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The Role of Earnings Forecasts in Asset Pricing Models and Estimates of the Cost of Capital

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To my wonderful wife and my lovely daughter.

Abstract

This dissertation focuses on the impact of earnings forecast accuracy and bias on estimates of Implied Cost of Capital (ICC). As a first step, I evaluate the correlation of ICC and returns across firms, over time, and in both dimensions at the same time. Although ICC has a strong correlation to returns over time, these results do not hold cross-sectionally. Given these results, I evaluate whether the weak cross-sectional correlation between returns and ICC is due to the underlying assumptions of the valuation models or the inaccuracy of analysts' earnings forecasts. To do so, I compare the properties of $ICC_{I/B/E/S}$, estimated with analysts' forecasts, to $ICC_{Perfect\,Foresight}$ estimated with ex-post realized earnings. The results show that the ICC valuation models work well empirically, and the analysts' forecasts are the main cause for the weak correlation. Given that the critical problem in the ICC calculation is analysts' forecasts, I propose a parsimonious earnings forecast model that combines the high accuracy of analysts' forecasts with the unbiasedness of mechanical earnings forecast models. The earnings forecasts estimated with this model have higher accuracy, lower bias, and a higher earnings response coefficient than the most popular methods from the literature. In addition, the ICC based on this model displays a stronger correlation to future returns compared to extant literature.

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Short Table of Contents

Contents

List of Figures

List of Tables

List of Abbreviations

$R_M - R_F$	Value-weighted Market Return Premium
ADRs	American Depositary Receipts
AF	Analysts' Forecasts
AMEX	American Stock Exchange
AR	Autoregressive
B/M	Book-to-market ratio
BPS	Book Value per Share
CAPM	Capital Asset Pricing Model
CM	Combined Model
CMA	Conservative-minus-Aggressive
CRSP	Center for Research in Security Prices
CSAF	Cross-Sectional Analysts' Forecasts (earnings forecast model)
CT	Claus and Thomas (ICC approach)
D/P	Dividend-to-Price ratio
DDM	Discount Dividend Model
DPS	Dividends per Share
EBITDA	Earnings Before Interest, Taxes, Depreciation and Amortization
EP	Earnings Persistence (earnings forecast model)
EPS	Earnings per Share
ERC	Earnings Response Coefficient
EW	Equal-Weighted
F&F5	Fama and French (2015) five-factor model
FE	Fixed-effects

FM	Fama and Macbeth (1973) (regression approach)
FYE	Fiscal year-end
GAAP	Generally Accepted Accounting Principles
GGM	Gordon Growth Model
GLS	Gebhardt, Lee, and Swaminthan (ICC approach)
GP	Gross Profits
GRS	Gibbons et al. (1989) statistic
HML	High-minus-Low
HVZ	Hou, van Dijk and Zhang (2012) (earnings forecast model)
I/B/E/S	Institutional Brokers' Estimate System
Inv	Investments
LTG	Long-Term earnings Growth rate
MIDAS	Mixed Data Sampling regression methods
MPEG	Modified PEG ratio (ICC approach)
OJ	Ohlson and Juettner-Nauroth (ICC approach)
OLS	Ordinary Least Squares
P/E	Price-to-Earnings ratio
P/Y	Payout Yield
PEG	Price-earnings ratio divided by the short-term earnings growth rate
PF	Perfect Foresight
POLS	Pooled Ordinary Least Squares
PR	Payout Ratio
RI	Residual Income
RIM	Residual Income Model
RMW	Robust-minus-Weak
ROE	Return on Equity
RW	Random Walk

SIC	Standard Industrial Classification
SMB	Small-minus-Big
STG	Short-Term earnings Growth rate
SZE	Size
TR	Thomson Reuters
TRD	Thomson Reuters Datastream
TV	Terminal Value
U.S.	United States of America
VW	Value-Weighted
VWICC	Value-Weighted Implied Cost of Capital

1. Introduction

1.1. Motivation

The central elements of the asset pricing theory are the stock's expected payoffs and the expected rate of return, which are used to discount the payoffs to the stock's price. In particular, proxies for the expected rate of returns are broadly used in many applications, such as asset allocation, firm valuation, performance evaluation, capital budgeting, as well as for asset pricing tests. Due to the great importance of proxies for the expected rate of returns, much literature focuses on developing a precise estimate of it.

The most used proxy for expected returns is realized returns, which are used in many studies in finance, accounting, and economics. However, the use of realized returns as a proxy for expected returns has important shortcomings. For example, Fama and French (1997) show that ex-post realized returns are a poor proxy for expected returns at the industry or firm level due to the difficulty of finding a suitable asset-pricing model and due to imprecise estimates of loadings on the risk factors as well as on the factor risk premia. Furthermore, Elton (1999) argues that information surprises highly influence the realized returns and introduce much noise to the estimate. As a consequence of this large amount of statistical noise in realized returns, financial researchers who test asset pricing models face the risk that economically significant relations can be rendered statistically insignificant (Lee et al., 2009). Similar to Lee et al. (2009), Lundblad (2007) shows that when realized returns are used as a proxy for expected returns, a very long sample period is needed to detect a positive risk-return relation in simulations.

To address the drawbacks of realized returns as a proxy for expected returns, accounting and finance studies propose the Implied Cost of Capital as an alternative approach to estimate the expected returns (Hou et al., 2012). The ICC is estimated as the internal rate of return that equates a firm's stock prices to the discounted expected cash flows. Among the advantages of ICC is that it can be estimated with forward-looking ex-ante information (see e.g., Tang et al. (2014)), can be decomposed into discount rate news and cash flow news (see e.g., Chen et al. (2013)), and the ICC has less than one-tenth the volatility compared to realized returns (see, e.g., Lee et al. (2009)).

Among the studies that employ ICC as a proxy for time-varying expected returns, Pástor et al. (2008) shed light on the tradeoff between risk and return. While the relation between conditional mean and variance of stock returns is inconclusive when adopting realized returns as a proxy for expected returns, the authors find a positive relation when employing ICC as such a proxy. Moreover, the authors show that, under plausible conditions, ICC is perfectly correlated with the conditional expected return over time. Another test using ICC was carried out by Frank and Shen (2016), who use ICC to analyze the relation between corporate investment and the cost of capital. They show that ICC better reflects the time-varying required return on capital. Finally, based on the assumption that ICC is a good proxy for expected returns, Li et al. (2013) report that ICC at the aggregate level is superior to other valuation ratios at predicting future excess market returns at horizons ranging from one month to four years, both in-sample and out-of-sample.

Although the ICC has shown important advantages compared to realized returns, there are still some crucial gaps regarding the use of ICC as a proxy for expected returns. Concerning the properties of ICC over time, it is not clear whether the strong power to predict future returns, which is strong at the aggregate level, also holds at the firm level. This gap in the literature is addressed in **Chapter 3**.

In addition, in the cross-sectional dimension, studies show a weak correlation between ICC and returns, which is important argument against the usage of ICC in cross-sectional tests. Easton and Monahan (2005) find that the ICC estimates have little ability to explain realized returns after controlling for the bias and noise in realized returns attributable to contemporaneous information surprises. The weak correlation between ICC and ex-post returns is also reported by Guay et al. (2011) in cross-sectional tests with monthly as well as yearly returns. The authors find that the coefficients of ICC explaining returns are not statistically different from zero, neither in regressions at the firm-level nor the industry-level.

The reason for the low correlation between ICC and realized returns is still a puzzle. Mohanram and Gode (2013) assume that the possible cause of this weak correlation is either that underlying assumptions of the ICC valuation models are not adequate to infer the risk premium or that earnings forecast errors, which are the main inputs for the ICC models, might drive the results. This puzzle is addressed in **Chapter 4** and the evidence is that the inaccuracy in analysts'[1] forecasts is the primary cause of the weak correlation between ICC and returns.

The evidence that analysts' forecasts do not seem to be sufficiently accurate to compute reliable estimates of the ICC is not the only drawback of their use. Another point is the optimistic bias in their forecasts (see, e.g., Claus and Thomas (2001)). Easton and Sommers (2007) find that the analysts' forecast bias lead to an upward bias of 2.84% in estimates of the cost of capital. Due to these two weaknesses, the literature tries to find alternative estimates of earnings forecasts.

The alternative to analysts' earnings forecasts is a mechanical model. The recent models are based on a two-stage cross-sectional regression. In the first stage (in-sample), current earnings are regressed on lagged explanatory variables. In the second stage (out-of-sample), current explanatory variables are multiplied by the coefficients from the first-stage regression. Among the explanatory variables, Hou et al. (2012) develop a cross-sectional model based

[1] In this dissertation the term analysts refers specifically to sell-side analysts, which are defined as analysts employed by brokerage firms that provide financial research and forecasts to their clients (Jackson, 2005).

on assets, earnings, and dividends. Li and Mohanram (2014) implement an Earnings Persistence (EP) and a Residual Income (RI) model to forecast earnings.

By comparing analysts' forecasts to mechanical models' forecasts, Hou et al. (2012) find that the mechanical models can outperform the analysts' forecasts in terms of bias and Earnings Response Coefficient (ERC), which is an indication that these forecasts are closer to the market consensus. However, the literature shows that the mechanical models are even more inaccurate than the analysts' forecasts (O'Brien, 1988; Hou et al., 2012). Thus, the literature lacks an estimate of earnings forecasts that is unbiased, accurate, and displays a strong ERC; a lack addressed in **Chapter 5**. In the next section, I present the structure of the dissertation and the contributions of each chapter.

1.2. Dissertation structure and contributions

Chapter 2 offers a literature review of ICC. The chapter explains the motivation behind the ICC approaches and presents the valuation models used to estimate it. Furthermore, I review some important studies that use ICC as a proxy for expected returns.

In **Chapter 3**, I analyze the relation between ICC and returns cross-sectionally, and over-time at the firm level. In terms of methods to perform cross-sectional asset pricing tests at the firm level, most of the literature relies on the Fama-Macbeth cross-sectional regressions to test the cross-section of expected stock returns. However, the literature lacks models to perform asset pricing tests over-time at the firm level. In this dissertation, I introduce a novel regression approach for time-series tests. This method is an orthogonal Fama-Macbeth regression, in which time-series regressions are performed for each firm and the average coefficients, as well as the t-statistics, are used to determine whether the relation between firm's characteristics and future returns is statistically significant. By using this method as well as a fixed-effect regression, I contribute to the literature by finding that the ICC has a strong predictability power even at the firm-level. Furthermore, I also confirm the previous findings of the weak correlation between ICC and returns cross-sectionally. In particular, this weak correlation may be the most critical shortcoming of the use of ICC as a proxy for expected returns. The literature lacks a clear reason for this weak correlation.

In **Chapter 4**, I evaluate whether future returns and ICC are weakly correlated due to the underlying assumptions of the valuation models or the inaccuracy of analysts' earnings forecasts. I contribute to the literature by showing that the use of analysts' forecasts as an input for the ICC model is the main cause. Specifically, when ex-post realized (perfect foresight) earnings are used to this end, the ICC shows a markedly strong relation to future returns in the Fama-Macbeth regressions as well as in portfolio analyses.

Furthermore, to the best of my knowledge, I am the first one to measure the impact of analysts' forecast errors on different estimates of the cost of capital. These analyses are relevant since it is important to evaluate whether the analysts' forecast errors can drive the results of ICC. I estimate the ICC absolute error not only at the firm level, where most of the literature focuses but also at the portfolio level. The advantage of performing such a measure at the portfolio level is that the results are not driven by different estimates of growth since this approach, developed in the section, is able to estimate the ICC error and growth error simultaneously. Then, I show that the inaccuracy in ICC estimates is correlated to firms' characteristics. Finally, I introduce a Fitted ICC measure that has a higher correlation to future returns and a perfect foresight ICC.

Based on the findings that the earnings forecast inaccuracy is the primary cause for the weak correlation between ICC and future returns and also based on evidence that the analysts' forecasts are overly optimistic biased, **Chapter 5** tackles the lack of earnings forecast estimates, which dominates other methods along the measures of accuracy and bias. I contribute to the literature by proposing a cross-sectional model that includes analysts' earnings forecasts, gross profits, and past stock performance. This model outperforms the most popular methods from the literature in terms of forecast accuracy, bias, and earnings response coefficient. In addition, the implied cost of capital estimated with earnings forecasts from this model leads to a substantially stronger correlation with realized returns compared to extant estimates.

Finally, **Chapter 6** summarizes the main findings and discusses their implications for both researchers and practitioners. Furthermore, potential directions for future research are highlighted.

2. ICC and Valuation Models

The Implied Cost of Capital (ICC) is a term introduced by Kaplan and Ruback (1995) and denotes the discount rate that equates the asset's price to the present value of its expected payoffs. Since its introduction, ICC has been used in many applications in corporate finance (e.g., capital budgeting and firm valuation) and asset management (e.g., performance evaluation, portfolio allocation, and to detect the relation between a firm's characteristics and returns).

One of the first studies to use the idea of estimating the discount rate of return given the stock's price and the expected cash flows was carried out by Malkiel (1979) and Harris (1986). Both studies aimed to measure the ex-ante equity risk premia. Another pioneer study that applied ICC was conducted by Kaplan and Ruback (1995). The authors not only estimate the ICC to measure the risk premia of highly leveraged transactions but also analyze the relation of ICC to a firm's market beta, size, and the book-to-market ratio.

To have a better understanding of all assumptions of the ICC estimates, I present in this chapter the most used valuation models for estimating ICC as well as details on the most critical input for the ICC computation, the earnings forecasts. I start this review with the dividend discount model, which is the starting point for all valuation models discussed in this chapter.

2.1. Discount Dividend model

The general Discount Dividend Model (DDM) was introduced by Williams (1938) as follows:

$$P_0 = \sum_{t=1}^{\infty} \frac{D_t}{(1+r)^t}, \tag{2.1}$$

where P_0 is the share's price[1] at time t, D_t is the expected dividend at time t, and r is the expected rate of return, which is commonly called implied cost of capital.

Note that the DDM assumes a constant r (ICC), which does not necessarily hold in reality. For this reason, even if it is possible to predict perfectly the expected dividends, the ICC may differ from the expected returns. One of the studies that address this issue is carried out by Pástor et al. (2008). The authors test whether the ICC and expected returns are correlated over time. They find that if the conditional expected return follows an autoregressive AR(1) process, "the ICC is perfectly correlated with the conditional expected return over time."[2] In addition, in Chapter 4, I empirically test the association between ICC and future returns cross-sectionally. The results show that if ICC is estimated with accurate earnings forecasts, the ICC has a markedly strong correlation to future returns, which is another evidence that the assumption that cost of capital is constant may hold in empirical settings.

Assuming that the condition of a constant cost of capital holds, a critical challenge to estimate the ICC based on the DDM is predicting the vector of expected dividends.[3] As an alternative to predicting an infinite number of expected dividends, it is possible to assume a constant rate of growth, so that "the infinite series of future cash flows is truncated by a terminal value."[4]

[1] In the DDM, it is common to assume that the sum of the discounted expected future dividends is the intrinsic value. In this dissertation, I assume the share's price equals to its intrinsic value.
[2] Pástor et al. (2008, pp 2861)
[3] Note that in Equation 2.1, it is necessary to forecast dividends from time t+1 to the infinity.
[4] Botosan and Plumlee (2005, pp. 22)

Based on previous work from Williams (1938), Gordon and Shapiro (1956) derived the Gordon Growth Model (GGM):[5]

$$P_0 = \frac{D_1}{r - g}, \tag{2.2}$$

where P_0 is the share's price at time t, D_1 is the dividend at time t+1, r is the expected rate of return (i.e., the ICC), and g is the constant growth rate in the dividends. In this model, a condition for solution is $r > g$, otherwise, P_0 would be negative or infinite.

Of course, a stable growth rate in the dividends is a condition that does not hold for many companies. Due to that, it is common to find some derivation of the GGM, such as the following one:

$$P_0 = \sum_{t=1}^{T} \frac{D_t}{(1+r)^t} + \frac{D_{T+1}}{(1+r)^T \times (r-g)}. \tag{2.3}$$

In this version of the model, expected dividends are included in the model until year T. After time T, a constant rate of growth in the dividends is assumed. For instance, the model estimates the dividends for the next five years, and from the year t+6 on, a constant rate of growth is assumed. This version mitigates the effect of a constant rate of growth in the dividends because it starts after time T. However, an assumed growth rate of dividends from time T to the infinity is still an assumption that can lead to inaccurate estimates. In other words, this model may lead to inaccurate estimates because a small change in the dividends growth rate from the GGM has a substantial effect on the model. Furthermore, Kothari et al. (2016) argue that a key challenge in estimating the GGM is the need to forecast the stream of firms' future dividends, particularly among firms that do not issue dividends. Recognition of this issue gave rise to valuation models that rely on future earnings instead of dividends, such as the residual income model.

[5] This model is denominated the Gordon Growth Model (GGM) because it is named after Myron Gordon.

2.2. Residual Income model

The residual income model has been derived by diverse economists and accountants, such as Edwards and Bell (1961) and Feltham and Ohlson (1996). The residual income model can be written as follows:

$$P_0 = bv_0 + \sum_{\tau=1}^{\infty} \frac{ae_{t+\tau}}{(1+r)^{t+\tau}}, \tag{2.4}$$

where P_0 is the price of firm i in time t, r is the expected rate of return, i.e. the implied cost of capital, $bv_{t+\tau}$ is the expected book value at the end of year t, $e_{t+\tau}$ is the earnings forecast for year $t+\tau$, and $ae_{t+\tau} = e_{t+\tau} - r(bv_{t-1+\tau})$, i.e. earnings forecast for year $t+\tau$ minus a charge for the cost of equity.

By comparing the DDM to the Residual Income model, Claus and Thomas (2001) show that in the residual income model, the terminal value[6] has a lower fraction of the market value. The authors show that in the DDM, the terminal value has a fraction of more than 80% of the market value, while for the residual income model it is roughly 40%, which is an advantage of the residual income model. This happens because, in the residual income model, a large part of a firm's value is explained by its current book value of equity, and the difference between the current price of a firm's stock and the book value per share is the abnormal earnings, or the capacity to generate earnings that exceed the charge of the cost of equity. According to the authors, another advantage of the residual income model is that it is easier to make plausible assumptions about the residual income growth rate than for dividends. In theory, in the long run in a competitive market, the residual income (economic profits) growth rate tends to become zero.

For the ICC calculation, two main approaches are based on residual income models: the GLS and the CT approaches. In the next section, both models are going to be discussed.

[6] The present value of expected cash flows after year t+5.

2.2.1. CT approach

The CT approach is estimated as follows:

$$P'_{i,t} = BPS_{i,t} + \sum_{\tau=1}^{5} \frac{(ROE_{i,t+\tau} - r_i) \times BPS_{i,t+\tau-1}}{(1+r_i)^k} + \frac{(ROE_{i,t+5} - r_i) \times BPS_{i,t+4}(1+g_i)}{(r_i - g_i) \times (1+r_i)^5}, \tag{2.5}$$

where $P'_{i,t}$ is the adjusted price of firm i in time t, r_i is the ICC, and $BPS_{i,t}$ is the book value per share. $(ROE_{i,t+\tau} - r_i) \times BPS_{i,t+\tau-1}$, denotes the residual income of firm i in year $t + \tau$, i.e. the difference between the ROE and the r_i multiplied by book value of equity in the previous year. The ROE from years t+1 to t+5 are computed as $EPS_{i,t}/BPS_{i,t-1}$, where the $EPS_{i,t+\tau}$ is the expected earnings of firm i for year $t + \tau$. The analysts' earnings forecasts from years t+1 to t+5 are estimated with one- and two-year-ahead earnings forecasts and the five-year growth forecast, all provided by I/B/E/S. g_i is the growth rate of the residual incomes after the year t+5. Based on the assumption that the real growth rate of the residual incomes tends to become closer to zero, g_i is estimated as the expected inflation rate. Claus and Thomas (2001) propose the use of 10-year government T-bond yields minus three percent for such a proxy, based on historic data that the real risk-free rate is approximately three percent. As the CT approach was created to estimate the equity risk premia at the aggregate level, the model does not distinguish the long-term growth rates across firms.

2.2.2. GLS approach

The cost of capital based on the GLS approach can be estimated as follows:

$$P'_{i,t} = BPS_{i,t} + \sum_{\tau=1}^{11} \frac{(ROE_{i,t+\tau} - r_i) \times BPS_{i,t+\tau-1}}{(1+r_i)^k} + \frac{(ROE_{i,t+12} - r_i) \times BPS_{i,t+11}}{r_i \times (1+r_i)^{11}}, \tag{2.6}$$

where $P'_{i,t}$ is the adjusted price of firm i in time t, r_i is the ICC, $BPS_{i,t}$ is the book value per share of firm i in time t, and $(ROE_{i,t+\tau} - r_i) \times BPS_{i,t+\tau-1}$, denotes the residual income of firm i in year $(t+\tau)$, i.e. the difference between the return on equity (ROE) and r_i multiplied by the book value of equity of the previous year.

