Quarterly Earnings Information: Implications for Annual Earnings Forecast Models[π]

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Abstract

We substantially improve cross-sectional earnings forecast models, such as Hou, van Dijk, and Zhang (2012), by modeling differences in earnings growth across firms. In particular, we use firm-specific year-over-year changes in earnings extracted from current quarterly reports to differentiate between low- and high-growing firms in the cross-section. This offers two important advantages to investors: First, out-of-sample earnings forecasts become substantially more accurate, yielding more reliable implied cost of capital estimates. Second, investors receive earlier forecast updates that contain new important information. As a result, portfolio strategies earn significantly higher excess returns and offer significantly better risk-return profiles when built on our forecasts than on forecasts from existing models or from analysts. Furthermore, additional tests suggest that analyst ICCs are generally unsuitable for constructing buy-portfolios, as they tend to select overvalued stocks that underperform the market during the holding period.

Keywords: Earnings Forecasts, Cross-Sectional Earnings Models, Quarterly Earnings Announcements, Cost of Capital, Expected Rate of Return, Asset Management, Portfolio Management

JEL Classification: G10, G11, G12, G17, M40, M41

1. Introduction

Future earnings are the key to a firm's value. For example, Feltham and Ohlson (1995) argue that the difference between a firm's book and market value is the present value of future abnormal earnings over the firm's lifetime. This link between expected earnings, firm values, and stock returns has been studied intensively in finance and accounting research in the meantime (see Monahan (2018) for a survey). Forecasting future earnings is also of immense practical relevance, for example in asset management.[1] Hence, portfolio managers, banks, and investors devote a lot of effort to acquiring earnings forecasts that are timely and accurate. Typically, firm-specific earnings forecasts come from sell-side analysts and, more recently, also from econometric models. For the latter, cross-sectional linear models as established by Hou et al. (2012) and Li and Mohanram (2014) are currently state of the art. In short, they use a large cross-section of firms to model and forecast future annual earnings based on current annual fundamentals. The main advantage of such models is that they overcome sell-side analysts' drawbacks of structural bias (e.g., O'Brien (1988)) and insufficient firm coverage (e.g., La Porta (1996)). Further, those models do not suffer from high data requirements as, for example, time-series models do (e.g., Bradshaw, Drake, Myers, and Myers (2012)).

Due to the advantages of cross-sectional earnings forecast models, the attention to and interest in these models continue to grow in the current literature, with a focus on continuously improving them. For example, numerous papers enhance forecast accuracy by replacing ordinary least squares (i.e., OLS) estimation with more robust regression techniques, like Theil-Sen estimation (e.g., Ohlson and Kim (2015)) or median regression (e.g., Evans, Njoroge, and Yong (2017), Chang, Monahan, Ouazad, and Vasvari (2021), and Tian, Yim, and Newton (2021)). Others implement machine learning methods (e.g., Cao and You (2020), Hendriock (2022), and Chen, Cho, Dou, and Lev (2022)). Clearly, those previous advances focus on econometric aspects. In contrast, the objective of our study is to improve existing models from an economic perspective. Previous literature limits cross-sectional earnings forecast models to annual firm fundamentals as predictor variables. Further, those models only use information from a single annual statement in order to keep data requirements at a minimum. Additionally, these models rely on a firm-unspecific

[1] For example, Monahan (2018) provides analytical evidence that investors indeed forecast earnings instead of dividends when valuing a firm and making investment decisions, and supports his arguments by empirical evidence from capital market research (e.g., Penman and Sougiannis (1998)). He concludes: "(…) earnings are a fundamental economic variable and forecasting them is a central part of valuation" (Monahan (2018), p. 27).

earnings growth coefficient that is not able to account for nuances in the cross-section. As a result, they cannot adequately capture firm-specific earnings growth in their predictions. We provide a solution to this by incorporating firms' earnings trends extracted from current quarterly reports into existing models. Therefore, the economic information set the models can use to forecast annual earnings is enriched by firm-specific earnings growth information. This leads to substantially more differentiated and precise earnings forecasts, effectively closing the previously reported accuracy gap to sell-side analysts by a surprisingly large margin. Furthermore, our improved forecasts lead to more reliable stock return predictions compared to previous models.

We include quarterly earnings information into cross-sectional models using a forward-looking difference variable termed "interim earnings growth". This variable measures the currently observed change in year-to-date earnings in comparison to the corresponding period of the previous fiscal year. As a result, our new variable identifies and extrapolates an already observable intra-year earnings trend, providing insights into a firm's upcoming annual earnings. The concept is straightforward: If a company's first-quarter earnings are unexpectedly strong (weak), it is likely that the company will continue to perform better (worse) than expected in the subsequent quarters of the same fiscal year, resulting in higher (lower) annual earnings. Similarly, if second- and third-quarter earnings are surprisingly strong (weak), the trend presumably will continue for the rest of the fiscal year as well. With our variable, models can effectively control for differences in current earnings growth across firms without requiring additional data (e.g., an earnings history). In other words, they can incorporate firm-specific earnings growth jointly with the cross-sectional average growth measured by the model's earnings persistence parameter.[2] This offers a parsimonious means to individualize earnings growth within a cross-sectional model, allowing to differentiate between low- and high-growing firms in the cross-section. Moreover, our variable does not only enrich the model's information set with an additional variable, but does also introduce an important change to the characteristics of the information set itself, by incorporating information at a higher frequency than just annual data. In addition to annual reports, firms disclose quarterly reports on a regular basis. Therefore, each firm's information set changes every three months. The advantage of our new variable is that it allows detecting new earnings trends in this additional information.

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[2] Note that the interpretation of the earnings persistence coefficient as "one plus growth rate" is only valid in a univariate model. In a multivariate model, such as those models tested within this paper, earnings persistence is conditional on the other explanatory variables as well. Hence, we observe an earnings persistence coefficient below one in our paper, in line with previous literature, e.g., Hou et al. (2012) and Li and Mohanram (2014).

This enables our model to produce updates of earnings forecasts earlier and more frequently, i.e., every three months. In contrast, as existing standard models rely solely on annual information, they essentially neglect available interim reports altogether. As it then takes 12 months for a firm's information set to change, re-estimating standard models within a year yields virtually no changes to their forecasts.

Following previous studies, such as Hou et al. (2012) or Li and Mohanram (2014), we test cross-sectional earnings forecast models along two dimensions: First, we evaluate earnings forecasts based on their out-of-sample forecast accuracy and forecast bias. Second, we use earnings forecasts to calculate implied cost of capital (ICC) estimates and test their reliability as future stock return proxies using both portfolio and firm level tests. For our empirical analysis, we use earnings forecasts from several standard cross-sectional models, in particular, the ones introduced by Hou et al. (2012), Li and Mohanram (2014) and Konstantinidi and Pope (2016). Among these models, the Residual Income (RI) model of Li and Mohanram (2014) is typically found to provide the most accurate forecasts (e.g., Li and Mohanram (2014) or Hendriock (2022)). Therefore, we use the RI model as the main benchmark for evaluating our own forecasts.[3] Moreover, like Hou et al. (2012), we also benchmark models against sell-side analysts along these two dimensions: First, we scrutinize earnings forecasts because we want to learn whether quarterly earnings information helps to decrease the well documented forecast accuracy gap that models have as compared to analysts. Second, we investigate ICCs derived from these forecasts, because we want to infer whether interim earnings information helps to enlarge the previously reported performance lead that models have over analysts when it comes to predicting future stock returns.

We find that our extended model substantially outperforms the standard RI model along both dimensions. Starting with earnings forecasts, we document that our interim growth variable indeed adds new information to the model, indicated by a statistically significant coefficient and a substantially larger adjusted R^2. Hence, our extended model captures more variation in future earnings across firms than the standard RI model. Moreover, we find that including our interim growth variable substantially reduces out-of-sample forecast errors, and therefore, increases forecast accuracy by a large margin. For one-year ahead forecasts, we document that the absolute

[3] Untabulated tests show that inferences are unaltered when we use alternative models, for example Li and Mohanram (2014)'s Earnings Persistence model, the model introduced by Hou et al. (2012), or the model introduced by Konstantinidi and Pope (2016). Results are available upon request.

forecast error is reduced by one-third on average. Analogously, for two- and three-year ahead forecasts, our variable reduces the absolute forecast error by approximately 11% and 7% on average, respectively. This is particularly interesting as our interim growth variable primarily builds on information from the current fiscal period. Nevertheless, this information turns out to be useful for longer-term forecasts as well. Particularly important, our results are robust over time and across industries, i.e., our interim earnings growth variable reduces the absolute forecast error in every single year and industry.

In a next step, we delineate the mechanism how our variable improves forecast accuracy. We find that the forecast accuracy of our model is directly related to the strength of the observed interim growth in a firm's quarterly report: The stronger a firm's observed interim growth is, the more our forecast deviates from the forecast of the standard RI model, and consequently, the more our extended model outperforms the standard model. This suggests that picking up firm-specific current earnings trends, i.e., adjusting forecasts upwards in case of positive interim growth and downwards in case of negative interim growth, leads to more realistic forecasts of annual earnings. Moreover, we show that our model's forecast accuracy is directly related to the number of already released quarterly reports by a firm. For firms with more quarterly reports filed at a given estimation date, our annual forecasts are more accurate, leading to a stronger outperformance of the standard RI model. For example, for firms with three quarterly reports filed, our model cuts the average absolute forecast error in half for one-year ahead annual forecasts. This suggests that updating a firm's earnings forecast, once it has released an additional quarterly report, indeed provides investors with more precise earnings expectations when they use our model.

Comparing models to analysts, we document that including quarterly earnings information into models diminishes the information and timing advantage analysts had so far, and by that, substantially reduces the accuracy gap when forecasting earnings. Specifically, for one-, two-, and three-year ahead earnings forecasts, we reduce the accuracy gap with our interim growth variable by approximately 55%, 36%, and 37% on average, respectively. This result is surprising given that analysts process a lot of complex information, including firm- and industry-specific data as well as macroeconomic information (e.g., Brown, Call, Clement, and Sharp (2015)), as the result implies that a linear extrapolation of interim earnings growth largely captures the effect the information processing of analysts has on forecast accuracy. At the same time, our result strongly suggests that analysts do simply focus on firms' quarterly reports to produce or update their earnings forecasts, and that this focus largely explains the better performance of analysts compared to standard models in terms of shorter-term earnings forecasts.

Turning to stock return predictions, we find that our more accurate earnings forecasts lead to more reliable ICC estimates on both the portfolio and firm level. Investors that build zero investment portfolios by going long stocks with the highest ICCs and shorting stocks with the lowest ICCs earn an additional return of 1.77, 1.12, and 0.83 percentage points p.a. over holding periods of one, two, and three years, respectively, when using ICCs based on our extended RI model's forecasts instead of the standard RI model's forecasts. This finding also holds after controlling for risk, i.e., our investment portfolios exhibit higher Sharpe ratios (e.g., Sharpe (1966)) for all holding periods than investments based on ICCs using the standard RI model's forecasts. Moreover, on the firm level, we find that our ICCs have stronger and more significant relations to future stock returns than ICCs based on forecasts from the standard RI model as inputs. While our ICCs show statistically significant and positive parameter estimates from Fama and MacBeth (1973) regressions of 0.50, 0.36, and 0.29 for one-, two-, and three-year ahead returns, respectively, the standard model's ICCs exhibit weaker and sometimes even insignificant coefficients of 0.34, 0.21, and 0.16, respectively. Unsurprisingly, our ICCs also capture more variation in future stock returns across firms (i.e., a higher adjusted R^2).

We obtain consistent results when we include analysts into the comparison and restrict the sample accordingly. In particular, for firms covered by sell-side analysts, we still document that our ICCs are more reliable predictors of future stock returns as compared to ICCs based on the standard RI model's forecasts. We find this to hold at the portfolio level as well as at the firm level. In addition, we find that both our model and the standard RI model produce significantly more accurate ICCs compared to those based on analysts' earnings forecasts. Moreover, we provide novel insights regarding the suitability of model ICCs for real-world asset management applications. Analyzing buy-only strategies, for example, we document that stocks selected by our model ICCs generate significantly higher holding returns compared to stocks chosen according to ICCs derived from analysts' earnings forecasts. Furthermore, when examining specific stock recommendations derived from either our model's ICCs or analyst ICCs, we find that stocks exclusively selected by our model outperform the market portfolio by 3.40%, whereas stocks exclusively chosen by analysts underperform the market by 1.22%. We identify a key difference in the security selection between our model and analysts as a possible reason for this result: Our model selects stocks into a buy-portfolio that are “undervalued”, as indicated by, for example, a higher book-to-market ratio at the beginning of the holding period than at the end. In contrast, ICCs based on analysts’ forecasts tend to select “overvalued” stocks and thus underperform relative to the market throughout the holding period. From an economic point of view, this renders analyst ICCs essentially unsuitable for security selection, leaving model ICCs as the only viable alternative. Further and particularly interesting to investors, our research shows that the stocks selected by our model ICCs do not come with more risk. In fact, our buy-portfolio has, on average, a significantly higher Sharpe ratio and significantly lower systematic risk factor exposures (except for value risk) compared to the corresponding buy-portfolio based on analyst ICCs. Overall, our findings strongly support the notion that incorporating quarterly earnings information enhances the performance lead of models over analysts when predicting future stock returns.

With our findings, we contribute to the existing literature in multiple ways. First, we structurally advance existing cross-sectional forecast models using interim reports to differentiate earnings growth across firms. Once we integrate this aspect into existing models, their earnings forecasts and stock return predictions become more accurate and can be updated more often. In consequence, this makes our forecasts particularly attractive for active asset management. More accurate forecasts directly translate into higher portfolio returns. More frequently updated forecasts allow asset managers to adjust their portfolios earlier, even before sell-side analysts may have issued new reports.

Second, we contribute to the previous literature that has reported the puzzling result that models’ earnings forecasts are less accurate than analysts’ forecasts, while ICCs derived from these models’ forecasts are more reliable stock return predictors (e.g., Hou et al. (2012) or Evans et al. (2017)). Our empirical analyses contribute to solving this puzzle. Specifically, we show that buy-portfolios using analyst ICCs consist of overvalued stocks that underperform the market and exhibit higher systematic risk factor exposures. Models, in contrast, tend to select undervalued, less risky stocks that indeed outperform the market by a large margin. This suggests that the solution to this puzzle is inside the security selection, and that the optimism bias inherent in analysts’ forecasts is the key factor that causes analyst ICCs to perform poorly.

Lastly, we contribute to the literature on sell-side analysts by providing new insights into their information processing. Previous literature mainly attributes the performance gap between sell-side analysts and forecast models to the fact that those models do not incorporate complex information, such as private information and macroeconomic data (e.g., Brown et al. (2015)). In contrast, we show that integrating quarterly earnings information into models largely closes the performance gap and results in a pattern of accuracy improvements throughout the year, i.e., more accurate forecasts with the release of each quarterly report. This pattern closely resembles the one we observe for analysts' forecasts. This suggests that sell-side analysts mainly learn and benefit from quarterly earnings information throughout the year, and therefore, attach substantial importance to quarterly earnings when updating their forecasts. Consequently, using quarterly earnings information in models mimics this learning process of analysts, and thus, substantially reduces the information advantage reported for analysts by previous studies (e.g., Bradshaw et al. (2012), Hou et al. (2012), and Evans et al. (2017)).

Overall, our results suggest that models can closely match analysts once they include quarterly earnings. Consequently, they can serve as a reliable alternative to analysts in terms of forecasting earnings. Given those findings, we strongly recommend that researchers and practitioners include a firm's interim earnings growth into their forecast models.

The remainder of this paper is organized as follows. Section 2 presents the methodology of our paper, including our interim earnings growth variable and our two-step estimation and forecast approach. Moreover, it outlines how we evaluate earnings forecasts out-of-sample and presents our data sample. In Section 3, we compare the performance of our extended RI model to the standard RI model's performance. Section 4 evaluates the performance of models compared to sell-side analysts. Section 5 concludes.

