Panel B using an OLS decile-rank regression approach. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Appendix to Chapter 3

Variable Definition

Panel A: Li and Mohanram (2014) and Hou, Van Dijk and Zhang (2012)		
Variable	Description	COMPUSTAT Variable
$Earn$	Earnings divided by number of shares outstanding.	IB-SPI
$NegE$	Indicator variable that equals 1 for firms with negative earnings and 0 otherwise.	
$NegExE$	Interaction term of E and NegE.	
$BkEq$	Book value of equity divided by number of shares outstanding.	CEQ
$TACC$	Sum of change in WC, change in NCO, and change in FIN, divided by number of shares outstanding.	WC= (ACT-CHE)-(LCT-DLC) NCO = (AT-ACT-IVAO)-(LT-LCT-DLTT) FIN = (IVST+IVAO)-(DLTT+DLC+PSTK)
Div	Common dividends divided by shares outstanding.	DVC
$DivD$	Indicator variable that equals 1 for dividend payers and 0 otherwise.	
AT	Total assets divided by number of shares outstanding.	AT

Panel B: Dechow, Sloan and Sweeney (1995)		
Variable	Description	COMPUSTAT Variable
$Rev - Rec$	Change in revenues minus change in receivables, divided by number of shares outstanding.	REV, REC
PPE	Gross total property, plants, and equipment divided by number of shares outstanding.	PPEGT

Implied Cost of Capital

This section presents the five ICC metrics used to compute the composite ICC. The notation is akin to Hou, Van Dijk and Zhang (2012).

Gebhardt, Lee and Swaminathan (2001) derive the ICC_{GLS} using the following definition:

$$P_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[(ROE_{t+\tau} - ICC_{GLS})B_{t+\tau-1}]}{(1+ICC_{GLS})^{\tau}} + \frac{E_t[(ROE_{t+12} - ICC_{GLS})B_{t+11}]}{ICC(1+ICC_{GLS})^{11}}, \tag{16}$$

where P is the stock price, ROE reflects the return on equity, $E_t[\,]$ are the market expectations based on information available in year t and $(ROE_{t+\tau} - ICC)B_{t+\tau-1}$ is the residual income per share in year $t+\tau$. To estimate the expected ROE for the years $t+1$ to $t+3$, the model-based earnings forecasts and book equity per share based on clean surplus accounting, i.e. $B_{t+\tau} = B_{t+\tau-1} + Earn_{t+\tau} - D_{t+\tau}$, where D reflects dividends per share, is used. For firms with positive earnings, dividends are calculated using the current payout ratio. For firms with negative earnings, the payout ratio is estimated by dividing current dividends by $0.6 \times$ *total assets*. It is assumed that following $t+3$, the expected ROE mean-reverts to the industry median value by year $t+11$ (e.g., Hou, Van Dijk and Zhang (2012)).

Claus and Thomas (2001) estimate their ICC_{CT} by solving the following equation:

$$\begin{aligned} P_t = B_t + \sum_{\tau=1}^{5} & \frac{E_t[(ROE_{t+\tau} - ICC_{CT})B_{t+\tau-1}]}{(1+ICC_{CT})^{\tau}} \\ & + \frac{E_t[(ROE_{t+5} - ICC_{CT})B_{t+4}](1+g_a)}{(ICC_{CT} - g_a)(1+ICC_{CT})^5}. \end{aligned} \tag{17}$$

To estimate the expected ROE in the years $t+1$ to $t+5$ the model-based earnings forecasts and book equity per share B based on clean surplus accounting, analogous to the ICC_{GLS} metric by Gebhardt, Lee and Swaminathan (2001), is used. In line with Hou, Van Dijk and Zhang (2012), the growth-rate g_a is set to the 10-year government bond yield minus an assumed real risk-free rate of 3%.