Different from the CT approach, the GLS is designed to estimate ICC at the firm level, which requires an estimate of the perpetual growth more specific for each firm. To do so, Gebhardt et al. (2001) propose a two-stage approach to estimate the ICC. In the first stage, the model has the ROE from years $t+1$ to $t+3$ as input, which is estimated with I/B/E/S analysts' forecasts from years t+1 to t+3. The $ROE_{t+\tau}$ is computed as $EPS_{t+\tau}/BPS_{t+\tau-1}$. In the second stage, the ROE linearly mean reverts for the next nine years to the median industry ROE. The median industry ROE is a rolling industry median over 10 years, considering only firms that have a positive ROE. The authors use the 48 industry classifications from Fama and French (1997). The ROE mean reversion is based on the assumption that, the firms' economic profits tend to become more similar to their industry peers in the long-run. The authors add that "the mean reversion in ROE attempts to capture the long-term erosion of abnormal ROE over time."[7] Finally, after period $t+12$, the terminal value is determined as simple perpetuity of the residual incomes, i.e., it assumes that, after year t+12, any incremental economic profits are zero.

2.2.3. Clean surplus

As Claus and Thomas (2001) explain, the Residual Income model is simply an algebraic restatement of the DDM. However, to satisfy the condition that dividends are related to earnings forecasts, an additional assumption is necessary, which is the "clean surplus" relation. This relation assumes that all retained earnings are reinvested into the firm, and, accordingly, become

[7] Gebhardt et al. (2001, pp 142)

equity. The clean surplus can be written as:

$$bv_{t+1} = e_{t+1} - d_{t+1} + bv_t, \tag{2.7}$$

in this equation, the book value at the end of year t+1 is estimated as earnings forecasts from year t+1 minus dividends from the same period plus the previous book value of equity.

Claus and Thomas (2001) support this assumption by arguing that "under U.S. accounting rules, almost all transactions satisfy the clean-surplus assumption."[8]. Furthermore, the transactions that do not satisfy the clean surplus occur most of the time ex-post and are not anticipated in analysts' forecasts. However, Ohlson (2005) points out that capital transactions that change the number of shares outstanding generally imply that the clean surplus relation does not hold, which is a strong argument against the residual income model. Due to this shortcoming, the author proposes the use of the abnormal earnings growth model, which does not rely on the clean surplus assumption.

2.3. Abnormal Earnings Growth model

The abnormal earnings growth model was developed by Ohlson and Juettner-Nauroth (2005) and is another derivation of the DDM. In order to show an intuition of this model, I start by assuming a full payout, i.e., the dividends are equal to earnings. Then, the DDM could be rewritten as:

$$P_0 = \frac{E_1}{r - g}, \tag{2.8}$$

where, E_1 is the expected earnings at the end of year t. Now, following Gode and Mohanram (2003), if I add and subtract E_1/r from the right side of the

[8] Claus and Thomas (2001, pp. 1635)

above equation respectively, the equation follows as:

$$P_0 = \frac{E_1}{r} - \frac{E_1}{r} + \frac{E_1}{r-g} = \frac{E_1}{r} + \frac{g \times E_1}{r(r-g)}. \tag{2.9}$$

Based on the constant growth rate of the Gordon growth model, $g \times E_1 = (E_2 - E_1)$. So, the equation can be rewritten as follows:

$$P_0 = \frac{E_1}{r} + \frac{E_2 - E_1}{r(r-g)}. \tag{2.10}$$

The above model describes the case of a full payout, where $E_2 - E_1 = D_2 - D_1$. To generalize the model to all cases, based on the assumption of a fixed payout ratio, the model needs to be adjusted as follows:

$$P_0 = \frac{E_1}{r} + \frac{E_2 - E_1 - r(E_1 - D_1)}{r(r-g)}. \tag{2.11}$$

In this case, the abnormal change in earnings is estimated as the change in earnings minus the return on net reinvestment during the period. In the ICC literature, two main approaches rely on the abnormal earnings growth model. The OJ approach and the MPEG. The difference between these two models is that the MPEG approach assumes a perpetual growth of zero.

2.3.1. OJ model

The OJ estimation of ICC follows as:

$$P'_{i,t} = \frac{E_{i,t+1}}{r_i} + \frac{STG_{i,t} \times E_{i,t+1} + r_i \times (D_{i,t+1} - E_{i,t+1})}{r_i \times (r_i - g_i)}, \tag{2.12}$$

where $P'_{i,t}$ is the adjusted price of firm i in time t, and r_i is the ICC. $E_{i,t+1}$ is the earnings forecast of firm i in years t+1, $D_{i,t+1}$ is the dividend in year t+1, STG_i is the short-term growth rate, computed as the growth rate between EPSt+1 and EPSt+2, and g_i is the perpetual growth rate in abnormal earnings beyond the forecast horizon. Following Gode and Mohanram (2003), it is assumed that the perpetual growth rate is equal to a 10-year government bond yield minus three percent. The dividends are estimated by multiplying the $E_{i,t+1}$ by the current payout ratio.

2.3.2. MPEG model

The MPEG approach is estimated by means of the following equation:

$$P'_{i,t} = \frac{E_{i,t+2} + r_i \times D_{i,t+1} - E_{i,t+1}}{r_i^2}, \tag{2.13}$$

where $P'_{i,t}$ is the adjusted price of firm i in year t, r_i is the ICC, $E_{i,t+1}$ and $E_{i,t+2}$ are the earnings forecasts in years t+1 and t+2, respectively, and $D_{i,t+1}$ is the dividend in year t+1.

By comparing the ICC methods, one can see that for the long-term growth, different assumptions are taken. For the estimation of the ICC based on the CT and OJ approaches, usually, perpetual growth of 10-year government bond yield minus three percent is assumed (e.g., Claus and Thomas (2001); Gode and Mohanram (2003)). For the MPEG approach, perpetual growth of zero percent is assumed. Finally, for the GLS approach, it is assumed that the ROE of each company reverts to its industry median. However, earnings forecasts and short-term growth are typical in all approaches. In Chapter 4, I discuss the differences in terms of sample among the ICC methods.

2.4. Inputs to estimate the implied cost of capital

2.4.1. Analysts' forecasts

The most used estimate for earnings forecasts in the ICC computation is undoubtedly the analysts' forecasts. The analysts' forecasts can be accessed by several firms such as First Call, I/B/E/S, Value Line, and Zacks. These firms maintain databases of analysts' forecasts on thousands of companies all over the world and can be directly used by academics and practitioners.

In addition to the ease of use, an important reason for the ample use of the analysts' forecasts is the accuracy.[9] The accuracy is measured as the absolute difference between the ex-post realized earnings and the earnings forecasts. In particular, when cross-sectional tests of ICC are performed, the use of an earnings forecasts estimate with the highest accuracy (lowest absolute error) is extremely relevant.

Due to the fact that "forecast accuracy is perhaps the single most important attribute of the quality of an analyst's output."[10], many studies have analyzed the relation between accuracy and analysts' characteristics and experiences. Clement et al. (2007) find that the analyst's forecast accuracy is positively related to the analyst's experience in forecasting a particular type of situation or event, such as forecasting earnings when restructurings occur or forecasting earnings around an acquisition. Bradley et al. (2017) show that another important factor is the industry-related experience obtained before becoming an analyst. Sinha et al. (1997) show that analysts classified as superior regarding accuracy in estimation samples generally remain superior in holdout periods. Finally, Jiang et al. (2016) find that even political views influence the quality of the analysts' forecasts. The authors find that analysts who contribute to the Republican Party have a more conservative forecasting style and produce better quality research.

Although the high accuracy of the analysts' forecasts has been documented, an important shortcoming of analysts' forecasts is the significant optimism bias[11] (see, e.g., Francis and Philbrick (1993); McNichols and O'Brian (1997); Easton and Sommers (2007); Hou et al. (2012)). A reason for the optimism bias can be related to how the analysts react to negative or positive information. Easterwood and Nutt (1999) find that analysts underreact to negative information, but they overreact to positive information. Their sample was composed of 10,694 firm-year observations in the period between 1982 and

[9] Extant literature finds that analysts' forecasts are more accurate than mechanical models (e.g., Fried and Givoly (1982); O'Brien (1988); Hou et al. (2012)).
[10] Kothari et al. (2016, pp. 7)
[11] Bias is defined as the difference between the actual earnings and earnings forecast.

1995. Although the optimistic bias may be related to analysts' behavioral reasons, Hou et al. (2012) argue that the optimism bias is likely due to the conflicts of interest the analysts are subject to.

Bradshaw (2011) lists six important reasons for the conflicts of interest: i) Banking fees, as the sell-side analysts may be rewarded by the investment bank side for providing favorable coverage of deals that their houses are underwriting; ii) Currying favor with management since the analysts can be optimistic in order to maintain access to firm managers- who are a primary source of information; iii) Trade generation incentives, the analysts' firms can generate more trades if the reports suggest that the investors should buy stocks; iv) Institutional investor relationship, due to the close relationship between the analysts' houses and some institutional investors, it could be unfavorable to suggest downgrading stocks taken by some institutional investors; v) Research for hire, it is getting more common to pay for analysts to conduct the research in some companies; vi) Themselves, i.e., the affinity between analysts and firms' managers can drive the forecasts.

The importance of the conflicts of interest on the analysts' work has been documented empirically and even in surveys. In a survey of 365 analysts, Brown et al. (2015) find that 44% of respondents say their success in generating underwriting business or trading commissions is very important for their compensation. Groysberg et al. (2011) find that the analysts' annual compensation is associated positively with investment banking contributions, the size of the portfolios of the analysts, recognition by Institutional Investor magazine as an "All-Star", and being identified by the *Wall Street Journal* as a top stock-picker. However, they find no evidence that compensation is positively related to earnings forecast accuracy. This evidence is consistent with the hypothesis that the analysts are rewarded by actions that increase brokerage and revenues to their houses. In line with this hypothesis, Hong and Kubik (2003) show that when analysts cover stocks underwritten by their houses, their promotion depends less on accuracy and more on optimism.

As a result, the use of analysts' forecasts to estimate ICC can lead to upwardly biased estimates. Claus and Thomas (2001) infer that because analysts' forecasts are positively biased and because the bias increases with the forecast horizon, the equity premium estimates may be biased upward. Easton and Sommers (2007) estimate that the bias in the equal-weighted ICC at the portfolio level, computed as the difference between the estimates of the ICC based on analysts' earnings forecasts and estimates based on current earnings realizations, is 2.84%. Moreover, the value-weighted bias in the ICC estimates is 1.6%. The authors argue that the optimistic bias has important implications, especially because several extant studies estimate an equity premium of around 3%, which could be close to zero after removing the bias.

In order to improve the quality of the analysts' forecasts, some studies propose adjusting the predictable errors of analysts. Guay et al. (2011) develop two different approaches to mitigating the errors of analysts' forecasts due to their sluggishness. The first approach uses the median error in portfolios formed with firms with similar recent returns. The second approach mitigates the forecasts' errors by using the predicted value from a regression of forecasts' errors on some firm characteristics. When the ICC is estimated with the adjustment of these methods, the estimates have a higher cross-sectional correlation to future stock returns. Larocque (2013) also proposes a method to eliminate predictable errors based on a regression approach. Unlike Guay et al. (2011), the author does not find that this method improves the correlation between ICC and returns. Finally, Mohanram and Gode (2013) propose a method to adjust forecasts for predictable errors based on factors based on analysts' predictable overreaction and underreaction. They find that the correlation between ICC and future returns can be improved by these methods after controlling for discount rate news and cash flow news.

2.4.2. Mechanical earnings

A common alternative to analysts' forecasts is mechanically forecast earnings. The first mechanical earnings models were based on time-series, and the forecasts are neither unbiased nor accurate (see, e.g., Fried and Givoly (1982); O'Brien (1988)). However, the literature adjusted the mechanical models to a cross-sectional dimension, and the performance of the forecasts has improved.

One of the first cross-sectional models to predict earnings and profitability was developed by Fama and French (2000). The authors forecast earnings and profitability with year-by-year cross-section regressions of earnings on accounting variables. Then, they use the average slopes and the t-statistics to draw inferences. Some years later, Fama and French (2006) developed a new model to predict profitability with a similar approach. However, the authors include not only accounting variables as explanatory variables, but also market capitalization, the firms' stock returns for fiscal year (t), analysts' earnings forecasts for ($t + 1$), the composite measure of Piotroski (2000) and Ohlson (1980) for firm's strength, and lagged returns. They show that earnings as an independent variable are highly persistent in forecasting profitability.

Then, Hou et al. (2012) develop a cross-sectional model based on assets, earnings, and dividends. Their model, which is based on previous work from Fama and French (2000), Fama and French (2006), and Hou and Robinson (2006), is superior to analysts' forecasts in terms of coverage, Earnings Response Coefficients (ERC),[12] and forecast bias but underperforms the analysts in terms of accuracy.

An important contribution from the paper from Hou et al. (2012) is that they show that mechanical earnings can also be used to estimate ICC. In fact, they even show that the ICC based on mechanical earnings has a higher correlation to future returns compared to the ICC based on analysts' forecasts.

Given the promising results of Hou et al. (2012), other studies have analyzed and proposed new mechanical models in cross-sectional settings. Gerakos and

[12] The ERC estimates the relationship between earnings surprises and stock returns.

Gramacy (2013) have demonstrated that by using more independent variables than in other cross-sectional models, forecasting accuracy can be improved in stable times. However, at a one-year horizon, the random walk model performs as well as other mechanical models that use larger predictor sets. Li and Mohanram (2014) propose an Earnings Persistence (EP) and a Residual Income (RI) model to forecast earnings. They show that both models are superior to the HVZ and RW models in terms of earnings forecasts' bias, accuracy, ERC, and correlations of the ICCs with future returns and risk factors. Azevedo and Gerhart (2016) compare the accuracy and bias of earnings forecasts estimated with mechanical models to analysts' earnings forecasts in the European markets. The results show that for almost all European regions, the cross-sectional models of earnings forecasts have a lower bias but higher forecasts' errors (lower accuracy) compared to the analysts' earnings forecast. Moreover, they show that cross-sectional models of earnings forecasts tend to be more accurate for long-term earnings forecasts, whereas for short-term forecasts, analysts' earnings forecasts are more accurate. Finally, the authors propose a model based on gross profitability from Novy-Marx (2013). They show that the earnings forecasts estimated with this model outperform other estimates in all the observed regions.

Although most of the literature has switched towards cross-sectional settings, Ball and Ghysels (2017) show that time-series forecasting models can also outperform analysts' forecasts in some situations. The authors propose a model based on mixed data sampling regression methods (MIDAS), which combines a broad spectrum of high-frequency time-series data to forecast earnings. They find that the MIDAS forecasts are more accurate than analysts' for smaller firms and when forecast dispersion is high. Furthermore, a combination of MIDAS forecasts with analysts' forecasts outperforms raw analysts' forecasts. This is evidence that the MIDAS models provide orthogonal information to analysts.

2.5. Studies using ICC

Since the introduction of ICC, many studies rely on this estimate to solve puzzles in finance. Among these puzzles, a crucial one is a tradeoff between risk and return. Pástor et al. (2008) find that ICC outperforms realized returns in detecting this tradeoff. The authors find evidence of a positive relation between the conditional mean and variance of market returns in the G-7 countries when they use ICC. The results hold even when earnings forecasts are poor.

Another important application of ICC is as a measure of equity premia. The most common approach is the historical return of the stock market over the risk-free rate. According to Claus and Thomas (2001), these historical estimates range from seven to nine percent and are too high. Malkiel (1979) was one of the first authors to use ICC to estimate the market risk premium. He uses an adaptation of the DDM to estimate the cost of capital in the period from 1960 to 1977. The market risk premium ranges in this period between three and seven percentage points. More recently, Claus and Thomas (2001) estimate the ICC in the period between 1985 and 1998 using a model based on residual income. The authors show that the equity premia from the U.S. were on average 3.4% per year in the studied period.

Campbell and Shiller (1988b) and Campbell and Shiller (1988a) suggest that unexpected asset returns can be decomposed into discount rate news and cash flow news. Chen et al. (2013) propose a model that relies on ICC to decompose these two components. They find that cash flow news is a significant component in stock returns and that its importance increases with the investment horizon. For horizons over two years, cash flow news may become more relevant than discount rate news to explain stock returns.

Another relevant study was carried out by Gebhardt et al. (2001). The authors examine the relation of firms' characteristics and cost of capital. They find in a period sample from 1979 to 1995 that ICC has a positive and significant relation to book-to-market, long-term growth, and industry membership, and a negative and significant relation to the dispersion in analysts' earnings forecasts. Furthermore, they find evidence that market β, leverage, and size are redundant to explain the cost of capital.

In an international sample, Lee et al. (2009) find that expected returns increase with world market β, book-to-market ratio, idiosyncratic volatility, and have a negative relation to size and currency β. In addition, they find that ICC has one-tenth of the volatility of expected returns. The analysis focuses on G-7 countries in the period between 1990 and 2000.

Another essential property of ICC is the strong predictability power. Li et al. (2013) compare the predictability power of ICC to other valuation ratios, such as dividend-to-price-ratio (D/P), earnings-to-price ratio (E/P), book-to-market ratio(B/M), and payout yield (P/Y), and business cycle variables such as Term spread, Default spread, Treasury-bill rate, and Long-term Treasury-bill yield. They find that ICC is superior to all of these estimates predicting future excess market returns. The ICC shows strong predictability power at horizons ranging from one month to four years, and the results hold in-sample and out-of-sample.

3. Asset Pricing Anomalies: A multidimensional analysis

This chapter examines the joint roles of market βs, book-to-market, size, operating profitability, investments and Implied Cost of Capital (ICC) in explaining returns across firms, over time, and in both dimensions at the same time. For that purpose, I apply novel regression approaches for asset pricing, such as an orthogonal Fama-Macbeth approach and a Fixed-effects estimation to evaluate the relation between risk proxies and expected returns over time, and a Pooled OLS regression with standard errors clustered by firms and months to evaluate this relation in both dimensions at the same time. The results show that, over time, ICC can predict returns not only at the aggregate level but also at the firm level. Moreover, market βs have a negative and highly significant impact on expected returns.

3.1. Introduction

Since the first empirical asset pricing studies, most research has focused on analyzing anomalies cross-sectionally and using monthly realized returns as a proxy for expected returns. According to Fama and French (1996), anomalies correspond to patterns in average returns that apparently are not explained by the asset pricing model of Sharpe (1964), Lintner (1965), and Black (1972), also known as the SLB model. Based on this model, the efficiency of the market portfolio implies that expected returns on securities are a linear function of their market βs (the slope in the regression of a security's return on the market's return) (Fama and French, 1992).

Based on evidence from Banz (1981) and Chan et al. (1991), Fama and French (1992) find that two empirically determined variables, size, and book-to-market (B/M) equity, do a good job explaining the cross-section of average returns on the NYSE, Amex, and NASDAQ stocks for the 1963-1990 period. However, based on the discount valuation model of Miller and Modigliani (1961), Fama and French (2006) argue that B/M is a noisy proxy for expected return because higher expected earnings imply a higher expected return. Moreover, for fixed values of B/M and expected earnings, higher expected growth in book equity - investments - implies a lower expected return. In other words, B/M cannot explain the variation of profitability and investments.

The importance of cross-sectional estimates is widely understood, but the consensus is lacking on how risk proxies behave over time or over both dimensions (cross-sectionally and over time) at the same time. While the cross-sectional dimension can explain the variation of expected returns between firms at a specific point in time, this dimension does not aim to look further and to estimate whether the stock market is overpriced or underpriced, nor to evaluate the risk of a financial bubble. Furthermore, a better understanding of the relation between risk proxies and expected returns over time is crucial in financial topics, such as asset management and intertemporal asset pricing models.

Among the studies that analyze risk proxies on expected returns over time, Pástor et al. (2008) and Li et al. (2013) find that Implied Cost of Capital (ICC) is a good proxy for time-varying expected returns. ICC for a given asset is described as the discount rate that equates the asset's market value to the present value of its expected future payoffs. Pástor et al. (2008) estimate monthly, in the period 1981-2002 (for the United States) and 1990-2002 (for Canada, France, Germany, Italy, Japan, and U.K.), an aggregate ICC across firms to compute market-wide ICC for each country and, then, examine the intertemporal asset pricing relationship between expected returns and volatility. The results show that the ICC outperforms realized returns in detecting a positive risk-return trade-off. Furthermore, Li et al. (2013) analyze the aggregate ICC, based on a sample from NYSE/AMEX/Nasdaq in the period from January 1977-December 2011, and find that the aggregate ICC strongly predicts future excess market returns at horizons ranging from one month to four years.

Although there is evidence of the relation of the aforementioned variables and expected returns across firms or over time, there is a lack of evidence about whether these variables can also help to explain expected returns in other dimensions. Thus, I reexamine the joint roles of market βs, B/M, Size, OP, Inv and ICC to explain returns across firms, over time and both dimensions at the same time. The variables, market βs, B/M, Size, OP, Inv are based on the Fama and French (2015) five-factor model, which according to the authors performs better than the three-factor model from Fama and French (1993). Moreover, the variable ICC is chosen based on the evidence of Li et al. (2013) that this variable forecasts future returns better than existing forecasting variables, both in-sample and out-of-sample, because it is estimated based on a theoretically justifiable discounted cash flow valuation model that takes into account future growth opportunities ignored by traditional valuation ratios. I explain that as ICC has different approaches, I perform the analysis based on the models of Claus and Thomas (CT, 2001), Easton (modified price-earnings growth or MPEG, 2004), Gebhardt et al. (GLS, 2001), and Ohlson and Juettner-Nauroth (OJ, 2005). In addition, I also estimate a composite ICC, based on the composition of these four mentioned approaches.