2. Methodology and Data

A. Empirical Methodology

We implement several cross-sectional models, in particular, the models introduced by Hou et al. (2012), Li and Mohanram (2014), and Konstantinidi and Pope (2016). In line with previous studies (e.g., Li and Mohanram (2014) or Hendriock (2022)), we find that the Residual Income (RI) model of Li and Mohanram (2014) yields the most accurate forecasts and the most reliable ICCs. Therefore, we focus on the RI model as our main benchmark, and report results only for this model in order to conserve space.[4] The RI model of Li and Mohanram (2014) is defined as

$$\begin{aligned} E_{i,t} &= \beta_0 + \beta_1 \cdot E_{i,t-\tau} + \beta_2 \cdot NegE_{i,t-\tau} + \beta_3 \cdot E_{i,t-\tau} \cdot NegE_{i,t-\tau} \\ &\quad + \beta_4 \cdot B_{i,t-\tau} + \beta_5 \cdot AC_{i,t-\tau} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where $E_{i,t}$ denotes firm i's annual earnings in fiscal year t. Correspondingly, $E_{i,t-\tau}$ describes the firm's earnings lagged by τ years, $B_{i,t-\tau}$ is the past book value of equity, and $AC_{i,t-\tau}$ is past accruals. Moreover, $NegE_{i,t-\tau}$ is a loss dummy that equals 1 in case earnings in fiscal year t-τ are negative, and 0 otherwise. Lastly, $E_{i,t-\tau} \cdot NegE_{i,t-\tau}$ is an interaction term that accounts for differences in earnings persistence between profit and loss firms.[5] To control for size, all variables are scaled by the number of shares outstanding, lagged by τ years.

We propose to extend cross-sectional models, for example, the RI model, by including a variable that accounts for a firm's interim earnings growth. To be precise, $Growth_{i,t}$ is defined as a firm i's already observable year-to-date earnings, i.e., the sum of quarterly earnings for the ongoing fiscal year t+1 which have been reported so far, minus the sum of quarterly earnings during the corresponding period of the previous year t.[6] Specifically, at a given estimation date, let q_i denote the number of quarterly reports a firm i has disclosed for its ongoing yet unfinished fiscal year, i.e., for t+1. Furthermore, let $YtD_{i,t+1}$ denote the firm's current year-to-date earnings, i.e., the sum of earnings reported for these q_i quarters, and let $YtD_{i,t}$ denote the sum of quarterly earnings over the corresponding quarters of the previous fiscal year, i.e., year t. Then, we calculate

[4] We obtain qualitatively equal results for the Hou et al. (2012) model, the earnings persistent (EP) model of Li and Mohanram (2014), and the Konstantinidi and Pope (2016) model. Results are available on request.

[5] See for example Li (2011) for how loss persistence differs from persistence in profits.

[6] Throughout this paper, we define the term "year-to-date" as the period beginning with the first day of a firm's fiscal year up to a specific estimation date, i.e., not as a period beginning with the first day of a calendar year.

the already observable change in interim earnings as $YtD_{i,t+1}$ minus $YtD_{i,t}$. Hence, depending on q_i, the earnings change is calculated over one, two, or three quarters, i.e., $q_i \in \{1, 2, 3\}$. Since firms have different fiscal year end dates, at any specific estimation date, q_i can differ across firms. Therefore, the measured earnings change can be more pronounced for a firm that has reported already three quarters than for a firm having reported only one quarter so far. To address this issue, we standardize the interim earnings change, i.e., we annualize[7] our measure by multiplying it by $\frac{4}{q_i}$. This yields the final definition of our interim growth variable:

$$Growth_{i,t} = \begin{cases} \frac{4}{q_i} \cdot \left(YtD_{i,t+1} - YtD_{i,t}\right), & \forall\, q_i = 1, 2, 3 \\ 0, & \forall\, q_i = 0. \end{cases} \tag{2}$$

The intuition behind $Growth_{i,t}$ is straightforward. For example, given surprisingly strong (weak) first-quarter earnings, chances are that this firm i will perform unexpectedly strong (weak) in subsequent quarters of the same fiscal year as well, leading to higher (lower) annual earnings.[8] The same logic applies to surprisingly strong or weak year-to-date earnings after observing results for a firm's second and third quarter. To include this interim growth variable into the regression equation, we lag it by τ periods and scale it by the corresponding number of shares outstanding:

$$\begin{aligned} E_{i,t} \; &= \beta_0 + \beta_1 \cdot E_{i,t-\tau} + \beta_2 \cdot NegE_{i,t-\tau} + \beta_3 \cdot E_{i,t-\tau} \cdot NegE_{i,t-\tau} \\ &\quad + \beta_4 \cdot B_{i,t-\tau} + \beta_5 \cdot AC_{i,t-\tau} + \beta_6 \cdot Growth_{i,t-\tau} + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

Our interim growth variable structurally advances the forecast model by capturing interim earnings growth and extrapolating it to annual earnings. In other words, our variable adds firm-specific growth information that differentiates the cross-section of firms, essentially distinguishing between low- and high-growing firms. Lacking such a growth variable, the standard model is unable to utilize firm-specific earnings growth information. In fact, as the standard model is

[7] Untabulated tests show that the tenor of results is unchanged when not annualizing the growth measure. However, as the parameter estimates then are more difficult to interpret, as the variable is no longer capturing the effect over a total fiscal year, we decide to stick to the annualization. In addition, if the model is fitted at a higher frequency (e.g., quarterly), the interim growth measure would represent an increasing number of quarterly releases as firms release new statements. Then, this structural change in the variable would complicate the averaging process when reporting the parameter estimate.

[8] Untabulated tests show that 72.56% of the firm-quarters in our sample show consistent growth to the previous quarter. For example, if a firm-year's first quarter shows positive growth, we observe positive growth in the second quarter of this exact firm-year as well.

constrained to use only a single annual statement and to rely on a common cross-sectional parameter estimate, it cannot utilize *firm-specific* earnings growth at all.

Figure 1 visualizes the differences in available earnings information that is picked up by both models. For example, consider Amazon (Ticker Symbol: $AMZN$), a firm which fiscal year equals the calendar year. At the end of June 2021, we can draw on Amazon's 2020 annual report filed on February 3, 2021, and in addition on their 2021 first quarter earnings reported on April 30, 2021. The standard model, however, only incorporates the annual earnings information, indicated by the dark-grey area in Figure 1, but not the quarterly result (i.e., the grey-shaded area). Intuitively, the difference in the information sets between both models becomes even more pronounced when looking at a firm with an earlier fiscal year end. For example, Cisco's (Ticker Symbol: $CSCO$) fiscal year ends in July. Therefore, at the end of June 2021, they have already published three quarterly reports of their ongoing fiscal year (e.g., Q3: May 25, 2021). While the interim earnings information contained in these three reports is processed by our extended RI model, it is neglected by the standard RI model. This gives our model a competitive advantage, especially in situations where a firm's earnings trend abruptly changes within the year, e.g., because the firm loses a key market, or in situation where market-wide earnings persistence increases or decreases, e.g., due to the impacts of the COVID-19 pandemic starting in 2020 or due to the impacts of the Russian war against Ukraine starting in 2022 and the energy crisis in Europe that resulted from it. Through our interim earnings growth variable, our extended model can account for such changes in current earnings trends and can adjust annual earnings forecasts accordingly. In Section 3 and Section 4, we show that adding this variable to cross-sectional models is indeed a simple yet effective way to make use of quarterly earnings information when forecasting annual earnings to improve forecast accuracy substantially.

(Please insert Figure 1 here)

To forecast annual earnings, we follow Hou et al. (2012) and Li and Mohanram (2014), among others, and apply a two-step estimation and forecast approach. First, the model is estimated on a rolling window of ten years of previous data, i.e.,

$$E_{i,t} \quad = \beta_0 + \beta_1 \cdot E_{i,t-\tau} + \cdots + \varepsilon_{i,t}. \tag{4}$$

Second, to obtain out-of-sample forecasts of future earnings, the parameter estimates ($\hat{\beta}$) for a given estimation date are combined with the most recent firm fundamentals at that estimation date:

$$\hat{E}_{i,t+\tau} = \hat{\beta}_0 + \hat{\beta}_1 \cdot E_{i,t} + \cdots. \tag{5}$$

As outlined by, for example, Hou et al. (2012), this stepwise cross-sectional approach reduces survivorship requirements, as only current data is required to forecast future earnings for a firm. In addition, the parameter estimates profit from high statistical power as the model is fitted on a pooled cross-section, and therefore, draws on a large set of observations.[9] We use this two-step estimation and forecast approach to obtain annual earnings forecasts for up to five-years ahead (τ = 5). We employ the models at a quarterly frequency, i.e., we rerun the two-step estimation and forecast exercise based on the information sets available at the end of each calendar quarter.[10] Thereby, we can better analyze whether including our interim growth variable leads to more and more improved forecasts during a year, in particular, when new quarterly reports are released (i.e., when q_i increases). In addition, running the analysis at a quarterly instead of an annual frequency corresponds more closely to practitioners' demands, as they require timely forecasts that reflect the most recent earnings information. Intuitively, models that can utilize more information should produce forecasts that are more precise. As the information set changes for all firms with each additional quarterly report, and our model can use this new information, annual forecasts from our model should become more and more accurate during the year. In contrast, the standard RI model uses only information from annual statements. As a firm's annual financial information does only change once every 12 months, the standard RI model's predictions for this firm remain virtually unchanged during the year.[11]

The evaluation of our extended model against the standard RI model proceeds in two major steps: In a first step, we focus on statistical performance and benchmark the out-of-sample bias and accuracy of our earnings forecasts. In a second step, we scrutinize economic performance and

9 These characteristics separate modern, cross-sectional forecast models from time-series approaches as applied in earlier research on earnings forecasting (e.g., Brown, Hagerman, Griffin, and Zmijewski (1987)).

10 For robustness, we also show results when running the prediction annually at the end of June in line with Hou et al. (2012) and Li and Mohanram (2014). We find similar improvements. See Appendix C for results.

11 Note that changes in forecasts are mainly driven by releases of new financial information, not by parameter changes. This can be seen from Equation (5) which states that forecasts are obtained by multiplying parameter estimates with currently available financials (e.g., annual earnings). Parameter estimates change only slowly during a year as more and more firms report earnings. In contrast, changes in a firm's financials can be huge.

analyze whether implied cost of capital (ICC) derived from our earnings forecasts can better predict future stock returns.

To obtain empirical evidence regarding the statistical out-of-sample performances of both our extended and the standard RI model, we follow the procedures laid out in Hou et al. (2012) and Li and Mohanram (2014), i.e., we calculate measures for bias and accuracy of forecasts. Forecast bias is measured by the price-scaled forecast error ($PFE_{i,t+\tau}$). For an individual firm i, this is the difference between the firm's future realized earnings ($E_{i,t+\tau}$) and its forecasted earnings ($\hat{E}_{i,t+\tau}$), scaled by the firm's stock price at the end of the fiscal year preceding the estimation date ($Price_{i,t}$):

$$PFE_{i,t+\tau} \quad = \frac{E_{i,t+\tau} - \hat{E}_{i,t+\tau}}{Price_{i,t}}. \tag{6}$$

Like Hou et al. (2012), we define a model's forecast bias at an estimation date for a given forecast horizon τ as the median of corresponding PFEs for fiscal year t+τ across all firms. A negative bias indicates that forecasts of a model systematically exceed future earnings, and hence, that a model systematic overestimates future earnings. If these forecasts stem from equity analysts, we would assume that they are too optimistic. Vice versa, a positive bias implies too pessimistic forecasts. Intuitively, the closer a model's median PFE is to zero, the better the model performs.

To evaluate the accuracy of forecasts from a statistical point of view, the absolute price-scaled forecast error ($PAFE_{i,t+\tau}$) for a firm i is calculated as

$$PAFE_{i,t+\tau} \quad = \frac{\left|E_{i,t+\tau} - \hat{E}_{i,t+\tau}\right|}{Price_{i,t}}. \tag{7}$$

Again, medians across all firms are calculated for each forecast horizon τ at each estimation date. $PAFE$s generally provide a clearer picture of the predictive performance of a model as they simply measure how close forecasts match realized earnings. Intuitively, the closer a model's median $PAFE$s are to zero, the more accurate its forecasts are.

In the second step, we focus on the economic reliability of the models' forecasts. Therefore, we analyze how well ICC estimates derived from our earnings forecasts predict future stock returns in comparison to ICCs based on the standard RI model. A firm's ICC is the internal rate of return that sets the present value of the firm's forecasted future earnings equal to its current stock price. Following Hou et al. (2012), we calculate ICCs using five different valuation models, namely the

Ohlson and Juettner-Nauroth (2005) abnormal earnings growth model (OJ), the Gebhardt, Lee, and Swaminathan (2001) and Claus and Thomas (2001) residual income valuation models (GLS and CT), the Easton (2004) price-earnings to growth model (PEG), and the Gordon and Gordon (1997) dividend discount model (GG).[12] Since each ICC requires earnings forecasts over different forecast horizons along with additional inputs, like risk-free rate, industry return-on-equity, etc., the resulting expected return proxies differ. To ensure that results are not driven by a specific method to calculate ICCs, we follow Hou et al. (2012) and Li and Mohanram (2014), among others, and use a composite ICC estimate for our analyses. That is, we calculate a composite ICC as the arithmetic mean out of the five individual ICC estimates.[13]

Following previous literature, we evaluate the reliability of ICCs by their strength in predicting future stock returns on the portfolio as well as on the firm level (e.g., Easton and Monahan (2005), Hou et al. (2012), or Li and Mohanram (2014)). For the portfolio level test, we sort stocks into deciles according to their composite ICC estimates at each estimation date. Then, we construct zero investment portfolios by going long stocks in the top decile and shorting stocks in the bottom decile. Afterwards, we calculate buy-and-hold returns of equally weighted portfolios over holding periods of one, two, and three years. The larger those buy-and-hold returns are, i.e., the larger the return spreads between the top and bottom decile are, the more reliable are the ICC estimates. Moreover, when comparing model ICC estimates to analysts ICCs in Section 4, we additionally perform a portfolio level test in a more practical setting. Given that investors typically face noticeable short-sale restrictions, a buy-only portfolio based on ICCs may be of particular interest to them. To address this issue, we analyze separately for buy- and sell-portfolios whether and how risk-return profiles as well as valuation metrics differ between the stocks selected by model ICCs and those selected by analyst ICCs. For the firm level test, we run Fama and MacBeth (1973) cross-sectional regressions of up to three-year ahead stock returns on composite ICCs at each estimation date. Since ICCs correspond to average one-year stock return expectations, we annualize stock returns covering periods of more than one year:

$$r_{i,t+\tau} = \alpha_t + \beta_t \cdot ICC_{i,t} + \varepsilon_{i,t+\tau}, \tag{8}$$

[12] See Appendix B for a more detailed description of the ICC estimates incl. required variables.

[13] To minimize data requirements, we only require at least one non-missing individual ICC estimate when calculating the composite estimate (see e.g., Hou et al. (2012)). Results for the individual ICCs are available upon request. Moreover, following previous studies (e.g., Lewellen (2015)), we exclude ICC estimates outside 0% and 100%.

where $r_{i,t+\tau}$ is the annualized stock return over a τ-year holding period and $ICC_{i,t}$ is the composite ICC estimate. A reliable future stock return proxy should exhibit a $\hat{\beta}_t$ roughly equal to 1 and a high adjusted R^2. In contrast, an unreliable estimate should be uncorrelated with future realized stock returns, i.e., produce a $\hat{\beta}_t$ coefficient of roughly 0 along with a low adjusted R^2.

B. Sample Selection

Our sample consists of US American firms in the intersection of the North-American annual and quarterly fundamentals files from COMPUSTAT and the monthly stock return file from CRSP for the period 1968 through 2019.[14] Following Hou et al. (2012), we restrict our sample to common shares of NYSE, AMEX, and NASDAQ listed firms.[15] Moreover, we use firms' actual reporting dates as provided by the COMPUSTAT item RDQ to state when annual and quarterly reports become available to the public. This ensures that we use only publicly available information at every estimation date. In case RDQ is missing, we assume a three-month reporting lag in line with Hou et al. (2012). Additionally, to compare models with sell-side analysts in Section 4, we collect median analysts' consensus forecasts at the end of each calendar quarter and actual earnings from the I/B/E/S summary files from 1976 to 2019. Moreover, we collect consensus long-term growth rate estimates to substitute missing analysts' forecasts for periods longer than two years in order to facilitate the calculation of analysts' ICCs using valuation models that require such longer-term earnings forecasts (e.g., Hou et al. (2012)). For example, we substitute missing three-year ahead analysts' earnings forecasts by assuming that available two-year ahead forecasts grow at the long-term growth rate estimate provided by analysts. Furthermore, to compare investment portfolio returns to market returns in Section 4 and to calculate these portfolios' systematic risk factor exposures and valuation multiples, we additionally collect monthly market return data from CRSP, daily stock returns and factor return data from CRSP, and financial ratio information based on CRSP and COMPUSTAT data.