Ohlson and Juettner-Nauroth (2005) calculate the ICC_{OJ} as follows:

$$P_t = \frac{E_t[Earn_{t+1}] \times (g_o - (\gamma - 1))}{(ICC_{OJ} - A) - A^2} \tag{18}$$

where

$$A = 0.5\left((\gamma - 1) + \frac{E_t[Earn_{t+1}] \times payout}{P_t}\right),$$

$$g_{st} = 0.5\left(\frac{E_t[Earn_{t+3}] - E_t[Earn_{t+2}]}{E_t[Earn_{t+2}]} - \frac{E_t[Earn_{t+5}] - E_t[Earn_{t+4}]}{E_t[Earn_{t+4}]}\right).$$

In this case, g_{st} is the short-term growth rate calculated as the mean of forecasted earnings growth in $\tau = 3$ and $\tau = 5$ in line with Hou, Van Dijk and Zhang (2012). Furthermore, the perpetual growth rate of abnormal earnings beyond the forecast horizon γ is calculated as the 10-year government bond yield minus an assumed real risk-free rate of 3% and *payout* is the current payout ratio.

Easton (2004) shows that the ICC_{MPEG} can be calculated using the following equation, with dividends calculated analogously to Gebhardt, Lee and Swaminathan (2001):

$$P_t = \frac{E_t[Earn_{t+2}] + ICC \times E_t[D_{t+1}] - E_t[Earn_{t+1}]}{ICC^2_{MPEG}}. \tag{19}$$

Gordon and Gordon (1997) use the following equation to derive the ICC_{GG} estimate:

$$P_t = \frac{E_t[Earn_{t+1}]}{ICC_{GG}}. \tag{20}$$

Results for the EP Model

Table A.5: The Relationship Between EM and Earnings Forecast Accuracy for the EP Model

	$PAFE_{t+1}$	$PAFE_{t+2}$	$PAFE_{t+3}$
Coefficient	0.0193***	0.0181***	0.0165***
	(8.28)	(10.54)	(11.19)
R^2	0.1198	0.1356	0.1390
Controls	Yes	Yes	Yes

Table A.5 depicts the relationship between EM and the EP model-based earnings forecast accuracy. It contains the time-series averages of the parameter estimates, Newey and West (1987) t-statistics and R^2 values from the annual regressions of PAFE on the EM measure. We control for firm size by including the logarithm of total assets and for industry by adding industry dummies according to the Fama and French 48 industry classification. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table A.6: Earnings Forecast Error Comparison for the EP Model

	Median $PAFE_{t+1}$	Mean $PAFE_{t+1}$	Median $PAFE_{t+2}$	Mean $PAFE_{t+2}$	Median $PAFE_{t+3}$	Mean $PAFE_{t+3}$
EP	0.0362***	0.1278***	0.0499***	0.1439***	0.0614***	0.1596***
Model	(23.07)	(15.18)	(21.03)	(21.33)	(19.62)	(20.76)
Interacted	0.0317***	0.1163***	0.0459***	0.1316***	0.0566***	0.1449***
Model	(21.72)	(14.21)	(19.04)	(19.74)	(17.90)	(20.96)
Difference	-0.45***	-1.15***	-0.40***	-1.23***	-0.48***	-1.47***
	(−5.59)	(−6.16)	(−11.32)	(−8.21)	(−10.01)	(−6.27)

Table A.6 compares time-series averages of median and mean PAFEs from the EP earnings forecast model and the model interacted with EM quintiles. One-, two-, and three-year ahead forecasts are analyzed. Further, we test if the difference in PAFE between both models (interacted model minus EP model) is statistically significant. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table A.7: ICC Firm-Level Test Based on the EP Earnings Forecast Model

Panel A: Ret$_{t+1}$			
	Intercept$_{t+1}$	ICC$_{t+1}$	R^2
EP Model	0.1120***	0.1484*	0.0095
	(3.90)	(2.02)	
Interacted Model	0.1099***	0.1571**	0.0106
	(3.87)	(2.07)	
Panel B: Ret$_{t+2}$			
	Intercept$_{t+2}$	ICC$_{t+2}$	R^2
EP Model	0.0541**	0.0915	0.0106
	(2.61)	(1.57)	
Interacted Model	0.0498**	0.1302**	0.0129
	(2.47)	(2.07)	
Panel C: Ret$_{t+3}$			
	Intercept$_{t+3}$	ICC$_{t+3}$	R^2
EP Model	0.0465***	0.0727	0.0112
	(2.89)	(1.45)	
Interacted Model	0.0413**	0.1251**	0.0137
	(2.68)	(2.22)	