In order to evaluate the relationship of explanatory variables and returns over time and both dimensions, I apply novel regression approaches for asset pricing. Firstly, I perform an adaptation of the Fama and Macbeth (1973) approach, which explains the time-series of expected returns. Secondly, due to the fact that an orthogonal Fama-Macbeth approach is a novel approach, I apply a Fixed-effect (within) estimation with standard errors clustered by months to compare the results over time. I explain that the Fixed-effect estimation aims to explain the association between individual specific deviations of explanatory variables from their time-averaged values and individual-specific deviations of the expected returns from their time-averaged values; while in an orthogonal Fama-Macbeth approach, I estimate, for each stock, the time-series of expected returns and, then, I perform standard tests in order to evaluate whether the coefficients' averages of explanatory variables are statistically significant. In other words, the fixed-effects estimation explains the variation of the variables (of each firm) compared to their averages, and an orthogonal Fama-Macbeth approach evaluates whether the average of the univariate time-series of expected returns (of each firm) is statistically significant. Finally, I apply a Pooled Ordinary Least Squares regression (POLS) with standard errors clustered by firms and months (as proposed by Petersen (2009) and Thompson (2011)) in order to evaluate the impact of variables on returns not only through time or companies but also the variation of these two dimensions simultaneously. Although this approach does not yield information about the relative contribution of anomalies in each dimension of expected returns, this approach adds further evidence of the impact of risk proxies on expected returns after the estimation of the cross-sectional as well as the time-series of expected returns.

Among the results, I find evidence that market βs' slopes have contradictory results at the firm level when seeking to explain expected returns. This evidence comes from the cross-sectional Fama-Macbeth regression, where βs' slopes are positive and significant, in contrast to the Fixed-effect estimation and an orthogonal Fama-Macbeth approach, where βs' slopes are negative yet significant. This result seems to be further evidence against market βs, especially against their use to predict future returns over time.

Additionally, I find significant evidence that ICC is able to predict future realized returns at the portfolio level and the firm level. Initially, at the portfolio level, I find a robust relation between the returns of value-weighted ICC and 12-month-forward value-weighted market returns. For the period

July 1989-June 2014, the correlation between the CT approach of ICC and expected returns is 0.32, and when I run a regression with expected returns on the CT approach, I find an R-squared of 0.102, highly significant slopes, and nonsignificant intercepts. At the firm level, all four ICC approaches, as well as the composite one, are statistically significant as a control variable in order to explain expected returns over time. Therefore, I do not only find evidence that ICC is a good proxy for expected returns, but I also find evidence that ICC could be used in investment strategies, due to this statistically significant relation with expected returns.

Finally, I determine that although all risk proxies used in the Fama and French five-factor asset-pricing model have a statistically significant relation with returns, when operating profitability is the only explanatory variable, its relation with expected return becomes negative over time and in both at the same time. This evidence comes from an orthogonal Fama-Macbeth approach as well as from the Fixed-effect estimation, where operating profitability has a negative and significant slope explaining the time-series of expected returns. In addition, the POLS model shows that the negative impact of Operating profitability on returns is also persistent when I evaluate both dimensions at the same time.

Therefore, this study makes three contributions to the literature: (a) I provide substantial evidence in favor of ICC explaining expected returns over time, at the firm level and at the aggregate level; (b) I find substantial evidence that the market βs have a negative relation with expected return over time, which goes against the assumptions of the SLB model; (c) I present novel regression approaches to analyze anomalies over time and over both dimensions at the same time.

The structure of this chapter is as follows. First, I provide the materials and methods, where I demonstrate the sources of data, rating periods, and risk proxies. Secondly, I analyze the performance of ICC in predicting expected returns. Thirdly, I evaluate the relation of ICC and other risk proxies with expected returns. Finally, I present the main results, discussion, and the conclusion.

3.2. Materials and methods

3.2.1. Data collection

The sample of firms consists of all U.S. companies (excluding American Depositary Receipts (ADRs) downloaded from Thomson Reuters Datastream (TRD). I focus the analysis on the period July 1989–June 2015 to assure a reasonable number of firm observations in each time-period. To ensure the data quality, following Ince and Porter (2006), I restrict the sample to the primary quotation of common stocks of type equity, listed and located in the U.S. If I have more than one equity security, I keep the major one, which is the security with the biggest market capitalization. Moreover, I delete companies with mismatching words such as “ADR”, “DUPL”. “PREF”, “ETF”, “PREFERENTIAL”. After this screening process, the sample has 31,872 securities.

For data source, I use realized return as well as market capitalization from Datastream and accounting data from Worldscope. Analysts’ forecasts and share prices are obtained from the Institutional Brokers’ Estimate System (I/B/E/S). I use I/B/E/S instead of earnings forecasts estimated with mechanical earnings (see Hou et al. (2012)) because I intend to calculate the ICC on a monthly basis and usually, the mechanical earnings approach does not permit monthly adjustments of forecasts as does I/B/E/S. The proxy for the risk-free rate is yields of the U.S. 10-year government bond from TRD.

I analyze the following independent variables in this study: i) Operating Profitability (OP): is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus depreciation, minus other operating expenses, minus interest expense, all divided by book equity (Fama and French, 2015). ii) Investments (Inv): is the change in total assets from the fiscal year in year t-1 to the fiscal year in t, divided by the fiscal year in t-1 total assets.

iii) Book-to-market (B/M): is book equity, which I define as common equity, plus deferred taxes if available, divided by market capitalization. iv) βs are estimated on 24 to 60 monthly returns (as available) in the 5 years before the month t, based on the value-weighted portfolio of the sample of stocks used as the proxy for the market. v) Implied Cost of Capital (ICC): is the discount rate that the market uses to discount the expected cash flows of the firm. Finally, vi) Size (SZE) is the market capitalization.

In order to avoid outlier bias driving the results, I winsorize realized returns and ICC returns in the 1st and 99th percentiles (observations beyond the extreme percentiles are set to equal the values at those percentiles), and I transform the variables $(1 + OP)$, $(1 + Inv)$, B/M and SZE into natural logarithms. In addition, the βs are estimated by using winsorized returns.

3.2.2. Estimating the ICC

As there are different approaches to calculate the ICC, I choose the four most common approaches in the literature, which can be commonly grouped into two categories: the CT and GLS are based on the residual income valuation model, and OJ and MPEG are based on abnormal earnings growth-based models. In addition, I estimate a composite ICC, which is the average of the four approaches mentioned above. To maximize the coverage of the composite ICC, similar to Hou et al. (2012), I only require a firm to have at least one non-missing individual ICC estimate.

For the calculation of ICC, each firm must have a one-year-ahead, a two-year-ahead, and three-year-ahead mean earnings forecast. If a three-year-ahead forecast is not available, I use the consensus long-term growth rate to estimate it. Moreover, if neither the three-year-ahead earnings forecast nor the long-term growth rate is available, I compute the growth between one-year and two-year-ahead earnings forecasts as an implicit growth. I assume that the annual report date is 120 days after the fiscal year-end, in order to ensure that the value estimates are based only on publicly available information; I create a synthetic book value and synthetic earnings in case this information is not yet public. The synthetic I/B/E/S earnings refer to the earnings forecasts of the previous fiscal year-end. Based on synthetic I/B/E/S earnings, I calculate the book value per share. Finally, I exclude all observations with negative book value per share and, I winsorize growth rates below 2% and above 100%. In Sections 2.2 and 2.3, I present a detailed description of individual ICC estimates.

In order to have a better understanding of the interaction between ICC and realized returns, I use the discount dividend model to explain this relationship:

$$M_t = \sum_{\tau=1}^{\infty} \frac{D_{t+\tau}}{(1 + ICC)^{(t+\tau)}}. \tag{3.1}$$

In this equation, M_t is the share price at time t, $D_{t+\tau}$ is the expected dividend per share for period $t+\tau$, and ICC is Implied Cost of Capital based on expected dividends. According to Equation 3.1, if at time t the stocks of two firms have the same expected dividends but different prices, the stock with a lower price has a higher ICC. Although price in time t or even in a previous period can affect the result of ICC, the future returns are not supposed to affect the ICC. Another point is that the ICC is supposed to be less sensitive than realized returns concerning price changes, because a change in the share price affects the return only at time t, while for ICC the share price change affects expected returns over endless time-periods. In order to have a better understanding of the ICC properties and to evaluate whether this proxy is able to predict forward-realized returns, I start the analysis with ICC as the only risk proxy.

3.3. ICC analysis

In this section, I examine the ability of ICC approaches to predicting forward-realized returns (realized returns forward-looking). I run a correlation analysis in order to evaluate the correlation of ICC and returns in different periods.

Then, I compare the value-weighted ICC and value-weighted forward-returns at the aggregate level.

3.3.1. Correlation analysis between ICC and returns

To evaluate and compare the performance of ICC approaches predicting future returns at the firm level, and determining in which periods this relation is stronger, I start with a correlation analysis. The first correlation analysis is based on monthly data and the second one is based on annual data. I explain that the correlations are usually calculated by vectors, and in this case, I intend on calculating the correlations based on combinations of two matrices: a matrix m x n (m= 312 monthly data firms and n=31,872 firms) for realized returns, and a matrix m x n for each ICC approach. Thus, the output is a matrix m x m of correlation of the vectors of all firms' ICC and returns in 312 periods. To make it easier to analyze, I calculate the average of correlations within the same lag period. Based on the evidence of Corey et al. (1998) – that when correlations from a matrix are averaged, the use of z decreases bias – I transform the Pearson r (correlation) values using a Fisher (1921) z transformation. Then, I average the z-values and convert the average back to an r-value.

Table 3.1.: Correlation between ICC and returns

Average correlation results

Panel A: Correlation between monthly-realized returns premium and monthly ICC premium

	Mean					t-statistics				
	Composite	CT	GLS	MPEG	OJ	Composite	CT	GLS	MPEG	OJ
t	0.03	0.04	0.03	0.03	0.03	0.55	0.67	0.58	0.54	0.55
t+1	0.03	0.03	0.03	0.03	0.02	0.45	0.48	0.46	0.49	0.40
t+2	0.03	0.03	0.03	0.01	0.01	0.48	0.48	0.49	0.23	0.26
t+3	0.03	0.03	0.03	0.02	0.02	0.50	0.46	0.47	0.34	0.35
t+4	0.03	0.02	0.03	0.01	0.02	0.52	0.40	0.44	0.14	0.35
t+5	0.03	0.02	0.02	0.00	0.01	0.45	0.35	0.41	0.07	0.17
t+6	0.03	0.02	0.02	0.01	0.01	0.44	0.34	0.42	0.17	0.17
t+7	0.03	0.02	0.02	0.01	0.02	0.47	0.35	0.41	0.23	0.28
t+8	0.03	0.03	0.03	0.02	0.01	0.46	0.44	0.49	0.26	0.16
t+9	0.03	0.02	0.03	0.02	0.01	0.44	0.35	0.51	0.27	0.19
t+10	0.02	0.02	0.03	0.01	0.01	0.40	0.35	0.54	0.19	0.14
t+11	0.03	0.03	0.04	0.01	0.01	0.47	0.46	0.61	0.18	0.21
t+12	0.03	0.03	0.04	0.02	0.02	0.50	0.44	0.62	0.26	0.28
t+13	0.03	0.02	0.04	0.02	0.01	0.50	0.41	0.61	0.33	0.19
t+14	0.03	0.02	0.03	0.01	0.01	0.53	0.40	0.58	0.20	0.15
t+15	0.03	0.02	0.03	0.01	0.01	0.51	0.43	0.54	0.20	0.17
t+16	0.03	0.02	0.03	0.02	0.00	0.47	0.40	0.48	0.30	0.08
t+17	0.02	0.02	0.02	0.03	0.01	0.42	0.37	0.40	0.43	0.14
t+18	0.02	0.02	0.02	0.03	0.01	0.42	0.33	0.39	0.44	0.14

Panel B: Correlation between annual ICC premium and annual returns premium

	Mean					t-statistics				
	Composite	CT	GLS	MPEG	OJ	Composite	CT	GLS	MPEG	OJ
t	0.07	0.06	0.08*	0.03	0.03	1.21	1.05	1.34	0.51	0.55
t+1	0.1**	0.09*	0.1**	0.05	0.05	1.66	1.54	1.80	0.82	0.95
t+2	0.09*	0.08*	0.1**	0.04	0.05	1.62	1.44	1.79	0.73	0.82
t+3	0.09*	0.08*	0.11**	0.04	0.04	1.62	1.41	1.82	0.73	0.75
t+4	0.09*	0.08*	0.11**	0.04	0.04	1.62	1.38	1.84	0.74	0.71
t+5	0.09*	0.08*	0.11**	0.04	0.04	1.60	1.38	1.85	0.74	0.65
t+6	0.09*	0.08*	0.11**	0.04	0.03	1.55	1.38	1.85	0.75	0.51
t+7	0.09*	0.08*	0.11**	0.05	0.03	1.54	1.41	1.84	0.86	0.47
t+8	0.09*	0.08*	0.11**	0.06	0.03	1.54	1.42	1.83	0.95	0.48
t+9	0.09*	0.08*	0.11**	0.06	0.03	1.53	1.41	1.82	1.03	0.47
t+10	0.09*	0.08*	0.1**	0.06	0.03	1.52	1.35	1.78	1.10	0.48
t+11	0.09*	0.08*	0.1**	0.07	0.03	1.52	1.35	1.74	1.16	0.52
t+12	0.09*	0.08*	0.1**	0.07	0.03	1.54	1.33	1.69	1.23	0.59
t+13	0.09*	0.08*	0.1*	0.08*	0.04	1.58	1.31	1.64	1.30	0.67
t+14	0.09*	0.08*	0.09*	0.08*	0.04	1.58	1.31	1.58	1.30	0.73
t+15	0.09*	0.08*	0.09*	0.08*	0.05	1.56	1.31	1.50	1.28	0.79
t+16	0.09*	0.08*	0.08*	0.08*	0.05	1.50	1.31	1.42	1.30	0.89
t+17	0.09*	0.08	0.08*	0.08*	0.06	1.45	1.28	1.33	1.30	0.97
t+18	0.08*	0.07	0.07	0.08	0.07	1.42	1.25	1.26	1.27	1.10
t+19	0.08*	0.07	0.07	0.07	0.07	1.41	1.24	1.22	1.23	1.18
t+20	0.08*	0.07	0.07	0.07	0.07	1.37	1.19	1.17	1.18	1.25
t+21	0.08*	0.07	0.07	0.07	0.08*	1.32	1.19	1.13	1.17	1.32
t+22	0.08	0.07	0.07	0.07	0.08*	1.28	1.21	1.11	1.17	1.38
t+23	0.07	0.07	0.07	0.07	0.08*	1.24	1.20	1.08	1.21	1.39
t+24	0.07	0.07	0.06	0.07	0.08*	1.21	1.22	1.06	1.23	1.36

This table presents the results of the averaged correlation results and the statistics. Panel A reports the results of the correlation between monthly-realized returns and monthly ICC on the yields of the U.S. 10-year government bond. Panel B reports the results of the correlation between annual ICC premium and annual returns premium. As a proxy for annual returns premium, I use 12-month-realized returns minus the yields of the U.S. 10-year government bond and the ICC premium is computed as the differences between the implied cost of capital and the yields of the U.S. 10-year government bond. I estimate the results based on combinations of two matrices: a matrix m x n (m= 312 monthly data firms and n=31.872 firms) for realized returns and a matrix m x n for each ICC approach. Thus, my output is a matrix m x m of correlation of the vectors of all firms' ICC and firms' returns in the period July 1989-June 2015. I group the correlations based on the lag periods. To calculate the average, I transform the Pearson r (correlation) values using a Fisher (1921) z transformation. Then, I average the z-values and convert the average back to an rvalue. *,**,*** indicate one-tailed significance at the 0.1, 0.05, and 0.01 levels, respectively. I use a one-tailed significance level because I want to evaluate whether I can reject the null hypothesis that the correlation is equal or less than zero.

Panel A of Table 3.1 reports the average and the t-statistics of the monthly correlation of the ICC monthly premium and the monthly realized excess of returns (correlation 1) from the period t (i.e., $ICC_{t+\tau}$ and return at time t+τ) to the period t+12 (i.e., ICC at time t+τ and return at time t+τ+12). While ICC monthly premiums are calculated as the monthly ICC minus the yields of the U.S. 10-year government bond, monthly realized excess of returns are computed as the monthly-realized return on the yields of the U.S. 10-year government bond. With regard to the correlation from the period t+0 to t+12, all correlations are positive but not statistically significant. Therefore, I conclude that all ICC approaches have limited power to predict monthly returns at the firm level.

The second correlation analysis (Panel B of Table 3.1) is estimated with annual data. Thus, I estimate the correlation between the annual ICC premium and annual excess of returns. Panel B of Table 3.1 presents the average and t-statistics of the correlation 2. As a proxy for annual excess of returns, I use a 12-month series of realized returns minus the U.S. 10-year government bond yields. The ICC premium is computed as the difference between the implied cost of capital and the yields of the U.S. 10-year government bond. The sample covers the period July 1989-June 2015. Just to clarify the results, for instance, t+1 means the period between $ICC_{t+\tau}$ premium and realized excess of returns for the period t+τ+1 to t+τ+13.

Panel B of Table 3.1 shows that the averaged correlation is stronger for the annual excess of returns than for the monthly excess of returns. The GLS presents a significant correlation, at a significance level of 0.05, from t+1 to t+12. At the significance level of 0.10, the composite ICC presented significant correlations from t+1 to t+21, the CT from t+1 to t+16, the MPEG from t+13 to t+17, the OJ from t+21 to t+24 and GLS from t to t+17. The reason why the ICC has a stronger predictability power in predicting annual returns than monthly returns may be due to the fact the annual returns are less noisy than monthly. The results suggest that ICC can positively predict future returns not only at the aggregate level, as Li et al. (2013) do, but also at the firm level. In addition, I point out that all approaches presented significant results and I find evidence that MPEG and OJ - models based on abnormal earnings growth-based models - may have the most precise ability to predict long-term returns.

Based on the results, – and on the evidence of Lee et al. (2009) that due to the fact that realized returns are excessively noisy, financial researchers testing asset pricing models face the risk that, during the period of study, economically significant relations can be rendered statistically insignificant – the usage of annual returns instead of monthly returns may show in a clearer way the relation between expected returns and other risk proxies. Thus, I continue the analysis using the annual excess of returns as a proxy for expected returns. Until now, I have estimated the correlation at the firm level using an equal weight for each company. My further analysis is based on the aggregate level and, to avoid results driven by only small companies, I use a value-weighted approach.

3.3.2. Value-weighted ICC and returns analysis

In this section, I estimate the value-weighted ICC and value-weighted market return premium in order to compare the ability of different ICC proxies in predicting 12-month-forward value-weighted market returns at the aggregate level. The value-weighted ICC premium (VWICC) is the value-weighted ICC on the market portfolio of all sample stocks for a 12-month period minus the yields of the U.S. 10-year government bond. The value-weighted market return premium ($R_M - R_F$) is the value-weighted market return on the market portfolio of a sample in the period of 12 months minus the yields of the U.S. 10-year government bond. I restrict the sample of $R_M - R_F$ to the companies that also have ICC. The sample period is July 1989-June 2014. Unlike Li et al. (2013), I do not just evaluate the ability of ICC to predict $R_M - R_F$, but I also compare the results of different ICC approaches.

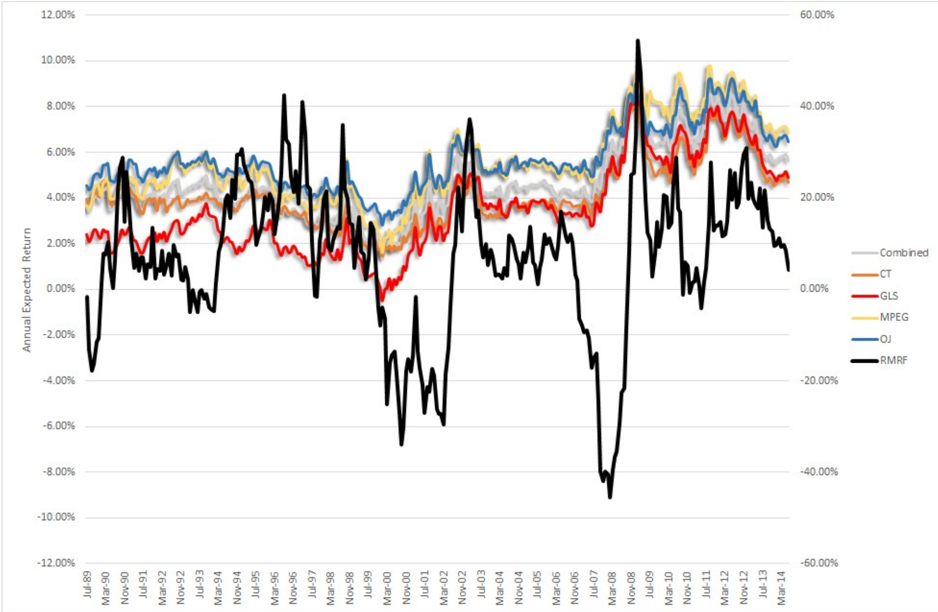

Figure 3.1.: Time-series of ICC and ex-post realized returns.