We follow Li and Mohanram (2014) and define earnings as earnings before extraordinary items and discontinued operations (COMPUSTAT item IB) minus special items (COMPUSTAT item SPI). We set special items to zero in case they are missing. To obtain accruals (AC), we apply

[14] We deal with delisting returns in CRSP by adjusting returns following Beaver, McNichols, and Price (2007).
[15] Moreover, our results are robust to excluding financial firms, regulated firms, and penny stocks.

the balance sheet method prior to 1988, i.e., before SFAS No. 95, Statement of Cash Flow, came into force. Thereafter, we apply the cash flow statement method.[16] Analogously to special items, we set missing accruals to zero as well. Moreover, we follow Li and Mohanram (2014) and scale all variables by the number of shares outstanding (COMPUSTAT item $CSHO$). To mitigate the effect of outliers, we winsorize all variables at the 1st and 99th percentiles at each estimation date. To scale forecast errors, we use firms' stock prices at their fiscal year-ends prior to the estimation date (COMPUSTAT item $PRCC\_F$). We provide a more detailed description of all variables in the Appendix A.

(Please insert Table 1 here)

Table 1 provides summary statistics in Panel A and correlations in Panel B for the explanatory variables in our earnings regressions. We collect 195,346 firm-year observations for the total sample (1968-2019). Summary statistics are in line with economic rationale as well as previous literature (e.g., Hou et al. (2012)). That is, we observe on average positive earnings (E_t), book values of equity (B_t), and interim growth ($Growth_t$).[17] Moreover, accruals (AC_t) are negative on average. In addition, correlation analysis in Panel B reveals that our interim growth variable is only moderately correlated to other explanatory variables. This suggests that our variable captures complementary rather than substitutive information, and thus, adds new information to the RI model. For example, Pearson correlation between current earnings (E_t) and interim growth ($Growth_t$) is 0.07, while Spearman correlation is 0.15. Correlations between the other explanatory variables are also in line with expectations. For example, large companies tend to have large earnings, and earnings (E_t) are negatively correlated with accruals (AC_t).

16 Note that we follow Hou et al. (2012) to calculate accruals. We decide to deviate from Li and Mohanram (2014) to have lower data requirements. However, the tenor of results is unchanged when accruals are defined in accordance with Li and Mohanram (2014).

17 Simultaneously, we observe a relatively large share of loss firms (more than 25%) in line with previous research (e.g., Joos and Plesko (2005) and Li (2011)).

3. Extended Model versus Standard Model

In this section, we compare our extended RI model to the standard RI model. Thus, we evaluate whether our model that incorporates firm-specific interim growth outperforms the standard RI model.[18] We follow previous literature, in particular Hou et al (2012) and Li and Mohanram (2014), and focus on two different aspects when comparing models to each other:

(i) Forecasting future earnings.

(ii) Predicting future stock returns based on ICC estimates.

We address aspect (i) by analyzing whether our interim growth variable improves in-sample and out-of-sample earnings forecasts. If so, our model must better explain and forecast future earnings than the standard RI model. For that purpose, we test the following two hypotheses:

H.1: Earnings Forecast – In-Sample:
Our interim growth variable helps to better explain future earnings in-sample, leading to a substantially increased adjusted R^2.

H.2: Earnings Forecast – Out-Of-Sample:
Our interim growth variable significantly improves out-of-sample forecasts of future earnings. Thus, forecasts from our extended RI model show substantially lower out-of-sample forecast errors than forecasts from the standard RI model.

To address aspect (ii), we analyze whether ICCs derived from our earnings forecasts are more accurate predictors of future stock returns than ICCs based on the standard RI model's forecasts. This analysis is particularly important for asset managers, portfolio managers, and other market participants that, for instance, look for automated investment decision tools that incorporate firms' most recent information, e.g., quarterly reports. As previous literature, our analysis includes portfolio and firm level tests for the following hypothesis:

[18] Note that we focus on the RI model introduced by Li and Mohanram (2014) because previous literature shows that this model outperforms alternative models (e.g., Li and Mohanram (2014)). However, we find similar improvements for alternative models as well, including those introduced by Hou et al. (2012) and Konstantinidi and Pope (2016). Results are available upon request.

H.3: Stock Return Prediction:

Our earnings forecasts lead to ICCs that better predict future stock returns than ICCs derived from the standard RI model's forecasts, and thus, are more reliable.

To test these hypotheses, we deviate from previous studies and run analyses at a quarterly instead of an annual frequency, as outlined in Section 2.A. This allows us to delineate the effects our interim growth variable has on earnings forecasts and forecast accuracy during the year, i.e., with the release of new earnings information.

A. Earnings Forecasts

i. In-Sample Results

Table 2 addresses our hypothesis H.1 and presents the Newey-West time-series average coefficient estimates and average adjusted R^2s from our rolling regressions.[19] We document the following findings:

First, we find that the coefficient of our interim growth variable is statistically significant and equals 0.67 for one-year ahead forecasts, i.e., roughly two-thirds of the observed interim growth extrapolates to future earnings. This indicates that our annual earnings forecasts will be substantially increased for firms for which we observe a positive interim earnings growth, whereas it will be smaller for firms with a negative interim earnings growth. Moreover, we document that the overall explanatory power increases once we add our growth variable to the model. That is, the adjusted R^2 increases by 7.88 percentage points from 76.09% to 83.97% for one-year ahead forecasts, indicating that our variable captures additional variation in future earnings. Second, all other explanatory variables' coefficients are statistically significant and consistent with economic theory. Their signs and magnitudes are qualitatively comparable with previous studies (e.g., Li and Mohanram (2014)), i.e., including our interim growth variable has little to no effect on the other parameter estimates.[20] Third, we even find improvements for multi-period ahead forecasts, although these improvements are more moderate. The coefficient of our interim growth variable decreases to 0.56 and 0.49 for two- and three-year ahead earnings. However, this decrease is

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19 Results for up to five-year ahead forecasts are available upon request.

20 Only the coefficient of the interaction term drops by roughly 20% on average once we include our growth variable.

unsurprising, as our measure captures growth over a fixed one-year horizon. Therefore, it is intuitively less informative for multi-period ahead forecasts than it is for one-year ahead forecasts.[21] Coinciding with the decreasing coefficient for growth, the increase in adjusted R^2 is slightly less pronounced as well. Adding our interim growth variable to the model improves the in-sample adjusted R^2 by 4.08 percentage points for two-year ahead forecasts, and by 2.71 percentage points for three-year ahead forecasts.

(Please insert Table 2 here)

To summarize, our results regarding the in-sample fit strongly support hypothesis H.1. That is, we document positive and statistically significant coefficients for interim growth. Moreover, adding our variable has little to no effect on the other coefficients, indicating that our variable adds new information to the model. The observed increases in adjusted R^2s indicate a better in-sample fit for all forecast horizons.

ii. Out-of-Sample Results

Next, we analyze whether the superior in-sample fit of our model also translates into better out-of-sample earnings forecasts. Table 3 reports descriptive statistics of out-of-sample forecasts from both models. While both models yield similar average earnings forecasts, our forecasts exhibit wider variability with larger standard deviations (STD) and interquartile ranges (IQR). This suggests that our forecasts may better capture the variation in future earnings across firms. For instance, for one-year ahead forecasts, both models have similar means of 1.12 and medians of 0.74. However, our forecasts show a larger standard deviation of 1.89, compared to the standard RI model's smaller standard deviation of 1.77. Similarly, our interquartile range is 1.98, whereas the standard RI model's interquartile range is 1.94. Those differences in STD and IQR stem from the fact that our forecasts deviate from the standard RI model's forecasts whenever we observe growth for a firm. That is, as the other coefficients are more or less equal for both models, our model simply alters the standard RI model's forecasts using interim growth information. In case a firm has positive earnings growth, our model raises the earnings forecast, and vice versa, produces

[21] Defining the growth measure over a multi-period horizon could resolve this. However, this would require an earnings history for a given firm. Thus, data requirements would rise, ending in a selection bias. Hence, we refrain from defining a multi-period growth measure.

lower forecasts for negative earnings growth. As a result, our model generates more differentiated earnings forecasts by incorporating a firm's most recent interim earnings development. Whether this also leads to more realistic forecasts is analyzed next.

(Please insert Table 3 here)

Table 4 addresses hypothesis H.2 and compares both models in terms of forecast accuracy and forecast bias. Reporting Newey-West time-series average median $PAFE$s, Panel A shows that our extended RI model produces substantially more accurate earnings forecasts than the standard RI model for all forecast horizons.[22] Differences between both models are statistically significant. For example, for one-year ahead earnings, our model yields a median $PAFE$ of 2.12%. In contrast, the standard RI model leads to substantially less accurate forecasts, with a larger median $PAFE$ of 3.07%. Hence, including quarterly earnings information into the model reduces the absolute forecast error by approximately one-third on average. For two- and three-year ahead earnings, our model yields median $PAFE$s of 4.02% and 5.25%. Again, the standard RI model is less precise, having median $PAFE$s of 4.50% and 5.65%, respectively. Finding long-term forecasts to be more precise is particularly important, as applications like valuations and cost of capital estimations rely strongly on long-term forecasts. Reporting Newey-West time-series average median PFEs, Panel B compares both models in terms of forecast bias. We document that our model is significantly less biased for one-year ahead forecasts. Specifically, our model yields a median PFE of 0.36%, while the standard RI model leads to more biased forecasts, with a corresponding PFE of 0.50%. In contrast, for two-year ahead forecasts, we find that our forecasts are more biased, with a median PFE of 0.43% compared to 0.31%. For three-year ahead forecasts, both models are unbiased.

(Please insert Table 4 here)

In the following analyses, we demonstrate in two steps (i.e., in Table 5 and Table 6) why our interim growth variable enhances forecast accuracy. First, in Table 5, we illustrate that our model performs better than the standard RI model, particularly when we observe more extreme values (positive or negative) for our interim growth variable. To analyze differences in forecasts and forecast accuracy between both models, we rank firms into quintiles based on our interim growth variable. We scale our growth variable as well as earnings forecasts by stock price to be

22 Note that, throughout this paper, we use the term "Newey-West time-series average" to refer to an average value that is reported along with its statistical significance level according to its Newey-West t-statistic (Newey and West (1987)).

comparable to forecast accuracy (i.e., $PAFE$). As mentioned before, our model produces forecasts that are more differentiated than the earnings forecasts from the standard RI model, since it extrapolates already observable interim growth. Consequently, our forecasts particularly differ when we observe extreme interim earnings growth for a firm. Hence, for strongly positive (negative) interim growth, our model yields substantially increased (decreased) forecasts. Therefore, we expect absolute differences in forecasts to be U-shaped across growth quintiles.

Indeed, we find that the absolute forecast differences between both models exhibit such a U-shape for each of the three forecast horizons. For example, in the bottom quintile, our model produces one-year ahead forecasts that are about 4.77 percentage points lower than forecasts from the standard RI model. This is consistent with the strong negative growth we observe for those firms on average (-6.25%). In the middle quintile, we observe roughly no growth (0.38%). Consequently, the difference in forecasts between both models is roughly zero as well (0.18 percentage points). In the top quintile, i.e., for firms with the largest positive growth, we find that our model produces forecasts that are about 3.22 percentage points larger than forecasts from the standard RI model. Again, that coincides with the strong growth we observe on average for those firms (4.94%). Importantly, we find that differences in forecasts are statistically significant in each growth quintile. The patterns for two- and three-year horizons are quite similar.

(Please insert Table 5 here)

Consistent with those findings, we observe that our model outperforms the standard RI model in the top and bottom quintile the most, and in the middle quintile the least. Thus, we detect the same U-shaped patterns for the differences in forecast accuracies as for the absolute differences in forecasts. For example, for one-year ahead forecasts, our model leads to a median $PAFE$ that is 2.31 percentage points smaller than the corresponding $PAFE$ of the standard RI model for firms in the bottom quintile. Analogously, the improvement is 1.74 percentage points for firms in the top quintile. For the middle quintile, where we more or less observe neither growth nor differences in forecasts, our model reduces the median $PAFE$ by only 0.18 percentage points. Again, differences are statistically significant in each quintile. We also observe the same pattern for multi-period ahead forecasts. Therefore, our results show that including interim growth, i.e., a firm's current earnings development, leads to forecasts that are more realistic and, in consequence, more accurate.

In a second step, we document that the outperformance of our model increases with the amount of interim information it can use, i.e., with the number of quarterly reports (i.e., q) that a firm has already disclosed. As our model accounts for quarterly earnings information while the standard RI model does not, the information advantage of our model should increase with q. Hence, we expect our model to outperform the standard RI model more strongly, the more quarterly reports a firm has already disclosed.

Table 6 presents our empirical results starting with the point in time when the most reports have been released, i.e., one quarter before the release of the annual earnings (τ = 1, q = 3). As expected, we find that our model produces more and more accurate forecasts as the number of available quarterly reports q increases. This can be seen from reading Table 6 in reverse order, i.e., from q = 3 to q = 0. For example, our model's one-year ahead median $PAFE$ decreases from 3,14% to 2.55% when firms release their first quarterly earnings (i.e., q = 1 vs. q = 0). We observe that our forecasts improve again once firms release their second quarterly reports (i.e., q = 2), leading to an even lower $PAFE$ of 2.01%. Analogously, our model yields a further reduction of the median $PAFE$ to 1.60% when firms file their third quarterly report (i.e., q = 3). Consequently, our forecasts get better every three months, i.e., whenever a new report is observed. In contrast, the forecast accuracy of the standard RI model does not improve over time, showing a median $PAFE$ of roughly 3.20% for all q. This is simply due to the fact that it does not pick up quarterly information. The observed accuracy differences between both models are highly significant. As a result, including quarterly earnings into the model reduces the size of one-year ahead annual forecast errors by up to 50%, i.e., the most for q = 3. Overall, this leads to the conclusion that our model outperforms the standard RI model more and more with each additional quarterly report released.

(Please insert Table 6 here)

Interestingly, the information contained in current fiscal year's quarterly reports is also useful for forecasting longer-term earnings. That is, we document similar accuracy improvements for two- and three-year ahead forecasts, although intuitively, the observed forecast error reductions are smaller, i.e., we observe reductions in two-year ahead median $PAFE$s by approximately 15% and in three-year ahead median $PAFE$s by roughly 8%.

Further, to analyze the robustness of our results, Figure 2 compares one-year ahead forecast accuracies between the models, both over time (Panel A) and across industries (Panel B).[23] In short, our empirical results show that our extended RI model constantly outperforms the standard RI model. That is, the median $PAFE$ of our extended model is substantially lower than the corresponding $PAFE$ of the standard RI model in every single period from 1968 to 2019 (Panel A). Importantly, there is also a substantial performance difference between both models during periods of economic crises and their aftermath, i.e., during periods in which models generally have difficulties to predict future earnings. For example, during crises like the OPEC oil price shock in the first half of the 1970s, the early 1980s and 1990s recessions, and the financial crisis in the second half of the 2000s, the extended RI model has average median $PAFEs$ of 2.66%, 2.61%, 3.25%, and 2.49%, respectively.[24] In contrast, the standard RI model produces less accurate forecasts, with larger average median $PAFEs$ of 3.65%, 3.55%, 4.30%, and 3.29%, respectively. These results imply that quarterly earnings information remain important to accurately predict future earnings during economic downturns as well, which is intuitive, because the aftermath of such economic crises are first reflected in firms' interim reports.