Table A.7 depicts the relation between the composite ICC and buy-and-hold returns for one-, two-, and three-years ahead. We compare the EP earnings forecast model with the interacted model. The table show the time-series averages of the parameter estimates, Newey and West (1987) t-statistics and R^2 values from the annual regressions of realized future returns on the composite ICC. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table A.8: ICC Portfolio Test Based on the EP Earnings Forecast Model

	ICC	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}
EP Model	**0.5234*****	**0.1114*****	**0.0554*****	**0.0453****
	(19.99)	(3.77)	(2.72)	(2.00)
Interacted Model	**0.5081*****	**0.1069*****	**0.0665*****	**0.0641*****
	(15.48)	(3.02)	(2.78)	(3.00)

Table A.8 reports time-series averages of annualized buy-and-hold returns of decile portfolios based on the composite ICC for one-, two-, and three-years ahead. We compare the EP earnings forecast model with the interacted model. For the high-minus-low (H-L) return spread, we further show Newey and West (1987) t-statistics. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Results for the HVZ Model

Table A.9: The Relationship Between EM and Earnings Forecast Accuracy for the HVZ Model

	$PAFE_{t+1}$	$PAFE_{t+2}$	$PAFE_{t+3}$
Coefficient	0.0193***	0.0181***	0.0165***
	(8.28)	(10.54)	(11.19)
R^2	0.1198	0.1356	0.1390
Controls	Yes	Yes	Yes

Table A.9 depicts the relationship between EM and the HVZ model-based earnings forecast accuracy. It contains the time-series averages of the parameter estimates, Newey and West (1987) t-statistics and R^2 values from the annual regressions of PAFE on the EM measure. We control for firm size by including the logarithm of total assets and for industry by adding industry dummies according to the Fama and French 48 industry classification. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table A.10: Earnings Forecast Error Comparison for the HVZ Model

	Median $PAFE_{t+1}$	Mean $PAFE_{t+1}$	Median $PAFE_{t+2}$	Mean $PAFE_{t+2}$	Median $PAFE_{t+3}$	Mean $PAFE_{t+3}$
HVZ	0.0356***	0.1282***	0.0474***	0.1389***	0.0595***	0.1574***
Model	(19.14)	(13.58)	(21.03)	(18.22)	(20.63)	(16.88)
Interacted	0.0314***	0.1162***	0.0454***	0.1357***	0.0558***	0.1479***
Model	(21.47)	(13.99)	(19.49)	(18.32)	(18.95)	(19.86)
Difference	-0.42***	-1.20***	-0.20***	-0.32***	-0.38***	-0.95**
	(−4.07)	(−3.72)	(−6.14)	(−3.43)	(−3.45)	(−2.47)

Table A.10 compares time-series averages of median and mean PAFEs from the HVZ earnings forecast model and the model interacted with EM quintiles. One-, two-, and three-year ahead forecasts are analyzed. Further, we test if the difference in PAFE between both models (interacted model minus HVZ model) is statistically significant. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table A.11: ICC Firm-Level Test Based on the HVZ Earnings Forecast Model

Panel A: Ret$_{t+1}$

	Intercept$_{t+1}$	ICC$_{t+1}$	R^2
HVZ Model	0.1124***	0.1588**	0.0114
	(3.92)	(2.07)	
Interacted Model	0.1093***	0.2007**	0.0120
	(3.79)	(2.50)	

Panel B: Ret$_{t+2}$

	Intercept$_{t+2}$	ICC$_{t+2}$	R^2
HVZ Model	0.0503**	0.1465**	0.0139
	(2.50)	(2.23)	
Interacted Model	0.0461**	0.1930***	0.0161
	(2.33)	(2.75)	

Panel C: Ret$_{t+3}$

	Intercept$_{t+3}$	ICC$_{t+3}$	R^2
HVZ Model	0.0422**	0.1347**	0.0149
	(2.70)	(2.35)	
Interacted Model	0.0381**	0.1805***	0.0170
	(2.50)	(2.96)	