Figure 3.1 shows the value-weighted estimates for all ICC approaches used in this study and for the $R_M - R_F$. The minimum VWICC value (-0.49%) occurred in January 2000 based on the GLS approach, while the highest value (9.75%) occurred in August 2011 based on the MPEG approach. Concerning $R_M - R_F$, the minimum value was -45.47% in the period February 2008-February 2009, and the maximum value was 54.43% in the period February 2009 - February 2010. In the period July 1989-June 2014, the averages of VWICC are 4.68% based on the Composite ICC, 4.15% based on the CT, 3.53% based on the GLS, 5.55% based on the MPEG and 5.72% based on the OJ, while the average for the $R_M - R_F$ is 6.73%. This result confirms the findings of Claus and Thomas (2001) that the historical mean of excess returns earned by U.S. equities is higher than the market premium calculated by the ICC approach. In addition, the standard deviation is 1.62% for the Composite, 1.41% for CT, 2.02% for GLS, 1.79% for OJ, 1.37% for MPEG and 16.69% for $R_M - R_F$. This result confirms the findings of Lee et al. (2009) that ICC has one-tenth of the volatility of realized returns. Given these results, I proceed with a correlation analysis and a regression analysis, in order to have a better understanding of the relationship between VWICC and $R_M - R_F$.

Table 3.2.: Market risk premium and value-weighted ICC

Regression Specifications					
Panel A: Correlation between ICC and 12 months forward $(R_M - R_F)$					
	CT	GLS	MPEG	OJ	Composite
$(R_M - R_F)$	0.32***	0.22***	0.24***	0.26***	0.27***
Panel B: Regression with 12 months forward weighted $(R_M - R_F)$ on weighted ICC					
	CT	GLS	MPEG	OJ	Composite
Intercept	-8.77*	0.32	-5.28	-11.04	-6.34
	[-1.85]	[0.09]	[-1.01]	[-1.63]	[-1.24]
VWICC	3.74	1.82	2.18	3.12	2.79
	[3.59]***	[2.15]**	[2.50]**	[2.74]***	[2.78]***
R-squared	0.102	0.048	0.058	0.069	0.073

This table reports results of value-weighted ICCs and the value-weighted market return premium. The value-weighted ICC premium (VWICC) - is the value-weighted ICC on the market portfolio of all sample stocks for 12 months minus the yields of the U.S. 10-year government bond. Value-weighted market return premium, $(R_M - R_F)$, is the value-weighted return on the market portfolio of a sample of stocks that also have ICC data in the period of 12 months minus U.S. 10-year government bond. I calculate the results for the period: July 1989-June 2014. Panel A shows correlations between (VWICC) and $(R_M - R_F)$. Panel B presents the results of the regression of $(R_M - R_F)$ on (VWICC). The numbers in brackets are t-statistics computed using the Newey-West correction with three lags of autocorrelations. *,**,*** indicate two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A of Table 3.2 shows that the correlation values are statistically significant for all ICC approaches even at the significance level of 0.01. The strongest correlation (0.32) is achieved using the CT approach, and the weakest one (0.22) is achieved with the GLS approach. These results suggest that the ICC is able to predict future returns over time, independent of the specific ICC approach.

Panel B of Table 3.2 presents the results of the regression of $R_M - R_F$ on VWICC adjusted by the Newey-West correction with three lags of autocorrelations. As discussed in Section 3.3, the slopes of $R_M - R_F$ on VWICC are higher than one. This result confirms the assumption that $R_M - R_F$ is more sensitive than VWICC with regard to price changes. Based on a significance level of 0.05, all ICC approaches have a positive and statistically significant relationship with expected returns since CT has a correlation of 0.32, GLS of 0.22, MPEG of 0.24, OJ of 0.26 and Composite of 0.27. Another important finding is that no intercepts (α) are significant. According to Fama and French (2015), if an asset pricing model completely captures expected returns, the intercept should be indistinguishable from zero in a regression of an asset's excess return on the model's factor returns. Therefore, this result is strong evidence of the ability of ICC to predict expected returns, as even the FF five-factor asset pricing model has significant intercepts. This result also confirms the evidence of Pástor et al. (2008) and Li et al. (2013) that the value-weighted ICC is a good proxy for time-varying expected returns. The highest R-squared is achieved using the CT approach (0.102), which also represents the strongest correlation for the entire period.

This study is one of the first to evaluate asset pricing models including ICC. Thus, it is useful to evaluate the ability of value-weighted ICC to predict future returns among portfolios with different characteristics. Thus, I split the sample into 25 value-weighted Size-ICC portfolios. In order to save space, I present only the results for the entire period based on the CT approach of ICC, because this method has the strongest correlation and the highest R-squared in the study period. The time-series regressions are based on equation 3.2:

$$R_{it} - R_{Ft} = a_i + i_i(WVICC_t) + e_{it}. \tag{3.2}$$

In this equation, R_{it} is the return on portfolio i for period t, R_{Ft} is the riskfree return, $WVICC_t$ is the return on the value-weighted ICC, e_{it} is a zero-mean residual and i_i is the slope of portfolio i on VWICC.

Table 3.3.: Regressions for 25 value-weighted Size-ICC portfolios

Panel A: Coefficients and t-values lag(3)					
ICC	Low	2	3	4	High
			Intercepts of the regressions (a)		
Small	-1.26	-3.53	-3.92	-1.50	-6.01
	[-0.23]	[-0.58]	[-0.83]	[-0.25]	[-1.07]
2	-5.42	-4.80	1.09	-9.80	-3.74
	[-1.32]	[-0.90]	[0.24]	[-2.40]**	[-0.71]
3	-8.20	-8.2	-5.63	-11.20	-6.33
	[-1.81]*	[-1.77]*	[-1.30]	[-3.36]***	[-1.22]
4	-2.57	2.06	-10.30	-4.87	-12.10
	[-0.55]	[0.44]	[-1.82]*	[-0.88]	[-1.94]*
Big	-2.32	1.67	0.92	-3.99	-7.13
	[-0.44]	[0.27]	[0.14]	[-0.64]	[-1.08]
			Coefficients of ICC (i)		
Small	2.80	3.00	2.50	1.76	2.40
	[2.20]**	[2.24]**	[2.21]**	[1.40]	[2.11]**
2	3.50	3.90	1.80	3.80	2.40
	[3.60]***	[3.24]***	[1.66]*	[3.98]***	[2.34]**
3	4.20	3.90	3.00	4.00	3.10
	[3.77]***	[3.45]***	[2.96]***	[4.79]***	[2.91]***
4	2.70	1.90	4.40	2.90	5.00
	[2.35]**	[1.75]*	[3.15]***	[2.18]**	[3.72]***
Big	3.50	2.23	2.70	2.80	3.10
	[2.79]***	[1.50]	[1.82]*	[1.89]*	[1.85]*

Panel B: R-squared values					
ICC	Low	2	3	4	High
Small	0.04	0.05	0.05	0.02	0.05
2	0.11	0.10	0.03	0.14	0.05
3	0.13	0.09	0.06	0.13	0.06
4	0.05	0.02	0.09	0.05	0.13
Big	0.06	0.02	0.02	0.03	0.04

This table reports results of regressions for 25 value-weighted Size-ICC portfolios on VWICC. At the end of June each year, stocks are allocated to five Size groups (Small to Big) using the breakpoints of (60%, 70%, 80% and 90%). Stocks are allocated independently to five ICC groups (Low B/M to High B/M), using the breakpoints (20%,40%,60% and 80%). The intersections of the two sorts produce 25 Size-ICC portfolios. The LHS variables in each set of 25 regressions are the 12 month-forward excess returns on the 25 Size-ICC portfolios. The RHS variable is the value-weighted ICC premium based on the CT approach. The value-weighted ICC premium (VWICC) - is the value-weighted ICC on the market portfolio of all sample stocks for a 12-month period minus U.S. 10-year government bond. Panel A shows the slopes and intercepts and the respective t-statistics with the Newey-West correction with three lags of autocorrelations. Panel B shows the R-squared. *,**,*** indicate two-tailed significance at the 10%, 5%, and 1% levels. The sample is from July 1989-June 2014 (300 months).

Panel A of Table 3.3 presents the coefficients and t-statistics of regressions of 25 value-weighted Size-ICC portfolios on VWICC, based on the CT approach. At a significance level of 0.05, only two of 25 portfolios have a significant intercept. The two portfolios with significant intercepts have a medium-high ICC, one of them is comprised of medium size companies and the other of medium-small companies. In addition, 18 of 25 portfolios have significant VWICC slopes. From the seven portfolios where the VWICC slopes are not significant, four are portfolios of big firms. This result shows that the weakness of VWICC in explaining stock returns may be for big firms, which is the opposite of the Fama and French five-factor model, where the main problem is its failure to capture the low realized returns on small stocks (Fama and French, 2015).

Panel B of Table 3.3 reports the R-squared of regressions of 25 value-weighted Size-ICC portfolios on VWICC. Concerning R-squared, the lowest value (0.018) is from the portfolio of medium-big size and medium-low ICC, and the highest value (0.136) is from the portfolio of medium-small size and medium-high ICC. In order to evaluate the significance of the intercepts of the 25 portfolios together, I estimate the GRS statistic of Gibbons et al. (1989). The results show that the intercepts are non-statistically significant since the GRS statistic is 1.636, the F-statistic is 18.057 and, therefore, the p-value is 0.00. In addition, the mean absolute intercept is 5.139, and the averaged R-squared is 0.645. These results show that even when I use the VWICC to explain returns in 25 value-weighted Size-ICC portfolios, I do not find significant intercepts, which is more evidence that VWICC has a strong power to predict expected returns. Given the results at the portfolio level, I go back to a firm-level analysis in order to evaluate not just ICC, but other risk proxies on expected returns.

3.4. Risk proxies analysis

My empirical tests evaluate the performance of risk proxies to explain average returns. Accordingly, I run regressions with an expected excess of returns on the combination of the following explanatory variables: $[LN(SZE)_{t-1}]$,

$[LN(B/M)_{t-7}]$, $[LN(1+OP)_{t-7}]$, $[LN(1+Inv)_{t-7}]$, and $[\beta_{t-1}]$ as well as the premium of the ICC approaches in time t-1: $[CT_{t-1}]$, $[Composite_{t-1}]$, $[GLS_{t-1}]$, $[MPEG_{t-1}]$ and $[OJ_{t-1}]$. The ICC premium is computed as the difference between ICC based on the different approaches and the yields of the U.S. 10-year government bond. In addition, I calculate the expected excess of returns, as realized returns forward-looking from the period t to period t+12, minus the yields of the U.S. 10-year government bond. I use a lag of seven months for the variables B/M, OP and Inv in order to ensure that the information is already public when I run the regression. The sample covers the period July 1989-June 2014, but due to the fact that the proxy of expected returns is calculated from time t to time t+12, the time sample of this proxy ends in June 2015.

In order to have a better understanding of the relationships between the explanatory variables, individually and together, and expected excess of returns, I estimate 16 different regression specifications. The first 10 specifications, which I call individual models, are composed of the individual risk proxies of the Fama and French (2015) five-factor model (β, SZE, B/M, OP, and Inv) - which I will now call five-risk-proxies - and four ICC approaches (CT, GLS, MPEG, and OJ) as well as a combination of all four approaches (Composite ICC). The specifications 11 to 15 consist of the five-risk-proxies composite with each of the ICC approaches. Specification 16 is comprised of only the five-risk-proxies. I call specifications 11 to 16 "joint models" because in these specifications I estimate multivariate regressions.

As I aim to evaluate the joint roles of explanatory variables to explain returns across firms, over time and both dimensions simultaneously, I run four different regression approaches: a cross-sectional regression of the Fama-Macbeth approach (see Table 3.4) to evaluate the relation between independent variables and expected returns across firms (cross-section); an orthogonal Fama-Macbeth approach (see Table 3.5) to evaluate the relation between variables and expected returns over time (time-series); a Fixed-effects estimation (see Table 3.6) to analyze the expected returns within (over-time) variation; and a POLS regression (see Table 3.7) to analyze this relation over both dimensions (firms and time).

3.4.1. The cross-section of expected returns

3.4.1.1. Regression details

I regress, each month, the cross-section of expected returns on stocks on explanatory variables. The time-series means of the monthly regression slopes then provide standard tests of whether different explanatory variables are priced on average (Fama and French, 1992). As I have autocorrelations in the time-series, I apply the Newey and West (1987) correction, to have robust standard errors. I explain that since this approach estimates a series of cross-sectional regressions, this regression aims to capture only the cross-sectional variation in expected returns, i.e., this approach is not able to capture time-series variations in expected returns.

3.4.1.2. Results

Table 3.4 shows the results of the cross-sectional regression approach of Fama-Macbeth. Similar to the results of Fama and French (1992) and Chan et al. (1991), Table 3.4 reports that book-to-market equity, B/M, presents positive and significant slopes. Accordingly, B/M helps to explain the cross-section of expected returns. The positive relation between B/M and expected returns persists in almost all specifications since the t-statistics range from 1.93 (specification 12) to 4.75 (specification 8).

In addition to B/M, the results show a negative and strong relation of size, SZE, on expected returns among all specifications. These results confirm the evidence of Fama and French (1992) and Banz (1981) about the size effect (small firms have higher average returns than big ones). The t-statistics range from 2.23 (specification 12) to 3.39 (specification 7).

Table 3.4.: Cross-sectional approach of Fama-Macbeth regression

	Regression Specifications									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Composite	0.31	-	-	-	-	-	-	-	-	-
	[1.46]	-	-	-	-	-	-	-	-	-
CT	-	0.22	-	-	-	-	-	-	-	-
	-	[1.33]	-	-	-	-	-	-	-	-
GLS	-	-	0.57	-	-	-	-	-	-	-
	-	-	[1.69]*	-	-	-	-	-	-	-
MPEG	-	-	-	0.14	-	-	-	-	-	-
	-	-	-	[0.98]	-	-	-	-	-	-
OJ	-	-	-	-	0.18	-	-	-	-	-
	-	-	-	-	[0.99]	-	-	-	-	-
Beta	-	-	-	-	-	3.39	-	-	-	-
	-	-	-	-	-	[2.50]**	-	-	-	-
LnSZE	-	-	-	-	-	-	-0.90	-	-	-
	-	-	-	-	-	-	[-3.39]***	-	-	-
LnB/M	-	-	-	-	-	-	-	4.55	-	-
	-	-	-	-	-	-	-	[4.75]***	-	-
Ln(1+OP)	-	-	-	-	-	-	-	-	-1.38	-
	-	-	-	-	-	-	-	-	[-1.31]	-
Ln(1+Inv)	-	-	-	-	-	-	-	-	-	-3.20
	-	-	-	-	-	-	-	-	-	[-3.19]***
R-squared	0.011	0.008	0.016	0.011	0.011	0.009	0.005	0.014	0.002	0.003

Table 3.4.: Cross-sectional approach of Fama-Macbeth regression (Continued)

	Regression Specifications					
	S11	S12	S13	S14	S15	S16
Composite	-0.01	-	-	-	-	-
	[-0.07]	-	-	-	-	-
CT	-	0.03	-	-	-	-
	-	[0.27]	-	-	-	-
GLS	-	-	-0.04	-	-	-
	-	-	[-0.17]	-	-	-
MPEG	-	-	-	0.03	-	-
	-	-	-	[0.33]	-	-
OJ	-	-	-	-	0.03	-
	-	-	-	-	[0.28]	-
Beta	3.76	3.62	3.65	3.23	3.34	3.8
	[1.88]*	[1.84]*	[1.84]*	[1.82]*	[1.86]*	[2.06]**
LnSZE	-0.96	-0.89	-0.99	-0.80	-0.81	-1.57
	[-2.25]**	[-2.23]**	[-2.24]**	[-2.25]**	[-2.29]**	[-3.42]***
LnB/M	2.36	2.30	2.34	2.46	2.65	2.94
	[2.13]**	[1.93]*	[2.39]**	[2.00]**	[2.10]**	[3.07]***
Ln(1+OP)	8.12	8.46	8.23	10.94	12.1	6.26
	[3.71]***	[3.76]***	[3.80]***	[4.30]***	[4.63]***	[3.34]***
Ln(1+Inv)	-7.75	-7.34	-7.61	-6.21	-5.87	-5.01
	[-4.77]***	[-4.86]***	[-4.68]***	[-4.43]***	[-4.13]***	[-5.31]***
RÂš	0.059	0.057	0.060	0.055	0.055	0.042

This table presents the time-series average of slope coefficients from cross-sectional FM regressions of annual excess of returns on: $[LN(SZE)_{t-1}]$, $[LN(B/M)_{t-7}]$, $[LN(1+OP)_{t-7}]$, $[LN(1+Inv)_{t-7}]$, β_{t-1} and ICC_{t-1}, estimated in period July 1989-June 2014 (300 months). Annual excess of returns is 12 months realized returns, from the period t to period t+12, minus U.S. 10-year government bond. Operating Profitability, (OP), is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus depreciation, minus other operating expenses minus interest expense all divided by book equity. Investment, (Inv), is the change in total assets from the fiscal year in $t-1$ to the fiscal year in t, divided by the fiscal year in $t-1$ total assets. Book-to-market, (B/M), is book equity, which I define as common equity plus deferred taxes, if available, divided by market cap. βs are estimated on 24 to 60 monthly returns (as available) in the 5 years before the month t. Size, (SZE), is market cap. ICC is the differences between implied costs of capital by five different approaches (CT, Composite, GLS, MPEG, and OJ) and the yields of the U.S. 10-year government bond. I estimate the t-statistics with the Newey and West correction with 12 lags of autocorrelations and the averaged R-squared. I estimate various regression specifications (S1 to S16) using different combinations of these independent variables, with each column representing a different specification. *,**,*** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

Concerning β, unlike Fama and French (1992), who do not find statistically significant slopes for β in the cross-section of expected returns, I find positive and significant slopes, at a significance level of 0.10, among all specifications. In particular, in specifications 6 and 16, I find significant slopes even at a significance level of 0.05. These results may be different because I use different sample periods, whereas Fama and French (1992) used the period 1963-1990; the methodology for calculating βs is different since Fama and French estimate

βs for 100 size-β portfolios and then assign a portfolio's β to each stock in the portfolio; and the proxies for expected returns are different, since I use annual returns, while Fama and French (1992) use monthly returns.

Concerning the new proxies of the Fama and French five-factor model, the results confirm the assumptions of Fama and French (2006) about the negative impact of investments on returns. However, I find mixed results with regard to the positive impact of operating profitability on returns. When I evaluate OP among other risk proxies, even with the inclusion of ICC, I find a t-statistic approximately twice as high for OP as for B/M, similar to the results of Novy-Marx (2013). However, when I analyze the individual relation of OP to expected returns, I find insignificant t-statistics. Therefore, OP seems to significantly explain expected returns only when I include other control variables.

For ICC, at the significance level of 0.10, I find a positive relation between the GLS approach (individually) and expected returns. However, when I evaluate the ICC approaches together with the five-risk-proxies (specifications 11 to 16), I do not find statistically significant slopes. Accordingly, ICC does not seem to have a strong relation with a cross-section of expected returns on its own and, even if I find this relation, ICC becomes redundant when I include other variables. This is significant evidence that, at the firm level, ICC has no power to predict cross-sectional returns, confirming Easton and Monahan (2005). However, the results do not confirm the findings of Kang and Sadka (2015) that ICC has a negative cross-sectional relation with expected returns because stocks with a high level of ICC are systematically related to overly optimistic earnings forecasts.

3.4.2. Time-series of expected returns

3.4.2.1. Regression details

The most common approach of the Fama-Macbeth regression is the cross-sectional one (see Fama and Macbeth (1973)). However, I have modified the Fama-Macbeth regression in order to evaluate whether the different explanatory variables are priced over time. I call this modification an orthogonal Fama-Macbeth approach. I present the results in Table 3.5. In this regression, for each stock, the time-series of returns are regressed on explanatory variables. Then, I provide standard tests based on the cross-sectional means of the regression slopes. In order to eliminate outliers, I restrict the sample to firms with complete data for at least 24 sample periods, and I winsorize each slope and intercept in the 1st and 99th percentiles. Due to the fact that annual returns and most of the anomaly variables are highly serially correlated, the t-statistics can be boosted and should be interpreted with caution. In order to offer a robust approach to estimate the t-statistics, in Section 3.4.3 I report the results based on a Fixed-effect estimation with standard errors clustered by months.