Besides the strong dominance over time, our extended model also constantly outperforms the standard RI model across industries (Panel B). That is, our extended RI model produces substantially more precise earnings forecasts than the standard RI model in every single industry. For example, firms in the *consumer durables industry* (#2) and in the *manufacturing industry* (#3) benefit the most from including quarterly earning information into the model. On average, their earnings forecasts get more precise by approximately 30% and 28%, reducing the median $PAFE$ from 3.66% to 2.55% and from 3.13% to 2.25%, respectively. On the other end, firms in the *energy sector* (#4), the *telecommunication sector* (#6), and in the highly regulated *utilities industry* (#9) benefit the least from our model. However, in those industries, our extended RI model still reduces

[23] To avoid overloading the graph, we only show results for predicting one-year ahead earnings and for an annual estimation frequency at the end of June in line with Hou et al. (2012). However, the tenor of results is unchanged when estimating multi-period ahead earnings and when estimating the models at the end of every other calendar quarter as well. In fact, when estimating both models later in a year, e.g., at the end of September or December, our extended model outperforms the standard RI model even more. This is consistent with the idea that our extended model then has a larger information advantage over the standard model, because more firms have already released multiple quarterly reports (see Table 6). Analogously, our model outperforms the standard RI model slightly less when both models are estimated at the end of March. Results are available upon request.

[24] We calculate averages over the following periods: OPEC oil price shock, 1973 to 1975, early 1980s recession, 1980 to 1985, early 1990s recession, 1990 to 1992, and financial crisis, 2007 to 2009. However, these results are robust to lengthen and shorten the respective time spans, as can be seen from the graph.

the median $PAFE$ by a large margin of about 18%, 15%, and 8%, namely from 5.97% to 4.91%, from 2.77% to 2.35%, and from 1.28% to 1.17%. Overall, our results indicate that the importance of quarterly earnings information is not limited to certain industries, but is valid for the entire spectrum of firms.

(Please insert Figure 2 here)

Concluding, our results strongly support hypothesis H.2. We provide empirical evidence that including quarterly earnings into the model substantially and robustly reduces forecast errors, and therefore, increases forecast accuracy. Moreover, we delineate the mechanisms behind forecast accuracy improvements by showing that our model's forecast accuracy is directly related to the strength of the observed interim growth in a firm's quarterly report as well as to the number of already released quarterly reports by that firm. Clearly, as quarterly earnings information proves to be valuable, updating annual forecasts using quarterly reports improves their accuracy and timeliness throughout the year. Hence, our forecast model better matches with practitioners' demands and therefore, is more applicable in practice.

B. Stock Return Prediction

Turning to hypothesis H.3, we analyze whether our earnings forecasts yield ICC estimates that are more accurate predictors of future returns than ICCs based on the standard RI model's forecasts. We address this issue by performing both portfolio and firm level tests. Most notably, we recalculate ICCs at a quarterly frequency using the most recent earnings forecasts. This allows evaluating ICCs on a more realistic portfolio strategy, i.e., a more active management style that adjusts stock holdings in response to upcoming new quarterly information. As an ICC is the discount rate that equates current prices with forecasted future earnings, recalculated ICCs can change because (i) prices may change and because (ii) earnings forecasts may change every quarter. Consequently, active portfolio managers need to reassess every quarter whether observed prices still match with their earnings forecasts, and thus, decide whether to buy, hold, or sell a stock. Because our model accounts for new quarterly information, our earnings forecasts can change every three months, and therefore, their accuracy improves throughout the year (as shown in Section 3.A.2). In contrast, as the standard RI model does not include this information, its earnings forecasts remain virtually unchanged. Therefore, when investors recalculate ICCs at a quarterly frequency, but use the unchanged earnings forecasts from the standard RI model, they can only account for new information in prices. If, on the other hand, investors employ our extended model, they can profit from both new information in prices and new information in updated earnings forecasts. Whether these informationally more efficient ICCs also lead to better investment results is at the core of hypothesis H.3. This is basically an empirical question which we test in the following.

Panel A of Table 7 presents results for this hypothesis on the portfolio level. More precisely, we analyze whether our ICCs can better distinguish between out- and underperforming stocks in subsequent periods than ICC estimates based on the standard RI model's forecasts. Following Hou et al. (2012), we rank stocks into deciles based on their composite ICC estimates at every estimation date, i.e., at the end of every quarter. We then construct zero investment portfolios by going long stocks in the top decile and shorting stocks in the bottom decile and calculate buy-and-hold returns of equally weighted portfolios over holding periods of up to three years.

Most importantly, we find that our ICCs lead to investment portfolios that generate substantially larger and statistically more significant return spreads than the standard RI model's ICCs. This is observed for all holding periods. The annualized return spreads for one-, two-, and three-year horizons are 7.00%, 7.41%, and 7.68%, respectively. In contrast, an investment strategy based on the standard RI model's ICCs leads to lower return spreads, namely 5.23%, 6.29%, and 6.85%. Consequently, investors that use our more accurate earnings forecasts to select portfolios earn an additional return of 1.77, 1.12, and 0.83 percentage points p.a. on average over holding periods of one, two, and three years, respectively. In other words, using our informationally efficient earnings forecasts pays off for investors as they can increase their returns by up to one-third. Hence, we document that our ICCs better predict future stock returns on the portfolio level, and thus, are more reliable.

(Please insert Table 7 here)

Moreover, we find that this result is robust to controlling for risk, as our portfolios show higher Sharpe ratios than the respective portfolios based on the standard RI model's ICCs. For one-, two-, and three-year holdings, our investment strategy yields Sharpe ratios of 0.27, 0.29, and 0.29, respectively. In contrast, the standard RI model's ICCs lead to investment portfolios that show respective Sharpe ratios of 0.21, 0.25, and 0.25. Therefore, investors profit from our more accurate earnings forecasts and subsequent ICC estimates by a higher portfolio return per unit risk.

Panel B of Table 7 provides test results for hypothesis H.3 on the firm level. Following Hou et al. (2012), among others, we run Fama and MacBeth (1973) cross-sectional regressions of future stock returns on ICCs.[25] As in our portfolio level test, we analyze the relation to future returns on the firm level for up to three years ahead. As ICCs are the average one-year stock return expectations, we make future stock returns comparable by annualizing them for periods of more than one year (e.g., Hou et al. (2012)). A more reliable future stock return estimate should have a stronger relation to future returns ($\hat{\beta}_t$) and capture more variation in future returns (adjusted R^2).

We document that our ICCs indeed are more reliable future stock return proxies on the firm level than ICCs based on the standard RI model's forecasts. This finding holds for all holding periods. For our ICCs, we find statistically significant and positive $\hat{\beta}_t$ of 0.50, 0.36, and 0.29 for one-, two-, and three-year ahead returns, respectively. In contrast, the respective coefficient estimates for the standard RI model's ICCs are lower, namely 0.34, 0.21, and 0.16. Moreover, these coefficient estimates are substantially less significant for one- and two-year ahead returns than $\hat{\beta}_t$ of our ICCs, and even insignificant for three-year ahead returns.[26] Furthermore, our ICCs capture more variation in future stock returns than ICC estimates based on the standard RI model's forecasts. This coincides with the stronger and more significant coefficient estimates. For one-, two-, and three-year ahead returns, the adjusted R^2s equal 1.19%, 1.49%, and 1.79%, respectively. In contrast, the standard RI model's ICCs yield lower adjusted R^2s, namely 1.07%, 1.34%, and 1.66%.

Concluding, the portfolio and firm level tests strongly support hypothesis H.3. That is, our more precise earnings forecasts lead to ICC estimates that are more reliable. Consequently, considering quarterly information and following investment strategies based on ICCs derived from our model pays off for investors.

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[25] Like Hou et al. (2012), we exclude negative ICC estimates and winsorize ICCs at the top and bottom percentile at each estimation date to mitigate the impact of outliers.

[26] Additionally, the intercepts from the regression of future returns on our ICCs are marginally closer to zero than the intercepts using the standard RI model's ICC estimates.

4. Models versus Sell-Side Analysts

While the preceding section compares our model to the standard RI model, in this section, we benchmark our model to sell-side analysts. Specifically, we evaluate whether our extended RI model, enriched with quarterly earnings data, can better compete with sell-side analysts in terms of forecasting earnings and predicting future stock returns than the standard RI model.

Previous literature analyzes two aspects when comparing models to analysts:

(i) Do models provide more accurate earnings forecasts than analysts?

(ii) Are stock return predictions based on earnings forecasts from models more reliable than stock return predictions based on analysts' forecasts?

Regarding the first aspect, previous studies generally find a considerable forecast accuracy gap between models and analysts, i.e., models produce less accurate earnings forecasts than analysts (e.g., Hou et al. (2012)).[27] In contrast, for the second aspect, previous literature documents a substantial performance lead of models over analysts when predicting stock returns. That is, ICCs based on model forecasts are more reliable than ICCs based on analysts' forecasts (e.g., Hou et al. (2012) and Evans et al. (2017)).

Those findings are derived from forecast models that exclusively use annual information, while our model incorporates both, annual and quarterly earnings data. This should diminish the information and timing advantage analysts have over models (e.g., Brown and Rozeff (1978), Brown et al. (1987), Bradshaw et al. (2012), and Evans et al. (2017)). To what extent this affects the performance of models as compared to analysts is an empirical question. To analyze this, we test the following two hypotheses:

H.4: Earnings Forecast:
Including quarterly earnings information into the forecast model substantially reduces the "accuracy gap" to analysts when forecasting future earnings.

[27] A more recent paper by Evans et al. (2017) shows that a more complex two-stage model that is estimated with median regression instead of OLS and that predicts I/B/E/S actuals instead of GAAP earnings is able to compete with analysts for two-year ahead forecasts, and to beat consensus analysts' forecasts for longer-term forecasts.

H.5: Return Prediction:

Including quarterly earnings information into the forecast model substantially enlarges the “performance lead” over analysts when predicting future returns.

To level the playing field, we run these analyses on a common sample. That is, we follow Hou et al. (2012) and reduce our sample to firm-years for which model and analysts’ forecasts are both available. While models produce forecasts for all firm-years, requiring analysts’ forecasts shrinks the sample by approximately 40%.[28] Moreover, we benchmark model forecasts to the most recent I/B/E/S forecasts available at the end at each quarter.

A. Forecasting Future Earnings

Table 8 provides empirical results for our hypothesis H.4 by comparing the forecast accuracy of models to that of analysts. Panel A reports Newey-West time-series averages of the median price-scaled absolute forecast errors (i.e., $PAFE$) for earnings forecasts up to three years ahead. Panel B presents the corresponding accuracy gaps, where the accuracy gap is defined as the difference in $PAFE$ between the model and the analysts. Reinforcing our empirical results from Section 3.A.2 obtained on the entire sample (see Table 4), we document for the sample restricted to covered firms as well that our extended RI model produces substantially more accurate earnings forecasts than the standard RI model. Again, this finding holds irrespectively of forecast horizon. Consistent with the notion that firms covered by analysts are larger and tend to have less volatile earnings, we find that forecasts errors for these firms are smaller. For one-, two-, and three-year ahead earnings, our model yields median $PAFE$s of 1.59%, 2.95%, and 3.53%, respectively. In contrast, the standard RI model still leads to substantially less accurate forecasts, with median $PAFE$s of 2.28%, 3.28%, and 3.84%.

Including sell-side analysts into this comparison, we obtain $PAFE$s of 1.02%, 2.38%, and 3.02% for the corresponding horizons. Thus, as a result, we find that the forecast accuracy of model forecasts gets closer to that of analysts once we incorporate quarterly earnings into the model. Specifically, our extended RI model shows substantially smaller accuracy gaps (i.e., 0.57%, 0.58%, and 0.51% for one-, two-, and three-year horizons) as compared to the standard RI model (i.e.,

[28] See for example La Porta (1996), Hong, Lim, and Stein (2000), Diether, Malloy, and Scherbina (2002), and Hou et al. (2012) for the well-documented “coverage bias” of analysts’ forecasts.

1.26%, 0.90%, and 0.81%, respectively). Differences between the accuracy gaps of both models to analysts are statistically significant for all forecast horizons.

(Please insert Table 8 here)

To further investigate the forecast accuracy gap (i.e., H.4), Table 9 examines how this gap changes in relation to the number of quarterly reports (i.e., q) that firms have already disclosed.[29] By grouping firms based on this criterion, we gain insights into how the accuracy gap evolves over time. These insights are summarized below.

First, Panel A of Table 9 reinforces our previous findings in Section 3.B. on the restricted sample of analyst-covered firms (see Table 6). Specifically, it reveals that our extended RI model also generates notably more precise forecasts with every new quarterly report becoming available for analysis (i.e., for $q = 1$, 2, or 3).[30] In contrast, forecasts of the standard RI model cannot improve throughout the year, as it does not incorporate quarterly data. Consistent with previous literature, we also find that analysts' consensus forecasts become more accurate as the annual earnings announcement date approaches (e.g., Richardson, Teoh, and Wysocki (2004)). This is because analysts revise their forecasts with the release of relevant new information such as quarterly earnings announcements (e.g., Stickel (1989) and Keskek, Tse, and Tucker (2014)). Hence, our model mimics this characteristic of analysts' learning as it also integrates quarterly earnings information. This is the reason why we observe the same pattern for our model as well, i.e., that forecast accuracy substantially improves every three months.

Metaphorically speaking, one could say that in terms of forecast accuracy the analysts are running away, while the standard RI model simply stands still. Therefore, the accuracy gap of the standard RI model to analysts increases throughout the year (i.e., from 0.58% for $q = 0$ to 1.74% for $q = 3$). In contrast, our model is making a serious attempt to compete with analyst. In fact, we even catch up a little bit along the way. While our model initially has an accuracy gap of 0.61% ($q = 0$), we can reduce this gap to 0.30% after observing firms' first quarter. Falling back a bit, the accuracy gap slightly increases to 0.42% after a firm's second quarter report and to 0.54% after its

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29 We restrict our analysis to one-year ahead forecasts. However, untabulated tests show that inferences are unchanged when we analyze two-year and three-year ahead forecasts. Nevertheless, the absolute improvement our model brings is smaller.

30 Note that both models perform roughly equally for $q = 0$. Finding this is important as it proofs that our model is virtually identical to the standard RI model whenever we do not observe quarterly earnings information.

third report. Nevertheless, in the end, a small reduction remains (i.e., from 0.61% for q = 0 to 0.54% for q = 3). Given that the standard RI model does not improve at all throughout the year, our extended model shows a substantially reduced accuracy gap relative to this model. For example, for firms with one quarterly report (i.e., q = 1), the standard RI model shows an accuracy gap that is 2.7 times as large as the accuracy gap for our model (i.e., 0.82% vs. 0.30%). Once we observe a firm's second quarterly report, this multiple increases to 3.1, and after observing its third report, the multiple increases to 3.3.

(Please insert Table 9 here)

Finally, Panel C dissects the accuracy gap of the standard RI model into two components: the portion that can be accounted for by quarterly earnings information and the portion that cannot. In detail, we divide the accuracy gap of our extended RI model by the standard RI model's gap to infer what is still left unexplained. Previous literature shows that analysts make use of firms' quarterly and annual fundamentals as well as other information to generate their forecasts, such as conference calls, earnings guidance, or macroeconomic trends (e.g., Brown, Call, Clement, and Sharp (2015)). Models, however, exclusively focus on fundamental data, e.g. the standard RI model includes annual earnings, accruals, and book equity. We add information about quarterly earnings. So, the accuracy gap between models and analysts that remains after adding quarterly data must be attributed to information that is included by analysts, but not by our extended model, i.e., the other information mentioned above.[31] Our results show that quarterly earnings information accounts for roughly two-thirds of the accuracy gap between models and analysts (63% for q = 1 and up to 69% for q = 3). Consequently, only one-third of the performance of analysts comes from other information. Given that fundamental data is easily processible, e.g., using fully automated models like ours, while the more complex information analysts use is not, this result is surprising and emphasizes the relative importance of quarterly earnings information. Nevertheless, it also indicates that analysts mainly focus on fundamental data when producing or updating earnings forecasts, and use information besides fundamental data only complementary. This result helps to better understand the information processing of sell-side analysts.

Concluding, our empirical results strongly support our hypothesis H.4. Quarterly earnings information largely explains the accuracy gap between forecast models and analysts reported by

[31] Note that the accuracy gap might also stem from other things not captured by the forecast models, e.g., non-linearity. However, this affects both models, and thus, we neglect this argument.

previous studies (e.g., Hou et al. (2012)). Therefore, including this information into models diminishes the information and timing advantage analysts have and, by that, substantially reduces the accuracy gap when forecasting earnings. Hence, models can better compete with analysts. This strengthens the position that forecast models can serve as a sound alternative to analysts when predicting future earnings in research settings as well as practical applications.