Table A.11 depicts the relation between the composite ICC and buy-and-hold returns for one-, two-, and three-years ahead. We compare the HVZ earnings forecast model with the interacted model. The table show the time-series averages of the parameter estimates, Newey and West (1987) t-statistics and R^2 values from the annual regressions of realized future returns on the composite ICC. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Table A.12: ICC Portfolio Test Based on the HVZ Earnings Forecast Model

	ICC	Ret_{t+1}	Ret_{t+2}	Ret_{t+3}
HVZ Model	**0.6100*** **	**0.1029*** **	**0.0559** **	**0.0503** **
	(13.80)	(3.12)	(2.35)	(3.00)
Interacted Model	**0.5688*** **	**0.1238*** **	**0.0884*** **	**0.0794*** **
	(7.73)	(3.45)	(3.61)	(4.00)

Table A.12 reports time-series averages of annualized buy-and-hold returns of decile portfolios based on the composite ICC for one-, two-, and three-years ahead. We compare the HVZ earnings forecast model with the interacted model. For the high-minus-low (H-L) return spread, we further show Newey and West (1987) t-statistics. ***, **, and * indicate significance at an alpha level of 1%, 5%, 10%, respectively.

Appendix to Chapter 4

Variable Definitions

Panel A: Modelling the First Moment of Future Earnings		
Variable	Description	COMPUSTAT Variable
$Earn$	Earnings divided by number of shares outstanding.	(IB-SPI)/CSHO
d^-	Indicator variable that equals 1 for firms with negative earnings and 0 otherwise.	
d^-Earn	Interaction term of $Earn$ and d^-.	
$BkEq$	Book value of equity divided by number of shares outstanding.	CEQ/CSHO
OCF	Cashflow divided by number of shares outstanding. XIDOC set to 0, if missing.	(OANCF-XIDOC)/CSHO
$TACC$	$Earn$ minus OCF.	

Panel B: Modelling The Second Moment of Future Earnings		
Variable	Description	COMPUSTAT Variable
d^+	Indicator variable that equals 1 for firms with positive earnings and 0 otherwise.	
d^-TACC	Interaction term of $TACC$ and d^-.	
d^+TACC	Interaction term of $TACC$ and d^+.	
d^-OCF	Interaction term of OCF and d^-.	
d^+OCF	Interaction term of OCF and d^+.	
SPI	Special items divided by number of shares outstanding. Set to 0, if missing.	SPI/CSHO