3.4.2.2. Results

Table 3.5 reports that all ICC approaches are positively significant, with t-statistics from 42.81(MPEG) to 62.66 (GLS) for the individual models, and with t-statistics from 14.55 (MPEG) to 20.94 (GLS) for the specifications, including the five-risk-proxies. Importantly, the R-squared of the GLS individual model (specification 3) is 0.145, which is higher than the other ICC approaches. In addition, I have an R-squared of 0.527 when I include the GLS approach among the five-risk-proxies (specification 13), which is higher than the model without ICC (specification 16), where the R-squared is 0.48. These results represent more evidence about the ability of ICC to predict expected returns over time, even at the firm level. Thus, based on the poor results of

ICC across firms (cross-section) and on the strong results of ICC predicting returns over time (time-series), ICC should not be used, for instance, to decide whether firm A should be bought instead of firm B, but when to buy firm A or firm B. Strong evidence of this relationship over time is confirmed by the correlation analysis, by the analysis of the value-weighted ICC and by the time-series approach of FM regression.

With regard to the five-risk-proxies, market βs over time have a negative relation with expected returns in all specifications, which is unlike the assumptions of the SLB asset pricing that implies that expected returns on securities are a positive linear function of their market βs (the slope in the regression of a firm's return on the market's return). Thus, based on these results, the investors could bet against β over time in order to have higher expected returns. For example, when a firm is analyzed over time, the investors should buy stocks when the β of the company is lower (compared to the firm's beta history), and sell when it is higher.

As in the cross-sectional results, size (SZE) shows a strong and negative relation with returns over time. The SZE slopes have t-statistics ranging from -76.03 (specification 15) to -113.37 (specification 16) standard deviations from zero, in the joint models (specifications 11 to 16), and t-statistic of -155.71 (specification 7) standard deviations from zero, when I use size alone. Moreover, book-to-market equity (B/M) reports a positive and statistically significant relation with return over time among all specifications, which is evidence that the value effect is also strong over time, i.e., investors should buy a company when it has a high B/M and sell when it has a lower B/M. Another variable that has a similar relation to expected returns across firms and over time is investments since this risk proxy has a strong relationship with returns alone and in the joint models. The individual model has a t-statistic of -23.54 and the joint models present a range of t-statistics between -3.30 (specification 16) and -4.01 (specification 13).

Table 3.5.: Time-series approach of Fama-Macbeth regression

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Composite	3.47	-	-	-	-	-	-	-	-	-
	[50.85]***									
CT	-	3.11	-	-	-	-	-	-	-	-
		[44.14]***								
GLS	-	-	5.49	-	-	-	-	-	-	-
			[62.66]***							
MPEG	-	-	-	2.15	-	-	-	-	-	-
				[42.81]***						
OJ	-	-	-	-	2.93	-	-	-	-	-
					[44.00]***					
Beta	-	-	-	-	-	-1.07	-	-	-	-
						[-3.94]***				
LnSZE	-	-	-	-	-	-	-34.44	-	-	-
							[-155.71]***			
LnB/M	-	-	-	-	-	-	-	20.06	-	-
								[61.23]***		
Ln(1+OP)	-	-	-	-	-	-	-	-	-26.37	-
									[-10.15]***	
Ln(1+Inv.)	-	-	-	-	-	-	-	-	-	-28.25
										[-23.54]***
R-Squared	0.113	0.110	0.145	0.097	0.102	0.113	0.237	0.119	0.122	0.118

Table 3.5.: Time-series approach of Fama-Macbeth regression (Continued)

	S11	S12	S13	S14	S15	S16
Composite	1.20	-	-	-	-	-
	[20.66]***	-	-	-	-	-
CT	-	1.24	-	-	-	-
	-	[20.09]***	-	-	-	-
GLS	-	-	1.89	-	-	-
	-	-	[20.94]***	-	-	-
MPEG	-	-	-	0.59	-	-
	-	-	-	[14.55]***	-	-
OJ	-	-	-	-	0.84	-
	-	-	-	-	[15.25]***	-
Beta	-4.45	-4.83	-4.86	-3.88	-4.13	-4.59
	[-6.13]***	[-6.52]***	[-6.71]***	[-5.05]***	[-5.42]***	[-7.14]***
LnSZE	-48.40	-46.94	-48.18	-45.85	-45.93	-50.71
	[-83.22]***	[-80.37]***	[-77.66]***	[-76.18]***	[-76.03]***	[-113.37]***
LnB/M	5.98	6.65	5.20	7.95	7.84	6.66
	[13.28]***	[14.37]***	[11.67]***	[16.21]***	[16.06]***	[18.53]***
Ln(1+OP)	14.14	7.93	10.61	15.60	14.40	20.32
	[2.46]**	[1.32]	[1.88]*	[2.43]**	[2.22]**	[4.19]***
Ln(1+Inv.)	-8.74	-7.88	-8.15	-9.02	-8.70	-7.36
	[-3.99]***	[-3.67]***	[-3.78]***	[-4.01]***	[-3.84]***	[-3.30]***
R-Squared	0.520	0.521	0.527	0.509	0.511	0.480

This table presents the cross-sectional average of slope coefficients from time-series FM regressions of annual excess of returns on:$[LN(SZE)_{t-1}]$, $[LN(B/M)_{t-7}]$, $[LN(1+OP)_{t-7}]$, $[LN(1+Inv)_{t-7}]$, β_{t-1} and ICC_{t-1}, estimated in period July 1989-June 2014 (300 months). Annual excess of returns is 12 months realized returns, from the period t to period $t+12$, minus U.S. 10-year government bond. Operating Profitability, (OP), is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus depreciation, minus other operating expenses minus interest expense all divided by book equity. Investment, (Inv), is the change in total assets from the fiscal year in year $t-1$ to the fiscal year in t, divided by the fiscal year in $t-1$ total assets. Book-to-market, (B/M), is book equity, which I define as common equity plus deferred taxes, if available, divided by market cap. βs are estimated on 24 to 60 monthly returns (as available) in the 5 years before the month t. Size, (SZE), is market cap. ICC is the differences between implied costs of capital by five different approaches (CT, Composite, GLS, MPEG, and OJ) and the yields of the U.S. 10-year government bond. I estimate the t-statistics with the Newey and West correction with 12 lags of autocorrelations and the averaged R-squared. I estimate various regression specifications (S1 to S16) using different combinations of these independent variables, with each column representing a different specification. *,**,*** indicate two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively. To avoid results driven by outliers, I restrict the sample into firms with complete data for at least 24 sample periods, and I winsorize each slope and intercept in the 1st and 99th percentiles.

In contrast to the consistent explanatory power of SZE, B/M, and Investments, across firms and over time, the time-series FM regression approach reports that Operating Profitability yields mixed results at explaining expected returns over time in the period 1989-2014. The model based on OP alone (specification 9) presents a very significant and negative relation with expected returns, reporting a t-statistic of -10.15. On the other hand, when I analyze OP among the five-risk-proxies (specification 16), where this proxy has a t-statistic of 4.19, it is possible to see a positive relation to expected returns. Finally, when I include ICC in the joint models, the t-statistics are from 1.46 (specification 12) to 2.46 (specification 11).

3.4.3. Within variation of expected returns

3.4.3.1. Regression details

Due to the fact that an orthogonal Fama-Macbeth approach is a novel model, I also estimate the results based on a Fixed-effect estimation with standard errors clustered by months in order to double-check and to compare the results over time. The fixed-effects estimation is estimated based on equation 3.3:

$$\begin{aligned}(Exp_{i,t} - \overline{Exp_{(i)}}) = \beta_1(X_{i,t1} - \overline{X_{(i1)}}) + \cdots + \beta_k(X_{i,t,k} - \overline{X_{(i,k)}}) \\ +(u_{i,t} - \overline{u_{(i)}}) + (a_{i,t} - \overline{a_{(i)}}),\end{aligned} \tag{3.3}$$

where $(Exp_{i,t} - \overline{Exp_{(i)}})$ is the expected return of firm i at time t minus the average expected return of firm i; $(X_{i,t,k} - \overline{X_{(i,k)}})$ is the variable k of firm i at time t minus the average of variable k of firm i; β_k is the slope of the variable k; $(u_{i,t} - \overline{u_{(i)}})$ is the time-demeaning idiosyncratic error; $(a_{i,t} - \overline{a_{(i)}})$ are the unobserved effects (fixed-effects) that are eliminated through the fixed-effect estimation; k represents the explanatory variables; and, finally, t is the time period, which goes from time=1 until time=300.

Thus, the Fixed-effects approach estimates the relation between risk proxies and expected returns over time, because this approach uses the time variation in the dependent variable as well as in the explanatory variables within each cross-sectional observation. The benefit of this approach is the elimination of the unobserved effect a_i, i.e., the constant or "fixed effects" across firms that cannot be directly measured or observed (such as industry sector, location, competitive advantages and etcetera). Therefore, this approach permits one to estimate the impact of the explanatory variables on expected returns within firms (over time) without the heterogeneity bias. Moreover, I eliminate the serial correlation bias clustering the standard errors by months. Accordingly, I estimate unbiased standard errors even when the data present heterogeneity or an auto-correlation of the residuals.

3.4.3.2. Results

Table 3.6 shows that based on the joint models (specifications 11 to 16), each ICC approach together with other risk proxies becomes positively significant. In addition, the results of the individual models also confirm that ICC is able to explain expected returns. It should be noted that the model without ICC, presented in specification 16, presents a centered R-squared of 0.108 while the model including GLS (specification 13) reports a centered R-squared of 0.117. These results are evidence that although ICC does not have a significant relation with risk cross-sectionally, the impact of ICC on expected returns is positively significant over time. Concerning the other risk proxies, B/M is also positively significant, and SZE is negatively significant, as reported by Fama and French (1992), and Inv is negatively significant, confirming the findings of Aharoni et al. (2013).

These results confirm the evidence of an orthogonal Fama-Macbeth approach that market βs present a negative relationship with expected returns. The results are similar to the joint models as well as for the model with market β alone to explain expected returns. Moreover, like in an orthogonal Fama-Macbeth approach, OP has a negative relationship with returns in the individual model. However, OP has a positive and stronger relationship with expected returns in the joint models, compared to an orthogonal Fama-Macbeth approach, since the t-statistics are from 4.63 (specification 13) to 16.11 (specification 16).

Thus, the two approaches of time-series of expected returns (Fixed-effects estimation and an orthogonal Fama-Macbeth approach) have similar results, since except for the t-statistics of OP in the joint models, all other variables have very similar inferences.

Table 3.6.: Fixed-effect estimation with standard errors clustered by month

	Regression Specifications									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Composite	2.55	-	-	-	-	-	-	-	-	-
	[10.37]***	-	-	-	-	-	-	-	-	-
CT	-	1.98	-	-	-	-	-	-	-	-
	-	[9.92]***	-	-	-	-	-	-	-	-
GLS	-	-	4.12	-	-	-	-	-	-	-
	-	-	[10.65]***	-	-	-	-	-	-	-
MPEG	-	-	-	1.64	-	-	-	-	-	-
	-	-	-	[12.74]***	-	-	-	-	-	-
OJ	-	-	-	-	2.19	-	-	-	-	-
	-	-	-	-	[12.72]***	-	-	-	-	-
Beta	-	-	-	-	-	-0.88	-	-	-	-
	-	-	-	-	-	[-2.83]***	-	-	-	-
LnSZE	-	-	-	-	-	-	-14.50	-	-	-
	-	-	-	-	-	-	[-38.79]***	-	-	-
LnB/M	-	-	-	-	-	-	-	13.73	-	-
	-	-	-	-	-	-	-	[20.28]***	-	-
Ln(1+OP)	-	-	-	-	-	-	-	-	-2.14	-
	-	-	-	-	-	-	-	-	[-3.74]***	-
Ln(1+Inv)	-	-	-	-	-	-	-	-	-	-7.76
	-	-	-	-	-	-	-	-	-	[-13.67]***
R-squared	0.024	0.019	0.039	0.021	0.022	0.000	0.064	0.019	0.000	0.005
Num of Obs.	843,218	800,572	833,204	720,369	729,140	4,878,977	4,798,699	1,489,065	1,627,813	1,673,333

Table 3.6.: Fixed-effect estimation with standard errors clustered by month (Continued)

	S11	S12	S13	S14	S15	S16
Composite	1.78	-	-	-	-	-
	[8.25]***	-	-	-	-	-
CT	-	1.37	-	-	-	-
	-	[8.20]***	-	-	-	-
GLS	-	-	3.03	-	-	-
	-	-	[8.12]***	-	-	-
MPEG	-	-	-	1.10	-	-
	-	-	-	[9.56]***	-	-
OJ	-	-	-	-	1.49	-
	-	-	-	-	[9.75]***	-
Beta	-2.55	-2.43	-2.59	-2.44	-2.28	-2.82
	[-3.18]***	[-2.97]***	[-3.28]***	[-2.99]***	[-2.80]***	[-3.46]***
LnSZE	-19.25	-18.47	-19.40	-16.78	-16.76	-24.02
	[-15.69]***	[-15.94]***	[-16.56]***	[-15.56]***	[-15.55]***	[-20.27]***
LnB/M	5.58	6.58	2.68	7.74	8.25	6.51
	[4.94]***	[6.02]***	[2.07]**	[7.36]***	[7.78]***	[7.79]***
Ln(1+OP)	7.40	7.78	5.93	16.94	17.44	8.44
	[4.23]***	[4.49]***	[3.32]***	[8.78]***	[8.98]***	[8.56]***
Ln(1+Inv)	-13.88	-14.42	-9.53	-11.33	-12.04	-6.46
	[-8.87]***	[-9.21]***	[-7.27]***	[-8.22]***	[-8.42]***	[-6.40]***
R-Squared	0.110	0.104	0.117	0.099	0.101	0.108
Num of Obs.	733,712	707,993	732,991	633,978	642,350	1,217,053

This table presents the results of Fixed-effect (within) estimation of annual excess of returns on: $[LN(SZE)_{t-1}]$, $[LN(B/M)_{t-7}]$, $[LN(1+OP)_{t-7}]$, $[LN(1+Inv)_{t-7}]$, β_{t-1} and ICC_{t-1}, estimated in period July 1989-June 2014 (300 months). Annual excess of returns is 12 months realized returns, from the period t to period t+12, minus U.S. 10-year government bond. Operating Profitability, (OP), is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus depreciation, minus other operating expenses minus interest expense all divided by book equity. Investment, (Inv), is the change in total assets from the fiscal year in $t-1$ to the fiscal year in t, divided by the fiscal year in $t-1$ total assets. Book-to-market, (B/M), is book equity, which I define as common equity plus deferred taxes, if available, divided by market cap. βs are estimated on 24 to 60 monthly returns (as available) in the 5 years before the month t. Size, (SZE), is market cap. ICC is the differences between implied costs of capital by five different approaches (CT, Composite, GLS, MPEG, and OJ) and the yields of the U.S. 10-year government bond. I estimate the t-statistics with the Newey and West correction with 12 lags of autocorrelations and the averaged R-squared. I estimate various regression specifications (S1 to S16) using different combinations of these independent variables, with each column representing a different specification. *,**,*** indicate two-tailed significance at the 0.10, 0.05, and 0.01 levels, respectively.

3.4.4. Risk proxies on returns across firms and over time together

3.4.4.1. Regression details

In order to provide evidence of whether different explanatory variables simultaneously are priced over time and over firms, I propose a third analysis based on a POLS estimation with standard errors clustered by firms and months, as reported in Table 3.7. This approach was unusual in the past because the firm fixed-effects (the firms' characteristics that do not change over time) implicates in biased standard errors. However, by clustering standard errors by firm and months, as proposed by Thompson (2011) and Petersen (2009), the standard errors are unbiased even if the residuals are correlated over time, across firms or over both. The advantage of this approach is to examine simultaneously the time dimension as well as the firm dimension. Thus, it is possible to have a further overview of the impact of explanatory variables on expected returns after the estimation of the cross-sectional as well as the time-series of expected returns.

3.4.4.2. Results

Table 3.7 shows that ICC is related to expected returns, either ICC is the only explanatory variable (specifications 1 to 5), or it is included in the joint models (specifications 11 to 16). These results can confirm my previous results, since I do not find a significant relation between ICC and expected returns cross-sectionally, but I find a strong relation over time. Thus, when I analyze the results in both dimensions at the same time, I could expect a significant impact of ICC on returns.

Although the market βs present a negative relation with returns over time, in the POLS (like in the cross-sectional model), I find a positive relation between market βs and returns. As I mentioned, the POLS model is not able to determine the relative contribution of β (or any other anomaly) in each dimension of expected return. However, I argue that the cross-sectional dimension can drive the results since the panel is cross-sectional dominant (31,872 firms and 300 time periods).

Table 3.7.: Pooled OLS estimation with standard errors clustered by firms and months

	Regression Specifications									
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Composite	1.06 [5.11]***	-	-	-	-	-	-	-	-	-
CT	-	0.78 [4.60]***	-	-	-	-	-	-	-	-
GLS	-	-	1.70 [5.49]***	-	-	-	-	-	-	-
MPEG	-	-	-	0.55 [4.58]***	-	-	-	-	-	-
OJ	-	-	-	-	0.69 [4.55]***	-	-	-	-	-
Beta	-	-	-	-	-	2.31 [3.96]***	-	-	-	-
LnSZE	-	-	-	-	-	-	-1.00 [-9.64]***	-	-	-
LnB/M	-	-	-	-	-	-	-	6.30 [14.39]***	-	-
Ln(1+OP)	-	-	-	-	-	-	-	-	-1.59 [-2.92]***	-
Ln(1+Inv)	-	-	-	-	-	-	-	-	-	-5.64 [-11.13]***
R-squared Centered	0.006	0.004	0.011	0.003	0.003	0.001	0.002	0.009	0.000	0.003

Table 3.7.: Pooled OLS estimation with standard errors clustered by firms and months (Continued)

Regression Specifications

	S11	S12	S13	S14	S15	S16
Composite	0.90	-	-	-	-	-
	[4.30]***	-	-	-	-	-
CT	-	0.70	-	-	-	-
	-	[4.32]***	-	-	-	-
GLS	-	-	1.44	-	-	-
	-	-	[4.08]***	-	-	-
MPEG	-	-	-	0.53	-	-
	-	-	-	[4.56]***	-	-
OJ	-	-	-	-	0.68	-
	-	-	-	-	[4.56]***	-
Beta	1.99	1.85	1.87	1.13	1.22	2.73
	[2.52]**	[2.41]**	[2.46]**	[1.69]*	[1.80]*	[3.48]***
LnSZE	-1.06	-0.99	-1.03	-0.81	-0.77	-2.03
	[-4.14]***	[-4.05]***	[-4.02]***	[-3.27]***	[-3.14]***	[-7.43]***
LnB/M	3.03	3.43	1.47	3.92	4.08	4.8
	[4.35***	[5.15]***	[1.64]	[5.88]***	[6.09]***	[9.67]***
Ln(1+OP)	9.3	10.09	8.4	15.58	15.92	8.69
	[5.27]***	[5.98]***	[4.60]***	[8.05]***	[8.25]***	[8.49]***
Ln(1+Inv)	-15.48	-14.82	-13.74	-11.8	-12.12	-9.35
	[-8.77]***	[-9.00]***	[-9.28]***	[-8.50]***	[-8.29]***	[-10.79]***
R-squared Cent.	0.017	0.015	0.019	0.013	0.014	0.015

This table presents the results of a POLS regression of annual excess of returns on: $[LN(SZE)_{t-1}]$, $[LN(B/M)_{t-7}]$, $[LN(1+OP)_{t-7}]$, $[LN(1+Inv)_{t-7}]$, β_{t-1} and ICC_{t-1}, estimated in period July 1989-June 2014 (300 months). Annual excess of returns is 12 months realized returns, from the period t to period t+12, minus U.S. 10-year government bond. Operating Profitability, (OP), is revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus depreciation, minus other operating expenses minus interest expense all divided by book equity Investment, (Inv), is the change in total assets from the fiscal year in $t-1$ to the fiscal year in t, divided by the fiscal year in $t-1$ total assets. Book-to-market, (B/M), is book equity, which I define as common equity plus deferred taxes, if available, divided by market cap. βs are estimated on 24 to 60 monthly returns (as available) in the 5 years before the month t. Size, (SZE), is market cap. ICC is the differences between implied costs of capital by five different approaches (CT, Composite, GLS, MPEG, and OJ) and the yields of the U.S. 10-year government bond. I estimate the t-statistics with standard errors clustered by firms and months and the centered R-squared. I estimate various regression specifications (S1 to S16) using different combinations of these independent variables, with each column representing a different specification. *,**,*** indicate two-tailed significance at the 10%, 5%, and 1% levels, respectively.

Concerning OP, the relation of this variable and return in the individual model is negative. This result also confirms the previous results, since the OP presented a highly negative impact of return over time and nonsignificant impact cross-sectionally. Moreover, in the joint models, the relation between OP and expected returns becomes positive, like in the Fixed-effects estimation as well as in the cross-sectional approach of Fama-Macbeth.