B. Predicting Future Stock Returns

Table 10 and Table 11 address our hypothesis H.5 and analyze whether our model produces ICC estimates that predict future stock returns more accurately as compared to analysts' ICCs. That is, we analyze whether our model enlarges the previously reported performance lead of standard models over analysts. Note that by restricting the sample to firms covered by analysts, the models lose their edge in terms of being able to choose from a wider range of stocks. This sets aside the model's fundamental coverage advantage, reducing the average number of stocks the models can select from at an estimation date by about one-third, i.e., from 3,561 to 2,477 stocks.[32]

Panel A of Table 10 presents results for hypothesis H.5 on the portfolio level. As in Section 3.B., we rank stocks into deciles at each estimate date, construct zero investment portfolios, and analyze their return spreads, where larger return spreads still indicate better investment strategies.

Consistent with the results obtained on the unrestricted sample (Table 7, Section 3.B.), for covered stocks, we also find that using our ICCs generates larger and statistically more significant return spreads as compared to employing the standard RI model's ICCs. Again, this turns out to be valid for all holding periods. The annualized return spreads for a one-, two-, and three-year holding period are 5.14%, 5.77%, and 5.72%, respectively. In contrast, investment portfolios derived from the standard RI model's ICCs generate more moderate return spreads of 4.06%, 5.18%, and 5.29%, respectively. Unsurprisingly, these return spreads are somewhat smaller and less significant as compared to those spreads obtained on the unrestricted sample, because covered firms tend to be

[32] Our approach differs slightly from the approach in Hou et al. (2012). They restrict the sample to a "common sample period", i.e., to a sample period in which analysts' forecasts are available. Nevertheless, to our understanding, their model is still allowed to pick uncovered stocks. Intuitively, allowing models to have a larger investment universe improves results, leading to larger return spreads that are statistically more significant, as seen in Table 7 in Section 3.B.

larger, and thus, informationally more efficient.[33] Summarizing, as for the unrestricted sample, we can confirm that including quarterly information leads to ICCs that predict future returns on the portfolio level more precisely.

Moreover, we reinforce the findings of previous studies that investments based on analysts' ICCs yield the lowest return spreads for all holding periods (i.e., return spreads of 3.00%, 4.38%, and 4.14%, respectively). Hence, our results strongly suggest that quarterly earnings information indeed enlarges the performance lead of models over analysts in predicting future stock returns on the portfolio level. Furthermore, Sharpe ratios suggest that this phenomenon is not solely driven by risk. In other words, portfolios based on our ICCs outperform those based on analyst ICCs in terms of Sharpe ratios. Interestingly, even the standard RI model's ICCs generate higher Sharpe ratios than investments based on analyst ICCs. Results are consistent for all holding periods.

(Please insert Table 10 here)

Panel B of Table 10 presents results for our hypothesis H.5 on the firm level. We test this hypothesis by regressing firm-specific annualized future stock returns on ICCs, as before in Section 3.B. Specifically, we find that our ICCs are the most reliable future stock return estimates on the firm level. For one- and two-year ahead returns, we obtain statistically significant and positive $\hat{\beta}_t$ of 0.42 and 0.33. For three-year ahead returns, the coefficient (0.23) still is borderline significant. In contrast, we do not find such strong results for ICCs based on the standard RI model. Results are even weaker for ICCs based on analysts' forecasts.[34] We find no statistically significant relation between future stock returns and analyst-based ICCs for one- and two-year horizons. At the three-year horizon, this relation even turns out to be significantly negative, which is economically unreasonable. This is consistent with Easton and Monahan (2005) who find that ICCs based on analysts' forecasts are negatively correlated with future stock returns as well.

Reinforcing our results reported in Table 7 (Section 3.B.), we find that our ICC estimates capture more variation in future stock returns of covered firms as well. Thus, our ICCs show a generally larger explanatory power for future returns on the firm level. For one-, two-, and three-year ahead returns, the adjusted R^2s equal 2.10%, 2.14%, and 2.18%, respectively. In contrast,

[33] Note that for a one-year holding period, none of the investment portfolios yields a statistically significant return spread. This is driven by the sample as we only look at only covered firms (e.g., Hess, Meuter, and Kaul (2019)). For the same reason, we observe relatively small returns in general (compared to Table 7, Section 3.B.).

[34] Untabulated tests show that all differences in $\widehat{\beta_t}$ are statistically significant and positive.

ICCs based on the standard RI model's forecasts show adjusted R^2s of 1.94%, 1.86%, and 1.94%. Consistent with the insignificant and negative coefficients, ICCs based on analysts' forecasts perform even worse, with adjusted R^2s ranging from 1.49% to 1.89%.

In a next step, we compare investment strategies following model forecasts to those using analyst-based ICCs from a more practical perspective. For this purpose, we return to a portfolio level test. With our previous portfolio level tests, we assume that investors can easily short-sell numerous stocks. However, short-sale restrictions might make it difficult for investor to implement such zero investment strategies.[35] To address this concern, we disaggregate the portfolio into its components, i.e., into stocks bought and stocks sold by the strategy. The idea is to learn whether an investment strategy based on ICC estimates is profitable in case investors are only interested in buying stocks, or, even when admittedly less likely, in case they only focus on short-selling stocks. While Hou et al. (2012) and Li and Mohanram (2014), among others, already show returns for the buy- and sell-portfolio separately, we go further and address the following two additional aspects: First, to gain insights into what drives performance differences between investment strategies based on analysts' earnings forecasts and on model forecasts, we differentiate between stocks bought or sold by both strategies, and stocks exclusively bought or sold by only one of the strategies. Second, in case investors no longer follow zero investment strategies but decide to only buy or sell stocks, the investment's risk-return profile gets more important. To address this, we analyze whether a buy- or sell-portfolio based on ICCs outperforms alternative investments, e.g., a market portfolio, and whether such an investment comes with systematically more risk.

(Please insert Table 11 here)

Table 11 presents our empirical results. In Panel A, we compare the buy-portfolio of an ICC strategy using our extended model's earnings forecasts to the buy-portfolio following analyst ICCs.[36] We create three equally weighted portfolios out of the two buy-portfolios: First, one that covers stocks picked by both investment strategies jointly, second, a portfolio that includes stocks

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35 See for instance the SEC press release from 2010 "SEC Approves Short Selling Restrictions" or the "Regulation (EU) No 236/2012: On Short Selling and Certain Aspects of Credit Default Swaps" of the European Parliament and of the Council from 2012.

36 For simplicity, we only compare our extended model to analysts. However, results for including the standard model into the comparison are in line with the previous results of our paper. That is, while the standard model outperforms analysts, it underperforms our extended model. For example, a buy-portfolio including stocks exclusively selected by the standard model's ICCs yield an average holding return of 18.67% and an average excess return above the market of 2.79%. Hence, including quarterly earnings information into the forecast model improves the security selection of model ICCs. Results are available upon request.

only bought according to the model ICC's strategy, and third, the analyst ICC's counterpart of that. We report time-series averages of the stake each portfolio has in the overall buy-portfolio, the portfolios' one-year holding returns, their excess returns above the risk-free rate, and their returns above an equally weighted market portfolio. Moreover, we report time-series averages of their Sharpe ratios, their portfolio betas over the one-year holding period according to the Carhart four-factor model (e.g., Carhart (1997)), and their valuation multiples at the beginning and at the end of the holding period. We calculate the Sharpe ratios using monthly excess returns over a one-year holding period and annualize the resulting ratios in line with Sharpe (1994). We estimate the portfolios' systematic risk factor loadings by regressing daily excess returns on daily factor excess returns over the one-year holding period. For the regression, we require at least 126 daily return observations.

We find that the average buy-portfolio consists of about 41% stocks bought according to both investment strategies, whereas about 59% of selected stocks differ across strategies. Hence, we detect substantial differences in the investment decisions, i.e., both approaches disagree largely about the exact stocks expected to overperform over the next 12 months. For investors, this raises the question which investment strategy yields the better security selection.

We document that the portfolio part that is unique to our model ICCs substantially outperforms stocks in the portfolio selected only according to analyst ICCs. Most importantly, our strategy selects stocks that yield substantially higher returns than stocks selected exclusively by analyst ICCs. Specifically, stocks selected only via our model ICCs exhibit an average one-year holding return of 19.33%, in contrast to 14.71% earned by stocks solely bought following ICCs based on analysts' earnings forecasts. Differences between these holding returns are statistically significant. Interestingly, stocks picked by our model ICCs only also show a higher holding return than the stocks selected according to both investment strategies, i.e., 18.73%. When looking at market excess returns, results are even more striking. While the joint buy-portfolio and those stocks only bought following our model ICCs outperform the market by 2.81% and 3.40%, respectively, the portfolio that is buying stocks according to only analyst ICCs underperforms an equally weighted market portfolio by 1.22%. This strongly supports the notion that model ICCs lead to a substantially better security selection than analyst ICCs. In other words, investors are better off using our model ICCs to build buy-portfolios than investing in the market. In contrast, they should prefer a market portfolio over an investment strategy based on ICCs derived from analysts' earnings forecasts.

Particularly interesting for investors, portfolios based on model ICCs come with lower risk and therefore exhibit substantially larger Sharpe ratios, too. A buy-portfolio that invests in stocks exclusively bought according to model ICCs yields an average Sharpe ratio of 0.9614. In contrast, the Sharpe ratio of stocks selected via analysts ICCs is just half as large (0.4744). Again, differences between both strategies are statistically significant. Analogously to our findings for returns, the joint buy-portfolio shows an average Sharpe ratio that is smaller than the corresponding ratio of those stocks only bought by model ICCs, but larger than the respective ratio of stocks exclusively selected by an investment strategy following analyst ICCs. This indicates that model ICCs provide investors with a much better risk-return profile than corresponding portfolios based on analyst ICCs. Further, we compare each portfolio's systematic risk exposures over the one-year holding period using the Carhart four-factor model. Comparing the portfolio consisting of stocks exclusively bought following model ICCs with a portfolio including stocks picked only by analyst ICCs, we document that the former has a significantly lower exposure to market risk, size risk, and momentum risk than the later, but comes with a larger exposure to value risk. Particularly interesting to investors, those stocks picked by only our model ICCs show also lower exposures to market risk, size risk, and momentum risk than the joint buy-portfolio, and a roughly equally large exposure to value risk. Hence, the overall buy-portfolio benefits from adding those stocks only selected by our model ICCs in terms of systematic risk. In contrast, adding stocks only bought by an analyst-based ICC strategy to the buy-portfolio lowers the systematic risk exposure in terms of value risk and momentum risk, but increases its exposure to size risk while barely affecting the market risk exposure. Hence, consistent with our findings regarding returns and Sharpe ratios, our results support the notion that model ICCs select stocks with a better risk-return profile than analyst-based strategies for investors that implement buy-only investment strategies.

In a next step, we analyze why portfolios built using model ICCs offer a better risk-return profile to investors than strategies that follow analyst ICCs. To this end, we study the security selection in both portfolios from a valuation point of view, i.e., we analyze how the valuations of stocks in both portfolios change throughout the holding period. In more detail, we observe three valuation multiples often applied by value investors: book-to-market ratio (B/M), price-to-cash flow ratio (P/CF), and enterprise value-to-EBITDA ratio ($E/EBITDA$). Our results reveal that the security selection by model ICCs works as intended, while analyst ICCs fundamentally fail to select appropriate stocks for a long portfolio. That is, those stocks only selected by our model tend to be "undervalued" when picked, while analyst ICCs recommend to buy "overvalued" stocks. Throughout the holding period, the market resolves both "misevaluations" partly, which is advantageous for the model portfolio, but disadvantageous for the analyst portfolio. For example, the average B/M of stocks only bought by our model's ICCs decreases throughout the holding period from 1.1523 to 1.1190, indicating a higher relative valuation attached to those stocks at the end of the holding period. In contrast, the average B/M of stocks only bought according to analysts increases from 0.8662 to 0.9272, implying a lower relative valuation at the end of the holding period. The average P/CF and $E/EBITDA$ paint the same picture. For example, while the P/CF of stocks in the portfolio only picked by model ICCs increases by approx. 13% from 4.0596 to 4.5739, the multiple drops from 4.2664 to 4.1645 for stocks selected by analyst ICCs. That is, the relative valuation of stocks recommended by model ICCs increases throughout the holding period, while stocks bought by analysts lose in relative value. We interpret these results as support for the notion that models provide investors with a good security selection, while analysts do not. This is in line with the result that stocks only picked by our model outperform the market, whereas those stocks recommended by analysts in fact underperform the market. The optimism bias in analysts' earnings forecasts could be responsible for this result, as overestimating firms' future earnings can make their current stock prices more appealing. However, when the actual earnings of these firms fail to meet these optimistic expectations, stock prices may not develop as anticipated, and thus, leading to lower returns than expected.

Panel B of Table 11 repeats the analysis for the sell-portfolios. However, because strategies that exclusively short-sell stock are rather infeasible for most investors in practice, we discuss our results very briefly. Similar to the buy-portfolio, less than half of the stocks in the sell-portfolio (about 45%) are sold by both investment strategies, while about 55% stocks are different across strategies. Stocks sold by both strategies yield an average holding return of 15.12%, or 0,81% below the market. Importantly, both portfolios consisting of stocks exclusively picked by a specific investment strategy yield returns that are favorable to investors that short stocks relative to the market. In other words, both these sell-portfolios yield lower holding returns than an equally weighted market portfolio, indicating that the security selection works as indented and identifies underperforming stocks. The respective sell-portfolio based on model ICCs yields a holding return of 13.67%, i.e., 2.26% below the market return. The corresponding portfolio based on analyst ICCs generates a holding return of 12.31%, which is 3.62% below the market return. While model ICCs therefore seem slightly less able to select securities for short-sale portfolios than ICCs using analysts' earnings forecasts, differences are in fact statistically insignificant.

Those results are also supported by the changes in relative valuations and the portfolios' risk-return profiles. That is, the B/Ms tend to increase throughout the holding period, while the P/CFs and $E/EBITDA$s decrease. Further, stocks only sold by an analyst ICC strategy come with slightly higher Sharpe ratios and lower systematic risk exposures except for momentum risk than the joint sell-portfolio and the sell-portfolio consisting of stocks only picked by model ICCs. Overall, our results do not support a specific short-selling strategy to be superior.

Concluding, also for covered firms, the superior earnings forecast performance of our model directly translates into better stock return predictions. By that, we enlarge the performance lead of models over analysts in predicting future returns. Ultimately, this strongly supports our hypothesis H.5. Moreover, when considering that investors typically have limited access to short-selling and therefore usually decide to only buy stocks, our empirical results suggest that investment strategies based on ICC estimates are only profitable for investors if they use model earnings forecasts. As a consequence, investors are better off if they simply buy a market portfolio instead of picking stocks based on ICCs derived from analysts' earnings forecasts. Summarizing, in accordance with hypothesis H.5, we present empirical evidence that model ICCs provide investors with a better security selection than analyst ICCs.

5. Conclusion

We introduce a forward-looking difference variable that extrapolates firm-specific interim earnings growth to annual earnings changes. Our empirical results show that differentiating earnings growth in the cross-section substantially improves forecasting firms' future earnings as well as predicting their future stock returns. This finding holds on average, across industries, over time, and particularly important, for different forecast horizons and holding periods. Furthermore, we find that our variable largely closes the accuracy gap to analysts' earnings forecasts. In addition, buy-portfolios based on our model's ICCs outperform the market, have high Sharpe ratios, and moderate systematic risk factor exposures. In contrast, investments following analyst ICCs underperform the market and exhibit poor risk-return profiles.

Our study provides several significant contributions to the literature. First, we enable existing cross-sectional forecast models to account for firm-specific earnings growth without imposing higher data requirements. Hence, we structurally advance those models. In consequence, model forecasts become more accurate, can be updated more frequently, and get more relevant for researchers and practitioners that are looking for reliable and timely estimates of future earnings and stock returns. Future research could build on our paper and test whether further improvements in forecast accuracy can be achieved by incorporating our approach into more sophisticated econometric frameworks, such as robust regressions (e.g., Ohlson and Kim (2015) and Evans et al. (2017)) or machine learning approaches (e.g., Hendriock (2022) and Chen et al. (2022)).