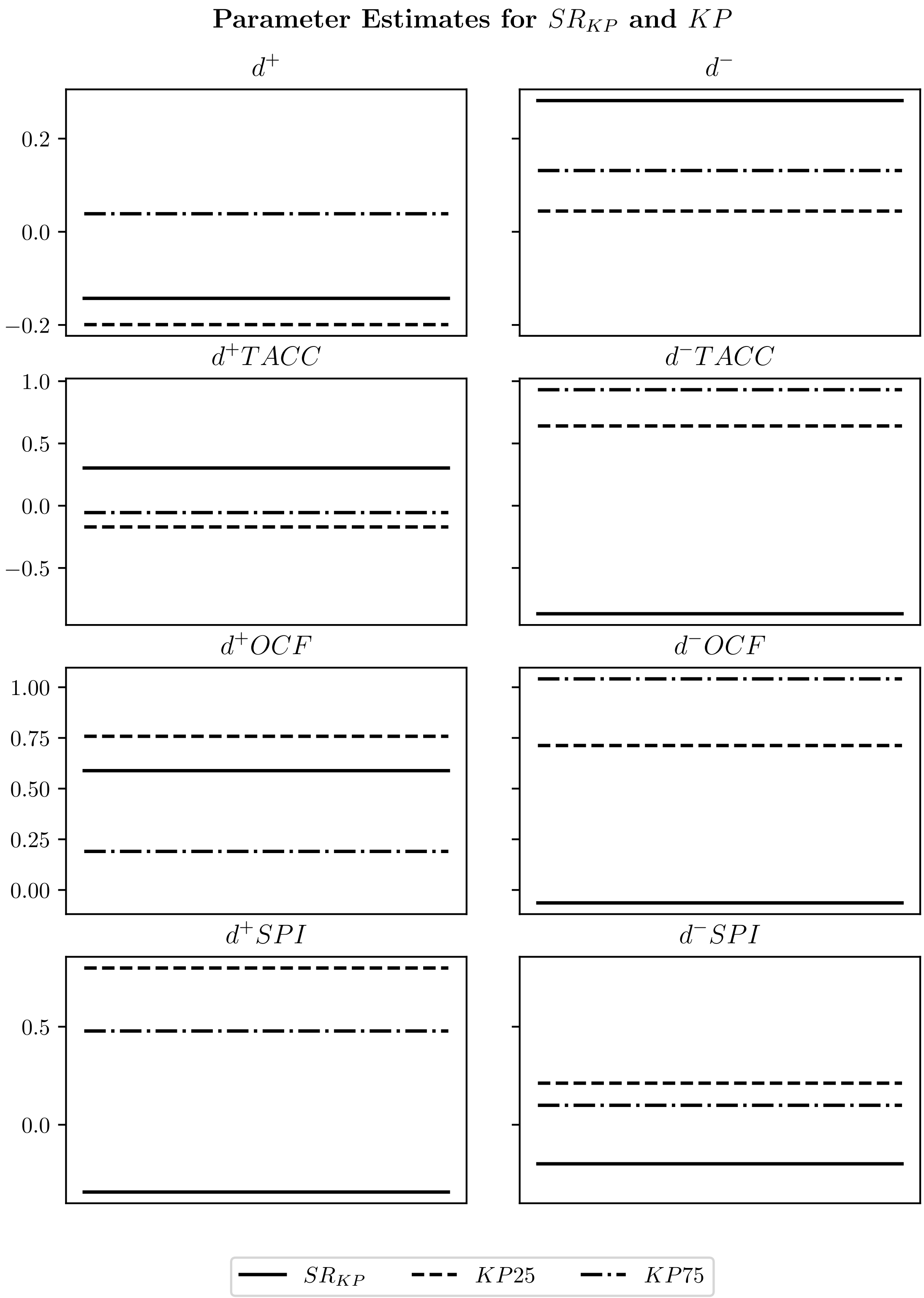
$d^{-}SPI$	Interaction term of SPI and d^{-}.	
$d^{+}SPI$	Interaction term of SPI and d^{+}.	
LEV	Total assets divided by book-value of equity.	AT/CEQ
$PAYOUT$	Common dividends divided by shares outstanding.	DVPSX_F /CSHO
$PAYER$	Indicator variable that equals 1 for dividend payers and 0 otherwise.	
Industry Dummy	12 dummies which equal 1 if the firm belongs to the respective industry and 0 is not. Based on FF12.	