The proxy for value, B/M, has a positive relation with returns in both dimensions in the individual model (specification 9) and the joint models, except the joint model that includes the five-risk-proxies and the GLS approach of ICC (specification 13). I believe that the collinearity can drive this result since the correlation between B/M and GLS is 0.408, which is highly significant. Another explanation could be that B/M becomes redundant when I include the GLS approach as an explanatory variable in the POLS. It should be noted that although all ICC models presented the same inferences about significance in all models analyzed, the specification that includes the GLS approach had the highest R-squared in all dimensions analyzed. Finally, with regard to the other risk proxies, the POLS can confirm the previous results. The risk proxies Inv (specifications 10 to 16) and SZE (specification 7 and specifications 11 to 16) present negative and significant coefficients in the univariate as well as in all of the multivariate regressions.

3.5. Conclusion

The most important asset pricing papers are based on cross-section results of risk proxies on average return. I understand the importance of this approach, but I point out that it is also useful to understand the relation of risk proxies over time as well as over both dimensions (across firms and over time) together on expected return. Thus, this paper examines the joint roles of market βs, B/M, size, operating profitability, investments and ICC to explain returns across firms, over time and both dimensions at the same time.

In order to evaluate the relation between returns and other risk proxies over time and at the firm level, I develop an orthogonal (time-series) Fama-Macbeth regression, where I run time-series regressions for each firm and estimate the average coefficients and the respective t-statistics. In addition, I perform Fixed-effect regressions with standard errors clustered by month as a robustness check. I run a cross-sectional regression approach of Fama and Macbeth (1973), in order to evaluate the results across firms, and a POLS with standard errors clustered by month and firms, to analyze the results over both dimensions (across firms and over time) at the same time. Furthermore, I evaluate this relation at the aggregate level as well as at the portfolio level based on sorts of size and book-to-market.

Based on these analyses, I find that ICC is able to predict stock returns over time and over both dimensions (across firms and over time) together, but not across firms, since none of the ICC approaches presented significant slopes in explaining cross-sectional returns. The results are robust in univariate regressions of returns on ICC as well as when ICC is tested among other risk proxies. These results support the use of ICC as a proxy of expected returns in time-varying tests, such as Pástor et al. (2008). However, the fact that the correlation between ICC and returns is weak in the cross-sectional dimension is evidence against the use of ICC as such a proxy in tests across firms.

Another impressive result is that over time, βs have a negative and highly significant relation with expected returns. In other words, when the beta of a certain company is high, the company will likely have negative or lower returns. This result ties in with the betting-against-beta hypothesis from Frazzini and Pedersen (2014). According to the authors, the constraints in the leverage that institutional investors can take may force these investors to overweight securities with high βs. Thus, risky high-beta assets may require lower risk-adjusted returns than low-beta assets. My evidence is that this pattern can be seen not only in cross-sectional tests but also time-varying tests.

For further studies, I suggest evaluating the predictability power of ICC at the firm level in other countries. In addition, given the promising results of ICC at predicting the market risk premium at the aggregate level, and evidence of Fama and French (1989) that the market risk premium is related to the business cycle, it is important to analyze whether the ICC is also able to predict the business cycle. If so, the ICC could be tested in a conditional asset pricing model that requires a proxy for the future business cycle. Finally, it is relevant to investigate whether the weak correlation between future returns and ICC cross-sectionally is due to the underlying assumptions of the ICC valuation models or due to the imprecise analysts' earnings forecasts. This latter issue, I am going to discuss in the next section.

4. The impact of analysts' inaccuracy on proxies for expected returns

The implied cost of capital (ICC) is widely used as a proxy for expected returns. However, an important unsolved puzzle is whether future returns and ICC are weakly correlated due to the underlying assumptions of the valuation models or the inaccuracy of analysts' earnings forecasts. This paper contributes to this puzzle by evaluating the effect of analysts' earnings forecast errors on ICC estimates. To this end, I compare ICC estimated with analysts' forecasts ($ICC_{I/B/E/S}$) to $ICC_{Perfect\,Foresight}$ estimated with ex-post realized earnings. I find that analysts' forecast inaccuracy causes an error of up to 5.21 percentage points in the ICC estimation. Moreover, the results show that $ICC_{Perfect\,Foresight}$ has a strong relation to realized returns, indicating that analysts' forecast errors are the main cause for the low correlation between ICC and realized returns. Finally, I propose a fitted ICC which displays a higher correlation to ex-post realized returns. Long-short strategies based on this fitted ICC generate significant risk-adjusted returns of up to 1 percent a month.

4.1. Introduction

The precise estimation of a firm's expected return (cost of capital) plays a central role in the capital market. Proxies for expected returns are widely used for firm valuation, portfolio selection, performance evaluation, capital budgeting, as well as for analyzing the relation between a firm's characteristics and its expected returns.

In order to analyze the relationship between risk factors and returns, many empirical asset pricing studies use ex-post realized returns as a proxy for the expected return (e.g., Fama and French (2015); Novy-Marx (2013); Fama and French (1992)). However, the extant literature has argued against using realized returns as such a proxy. For example, Elton (1999) shows that there have been periods longer than ten years in the United States during which there was a negative market risk premium,[1] which is economically counter-intuitive. In addition, Lundblad (2007) reports that when realized returns are used as a proxy for expected returns, a very long sample period is needed to detect a positive risk-return relation in simulations. Fama and French (1997) also show that ex-post realized returns are a poor proxy for expected returns at the industry or firm level. The weaknesses of ex-post realized returns include the difficulty of finding a suitable asset-pricing model and imprecise estimates of loadings on the risk factors as well as on the factor risk premia. Finally, Lee et al. (2009) report that due to a large amount of statistical noise in realized returns, financial researchers who test asset pricing models face the risk that, during the time period under analysis, economically significant relations can be rendered statistically insignificant.

Due to the shortcomings of realized returns as a proxy for expected returns in certain settings, many studies have been using the implied cost of capital (ICC) as a proxy for expected returns to analyze the relation between expected returns and firms' characteristics (e.g., Easton and Monahan (2005); Hail and Leuz (2006); Hou et al. (2012); Frank and Shen (2016)). The ICC is estimated as the internal rate of return that equates a firm's stock prices to the discounted expected cash flows. Among the advantages of ICC is that it does not rely on noisy realized returns and can be estimated with forward-

[1] In the period of 1973-1984, stock market realized returns were on average less than the risk-free rate

looking ex-ante information.

When ICC is used as a proxy for expected returns in time-series settings, the results are promising. Pástor et al. (2008) find that "ICC should be a good proxy for the conditional expected stock returns."[2] Frank and Shen (2016), when analyzing the relation between cost of capital and corporate investment, conclude that the ICC is superior to other proxies for the cost of capital to reflect the time-varying required return on capital. Li et al. (2013) find that the ICC at the aggregate level predicts future excess market returns at horizons ranging from one month to four years, both in-sample and out-of-sample. Finally, Azevedo (2016) shows that the ICC also has a strong predictability power at the firm level.

However, the evidence of the cross-sectional relation between the ICC and ex-post realized returns is weak. Easton and Monahan (2005) find that the ICC estimates have little ability to explain realized returns after controlling for cash flow news and discount rate news. Guay et al. (2011) also reports the weak correlation between ICC and ex-post returns. The authors, using a Fama and Macbeth (1973) (FM) regression with one-year-ahead stock returns on different estimates of ICC, find that the coefficients across 22 years of sample are not statistically different from zero, neither in regressions at the firm-level nor at the industry-level.

The reason for the low correlation between ICC and realized returns is still unclear. A potential explanation may be that the underlying assumptions of the ICC valuation models are not adequate to infer the risk premium. Alternatively, the analysts' forecasts may contain errors that drive these results since their forecasts are the main inputs for the ICC models. In particular, when I focus on analysts' forecasts, the literature lacks a measure of the impact of analysts' errors, neither on estimates of the cost of capital nor on future returns.

In this paper, I evaluate the impact of earnings forecasts (in)accuracy on proxies for expected returns. To do that, I compare ICC estimated with two

[2] Pástor et al. (2008, pp. 2861)

different inputs: ($ICC_{I/B/E/S}$), estimated with analysts' forecasts from Institutional Brokers' Estimate System (I/B/E/S) and the $ICC_{Perfect\,Foresight}$, estimated with ex-post realized earnings.

I start the analysis at the portfolio level by evaluating the impact of earnings inaccuracy on ICC estimates. In order to ensure that the results are not driven by different estimates of growth, I propose an adjustment in the model of Easton et al. (2002). Accordingly, it is possible to estimate the ICC error and growth error simultaneously. I find that ICC absolute error, which is measured as the absolute difference of ($ICC_{I/B/E/S}$) and the $ICC_{Perfect\,Foresight}$, is 5.21% in an equal-weighted setting and 1.81% in a value-weighted one.

As a next step, I evaluate the error of ICC estimates at the firm level by implementing four commonly used ICC approaches. The first two methods are based on a residual income model, namely Gebhardt et al. (2001) (GLS) and Claus and Thomas (2001) (CT).[3] The other two methods are based on an abnormal earnings growth model, namely Ohlson and Juettner-Nauroth (2005) (OJ) and Easton (2004) (modified price-earnings growth or MPEG). In addition to these four ICC approaches, I compute a composite ICC, which is the average of the four aforementioned approaches. I find that the estimates based on the abnormal earnings growth model have a much higher ICC absolute error. While the OJ and MPEG report 4.94% and 4.89%, respectively, the GLS and CT report 1.88% and 3.17%. The composite ICC shows a mean absolute error of 4.13%.

In order to determine whether the ICC inaccuracy is related to firms' characteristics, I run FM regressions of ICC absolute error on a number of firms' characteristics. I find that inaccuracy is positively correlated with firms' $ICC_{I/B/E/S}$, book-to-market ratio, market leverage, idiosyncratic volatility, and market beta, but negatively associated with size and gross profitability. These results hold for both upwardly and downwardly biased ICC.[4]

[3] Although the CT and GLS approaches are both based on a residual income valuation model, the methods have an important difference. While the CT model is designed to compute the market-level cost of capital, the GLS model computes the firm-level cost of capital.

[4] The bias is the difference of the $ICC_{Perfect\,Foresight}$ and the $ICC_{I/B/E/S}$. Thus, the

A good proxy for expected returns should positively correlate to future returns. I test the cross-sectional association of ICC and returns by means of a cross-sectional FM regression, as well as through regressions of portfolios formed on ICC. In line with previous literature, the results do not show any significant positive correlation between $ICC_{I/B/E/S}$ and returns. Surprisingly, in some portfolio regressions, I even find a significant negative correlation. However, the figures are completely different when I test the ICC estimated with perfect foresight earnings. The $ICC_{Perfect\,Foresight}$ shows strongly significant coefficients in the FM regression, and the long-short strategy of buying high ICC and short selling low ICC portfolios yields abnormal returns (excess of returns adjusted by the Fama-French Five-factor model) of up to 6.05% per month. Thus, the results indicate that the ICC valuation models can be used to outperform the market when the inputs are accurate.

Given the shortcomings of the $ICC_{I/B/E/S}$ as a proxy for expected returns and due to the fact that $ICC_{Perfect\,Foresight}$ relies on ex-post data, I propose an alternative for an ex-ante estimation of ICC. I estimate a fitted ICC based on five-year rolling pooled regressions of the $ICC_{Perfect\,Foresight}$ on risk proxies. This estimate has a higher correlation to the to ex-post realized returns, as well as the $ICC_{Perfect\,Foresight}$, and accordingly, may be a better alternative than the $ICC_{I/B/E/S}$ as a proxy for expected returns. When I test the fitted ICC in long-short portfolio strategies, this estimate yields abnormal returns of up to 0.962% per month.

The paper is organized as follows. In Section 4.2, I describe the sample selection and the variables used in the models. Section 4.3 provides details on the ICC estimation. In Sections 4.4 and 4.5, I estimate the ICC absolute error at the portfolio level and the firm level, respectively. Section 4.6 shows the relation between the ICC absolute error and firm's characteristics. In Section 4.7, I evaluate the performance of ICC estimates in a cross-sectional setting. The conclusion is presented in Section 4.8.

sample is upwardly biased when the $ICC_{I/B/E/S}$ is less than $ICC_{Perfect\,Foresight}$ and vice-versa.

4.2. Data and methodology

4.2.1. Sample selection

The sample is comprised by firms at the intersection of the Center for Research in Security Prices (CRSP), Compustat fundamentals annual, and Institutional Brokers Estimates Service (I/B/E/S) summary files in the period June 1985 to June 2015. Like Claus and Thomas (2001), the sample starts in June 1985, because in previous years I/B/E/S provided too few firms with complete data to represent the overall market.

I require non-missing one- and two-year-ahead earnings forecasts, price, and shares outstanding from I/B/E/S and book equity, earnings, and dividends from Compustat to include a firm-year in the sample. The proxy for the risk-free rate is the yield on the U.S. 10-year government bond, which is obtained from Thomson Reuters Datastream. I use the following variables from Compustat: income before extraordinary items (Compustat IB), gross profits (Compustat items: $(REVT - COGS)$), total assets (Compustat AT), dividends (Compustat DVC), book value of equity (Compustat CEQ), and book value of debt (Compustat items: $(DLC + DLTT)$).

As a proxy for I/B/E/S earnings forecasts, I use the first median I/B/E/S consensus forecast of earnings. Following Hou et al. (2012), I use I/B/E/S forecasts from June of each year including companies from all fiscal-year period ends. The forecasts' release date is always the third Thursday of each month. I avoid the use of data that was not publicly available at the estimation dates. To this end, I collect accounting data only for companies with fiscal-year-end between April of year $(t-1)$ to March of year (t). As a proxy for perfect foresight earnings forecasts, ex-post realizations of earnings per share provided by I/B/E/S are used.

4.2.2. Price adjustment

As I use earnings forecasts and prices from June of each year and the models to estimate ICC assume that the prices should match the fiscal-year-end, I adjust the prices to the fiscal-year-end using the following equation:

$$P'_{(i,t)} = \frac{P_{(i,t+\tau)}}{(1+r_i)^{\tau/365}}, \tag{4.1}$$

where $P'_{(i,t)}$ is the price adjusted to the last fiscal-year-end of firm i, $P_{(i,t+\tau)}$ is the price of firm i from June of year t, r_i is the ICC, and τ is the difference in days from the last fiscal-year-end and the release date of the forecast from June of year t.

4.2.3. Firm's characteristics

In order to infer the cross-sectional properties of ICC, I analyze its relationship with variables that affect a firm's risk as perceived by investors. In this study, seven commonly used firm's characteristics that have been previously shown to explain the cross-section of stock returns are analyzed. I compute all firm characteristics based on available data prior to June 30th of each year. The details on each firm characteristics are presented in the next subsections.

4.2.3.1. Market Beta (β)

The Capital Asset Pricing Model from Sharpe (1964), Lintner (1965), and Black (1972) derives a positive association between a firm's β and the firm's expected returns theoretically. Several studies have tested this association (see e.g., Fama and Macbeth (1973); Fama and French (1992, 2008)). I estimate market β for each stock using the stock's previous 60 monthly excess returns (I require a minimum of 24 months and excess returns be in excess of the one-month Treasury bill rate taken from Kenneth French's data library).

4.2.3.2. Idiosyncratic volatility

Merton (1987) suggests that in the presence of market frictions where investors have restricted access to information, firms with higher idiosyncratic volatility require higher average returns to compensate investors for holding portfolios that are not perfectly diversified. Following Ang et al. (2006) and Hou et al. (2015), I estimate Idiosyncratic volatility as the standard deviation of the residuals from regressing the stock's returns in excess of the one-month Treasury bill rate on the three Fama and French (1993) factors[5] estimated yearly at the end of June using the previous 60 monthly returns (I require a minimum of 24 months).

4.2.3.3. Asset growth

Based on a DDM, Fama and French (2006) suggest that given the book-to-market ratio and the expected earnings relative to book value of equity, companies with higher expected growth have lower stock returns due to reinvestment of earnings. This association has been tested empirically by Aharoni et al. (2013) and Fama and French (2008). Following Fama and French (2015), asset growth is measured as the change in total assets from the fiscal year ending in year (t-1) to the fiscal year ending in (t), divided by ($t-1$) total assets.

4.2.3.4. Size

Banz (1981) finds that smaller firms have higher risk-adjusted average returns than larger firms. This "size effect" has been demonstrated in many other studies (see, e.g., Fama and French (1992, 2008)) and remains statistically significant even after controlling for other risk factors. Size is the natural logarithm of market equity at the end of June in year (t).

[5] I download the three Fama-French factor returns from Kenneth French's website.

4.2.3.5. Book-to-market ratio

Chan et al. (1991) find that the returns are positively related to the ratio of book value of common equity to market value (book-to-market) in the Japanese stock market. Fama and French (1992) show that book-to-market ratio along with size captures the cross-sectional variation in average stock returns associated with other important risk proxies in the U.S. stock market. Following Fama and French (1992), I measure *Lnbeme* as the natural logarithm of the ratio of book value of equity to market equity at the previous fiscal year-end.

4.2.3.6. Gross profitability

Fama and French (2006) suggest that the book-to-market ratio is not able to explain variations in expected profitability. Novy-Marx (2013) shows empirically that gross profitability has roughly twice the t-statistic of book-to-market explaining the cross-section of average returns. In addition, the author finds that profitable firms generate markedly higher returns than unprofitable firms. Gross profitability is the ratio of gross profits (i.e., total revenue minus cost of goods sold) to total assets.

4.2.3.7. Market leverage

Modigliani and Miller (1958) suggest that the firm's risk should be an increasing function of its leverage. Bhandari (1988) finds that the expected common stock returns are positively related to the leverage, controlling for the beta and firm size. A similar result is also found in Fama and French (1992), who find a positive association between market leverage and average return. Market leverage is estimated as the book value of debt divided by market equity.

4.3. Estimation of ICC

4.3.1. ICC at the portfolio level

The method to estimate the ICC absolute error at the portfolio level is derived from the residual income valuation model, which is shown in the following equation:

$$V_{(i,t)} = BPS_{(i,t)} + \sum_{\tau=1}^{\infty} \frac{EPS_{(i,t+\tau)} - r_i \times BPS_{(i,t+\tau-1)}}{(1+r_i)^{\tau}}, \tag{4.2}$$

where $V_{(i,t)}$ is the intrinsic value per share of firm i at time t, $BPS_{(i,t)}$ is the book value per share of common equity of firm i at time t, $EPS_{(i,t)}$ is the earnings per share of firm i at time t, and r_i is the cost of capital of firm i. If the market is assumed to be efficient (the intrinsic value is equal to price), the finite horizon version of this model can be rewritten as follows:

$$P_{(i,t)} = BPS_{(i,t)} + \frac{EPS_{(i,t+1)} - r_i \times BPS_{(i,t)}}{(r_i - g_i)}, \tag{4.3}$$

where $EPS_{(i,t+1)}$ is the expected earnings per share of firm i for period (t+1), $P_{(i,t)}$ is the price of firm i in the period t, and g_i is the expected rate of growth in the residual income beyond the period (t+1). Following Easton et al. (2002), the equation can be rearranged to come up with:

$$\frac{EPS_{(i,t+1)}}{BPS_{(i,t)}} = g_i + (r_i - g_i)\frac{P_{(i,t)}}{BPS_{(i,t)}}. \tag{4.4}$$

The advantage of rearranging the model as Equation 4.4 is that one can estimate simultaneously r_i and g_i in a regression setting as follows:

$$\frac{EPS_{(i,t+1)}}{BPS_{(i,t)}} = \gamma_0 + \gamma_1 \frac{P'_{(i,t)}}{BPS_{(i,t)}} + u_{(i,t)}. \tag{4.5}$$

From this regression, I compute $\gamma 0$ (intercept), which is an estimate of g_i, and γ_1, an estimate of $(r_i - g_i)$. Thus, $(\gamma_0 + \gamma_1)$ is an estimate of r_i, i.e. ICC. As indicated in Easton et al. (2002), the most common approach to estimating

ICC relies on I/B/E/S earnings forecasts, as in the following equation:

$$\frac{EPS^{I/B/E/S}_{(i,t+1)}}{BPS_{(i,t)}} = \gamma_0 + \gamma_1 \frac{P'_{(i,t)}}{BPS_{(i,t)}} + u_{(i,t)}. \tag{4.6}$$

However, as Easton and Sommers (2007) show, I can estimate the $ICC_{Perfect\,Foresight}$ by using perfect foresight earnings as input:

$$\frac{EPS^{Perfect\,Foresight}_{(i,t+1)}}{BPS_{(i,t)}} = \gamma_0 + \gamma_1 \frac{P'_{(i,t)}}{BPS_{(i,t)}} + u_{(i,t)}. \tag{4.7}$$

By combining Equations 4.6 and 4.7, the absolute error in estimating r_i (the absolute difference between the $ICC_{I/B/E/S}$ to the $ICC_{Perfect\,Foresight}$ estimation) is calculated as follows:

$$\frac{\mid EPS^{Perfect\,Foresight}_{(i,t+1)} - EPS^{I/B/E/S}_{(i,t+1)} \mid}{BPS_{(i,t)}} = \gamma_0 + \gamma_1 \frac{P'_{(i,t)}}{BPS_{(i,t)}} + u_{(i,t)}. \tag{4.8}$$

In this regression, γ_0 represents the absolute error in the g_i and the sum of γ_0 and γ_1 represents the absolute error in the estimation of r_i.[6]

4.3.2. ICC at the firm level

In this section, I show details of the estimation of ICC at the firm level. I apply two methods that are based on a residual income model, GLS and CT, and two methods based on an abnormal earnings growth model, OJ, and MPEG. In addition, I estimate a composite ICC, which is the average of the four aforementioned approaches. To maximize the coverage of the composite ICC, I only require a firm to have at least one non-missing individual ICC estimate (as in Hou et al. (2012)).