Second, we address a prominent puzzle reported in previous literature that earnings forecasts from models are less accurate than analysts' forecasts, while the ICCs derived from model forecasts are better predictors of future stock returns. We provide empirical evidence that this puzzle can be solved by examining the security selection. ICCs derived from analysts' earnings forecasts tend to select overvalued, underperforming, and more risky stocks into buy-portfolios, most likely due to the inherent optimism bias in their forecasts. On the other hand, model ICCs works as intended by primarily selecting undervalued stocks. Therefore, we suggest that future research explores the portfolio selection of those ICC strategies further. This could involve linking our finding to existing literature that deals with valuation effects of analysts' forecasts and the debate over whether GAAP earnings and "Street" earnings contain value relevant information (e.g., Brown and Sivakumar (2003), Gu and Chen (2004), and Mohanram, White, and Zhao (2020)).

Third, our paper provides new insights into the information processing of sell-side analysts. Our results show that the previously reported information and timing advantages of analysts (e.g., Bradshaw et al. (2012), Hou et al. (2012), and Evans et al. (2017)) largely stem from their access to quarterly earnings information. Including that information into cross-sectional forecast models mimics the learning process of analysts and enables models to catch up with analysts in terms of forecast accuracy. Although analysts remain slightly more accurate than models, our model improves at a more or less constant rate with each additional report, whereas analysts tend to improve less with the first quarterly reports than they do with the second and third one. This suggests that analysts may either process information in some quarterly reports more effectively than our model or that they benefit from additional information sources beyond quarterly reports (e.g., Brown et al. (2015)). It would be interesting to investigate whether the remaining information advantage of analysts can be eliminated by including further publicly available data into prediction models, e.g., industry information or macroeconomic data. This avenue remains for future research.

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Appendix A: Variable Descriptions

Notation	**Description** (incl. COMPUSTAT item #X)	**Formula**
Earnings Forecasts		
q_i	Number of quarterly reports available at a specific estimation date.	
YtD_i	Year-to-Date earnings is defined as the sum of quarterly income before extraordinary items (#8) minus special items (#32) over q_i quarters. If firms do not report special items, we set special items equal zero. We standardize using shares outstanding (#25).	$\sum_{j=0}^{q_i} \frac{ibq_{i,j} - spiq_{i,j}}{csho_i}$
E_i	Income before extraordinary items (#18) minus special items (#17). If firms do not report special items, we set special items equal zero. We standardize using shares outstanding (#25).	$\frac{ib_i - spi_i}{csho_i}$
$NegE_i$	Negative earnings dummy equals one when earnings (E_i) are negative, and zero when earnings (E_i) are positive.	$\{0,1\}$
$E_i \cdot NegE_i$	Interaction term of the negative earnings dummy (E_i) and earnings ($NegE_i$) to account for different earnings persistence for loss firms.	$E_i \cdot NegE_i$
B_i	Book value of equity is defined as stockholder's equity (#216). In case stockholder's equity is missing, we use common equity (#60) or, if also missing, we calculate book equity from total assets (#6), total liabilities (#181) and minority interest (#38). We standardize using shares outstanding (#25).	$\frac{seq_i}{csho_i}$

AC_i	Starting in 1988, we calculate accruals using the cash flow statement method (CF/S). That is, we calculate accruals as the difference between earnings (#123) and cash flow from operations (#308). Prior to 1988, we calculate accruals using the balance sheet method (B/S) as the changes in non-cash current assets (#4 and #1) less changes in current liabilities (#5), excluding the change in short-term debt (#34) and changes in taxes payable (#71), minus depreciation and amortization expenses (#14). As for the other variables, we standardize accruals using shares outstanding (#25).	$\frac{ibc_i - oancf_i}{csho_i}$ **or** $\frac{\Delta act_i - \Delta che_i}{csho_i} - \frac{\Delta lct_i - \Delta dlc_i - \Delta txp_i}{csho_i} - \frac{dp_i}{csho_i}$
$Price_i$	To standardize forecast errors, we use stock prices at the fiscal year end (#24)	$prcc\_f_i$
Additional Variables for ICC Calculation		
P_i	To calculate ICCs, we use stock prices at the estimation date from CRSP. It is defined as absolute price (prc_i). Note that negative values are just an indicator that, when closing prices are not available, CRSP inserts the bid/ask average.	$\lvert prc_i \rvert$
ROE_i	For firms with positive earnings and book equity, we calculate return on equity as income before extraordinary items (#18) divided by previous period's (i.e., $t-1$) book equity (B_i).	$\frac{ib_i}{B_i}$
$payout_i$	For profit firms, payout ratio is defined as total cash dividends (#127) divided by income before extraordinary items (#18). If total cash dividends are not available, we sum up dividends on common and preferred stocks (#21 and #19) instead. For loss firms, payout ratio is defined as 6% of total assets (#6).	$\frac{dvt_i}{ib_i}$
Return Variables		
$r_{i,t,t+\tau}$	Return for a holding period of τ years. We use monthly stock return data from CRSP to calculate holding returns. If monthly return data for a stock is missing in CRSP but available in COMPUSTAT, we collect return data from the monthly COMPUSTAT stock file. We adjust returns for delistings following Beaver et al. (2007).	

$mkt_{t,t+\tau}$	Market return for a holding period of τ years. We use monthly return data for an equally weighted market portfolio as reported by CRSP.	$ewretd$
$rf_{t,t+\tau}$	Risk-free rate of return for a holding period of τ years. We use the Fama-French Factors database from WRDS to obtain monthly risk-free rate of return data.	rf
$\beta_{i,x,t,t+1}$	Systematic risk factor loading over a holding period of τ years. We use the Carhart four-factor model, such that x represents the following systematic risk factors: "market risk" (MKT), "size risk" (SMB), "value risk" (HML), and "momentum" (UMD). We calculate the risk factor loadings using daily returns from CRSP, daily risk factor data from WRDS, and a holding period of one year after portfolio building. We require at least 126 daily return observations for the regression.	
Firm Characteristics and Valuation Multiples		
$ATGrwth_{i,t,t+1}$	Growth in a firm i's total assets (AT, #6) over the holding period, i.e., from period t to period $t+1$.	$\frac{AT_{i,t+1}}{AT_{i,t}} - 1$
B/M_i	Firm i's book value of equity (B_i) divided by its market value of equity ($Price_i$). If $prcc\_f_i$ is missing, we use CRSP data.	$\frac{B_i}{Price_i}$
P/CF_i	Firm i's market value of equity ($Price_i$) divided by operating cash flow ($oancf_i$). If $prcc\_f_i$ is missing, we use CRSP data. If $oancf_i$ is missing, we derive it using balance sheet method.	$\frac{Price_i}{oancf_i}$
$E/EBITDA_i$	Firm i's enterprise value ($Price_i$ plus $Debt_i$) divided by its earnings before interest, taxes, depreciation and amortization ($ebitda_i$). We calculate $debt_i$ using the COMPUSTAT items $dltt_i$, dlc_i, mib_i, and $pstk_i$. Missing values are set to zero.	$\frac{Price_i + Debt_i}{ebitda_i}$

Appendix A contains a list of variables used throughout the paper including their definitions and formulas. We obtain variables for our earnings forecasts from COMPUSTAT's annual and quarterly fundamentals files, and market data from CRSP monthly return files, if not stated otherwise. Moreover, we obtain risk-free return data and factor information from WRDS' Fama-French factor database and analysts' consensus forecasts from I/B/E/S. For COMPUSTAT, we additionally report the corresponding item numbers #X. The time index for all variables is "current period" (t) if not stated otherwise in the description. The firm index is i. In line with Li and Mohanram (2014), we scale all explanatory variables in our earnings regressions as well as the left-hand side variable ($E_{t+\tau}$) by the current number of shares outstanding ($csho_t$).

Appendix B: Implied Cost of Capital (ICC) Models

ICC	Source and Formula (incl. Assumptions)
GLS	**Source:** Gebhardt et al. (2001) **Formula (incl. Assumptions):** $$P_t = B_t + \sum_{\tau=1}^{11} \frac{E_t[(ROE_{t+\tau} - R) \cdot B_{t+\tau-1}]}{(1+R)^{\tau}} + \frac{E_t[(ROE_{t+12} - R) \cdot B_{t+11}]}{(1+R)^{12}},$$ where P_t is stock price at the estimation date in year t, R is the constant implied cost of capital (ICC), B_t is book equity per share in year t, and ROE_t is return on equity in year t. ROE_t is calculated as earnings divided by book equity, i.e., as E_t divided by B_{t-1}. $E_t[x]$ denotes expectations based on information available at the estimation date in year t. We estimate expected $ROE_{t+\tau}$ for $\tau \in \{1, 2, 3\}$ using model or analysts' earnings forecasts. Afterwards, we follow previous literature and assume expected $ROE_{t+\tau}$ to mean-revert to the historical industry median by year $\tau = 11$ (e.g., Hou et al. (2012)). To calculate the industry median ROE, we use 10 years of data and exclude loss firms (e.g., Gebhardt et al. (2001)). After $\tau = 11$, ROE is expected to be constant. We calculate $B_{t+\tau}$ using the clean surplus relation, i.e., $B_{t+\tau} = B_{t+\tau-1} + (1 - payout) \cdot E_t[E_{t+\tau}]$. $E_{t+\tau}$ is the earnings per share forecast at the estimation date in year t for period $t + \tau$ that is also used to estimate expected $ROE_{t+\tau}$. $payout$ is the current payout ratio and is calculated as dividends divided by earnings for profit firms, and as dividends divided by 0.06 times total assets for loss firms (e.g., Hou et al. (2012)).
CT	**Source:** Claus and Thomas (2001) **Formula (incl. Assumptions):** $$P_t = B_t + \sum_{\tau=1}^{4} \frac{E_t[(ROE_{t+\tau} - R) \cdot B_{t+\tau-1}]}{(1+R)^{\tau}} + \frac{E_t[(ROE_{t+5} - R) \cdot B_{t+4}] \cdot (1+g)}{(1+R)^{5} \cdot (R-g)},$$ where P_t is stock price at the estimation date in year t, R is the constant implied cost of

capital (ICC), B_t is book equity per share in year t, and ROE_t is return on equity in year t. ROE_t is calculated as earnings divided by book equity, i.e., as E_t divided by B_{t-1}. $E_t[x]$ denotes expectations based on information available at the estimation date in year t. We estimate expected $ROE_{t+\tau}$ for $\tau \in \{1,2,3,4,5\}$ using model or analysts' earnings forecasts. In line with Hou et al. (2012), we calculate analysts' forecasts for $\tau \in \{4,5\}$ using the consensus three-year ahead analysts' earnings forecasts and the corresponding long-term growth rate forecasts. After $\tau = 5$, expected $ROE_{t+\tau}$ is assumed to grow by g in perpetuity. We follow previous literature and set g equal to the current risk-free rate minus 3% (e.g., Claus and Thomas (2001) or Hou et al. (2012)). We calculate $B_{t+\tau}$ using the clean surplus relation, i.e., $B_{t+\tau} = B_{t+\tau-1} + (1 - payout) \cdot E_t[E_{t+\tau}]$. $E_{t+\tau}$ is the earnings per share forecast at the estimation date in year t for period $t+\tau$ that is also used to estimate expected $ROE_{t+\tau}$. $payout$ is the current payout ratio and is calculated as dividends divided by earnings for profit firms, and as dividends divided by 0.06 times total assets for loss firms (e.g., Hou et al. (2012)).

OJ **Source:** Ohlson and Juettner-Nauroth (2005)

Formula (incl. Assumptions):

$$P_t = \frac{E_t[E_{t+1}] \cdot \left(g_{st} - (\gamma - 1)\right)}{(R-A)^2 - A^2} \; with$$

$$A = \frac{1}{2}\left((\gamma - 1)\,\frac{E_t[E_{t+1}] \cdot payout}{P_t}\right) \; and \;\; g_{st} = \frac{1}{2}\left(\frac{E_t[E_{t+3}] - E_t[E_{t+2}]}{E_t[E_{t+2}]} - \frac{E_t[E_{t+5}] - E_t[E_{t+4}]}{E_t[E_{t+4}]}\right),$$

where P_t is stock price at the estimation date in year t, R is the constant implied cost of capital (ICC), and $E_{t+\tau}$ is the model or analysts' earnings per share forecast at the estimation date in year t for period $t+\tau$. In line with Hou et al. (2012), we calculate analysts' forecasts for $\tau \in \{4,5\}$ using the consensus three-year ahead analysts' earnings forecasts and the corresponding long-term growth rate forecasts. $E_t[x]$ denotes expectations based on information available at the estimation date in year t. g_{st} is the short-term growth rate and equals the arithmetic mean of the expected earnings growth in $\tau = 3$ and $\tau = 5$ (e.g., Gode and Mohanram (2003) or Hou et al. (2012)). γ is the perpetual growth rate (i.e., beyond $\tau = 5$) and equals the current risk-free rate minus 3% (e.g., Hou et al. (2012)). $payout$ is the current payout ratio and is calculated as dividends divided by earnings for profit firms, and as dividends divided by 0.06 times total assets for loss firms (e.g., Hou et al. (2012)).

MPEG **Source:** Easton (2004)

Formula (incl. Assumptions):

$$P_t = \frac{E_t[E_{t+2}] + (R \cdot payout - 1) \cdot E_t[E_{t+1}]}{R^2},$$

where P_t is stock price at the estimation date in year t, R is the constant implied cost of capital (ICC), and $E_{t+\tau}$ is the model or analysts' earnings per share forecast at the estimation date in year t for period $t + \tau$. $E_t[x]$ denotes expectations based on information available at the estimation date in year t. payout is the current payout ratio and is calculated as dividends divided by earnings for profit firms, and as dividends divided by 0.06 times total assets for loss firms (e.g., Hou et al. (2012)).

GG **Source:** Gordon and Gordon (1997)

Formula (incl. Assumptions):

$$P_t = \frac{E_t[E_{t+1}]}{R},$$

where P_t is stock price at the estimation date in year t, R is the constant implied cost of capital (ICC), and $E_{t+\tau}$ is the model or analysts' earnings per share forecast at the estimation date in year t for period $t + \tau$. $E_t[x]$ denotes expectations based on information available at the estimation date in year t. Solving this formula for R equals the inverse of the forward Price-Earnings ratio.

Appendix B contains the definitions (incl. formulas and assumptions) of the five individual ICC estimates used to calculate the *composite ICC*. Note that, for simplicity, we dropped the firm index i for each variable and formula.

Appendix C: Results for Estimating at the End of June

Appendix C.1:
Forecast Accuracy and Forecast Bias of Earnings Forecast Models (Annual Estimation)

Panel A: Median $PAFE$ for up to Three-Year Ahead Earnings Forecasts (E_{t+3})

	Extended RI	Standard RI	Differences
$\mathbf{E_{t+1}}$	2.26% ***	3.08% ***	-0.82% ***
$\mathbf{E_{t+2}}$	4.08% ***	4.49% ***	-0.41% ***
$\mathbf{E_{t+3}}$	5.30% ***	5.64% ***	-0.34% ***

Panel B: Median PFE for up to Three-Year Ahead Earnings Forecasts (E_{t+3})

	Extended RI	Standard RI	Differences
$\mathbf{E_{t+1}}$	0.39% ***	0.52% ***	-0.14% **
$\mathbf{E_{t+2}}$	0.43% *	0.36%	0.07%
$\mathbf{E_{t+3}}$	0.08%	-0.14%	0.23% **

Appendix C.1 presents forecast accuracy in **Panel A**, i.e., the median absolute price-scaled forecast errors ($PAFE$), and forecast bias in **Panel B**, i.e., the median price-scaled forecast errors (PFE), for the standard RI model and our extended model. We run the prediction at an annual frequency in line with previous literature (e.g., Hou et al. (2012) and Li and Mohanram (2014)) from 1968 to 2019 for one-, two-, and three-year ahead earnings. Values are Newey-West time-series averages. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***.