Panel C: Outcome and Control Variables

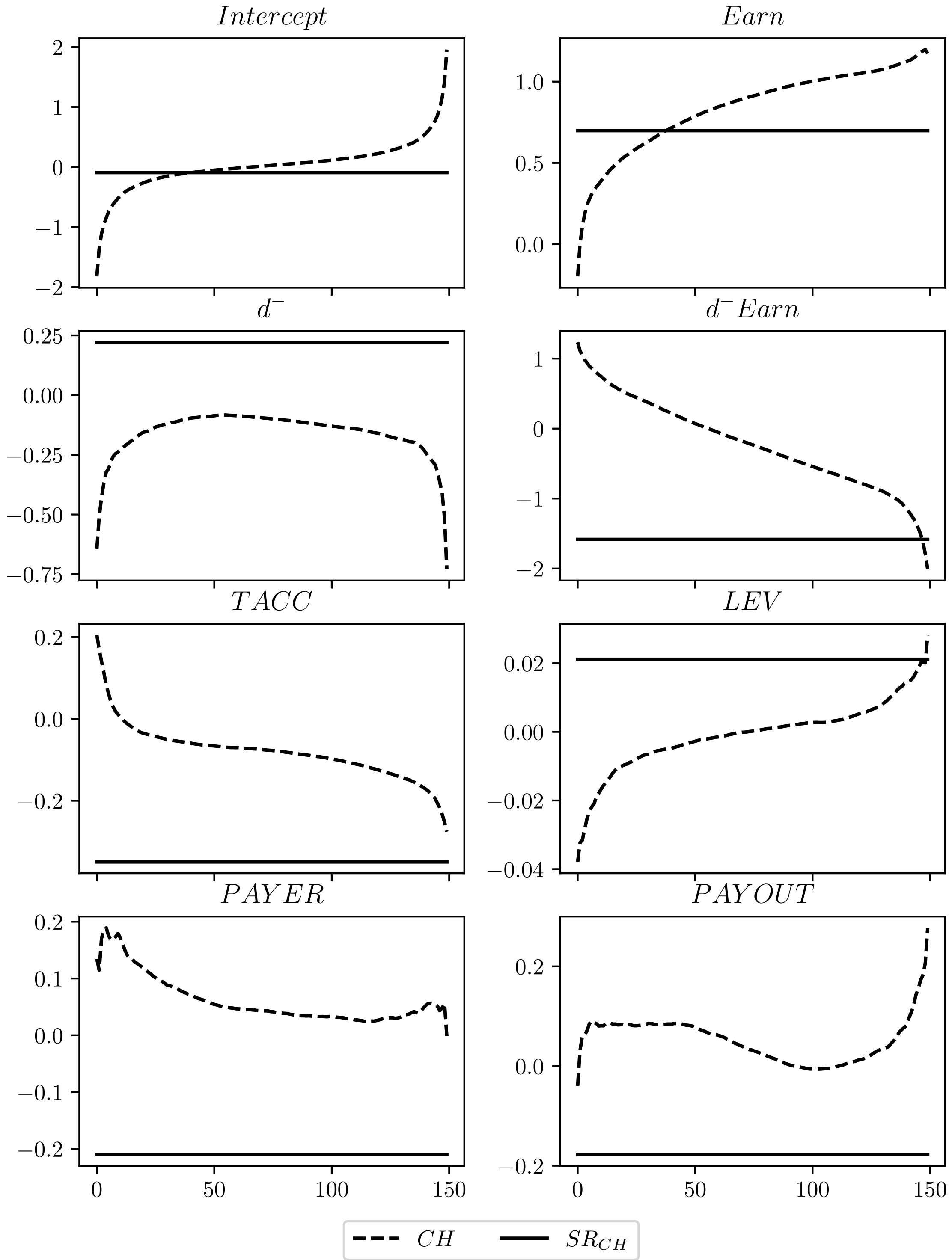
Variable	Description	COMPUSTAT/CRSP Variable
$EP_{i,t}$	Earnings-to-price ratio of firm i in year t.	((IB-SPI)/CSHO)/PRC
$BP_{i,t}$	Book-to-market ratio of firm i in year t.	CEQ/(CSHO x PRC)
$HflStd_{i,t+1}$	Forecasted firm-level standard deviation of earnings calculated as the standard deviation of firm i's realized earnings from year $t-9$ to t.	
$Size_{i,t}$	Equity market value of firm i in year t. Stock price data used from the CRSP monthly file.	PRC x CSHO
$Beta_{i,t}$	Market model beta of firm i in year t retrieved from WRDS Beta Suite.	
$AnnRet_{i,t}$	Firm i's annual stock return for year t. Calculation based on monthly returns of stock prices retrieved from the CRSP monthly file starting three months after fiscal-year end of year $t-1$.	

$RetStd_{i,t}$	Year t standard deviation of monthly market-model residuals for firm i resulting from regressing firm-level monthly returns on the respective market portfolio starting three months after fiscal-year end of year $t-1$. Prices and market portfolio returns are retrieved from CRSP.	PRC, VWRETD
$LNSize_{i,t}$	The natural logarithm of the ratio of firm i's year t market-value of equity to the sum of all firm's market-values of equity in the respective year.	
$LiabAsset_{i,t}$	Ratio of liabilities to assets of firm i in year t.	LT/AT
$EbitdaLiab_{i,t}$	Ratio of EBITDA to liabilities of firm i in year t.	EBITDA/LT

Parameter Estimates for the Variance Forecast Models



Parameter Estimates for SR_{CH} and CH



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Dr. Tim Vater (gemeinsame Projektarbeit für die Inhalte in Kapitel 3).

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