[6] Like Easton and Sommers (2007), the regression requires an iteration since I need the r_i to estimate $P'_{(i,t)}$ and $P'_{(i,t)}$ to estimate r_i. The price is adjusted according to Equation 4.1.

4.3.2.1. Residual Income models

I estimate the ICC based on the methods of Gebhardt et al. (2001) and Claus and Thomas (2001), both of which are derived from the residual income model. The book per share is estimated based on the clean surplus relation and a constant payout ratio (PR), i.e. $BPS_{t+\tau} = BPS_{t+\tau-1} + EPS_{t+\tau} \times (1 - PR)$. However, in order to avoid using a negative dividend yield as an implied assumption, the payout ratio is set to zero, when $EPS_{t+\tau}$ is negative. I exclude all observations where $BPS_{t+\tau}$ is negative in any of the (τ) periods necessary for the ICC estimation .

4.3.2.2. GLS approach

The cost of capital based on the GLS approach can be estimated as follows:

$$P'_{i,t} = BPS_{i,t} + \sum_{\tau=1}^{11} \frac{(ROE_{i,t+\tau} - r_i) \times BPS_{i,t+\tau-1}}{(1+r_i)^k} + \frac{(ROE_{i,t+12} - r_i) \times BPS_{i,t+11}}{r_i \times (1+r_i)^{11}}, \tag{4.9}$$

where $P'_{i,t}$ is the adjusted price of firm i in time t, r_i is the ICC, $BPS_{i,t}$ is the book value per share of firm i in time t, and $(ROE_{i,t+\tau} - r_i) \times BPS_{i,t+\tau-1}$, denotes the residual income of firm i in year $(t+\tau)$, i.e. the difference between the return on equity (ROE) and r_i multiplied by the book value of equity of the previous year.

I compute the ROE from years $t+1$ to $t+3$ as $EPS_{t+\tau}/BPS_{t+\tau-1}$, where the $EPS_{t+\tau}$ is the expected earnings per share of period $t+\tau$. After year $t+3$, the ROE mean reverts linearly for the next nine years to the median industry ROE. This proxy is calculated as a rolling industry median over 10 years, considering only firms that have a positive ROE. I use the 48 industry definition based on Fama and French (1997). Finally, after period $t+12$, the terminal value is determined as a simple perpetuity of the residual incomes.

To estimate the $ICC_{Perfect\,Foresight}$, I require ex-post earnings per share from one-, two-, and three-year-ahead. For the $ICC_{I/B/E/S}$, I/B/E/S one-and two-year-ahead earnings forecasts are required. If the three-year-ahead forecast is not available, I estimate it by multiplying the two-year-ahead median earnings forecast by one plus the consensus long-term growth rate (LTG). If neither the three-year-ahead earnings forecast nor the long-term growth rate is available, I compute the growth rate between the one-year and two-year-ahead earning forecasts and use this to estimate the three-year-ahead earnings forecast.

4.3.2.3. CT approach

I estimate the CT approach as follows:

$$P'_{i,t} = BPS_{i,t} + \sum_{\tau=1}^{5} \frac{(ROE_{i,t+\tau} - r_i) \times BPS_{i,t+\tau-1}}{(1+r_i)^k} + \frac{(ROE_{i,t+5} - r_i) \times BPS_{i,t+4}(1+g_i)}{(r_i - g_i) \times (1+r_i)^5}, \tag{4.10}$$

where $P'_{i,t}$ is the adjusted price of firm i in time t, r_i is the ICC, and $BPS_{i,t}$ is the book value per share. $(ROE_{i,t+\tau} - r_i) \times BPS_{i,t+\tau-1}$, denotes the residual income of firm i in year $t+\tau$, i.e. the difference between the ROE and the r_i multiplied by book value of equity in the previous year. I compute the ROE from years t+1 to t+5 as $EPS_{i,t}/BPS_{i,t-1}$, where the $EPS_{i,t+\tau}$ is the expected earnings of firm i for year $t+\tau$.

For the $ICC_{I/B/E/S}$, I use the consensus median I/B/E/S analysts' earnings per share of period t. I estimate the forecasts in the years t+3, t+4 and t+5 using a LTG and the two-, three-, and four-year-ahead forecast. For the $ICC_{Perfect\,Foresight}$, I require ex-post earnings from years t+1 to t+5. In particular for the estimation of ICC in 2011 and 2012, I estimate the EPS forecast for the period t+4 as $EPS_{t+3} \times (1+LTG)$ and t+5 as $EPS_{t+4} \times (1+LTG)$.

Following Claus and Thomas (2001), g_i is computed as 10-year government bond yield minus three percent. g_i is set to zero in case it is negative. Finally, after the period t+5, the terminal value is a simple perpetuity of the residual incomes. An estimation of r_i requires that r_i exceeds g_i, i.e. ICC greater than the perpetual growth rate.

4.3.2.4. Comparison of the CT and GLS approaches

The main difference between the CT and GLS approaches is that the latter estimates residual income from years t+1 to t+12, while the CT approach only estimates the period t+1 to t+5. Figure 4.1 shows the weight of the residual income in each period compared to the price. The proportion of book value of equity to market value is greater for the GLS model than for the CT approach. This variation is due to the different sample of each of the models and because the price is discounted with the r_i estimated with each of these approaches to the last fiscal-year-end. The residual income in t+1 negatively affects the price for the GLS approach, which occurs because the ROE falls short of the ICC in the respective year. The terminal value of CT has an impact of 34.4% on the price, while for the GLS the impact is 22.3%. This difference is not surprising since the terminal value in the CT starts in t+5 while it starts in t+12 in GLS.

By comparing the residual income model to the widely used Gordon Growth Model from Gordon and Shapiro (1956), the residual income has the advantage that the terminal value has a smaller fraction of the firms' value. Claus and Thomas (2001) show that the impact of the terminal value starting in t+5 on the market value based on the Gordon Growth model can be larger than 80%. However, a critical assumption used in the residual income models is the clean surplus relation, which assumes that all retained earnings are reinvested into the firm, and, hereby, are allocated to the book value of equity. Ohlson (2005) argues that the clean surplus relation does not hold when capital transactions change the number of shares outstanding. To circumvent the shortcomings of the clean surplus relation, Ohlson and Juettner-Nauroth (2005) propose the abnormal earnings growth model.

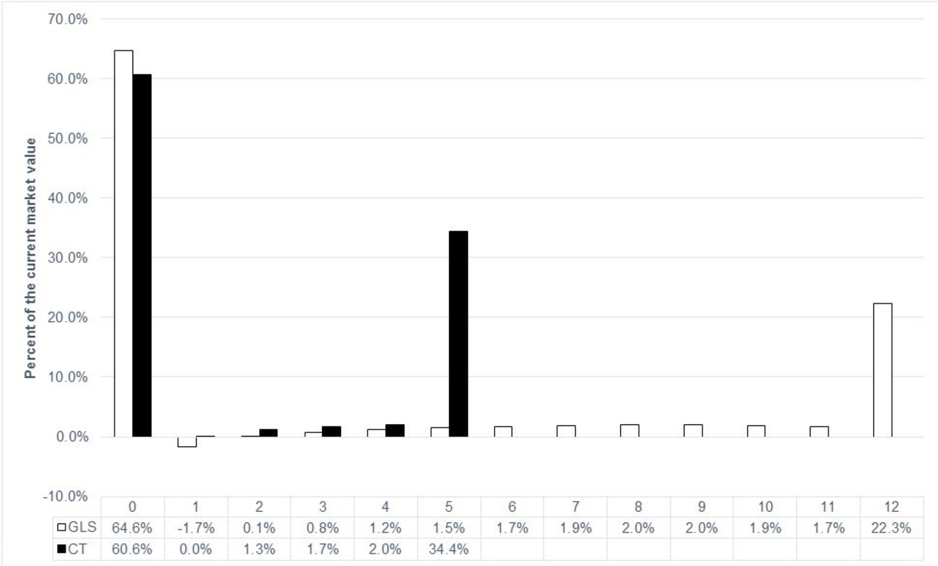

Figure 4.1.: Comparison of value profile for CT versus GLS ICC approaches from June 1985 to June 2012. Solid columns show the fractions of the book value of equity, abnormal earnings from years $t+1$ to $t+5$, and the terminal value based on Claus and Thomas (2001). The hollow columns shows the book value of equity, abnormal earnings from years $t+1$ to $t+12$, and the terminal value based on the Gebhardt et al. (2001) model.

4.3.2.5. Abnormal earnings growth models

I estimate the ICC based on abnormal earnings growth models employing the approaches from Ohlson and Juettner-Nauroth (2005) and Easton and Monahan (2005). The OJ estimation of ICC follows as:

$$P'_{i,t} = \frac{E_{i,t+1}}{r_i} + \frac{STG_{i,t} \times E_{i,t+1} + r_i \times (D_{i,t+1} - E_{i,t+1})}{r_i \times (r_i - g_i)}, \tag{4.11}$$

where $P'_{i,t}$ is the adjusted price of firm i in time t, and r_i is the ICC. $E_{i,t+1}$ is the earnings forecast of firm i in years t+1, $D_{i,t+1}$ is the dividend in year t+1, STG_i is the short-term growth rate, computed as the growth rate between EPSt+1 and EPSt+2, and g_i is the perpetual growth rate in abnormal earnings beyond the forecast horizon. Following Gode and Mohanram (2003), the perpetual growth rate is equal to 10-year government bond yield minus three percent. I estimate the ICC based on the MPEG approach by means of the following equation:

$$P'_{i,t} = \frac{E_{i,t+2} + r_i \times D_{i,t+1} - E_{i,t+1}}{r_i^2}, \tag{4.12}$$

where $P'_{i,t}$ is the adjusted price of firm i in year t, r_i is the ICC, $E_{i,t+1}$ and $E_{i,t+2}$ are the earnings forecasts in years t+1 and t+2, respectively, and $D_{i,t+1}$ is the dividend in year t+1. Concerning the inputs, the only difference between the $ICC_{Perfect\,Foresight}$ and the $ICC_{I/B/E/S}$ is that I use ex-post one-year-ahead realized earnings and two-year-ahead EPS instead of I/B/E/S median consensus EPS.

Table 4.1.: Sample composition for the abnormal earnings growth models (OJ and MPEG)

	I/B/E/S sample		PF sample	
Initial Sample	88,582	100.0%	81,840	100.0%
(-) Et1 Negative	10,782	12.2%	12,793	15.6%
(-) Et2 Negative	6,241	7.0%	13,795	16.9%
(+) Intersection of negative earnings	6,102	6.9%	8,939	10.9%
(-) Et1 or Et2 equal to zero	368	0.4%	204	0.2%
Sample of Et1 and Et2 positive	77,293	87.3%	63,987	78.2%
Assumption MPEG				
(-) STG Negative	3,500	4.0%	20,367	24.9%
Sample STG positive	73,793	83.3%	43,620	53.3%
Intersection of STG positive		38,900		
Assumption OJ				
(-) STG Lower than perpetual growth	5,799	6.5%	23,721	29.0%
Sample STG higher than perpetual growth	71,494	80.7%	40,266	49.2%
Intersection of STG > perpetual growth		36,481		

This table provides details on the sample composition of the OJ and MPEG ICC approaches. I split into (PF) Perfect Foresight and I/B/E/S earnings forecasts. I show the sample exclusions based on the conditions of having positive one- and two-year-ahead earnings forecasts and the STG rate being larger than the perpetual growth.

Unlike the residual income models, the abnormal earnings growth models require positive earnings and growth rates as input parameters. Both abnormal earnings models rely on two distinct growth parameters, an STG rate, defined as the growth from period t+1 to period t+2, and a perpetual growth from period t+2 onwards. The main difference between the OJ and MPEG model is that the latter assumes a perpetual growth of zero. This difference drives the sample composition of these two methods since a condition to estimate ICC based on abnormal earnings growth model is that the STG rate should be larger than the perpetual growth.

In Table 4.1, I show details on the sample composition from both models. The initial I/B/E/S sample is comprised of all firm-years with non-missing one- and two-year-ahead analysts' forecasts. The initial Perfect Foresight sample consists of all firm-years with non-missing one- and two-year-ahead ex-post realizations of earnings per share provided by I/B/E/S. From the I/B/E/S initial sample, 87.3% of observations have one- and two-year-ahead positive earnings, while 78.2% of the observations from the perfect foresight initial sample have the same characteristic.

Concerning the STG rate, the results are striking. For the I/B/E/S sample, the STG is negative in only 4.0% of the firm-years. However, in the perfect foresight sample, it happens in 24.9% of the firm-years. The same pattern becomes visible when I compare the number of observation where the STG is smaller than perpetual growth (estimated as the U.S. 10-year government bond). For the I/B/E/S sample, it happens 6% of the total of observations, while for the Perfect Foresight, it happens in 29.0%. In line with Easterwood and Nutt (1999), this result indicates an optimistic bias in the I/B/E/S sample since the analysts' fail to predict negative earnings and STG rate.

4.4. Effect of inaccuracy of earnings forecasts on the ICC at the portfolio level

Table 4.2 shows the coefficients of equal-weighted annual cross-sectional regressions as derived in Equation 4.8. As described in Section 4.3.1, I regress the absolute difference between the ROE estimated with one-year-ahead I/B/E/S earnings forecasts and the ROE estimated with ex-post one-year-ahead realized earnings per share on price scaled by book value per share of common equity. Year-by-year estimates, as well as the mean and Newey and West (1987) t-statistics of the average regression coefficients and the adj. r-squared, are provided in Table 4.2. The sample covers the period June 1985 to June 2012. In order to avoid results driven by outliers, the dependent variables, as well as the independent variables, are winsorized yearly at the first and 99th percentile.

Table 4.2 shows that the absolute error in ICC estimated with I/B/E/S earnings over perfect foresight earnings is on average 0.0521 with t-statistic of 20.30. These results indicate a huge deviation between the ICC estimated with I/B/E/S earnings and the $ICC_{Perfect\,Foresight}$, in particular, if these results are compared to Easton and Sommers (2007) where the ICC estimated with perfect foresight is on average 0.068.[7]

According to Easton and Sommers (2007), the accuracy of analysts' forecasts is correlated to size. Thus, to analyze whether the firms' size also has an impact on ICC accuracy, I perform value-weighted annual cross-sectional regressions based on Equation 4.8. In this regression, I weight observations

[7] The value of 0.068 represents the average across years of ICC estimated with Equation 4.7 from December 1992 to December 2013. The methodology of Easton and Sommers (2007) is slightly different to ours since the authors only include companies in their sample having fiscal-year-ends in December of each year, and they use the first forecast provided by I/B/E/S after the earnings are published. I use estimates from the third Thursday of June in each year and include companies independent of their fiscal-year-ends.

according to the market capitalization of each company in each yearly period.

Table 4.2.: Equal-weighted estimation of the absolute error of the Implied Cost of Capital at the portfolio level

Year	Nobs	γ_0	γ_1	$\tilde{r} = \gamma_0 + \gamma_1$	adj_r2
Jun-85	2,318	6.27%	0.36%	6.62%	4.37%
Jun-86	2,269	5.31%	0.49%	5.80%	3.86%
Jun-87	2,263	5.46%	0.61%	6.07%	7.48%
Jun-88	2,321	4.06%	0.79%	4.85%	3.46%
Jun-89	2,373	5.57%	0.38%	5.96%	6.50%
Jun-90	2,366	5.92%	0.24%	6.16%	7.79%
Jun-91	2,358	4.28%	0.17%	4.45%	2.29%
Jun-92	2,561	3.90%	0.33%	4.23%	6.86%
Jun-93	2,826	4.64%	0.01%	4.64%	1.42%
Jun-94	3,244	4.18%	0.01%	4.19%	2.39%
Jun-95	3,422	5.47%	0.01%	5.49%	1.29%
Jun-96	3,670	5.42%	0.04%	5.46%	3.67%
Jun-97	3,835	5.20%	0.03%	5.24%	2.79%
Jun-98	3,846	5.82%	0.03%	5.85%	2.13%
Jun-99	3,564	7.05%	0.03%	7.08%	3.91%
Jun-00	3,368	5.95%	0.20%	6.16%	10.06%
Jun-01	2,985	3.52%	0.51%	4.04%	9.00%
Jun-02	2,878	3.31%	0.20%	3.51%	7.26%
Jun-03	2,876	4.05%	0.01%	4.05%	1.66%
Jun-04	2,995	4.09%	0.01%	4.10%	3.08%
Jun-05	3,101	3.85%	0.12%	3.97%	4.79%
Jun-06	3,134	3.47%	0.43%	3.90%	15.69%
Jun-07	3,068	4.80%	0.16%	4.96%	8.80%
Jun-08	2,979	7.00%	0.10%	7.10%	8.80%
Jun-09	2,967	5.44%	0.66%	6.10%	12.16%
Jun-10	2,797	5.75%	0.00%	5.75%	2.11%
Jun-11	2,775	4.74%	0.23%	4.97%	10.31%
Jun-12	2,783	5.11%	0.06%	5.17%	5.19%
Mean across years		4.99%	0.22%	5.21%	5.68%
T-statistics		[20.75]	[3.779]	[20.30]	[6.734]

This table presents the results of annual equal-weighted cross-sectional regressions to estimate the ICC absolute error at the portfolio level by means of the following regression $\frac{abs(eps^{Perfect\,Foresight}_{(i,t+1)} - eps^{I/B/E/S}_{(i,t+1)})}{bps_{(i,t)}} = \gamma_0 + \gamma_1 \frac{p'_{(it)}}{bps_{(it)}} + u_{(it)}$, where $eps^{I/B/E/S}_{(i,t+1)}$ denotes one-year-ahead I/B/E/S analysts' forecasts earnings per share of firm i, $eps^{Perfect\,Foresight}_{(i,t+1)}$ denotes one-year-ahead perfect foresight earnings per share of firm i , and $bps_{(i,t)}$ is the book-value per share in year t for firm i. $\gamma 0$ represents the absolute difference of the growth rate based on the I/B/E/S estimation $g_i^{I/B/E/S}$ and the growth rate based on a Perfect Foresight Estimation $g_i^{PerfectForesight}$. γ_1 is the estimation of the absolute difference of the estimated ICC and the growth rate based on I/B/E/S $(r_i - g_i)^{I/B/E/S}$ and the estimated ICC and the growth rate based on a Perfect Foresight $(r_i - g_i)^{PerfectForesight}$. $\gamma_0 + \gamma_1$ represents the ICC (r_i) absolute error. I estimate $p'_{(it)} = \frac{p_{(it+\tau)}}{(1+r)^{\tau/365}}$ given that $p_{(it+\tau)}$ is the price in per share for firm i at time $t + \tau$ (on the I/B/E/S earnings announcement date, which are on the third Thursday of each month) and τ is the difference between the I/B/E/S earnings announcement date and the last fiscal year end of firm i. I winsorize the independent variables as well as the dependent variables annually at the 1% and 99% levels. The Newey-West t-statistics are presented in brackets. Nobs represents the number of observations in each year.