Appendix C.2:
Portfolio Level and Firm Level Tests of Composite ICCs (Annual Estimation)

Panel A: Portfolio Level Test: Return Spreads for ICC-based Investment Strategy

		Extended RI		**Standard RI**	
	$Spread_{t,t+1}$	6.12	**	4.06	*
$\mathbf{r_{t,t+1}}$	$SR_{t,t+1}$	0.25		0.17	
	t_{stat}	2.22		1.65	
	$Spread_{t,t+2}$	5.76	**	4.61	*
$\mathbf{r_{t,t+2}}$	$SR_{t,t+2}$	0.24		0.20	
	t_{stat}	2.16		1.84	
	$Spread_{t,t+3}$	6.70	**	5.76	**
$\mathbf{r_{t,t+3}}$	$SR_{t,t+3}$	0.26		0.23	
	t_{stat}	2.42		2.14	

Panel B: Firm Level Test: Univariate Regression of Future Returns on Composite ICCs

		Extended RI		**Standard RI**	
	$\hat{\alpha}_t$	0.09	***	0.10	***
$\mathbf{r_{t,t+1}}$	$\hat{\beta}_t$	0.46	**	0.28	*
	Adj. R^2 (%)	1.32		1.17	
	$\hat{\alpha}_t$	0.04	**	0.05	**
$\mathbf{r_{t,t+2}}$	$\hat{\beta}_t$	0.34	**	0.21	
	Adj. R^2 (%)	1.44		1.31	
	$\hat{\alpha}_t$	0.03		0.04	**
$\mathbf{r_{t,t+3}}$	$\hat{\beta}_t$	0.27	*	0.17	
	Adj. R^2 (%)	1.72		1.58	

Appendix C.2 presents results on the portfolio level and firm level tests of composite ICC estimates when estimated annually at the end of June in line with Hou et al. (2012) and Li and Mohanram (2014), among others. Values are Newey-West time-series averages. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***. **Panel A** shows results for an ICC-based investment strategy in which we go long stocks in the top decile of firms with the highest ICC estimates and short stocks in the bottom decile. Returns spreads ($Spread_{t,t+\tau}$) are annualized Newey-West time-series averages. $SR_{t,t+\tau}$ denotes the corresponding Sharpe ratio. **Panel B** shows the model fit for univariate regressions of one-, two-, and three-year ahead firm-specific future returns on ICC estimates of the standard RI model and our extended model.

Table 1:
Descriptive Statistics and Correlation Analysis for the Total Sample (1968-2019)

Panel A: Descriptive Statistics of the Explanatory Variables

Variable	N	P1	P25	Mean	P50	P75	P99	STD	IQR
E_t	195,346	-3.61	-0.02	1.04	0.70	1.82	8.02	1.87	1.85
$NegE_t$	195,346	0.00	0.00	0.26	0.00	1.00	1.00	0.44	1.00
$E_t xNegE_t$	195,346	-3.61	-0.02	-0.21	0.00	0.00	0.00	0.61	0.02
AC_t	195,346	-13.41	-1.53	-0.90	-0.40	0.02	9.03	2.89	1.55
B_t	195,346	-1.73	2.74	10.88	7.41	15.20	57.87	11.49	12.46
$Growth_t$	195,346	-4.44	-0.20	0.08	0.04	0.39	4.56	1.14	0.59

Panel B: Correlation Analysis of the Explanatory Variables

Variable	E_t	$NegE_t$	$E_t xNegE_t$	AC_t	B_t	$Growth_t$
E_t	**-**	**-0.76**	**0.77**	**-0.10**	**0.73**	**0.15**
$NegE_t$	**-0.58**	**-**	**-0.98**	0.00	**-0.51**	**-0.09**
$E_t xNegE_t$	**0.55**	**-0.57**	**-**	**0.03**	**0.48**	**0.08**
AC_t	**-0.07**	**-0.02**	**0.18**	**-**	**-0.25**	**-0.05**
B_t	**0.71**	**-0.37**	**0.15**	**-0.23**	**-**	**0.13**
$Growth_t$	**0.07**	**-0.03**	0.00	**-0.02**	**0.08**	**-**

Table 1 displays descriptive statistics and correlation analyses of the explanatory variables based on the total sample of 195,346 distinct firm-year observations. All explanatory variables except for the dummy are winsorized at the 1% and 99% percentile. **Panel A** presents the descriptive statistics for the explanatory variables. **Panel B** shows Pearson correlations (below diagonal) and Spearman correlations (above diagonal). Bold-printed values are significant at 1% level.

Table 2:
Parameter Estimates (Quarterly Estimation)

	RI Model	Intercept		E_t		$NegE_t$		$E_t xNegE_t$		AC_t		B_t		$Growth_t$		**Adj. R^2**
E_{t+1}	**Standard**	-0.01		0.92	***	-0.14	***	-0.46	***	-0.02	***	0.01	***			**76.09%**
	Extended	-0.01		0.90	***	-0.11	***	-0.34	***	-0.01	***	0.01	***	0.67	***	**83.97%**
E_{t+2}	**Standard**	0.03	**	0.87	***	-0.16	***	-0.64	***	-0.03	***	0.03	***			**65.60%**
	Extended	0.03	*	0.84	***	-0.14	***	-0.50	***	-0.02	***	0.03	***	0.56	***	**69.68%**
E_{t+3}	**Standard**	0.10	***	0.83	***	-0.18	***	-0.75	***	-0.03	***	0.04	***			**59.94%**
	Extended	0.08	***	0.81	***	-0.18	***	-0.65	***	-0.03	***	0.04	***	0.49	***	**62.64%**

Table 2 reports the Newey-West time-series average parameter estimates from our rolling regressions for the standard RI model and our extended model. We run the model quarterly from 1968 to 2019 for one-, two-, and three-year ahead earnings. All explanatory variables are winsorized at the 1% and 99% percentiles to mitigate the impact of outlying observations. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***, respectively.

Table 3:
Descriptive Statistics of Earnings Forecasts (Quarterly Estimation)

	RI Model	P1	P25	Mean	P50	P75	STD	IQR
E_{t+1}	**Standard**	-1.88	-0.08	1.12	0.74	1.86	1.77	1.94
	Extended	-2.58	-0.08	1.12	0.74	1.90	1.89	1.98
E_{t+2}	**Standard**	-1.12	0.01	1.26	0.83	1.99	1.76	1.98
	Extended	-1.78	-0.01	1.25	0.83	2.01	1.85	2.02
E_{t+3}	**Standard**	-0.75	0.11	1.43	0.97	2.18	1.83	2.07
	Extended	-1.30	0.08	1.41	0.96	2.19	1.89	2.11

Table 3 reports descriptive statistics of earnings forecasts from the standard RI model and our extended model. We run the model quarterly from 1968 to 2019 for one-, two-, and three-year ahead earnings. Forecasts are winsorized at the 1% and 99% percentiles to mitigate the impact of outlying observations.

Table 4:
Forecast Accuracy and Forecast Bias of Earnings Forecast Models (Quarterly Estimation)

Panel A: Median $PAFE$ for up to Three-Year Ahead Earnings Forecasts (E_{t+3})

	Extended RI	Standard RI	Differences
E_{t+1}	2.12% ***	3.07% ***	-0.95% ***
E_{t+2}	4.02% ***	4.50% ***	-0.48% ***
E_{t+3}	5.25% ***	5.65% ***	-0.40% ***

Panel B: Median PFE for up to Three-Year Ahead Earnings Forecasts (E_{t+3})

	Extended RI	Standard RI	Differences
E_{t+1}	0.36% ***	0.50% ***	-0.13% ***
E_{t+2}	0.43% ***	0.31% *	0.12% **
E_{t+3}	0.08%	-0.19%	0.28% ***

Table 4 presents forecast accuracy in **Panel A**, i.e., the median absolute price-scaled forecast errors ($PAFE$), and forecast bias in **Panel B**, i.e., the median price-scaled forecast errors (PFE), for the standard RI model and our extended model. We run the prediction at a quarterly frequency from 1968 to 2019 for one-, two-, and three-year ahead earnings. Values are Newey-West time-series averages. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***.

Table 5:
Differences in Earnings Forecast and Forecast Accuracy by Growth (Quarterly Estimation)

	Quintile	**Growth**		**Differences** in **Forecast**		**Differences** in $\boldsymbol{PAFE}$	
	1	-6.25%	***	-4.77%	***	-2.31%	***
	2	-1.23%	***	-1.19%	***	-0.47%	***
$\mathbf{E_{t+1}}$	3	0.38%	***	0.18%	***	-0.18%	***
	4	1.84%	***	1.09%	***	-0.67%	***
	5	4.94%	***	3.22%	***	-1.74%	***
	1	-6.25%	***	-4.09%	***	-0.84%	***
	2	-1.23%	***	-1.03%	***	-0.12%	***
$\mathbf{E_{t+2}}$	3	0.38%	***	0.12%	**	-0.07%	***
	4	1.84%	***	0.99%	***	-0.25%	***
	5	4.94%	***	2.92%	***	-0.79%	***
	1	-6.25%	***	-3.86%	***	-0.78%	***
	2	-1.23%	***	-1.09%	***	-0.24%	***
$\mathbf{E_{t+3}}$	3	0.38%	***	-0.09%	*	-0.07%	***
	4	1.84%	***	0.70%	***	-0.14%	***
	5	4.94%	***	2.62%	***	-0.29%	***

Table 5 presents differences in price-scaled forecasts and forecast accuracy (median $PAFE$) between our extended RI model and the standard RI model for earnings forecasts up to three years ahead. We rank observations at each estimation date by price-scaled growth. We run the prediction at a quarterly frequency from 1968 to 2019 for one-year ahead earnings. Values are Newey-West time-series averages. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***.

Table 6:
Forecast Accuracy by Number of Quarterly Reports (q) (Quarterly Estimation)

	q	**Extended RI**		**Standard RI**		**Differences**	
	3	1.60%	***	3.19%	***	-1.59%	***
$\mathbf{E_{t+1}}$	2	2.01%	***	3.17%	***	-1.16%	***
	1	2.55%	***	3.17%	***	-0.62%	***
	0	3.14%	***	3.26%	***	-0.12%	***
	3	3.97%	***	4.69%	***	-0.72%	***
$\mathbf{E_{t+2}}$	2	4.17%	***	4.66%	***	-0.49%	***
	1	4.44%	***	4.64%	***	-0.21%	***
	0	4.64%	***	4.77%	***	-0.13%	**
	3	5.41%	***	5.91%	***	-0.49%	***
$\mathbf{E_{t+3}}$	2	5.52%	***	5.82%	***	-0.31%	***
	1	5.70%	***	5.84%	***	-0.14%	***
	0	5.80%	***	6.01%	***	-0.21%	**

Table 6 presents forecast accuracy, i.e., the median absolute price-scaled forecast errors ($PAFE$) of our extended RI model and the standard RI model as well as their differences for earnings forecasts up to three years ahead. We separate firms ex-post depending on how many quarterly releases (q) they have filed. We run the prediction at a quarterly frequency from 1968 to 2019 for one-, two-, and three-year ahead earnings. Values are Newey-West time-series averages. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***.

Table 7:
Portfolio Level and Firm Level Tests of Composite ICCs (Quarterly Estimation)

Panel A: Portfolio Level Test: Return Spreads for ICC-based Investment Strategy

		Extended RI	Standard RI
	$Spread_{t,t+1}$	7.00 **	5.23 **
$\mathbf{r_{t,t+1}}$	$SR_{t,t+1}$	0.27	0.21
	t_{stat}	2.57	2.03
	$Spread_{t,t+2}$	7.41 ***	6.29 ***
$\mathbf{r_{t,t+2}}$	$SR_{t,t+2}$	0.29	0.25
	t_{stat}	3.52	3.06
	$Spread_{t,t+3}$	7.68 ***	6.85 ***
$\mathbf{r_{t,t+3}}$	$SR_{t,t+3}$	0.29	0.25
	t_{stat}	4.05	3.58

Panel B: Firm Level Test: Univariate Regression of Future Returns on Composite ICCs

		Extended RI	Standard RI
	$\hat{\alpha}_t$	0.09 ***	0.11 ***
$\mathbf{r_{t,t+1}}$	$\hat{\beta}_t$	0.50 ***	0.34 **
	Adj. R^2 (%)	1.19	1.07
	$\hat{\alpha}_t$	0.04 **	0.05 ***
$\mathbf{r_{t,t+2}}$	$\hat{\beta}_t$	0.36 ***	0.21 *
	Adj. R^2 (%)	1.49	1.34
	$\hat{\alpha}_t$	0.03 **	0.04 ***
$\mathbf{r_{t,t+3}}$	$\hat{\beta}_t$	0.29 ***	0.16
	Adj. R^2 (%)	1.79	1.66

Table 7 presents results on the portfolio level and firm level tests of composite ICC estimates when estimated quarterly. Values are Newey-West time-series averages. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***. **Panel A** shows results for an ICC-based investment strategy in which we go long stocks in the top decile of firms with the highest ICC estimates and short stocks in the bottom decile. Returns spreads ($Spread_{t,t+\tau}$) are annualized Newey-West time-series averages. $SR_{t,t+\tau}$ denotes the corresponding Sharpe ratio. **Panel B** shows the model fit for univariate regressions of one-, two-, and three-year ahead firm-specific future returns on ICC estimates of the standard RI model and our extended model.

Table 8:
Forecast Accuracy and Accuracy Gap between Analysts and Models (Quarterly Estimation)

Panel A: Median Forecast Accuracy for up to Three-Year Ahead Earnings Forecasts (E_{t+3})

	Extended RI	**Standard RI**	**Analysts**
$\mathbf{E_{t+1}}$	1.59% ***	2.28% ***	1.02% ***
$\mathbf{E_{t+2}}$	2.95% ***	3.28% ***	2.38% ***
$\mathbf{E_{t+3}}$	3.53% ***	3.84% ***	3.02% ***

Panel B: Accuracy Gap for up to Three-Year Ahead Earnings Forecasts (E_{t+3})

	Extended RI vs. **Analysts**	**Standard RI** vs. **Analysts**	**Differences**
$\mathbf{E_{t+1}}$	0.57% ***	1.26% ***	-0.69% ***
$\mathbf{E_{t+2}}$	0.58% ***	0.90% ***	-0.33% ***
$\mathbf{E_{t+3}}$	0.51% ***	0.81% ***	-0.30% ***

Table 8 presents the absolute price-scaled forecast errors ($PAFE$; forecast accuracy) for both residual income (RI) models and analysts as well as the accuracy gaps between models and analysts for up to three-year ahead forecasts. Values are Newey-West time-series averages for the common sample between 1976 and 2019. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***. **Panel A** shows the median accuracy for one-, two-, and three-year ahead earnings forecasts. **Panel B** presents the corresponding accuracy gaps.

Table 9:
Forecast Accuracy and Accuracy Gap by Number of Quarterly Reports (Quarterly Estimation)

Panel A: Median Forecast Accuracy for E_{t+1} Forecasts by Number of Quarterly Reports (q)

	q	**Extended RI**	**Standard RI**	**Analysts**
E_{t+1}	3	1.14% ***	2.34% ***	0.60% ***
	2	1.39% ***	2.28% ***	0.97% ***
	1	1.73% ***	2.25% ***	1.43% ***
	0	2.24% ***	2.21% ***	1.63% ***

Panel B: Accuracy Gap for E_{t+1} Forecasts by Number of Quarterly Reports (q)

	q	**Extended RI** vs. **Analysts**	**Standard RI** vs. **Analysts**	**Differences**
E_{t+1}	3	0.54% ***	1.74% ***	-1.20% ***
	2	0.42% ***	1.31% ***	-0.89% ***
	1	0.30% ***	0.82% ***	-0.52% ***
	0	0.61% ***	0.58% ***	0.03%

Panel C: *Explained* vs. *Unexplained* Accuracy Gap for E_{t+1} Forecasts

	q	**Explained** by Quarterly Earnings Information	**Not Explained** by Quarterly Earnings Information
E_{t+1}	3	69.12%	30.88%
	2	67.63%	32.37%
	1	63.00%	37.00%

Table 9 presents the absolute price-scaled forecast errors ($PAFE$; forecast accuracy) for both residual income (RI) models and analysts as well as the accuracy gaps between models and analysts for one-year ahead forecasts analyzed by the number of quarterly reports a firm has filed (q). Except for Panel C, values are Newey-West time-series averages for the common sample between 1976 and 2019. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***. **Panel A** analyzes how the median accuracy for one-year ahead earnings forecasts changes depending on the number of quarterly reports a firm has filed (q) at the estimation date. **Panel B** reports the corresponding accuracy gaps. **Panel C** shows how much of the accuracy gap between analysts and models can and cannot be explained by quarterly earnings information.

Table 10:
Portfolio Level and Firm Level Tests of Composite ICCs from Models and Analysts (Quarterly Estimation)

Panel A: Portfolio Level Test: Return Spread for ICC-based Investment Strategy

		Extended RI	**Standard RI**	**Analysts**
	$Spread_{t,t+1}$	5.14	4.06	3.00
$\mathbf{r_{t,t+1}}$	$SR_{t,t+1}$	0.16	0.13	0.10
	t_{stat}	1.46	1.25	0.97
	$Spread_{t,t+2}$	5.77 **	5.18 **	4.38 *
$\mathbf{r_{t,t+2}}$	$SR_{t,t+2}$	0.20	0.19	0.16
	t_{stat}	2.27	2.17	1.88
	$Spread_{t,t+3}$	5.72 ***	5.29 **	4.14 **
$\mathbf{r_{t,t+3}}$	$SR_{t,t+3}$	0.20	0.19	0.15
	t_{stat}	2.63	2.51	2.01

Panel B: Firm Level Test: Univariate Regressions of Future Returns on ICC Estimates

		Extended RI	**Standard RI**	**Analysts**
	$\hat{\alpha}_t$	0.11 ***	0.13 ***	0.14 ***
$\mathbf{r_{t,t+1}}$	$\hat{\beta}_t$	0.42 *	0.25	0.17
	Adj. R^2 (%)	2.10	1.94	1.49
	$\hat{\alpha}_t$	0.06 ***	0.07 ***	0.10 ***
$\mathbf{r_{t,t+2}}$	$\hat{\beta}_t$	0.33 **	0.17	-0.15
	Adj. R^2 (%)	2.14	1.86	1.75
	$\hat{\alpha}_t$	0.05 ***	0.06 ***	0.10 ***
$\mathbf{r_{t,t+3}}$	$\hat{\beta}_t$	0.23 *	0.08	-0.30 **
	Adj. R^2 (%)	2.18	1.94	1.89

Table 10 presents results on the portfolio level and firm level tests of composite ICC estimates based on model forecasts and analysts' forecasts. Numbers are Newey-West time-series averages. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***. **Panel A** shows results for an ICC-based investment strategy in which we go long stocks in the top decile of firms with the highest ICC estimates and short stocks in the bottom decile. Return spreads ($Spread_{t,t+\tau}$) are annualized. $SR_{t,t+\tau}$ denotes the corresponding Sharpe ratio. **Panel B** shows results for univariate regressions of one-, two-, and three-year ahead firm-specific future returns (annualized) on ICC estimates using model and analysts' forecasts.

Table 11:
Analysis of Buy- and Sell-Portfolios Using ICCs from Extended Model and Analysts

Panel A: Average Return and Risk Characteristics of Stocks in Buy-Portfolios

	Stocks Bought by:				
	Both	**Only Model**	**Only Analysts**	Difference	
Share:	(41.42%)	(58.58%)	(58.58%)	*Only* **Portfolios**	
Return:					
$r_{t,t+1}$	18.73%	19.33%	14.71%	4.62%	***
$r_{t,t+1}$ - $rf_{t,t+1}$	14.34%	14.94%	10.32%	4.62%	***
$r_{t,t+1}$ - $mkt_{t,t+1}$	2.81%	3.40%	-1.22%	4.62%	***
$SR_{t,t+1}$	0.5833	0.9614	0.4744	0.4870	***
Risk:					
$\hat{\beta}_{MKT,t,t+1}$	0.9971	0.9145	0.9826	-0.0681	***
$\hat{\beta}_{SMB,t,t+1}$	0.7333	0.6331	0.8400	-0.2069	***
$\hat{\beta}_{HML,t,t+1}$	0.4620	0.4800	0.3027	0.1774	***
$\hat{\beta}_{UMD,t,t+1}$	-0.2372	-0.1356	-0.1717	0.0360	***
$ATGrwth_{t,t+1}$	9.57%	6.31%	11.27%	-4.96%	***
Multiples:					
B/M_t	1.2356	1.1523	0.8662	0.2861	***
B/M_{t+1}	1.3016	1.1190	0.9272	0.1918	***
P/CF_t	2.8459	4.0596	4.2664	-0.2067	**
P/CF_{t+1}	2.9684	4.5739	4.1645	0.4094	***
$E/EBITDA_t$	6.5944	6.9494	7.7392	-0.7898	***
$E/EBITDA_{t+1}$	6.6435	7.2422	6.8773	0.3649	***

Panel B: Average Return and Risk Characteristics of Stocks in Sell-Portfolios

	Stocks Sold by:				
	Both	**Only Model**	**Only Analysts**	Difference	
Share:	(45.13%)	(54.87%)	(54.87%)	*Only* **Portfolios**	
Return:					
$r_{t,t+1}$	15.12%	13.67%	12.31%	1.35%	
$r_{t,t+1}$ - $rf_{t,t+1}$	10.73%	9.28%	7.92%	1.35%	
$r_{t,t+1}$ - $mkt_{t,t+1}$	-0.81%	-2.26%	-3.62%	1.35%	
$SR_{t,t+1}$	0.6095	0.4688	0.6456	-0.1768	***
Risk:					
$\hat{\beta}_{MKT,t,t+1}$	1.1391	1.1420	0.9776	0.1644	***
$\hat{\beta}_{SMB,t,t+1}$	0.7744	0.8558	0.7742	0.0816	***

$\hat{\beta}_{HML,t,t+1}$	-0.3769	-0.1746	0.1207	-0.2953	***
$\hat{\beta}_{UMD,t,t+1}$	0.0317	-0.0580	-0.0637	0.0057	
$ATGrwth_{t,t+1}$	35.93%	28.41%	12.78%	15.63%	***
Multiples:					
B/M_t	0.2360	0.3112	0.5822	-0.2710	***
B/M_{t+1}	0.2533	0.3445	0.5793	-0.2348	***
P/CF_t	23.1754	12.2778	10.6556	1.6223	***
P/CF_{t+1}	18.7073	11.2551	9.8835	1.3717	***
$E/EBITDA_t$	16.4613	12.2681	11.3417	0.9265	***
$E/EBITDA_{t+1}$	16.7753	11.4680	11.2951	0.1730	

Table 11 analyzes the average buy- and sell-portfolios from investment strategies based on composite ICC estimates from our extended model's earnings forecasts and analysts' earnings forecasts. In **Panel A**, we report results for the buy-portfolio. As outlined in Section 2, the buy-portfolio generally consists of the top 10% stocks each estimation date according to their ICC estimates. We analyze both buy-portfolios, i.e., the buy-portfolio following ICC estimates from our extended model's earnings forecasts and the respective portfolio when using analysts' forecasts, separated into three groups: Stocks bought by both strategies, stocks only bought when using model forecasts as inputs, and stocks only bought following an investment strategy based on analysts' ICCs. For each group, we report the average share it has of the overall buy-portfolio as well as the following return, risk, and firm characteristics as time-series averages: Equally weighted holding returns for an one-year holding period ($r_{t,t+1}$), and equally weighted holding returns for an one-year holding period in excess of the risk-free rate ($r_{t,t+1}$ - $rf_{t,t+1}$) and the equally weighted market return ($r_{t,t+1}$ - $mkt_{t,t+1}$). Moreover, we report the average, annualized monthly Sharpe ratios ($SR_{t,t+1}$). In line with Sharpe (1994), we calculate the Sharpe ratios using monthly returns over the holding period of 12 months. Next, we report the average risk factor loadings of the portfolios that have been realized throughout the one-year holding period as systematic risk measures using the Carhart four-factor model. We calculate the risk factor loadings using daily returns and a holding period of one year after portfolio building. We require at least 126 daily return observations for the regression. Finally, we report certain firm characteristics, namely the firm's average growth in assets (ATGrwth), the book-to-market ratio (B/M), the price to operating cash flow ratio (P/CF), and the enterprise value to earnings before interests, taxes, depreciation and amortization ratio (E/EBITDA) as valuation multiples. In the last column, we test for differences in return and risk characteristics between those stocks only selected by model ICCs and those stocks only selected by analyst ICCs for statistical significance. The 10%, 5%, and 1% significance levels are expressed by *, **, and ***. **Panel B** repeats the analysis for the sell-portfolios, i.e., the bottom 10% stocks at each estimation date according to their ICC estimates.

Figure 1:
Current Earnings Information *Ignored* by Standard Models when Estimated at the End of June (▼)

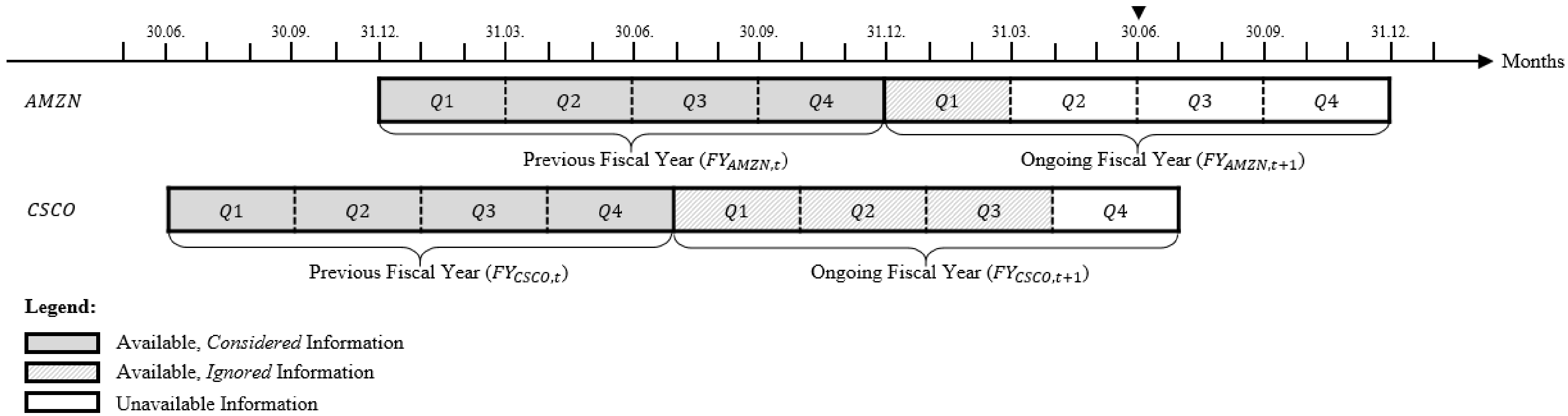
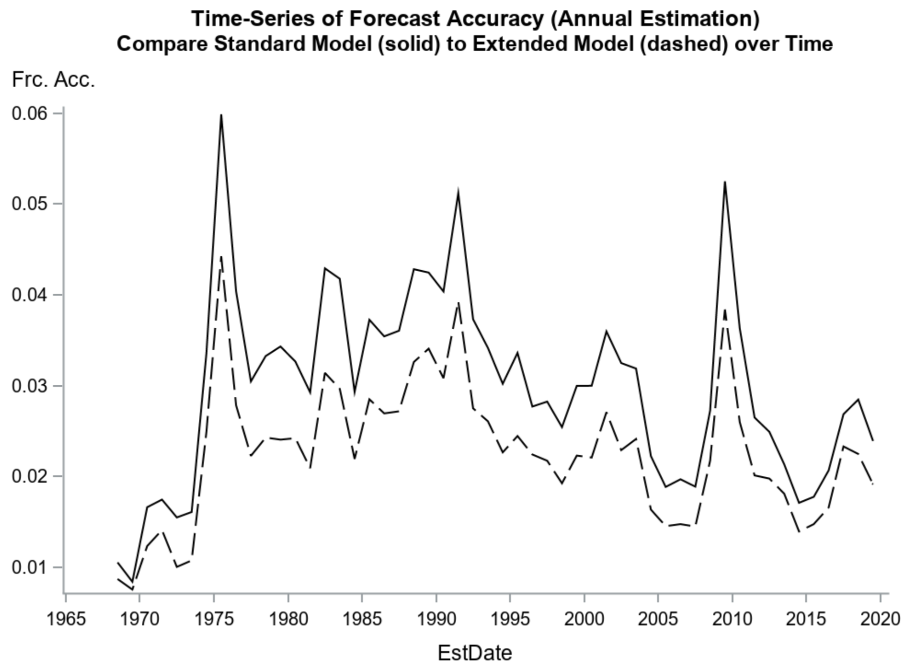


Figure 1 visualizes the amount of available earnings information that is ignored by the standard model when estimated at the end of June using two firms with different fiscal year-ends: Amazon (Ticker Symbol: $AMZN$) and Cisco (Ticker Symbol: $CSCO$). The dark-grey areas indicate earnings information of the previous fiscal years ($FY_{AMZN,t}$ and $FY_{CSCO,t}$) considered by the standard model. The grey-shaded areas represent available current earnings information of the ongoing fiscal years (FY_{t+1}) for $AMZN$ and $CSCO$ that is nevertheless ignored by the standard model. The white areas are unavailable earnings information of the ongoing fiscal years.

Figure 2:
Time-Series Analysis and Cross-Sectional Analysis of Forecast Accuracy (Annual Estimation)

Panel A:
Median *PAFE* for the Standard RI Model and Extended RI Model over Time



Panel B:
Time-Series Average Median *PAFE* for the Standard RI Model and Extended RI Model across Industries

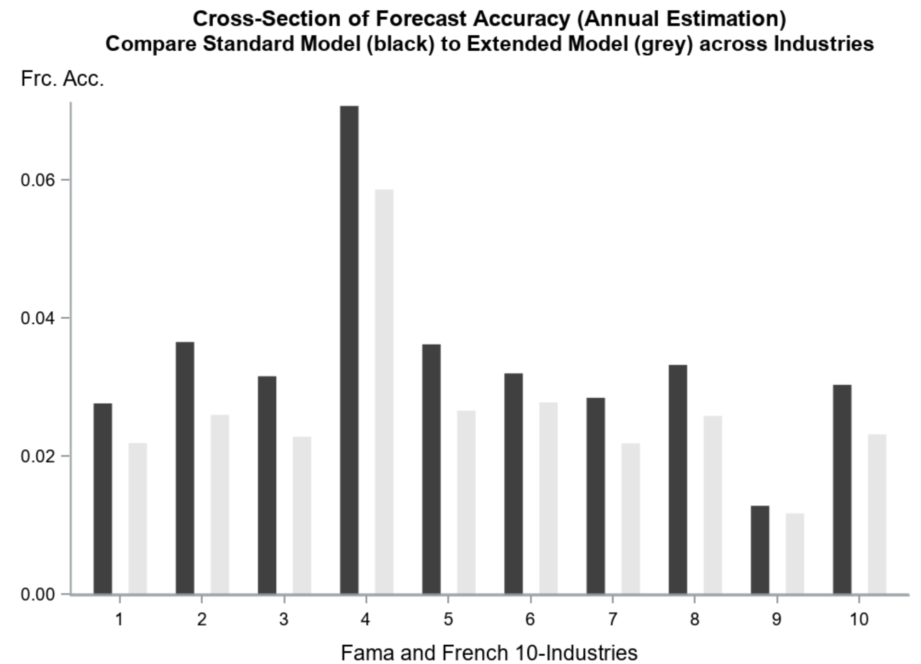


Figure 2 analyzes the forecast accuracy of the standard RI model and our extended RI model over time and across industries. To illustrate our results, we exemplarily apply an annual estimation frequency, i.e., we rerun the prediction once a year at the end of June. The tenor of results is unchanged when estimating at the end of each other calendar quarter as well. In fact, differences become even more pronounced when we estimate at the end of September or at the end of December, because then more firms have released more quarterly reports such that our model has a larger information advantage over the standard model (see **Table 6**). Analogously, the difference becomes slightly less pronounced when estimated earlier in a year. **Panel A** plots the median forecast accuracy ($PAFE$) for the standard RI model (*solid line*) and our extended RI model (*dashed line*) for each estimation date between 1968 and 2019. **Panel B** plots the time-series average median forecast accuracy ($PAFE$) for the standard RI model (*black*) and our extended RI model (*grey*) for each industry according to the Fama and French 10-industries classification.