Table 4.3.: Value-weighted estimation of the absolute error of the Implied Cost of Capital at the portfolio level

Year	Nobs	γ_0	γ_1	$\tilde{r} = \gamma_0 + \gamma_1$	adj_r2
Jun-85	2,318	1.83%	0.47%	2.30%	4.28%
Jun-86	2,269	1.17%	0.71%	1.88%	8.67%
Jun-87	2,263	1.96%	0.47%	2.43%	10.56%
Jun-88	2,321	1.26%	0.58%	1.85%	4.51%
Jun-89	2,373	2.08%	0.48%	2.57%	4.45%
Jun-90	2,366	1.83%	0.28%	2.11%	15.09%
Jun-91	2,358	1.65%	0.14%	1.79%	2.08%
Jun-92	2,561	1.23%	0.18%	1.42%	2.86%
Jun-93	2,826	1.96%	0.01%	1.96%	0.98%
Jun-94	3,244	1.58%	0.01%	1.59%	12.68%
Jun-95	3,422	1.97%	0.02%	1.99%	1.68%
Jun-96	3,670	1.90%	0.06%	1.96%	3.49%
Jun-97	3,835	1.72%	0.04%	1.76%	2.00%
Jun-98	3,846	1.84%	0.07%	1.91%	3.96%
Jun-99	3,564	2.03%	0.04%	2.08%	7.17%
Jun-00	3,368	2.59%	0.13%	2.73%	14.87%
Jun-01	2,985	-0.17%	0.53%	0.36%	22.96%
Jun-02	2,878	1.73%	0.05%	1.77%	1.88%
Jun-03	2,876	1.65%	0.01%	1.66%	0.62%
Jun-04	2,995	1.77%	0.02%	1.79%	2.22%
Jun-05	3,101	1.71%	0.08%	1.78%	12.51%
Jun-06	3,134	0.61%	0.31%	0.93%	19.13%
Jun-07	3,068	2.38%	0.13%	2.51%	7.45%
Jun-08	2,979	3.35%	0.12%	3.48%	9.18%
Jun-09	2,967	0.63%	0.56%	1.19%	19.71%
Jun-10	2,797	2.09%	0.00%	2.09%	18.25%
Jun-11	2,775	0.55%	0.42%	0.97%	31.35%
Jun-12	2,783	2.02%	0.04%	2.06%	16.99%
Mean across years		1.68%	0.21%	1.89%	9.34%
T-statistics		[21.84]	[3.550]	[21.55]	[4.811]

This table presents the results of annual value-weighted cross-sectional regressions to estimate the ICC absolute error at the portfolio level by means of the following regression $\frac{abs(eps^{Perfect\,Foresight}_{(i,t+1)} - eps^{I/B/E/S}_{(i,t+1)})}{bps_{(i,t)}} = \gamma_0 + \gamma_1 \frac{p'_{(it)}}{bps_{(it)}} + u_{(it)}$, where $eps^{I/B/E/S}_{(i,t+1)}$ denotes one-year-ahead I/B/E/S analysts' forecasts earnings per share of firm i, $eps^{Perfect\,Foresight}_{(i,t+1)}$ denotes one-year-ahead perfect foresight earnings per share of firm i , and $bps_{(i,t)}$ is the book-value per share in year t for firm i. $\gamma 0$ represents the absolute difference of the growth rate based on the I/B/E/S estimation $g_i^{I/B/E/S}$ and the growth rate based on a Perfect Foresight Estimation $g_i^{PerfectForesight}$. γ_1 is the estimation of the absolute difference of the estimated ICC and the growth rate based on I/B/E/S $(r_i - g_i)^{I/B/E/S}$ and the estimated ICC and the growth rate based on a Perfect Foresight $(r_i - g_i)^{PerfectForesight}$. $\gamma_0 + \gamma_1$ represents the ICC (r_i) absolute error. I estimate $p'_{(it)} = \frac{p_{(it+\tau)}}{(1+r)^{\tau/365}}$ given that $p_{(it+\tau)}$ is the price in per share for firm i at time $t + \tau$ (on the I/B/E/S earnings announcement date, which are on the third Thursday of each month) and τ is the difference between the I/B/E/S earnings announcement date and the last fiscal year end of firm i. I winsorize the independent variables as well as the dependent variables annually at the 1% and 99% levels. The Newey-West t-statistics are presented in brackets. Nobs represents the number of observations in each year.

The results of the value-weighted regression (see Table 4.3) clearly show that the error falls substantially when I weight the regression according to the market value of each company. On average, the ICC absolute error ($\hat{r}$) is 0.0189. In line with Easton and Sommers (2007), in all analyzed periods, the value-weighted ICC absolute error is lower than the equal-weighted ICC absolute error.

4.5. Effect of inaccuracy of earnings forecasts on the ICC at the firm level

In this section, I analyze the impact of earnings forecasts (in)accuracy on the ICC at the firm level. The (in)accuracy is measured as the absolute error between the $ICC_{Perfect\,Foresight}$ and the $ICC_{I/B/E/S}$, which can be calculated as follows:

$$ICC\,Absolute\,Error = \mid ICC_{Perfect\,Foresight} - ICC_{I/B/E/S} \mid . \qquad (4.13)$$

I measure the absolute error where both the $ICC_{Perfect\,Foresight}$ and the $ICC_{I/B/E/S}$ are available. Then, I calculate the mean, median, and value-weighted results for each year, and finally, I estimate the average across years. The yearly the results of absolute error are winsorized at the 1% and 99% level. Results are reported in Table 4.4. In appendix A.1, I provide the yearly ICC absolute error for each of the ICC approaches.

Table 4.4 shows that GLS is the ICC approach with the lowest mean absolute error (0.0188). The reason for this low error (high accuracy) is related to the fact that book value of equity is the main driver in the underlying model, as theoretically examined in Section 4.3.2.4. In addition, the GLS approach uses only one-, two-, and three-year-ahead earnings forecasts and then the ROEs are faded to the median Industry ROE, which is the same for the Perfect Foresight or for the I/B/E/S estimates. GLS is the ICC model for which the most substantial number of firm-year observations are obtained as an input since the assumptions of this model are less strict in comparison to the other approaches. In the GLS approach, it is possible to estimate ICC even when firms have negative expected earnings. However, firms should have a positive book value of equity in all periods used for the ICC estimation, and the ICC should be positive. CT is the ICC approach with the second lowest absolute error (0.0317). The reason for the low error is also related to the high impact of book-value on the estimation of the ICC. The OJ and MPEG approaches have quite similar results in terms of absolute error. The OJ mean absolute error is 0.0494, while for the MPEG it is 0.0489. The close results are not surprising since the models are highly similar, with the perpetual growth rate assumption being the only major difference. Finally, the Composite ICC has a mean absolute error of 0.0413.

The results for the median and value-weighted absolute errors are generally below their mean equivalents. However, the relative order of the models regarding accuracy remains the same. GLS has the lowest median and value-weighted errors with 0.0113 and 0.0121, respectively. CT ranks second in terms of absolute error, with a median value of 0.0234, and a value-weighted estimate of 0.0229. Next, the Composite ICC has absolute errors of 0.0296 (median) and 0.0272 (value-weighted). Finally, the OJ has absolute errors of 0.0342 (median) and 0.0331 (value-weighted), while the MPEG has errors of 0.0344 and 0.0336, respectively.

To sum up, the absolute error between the $ICC_{Perfect\,Foresight}$ and the $ICC_{I/B/E/S}$ is seemingly driven by the respective ICC approach applied and therefore strongly depends on the underlying assumptions of each model. The residual income models (CT and GLS) have a lower absolute error than the abnormal earnings growth models (OJ and MPEG). This is due to the strong impact of the book value of equity on residual income estimates of ICC, while abnormal earnings growth estimates do not incorporate book value as an input.

4.6. The relation between ICC inaccuracy and firms' characteristics

I analyze whether a set of firm characteristics which has previously been used to explain the cross-sectional variation of expected returns can explain the absolute error of ICC. I carry out FM cross-sectional regressions with ICC absolute errors as dependent variables. The independent variables are the following firm characteristics available prior to the end of June of year (t): $ICC_{I/B/E/S}$, market beta, size, book-to-market, gross profitability, asset growth, market leverage, and idiosyncratic volatility. Due to the fact that $ICC_{I/B/E/S}$ and book-to-market are highly correlated, in order to avoid collinearity between these two risk proxies, I perform the regressions in two different settings. In Table 4.5, I provide the average of the FM regression coefficients estimated yearly including book-to-market for the period from June 1986 to June 2012 and the respective t-statistics with Newey-West adjustment. Table 4.6 shows the results for the FM regression including $ICC_{I/B/E/S}$ instead of book-to-market.

In order to ensure that neither a positive nor a negative bias drives the results, I subset the sample according to the sign of the ICC bias. Bias is defined as the difference between $ICC_{Perfect\,Foresight}$ and $ICC_{I/B/E/S}$. Hence, negative bias means that the $ICC_{I/B/E/S}$ exceeds the $ICC_{Perfect\,Foresight}$ and vice-versa. In Panel A, I provide the results based on the entire sample. In Panel B, I report results for the subsample with positive ICC bias, and in Panel C for the subsample with a negative bias.

Table 4.4.: Estimation of the absolute error of the Implied Cost of Capital at the firm level

	Firm-Years	Mean Absolute Error	Median Absolute Error	Value-Weighted Absolute Error
GLS	52,689	1.88%	1.13%	1.21%
		[27.522]	[18.022]	[18.139]
CT	36,177	3.17%	2.34%	2.29%
		[26.244]	[45.492]	[28.009]
OJ	33,430	4.94%	3.42%	3.31%
		[32.225]	[34.402]	[17.312]
MPEG	36,241	4.89%	3.44%	3.36%
		[34.247]	[31.306]	[19.089]
Composite	61,498	4.13%	2.96%	2.72%
		[35.649]	[32.447]	[27.917]

This table summarizes the mean, median, and value-weighted annual absolute error in the ICC estimates from June 1985 to June 2012. The ICC absolute error is measured as the absolute difference between ($ICC_{I/B/E/S}$) and the $ICC_{Perfect\,Foresight}$. I estimate the ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. The Newey-West t-statistics are presented in brackets.

Table 4.5.: FM regression of the ICC absolute error on firm's characteristics including book-to-market

Panel A: Full Sample					
	GLS	CT	OJ	MPEG	Composite
Market Beta	0.003	0.004	0.002	0.003	0.003
	[3.545]***	[3.454]***	[3.796]***	[3.708]***	[3.213]***
Size	-0.001	-0.001	-0.002	-0.002	-0.003
	[-7.255]***	[-4.580]***	[-9.355]***	[-9.370]***	[-16.531]***
LnBeme	-0.001	0.004	0.013	0.012	0.003
	[-1.865]*	[5.715]***	[7.116]***	[8.106]***	[2.790]***
Gross Profitability	-0.002	-0.003	-0.006	-0.006	-0.006
	[-3.934]***	[-1.372]	[-3.423]***	[-3.651]***	[-3.908]***
Asset Growth	0.001	0.001	-0.006	-0.006	-0.001
	[1.707]*	[0.770]	[-4.877]***	[-4.496]***	[-0.663]
Market Leverage	0.002	0.002	0.003	0.003	0.002
	[3.401]***	[2.423]**	[5.074]***	[4.725]***	[4.174]***
Idios. Volatility	0.001	0.002	0.002	0.002	0.002
	[8.575]***	[6.099]***	[8.374]***	[8.351]***	[6.749]***
Intercept	0.007	0.025	0.052	0.050	0.042
	[3.227]***	[6.361]***	[27.344]***	[22.688]***	[17.750]***
Observations	45,093	31,735	27,786	30,217	51,475
R-squared	17.50%	12.00%	12.60%	11.80%	12.50%
Panel B: Subsample with positive ICC bias					
	GLS	CT	OJ	MPEG	Composite
Market Beta	0.001	0.003	0.002	0.003	0.001
	[1.807]*	[2.197]**	[2.091]**	[2.088]**	[0.807]
Size	-0.001	-0.001	-0.003	-0.003	-0.002
	[-3.458]***	[-2.658]**	[-7.755]***	[-8.201]***	[-6.954]***
LnBeme	-0.001	0.008	0.016	0.016	0.008
	[-2.062]**	[4.538]***	[7.099]***	[6.886]***	[4.355]***
Gross Profitability	-0.003	-0.006	-0.007	-0.008	-0.005
	[-3.701]***	[-1.278]	[-2.750]**	[-3.254]***	[-1.596]
Asset Growth	-0.002	-0.005	-0.008	-0.008	-0.005
	[-2.796]***	[-2.299]**	[-3.867]***	[-4.008]***	[-3.190]***
Market Leverage	0.001	0.002	0.004	0.004	0.002
	[5.158]***	[2.431]**	[5.306]***	[4.999]***	[4.272]***
Idios. Volatility	0.001	0.002	0.002	0.002	0.002
	[7.950]***	[5.575]***	[9.708]***	[9.871]***	[8.403]***
Intercept	0.002	0.021	0.061	0.060	0.040
	[1.002]	[3.775]***	[21.787]***	[19.798]***	[15.045]***
Observations	14,643	10,358	16,791	17,524	19,771
R-squared	15.60%	18.40%	14.10%	14.20%	12.30%
Panel C: Subsample with negative ICC bias					
	GLS	CT	OJ	MPEG	Composite
Market Beta	0.003	0.004	0.003	0.003	0.003
	[3.514]***	[3.494]***	[2.778]***	[3.539]***	[4.633]***
Size	-0.001	-0.001	-0.002	-0.002	-0.004
	[-7.411]***	[-4.000]***	[-5.904]***	[-5.076]***	[-17.386]***
LnBeme	-0.001	0.003	0.007	0.006	0.000
	[-1.630]	[4.907]***	[7.185]***	[7.458]***	[0.230]
Gross Profitability	-0.002	-0.001	-0.006	-0.005	-0.006
	[-2.284]**	[-0.677]	[-2.485]**	[-2.122]**	[-3.150]***
Asset Growth	0.002	0.003	-0.002	-0.002	0.001
	[2.881]***	[3.975]***	[-1.086]	[-0.759]	[1.146]
Market Leverage	0.002	0.001	0.000	0.000	0.002
	[3.089]***	[1.468]	[0.569]	[0.511]	[3.368]***
Idios. Volatility	0.002	0.001	0.002	0.002	0.002
	[8.516]***	[6.843]***	[5.166]***	[4.689]***	[5.397]***
Intercept	0.010	0.026	0.040	0.040	0.044
	[3.925]***	[6.946]***	[10.567]***	[11.303]***	[14.254]***
Observations	30,450	21,377	10,995	12,693	31,704
R-squared	19.80%	12.20%	14.10%	11.40%	15.50%

[7] Table 4.5 presents the time-series average of slope coefficients from cross-sectional FM

I start the analysis of Table 4.5 with market beta. Companies with higher beta show higher absolute errors in the ICC calculation. The results are significant in all cases at the 0.05 significance level, with the exception of the GLS and Composite ICC approaches for the subsample with a positive bias. In terms of size, a negative relation exists between market capitalization and ICC errors. This result is consistent with previous findings (e.g. Guay et al. (2011); Easton and Sommers (2007); Mohanram and Gode (2013).

In most cases, companies with higher book-to-market have higher ICC inaccuracy. This result is expected since many companies with high book-to-market are facing distress or negative earnings, their earnings forecasts are also more unpredictable, contributing to ICC inaccuracy. The exception for the positive relation between ICC absolute error and book-to-market is the GLS model, in which the book value of equity has a huge impact on the ICC estimation and the earnings forecast errors, therefore, have a lower effect. In the same way that negative earnings are more unpredictable than positive earnings, one can see that throughout all analyses, companies with lower gross profitability have a higher ICC inaccuracy.

regressions of ICC absolute error on risk factors. The following risk factors are employed: market β, size, gross profits, asset growth, market leverage, idiosyncratic volatility, and book-to-market. In Panel A, I provide the results based on the entire sample while in Panel B only for positive ICC bias. In Panel C, I report results for the subsample with a negative bias. I estimate ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. The ICC absolute error is measured as the absolute difference between ($ICC_{I/B/E/S}$) and the $ICC_{Perfect\,Foresight}$. I winsorize the dependent as well as the independent variables yearly at 1% and 99% levels. The Newey-West t-statistics are presented in brackets. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively. The sample covers the period from June 1985 to June 2012.

Table 4.6.: FM regression of the ICC absolute error on firm's characteristics

Panel A: Full Sample

	GLS	CT	OJ	MPEG	Composite
Market Beta	0.002	0.003	0.001	0.002	0.001
	[3.032]***	[3.179]***	[1.873]*	[2.039]*	[1.647]
Size	0.000	-0.001	-0.003	-0.003	-0.001
	[-0.860]	[-4.294]***	[-15.464]***	[-16.128]***	[-4.317]***
$ICC_{I/B/E/S}$	0.002	0.004	0.002	0.002	0.004
	[15.403]***	[11.674]***	[12.413]***	[13.947]***	[30.796]***
Gross Profitability	-0.001	-0.006	-0.013	-0.013	-0.007
	[-1.231]	[-3.440]***	[-6.971]***	[-7.931]***	[-8.378]***
Asset Growth	0.001	-0.002	-0.008	-0.008	-0.001
	[2.388]**	[-1.995]*	[-4.754]***	[-4.578]***	[-1.409]
Market Leverage	0.000	0.001	0.004	0.004	0.000
	[0.615]	[2.088]**	[7.664]***	[6.795]***	[1.223]
Idios. Volatility	0.001	0.001	0.001	0.001	0.001
	[9.454]***	[5.659]***	[9.704]***	[9.760]***	[9.507]***
Intercept	-0.004	0.012	0.046	0.045	0.010
	[-1.973]*	[3.505]***	[20.603]***	[18.577]***	[4.097]***
Observations	45,093	31,736	28,112	30,549	51,810
R-squared	21.30%	21.30%	13.10%	12.70%	27.50%

Panel B: Subsample with positive ICC bias

	GLS	CT	OJ	MPEG	Composite
Market Beta	0.001	0.003	0.002	0.002	0.000
	[1.811]*	[2.287]**	[1.852]*	[1.622]	[0.294]
Size	0.000	-0.003	-0.005	-0.005	-0.003
	[-2.146]**	[-5.460]***	[-12.458]***	[-12.172]***	[-8.041]***
$ICC_{I/B/E/S}$	0.000	0.000	0.001	0.001	0.001
	[-0.680]	[-0.236]	[4.944]***	[4.514]***	[9.712]***
Gross Profitability	-0.002	-0.012	-0.018	-0.020	-0.012
	[-1.946]*	[-2.852]***	[-7.112]***	[-7.686]***	[-3.906]***
Asset Growth	-0.002	-0.008	-0.012	-0.013	-0.008
	[-2.382]**	[-3.248]***	[-6.351]***	[-5.958]***	[-5.086]***
Market Leverage	0.001	0.004	0.006	0.006	0.003
	[4.155]***	[3.858]***	[9.358]***	[9.085]***	[8.378]***
Idios. Volatility	0.001	0.002	0.002	0.002	0.002
	[8.132]***	[5.348]***	[8.675]***	[9.367]***	[8.447]***
Intercept	0.001	0.026	0.066	0.065	0.036
	[0.539]	[4.715]***	[19.868]***	[18.638]***	[13.499]***
Observations	14,643	10,358	16,975	17,713	19,957
R-squared	15.40%	16.80%	12.60%	12.70%	12.20%

Panel C: Subsample with negative ICC bias

	GLS	CT	OJ	MPEG	Composite
Market Beta	0.002	0.002	0.001	0.001	0.001
	[2.779]***	[1.799]*	[0.991]	[0.824]	[1.652]
Size	0.000	-0.001	-0.001	-0.001	0.000
	[-0.577]	[-1.478]	[-1.694]	[-1.405]	[-0.211]
$ICC_{I/B/E/S}$	0.002	0.006	0.004	0.004	0.006
	[17.710]***	[27.913]***	[25.915]***	[26.040]***	[59.629]***
Gross Profitability	0.000	-0.001	-0.002	-0.002	-0.003
	[-0.396]	[-1.444]	[-1.767]*	[-1.781]*	[-2.253]**
Asset Growth	0.002	0.002	0.001	0.002	0.003
	[3.761]***	[3.148]***	[0.935]	[0.916]	[4.625]***
Market Leverage	0.000	-0.001	-0.002	-0.002	-0.002
	[-0.220]	[-1.654]	[-3.025]***	[-3.033]***	[-3.692]***
Idios. Volatility	0.002	0.001	0.001	0.001	0.001
	[9.245]***	[5.093]***	[3.199]***	[2.596]**	[6.917]***
Intercept	-0.005	0.001	0.002	0.010	-0.008
	[-2.437]**	[0.255]	[0.572]	[3.143]***	[-2.384]**
Observations	30,450	21,378	11,137	12,836	31,853
R-squared	26.30%	35.90%	35.30%	29.40%	47.80%

[7] Table 4.6 presents the time-series average of slope coefficients from cross-sectional FM

Regarding asset growth, the results for this firm characteristic are mixed. Applying the residual income models, I obtain insignificant results for the complete sample, positive and significant coefficients for the negative bias subsample, and negative and significant coefficients for the positive bias one. For the abnormal earnings growth model, a consistent and negative relation can be seen between ICC inaccuracy and asset growth for both the complete and positive bias sample, and insignificant coefficients for the sample consisting of negative bias observations. Finally, market leverage and idiosyncratic volatility relate positively to ICC absolute error. These relations are expected since companies with high leverage or high idiosyncratic volatility are riskier and more unpredictable, again translating into more inaccurate ICC estimates.

To sum up, the relation of firm characteristics and ICC accuracy is mostly independent of ICC bias. Overall, I find that ICC absolute error is mostly positively related to market beta, book-to-market, market leverage, and idiosyncratic volatility, and negatively to size and gross profitability. The results for asset growth are mixed.

Table 4.5 also shows the number of observations that have a positive or negative bias in each of the ICC approaches. For instance, of the total number of firm-years taken included in the GLS estimation (45,093), 30,450 have a negative (overly-optimistic) bias, and 14,643 have a positive (pessimistic) bias. The proportion for the CT model is similar to the one in the GLS model. However, for the abnormal earnings growth models, the proportions

regressions of ICC absolute error on risk factors. The following risk factors are employed: market β, size, gross profits, asset growth, market leverage, idiosyncratic volatility, and ICC premium. In Panel A, I provide the results based on the entire sample while in Panel B only for positive ICC bias. In Panel C, I report results for the subsample with a negative bias. I estimate ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. The ICC absolute error is measured as the absolute difference between ($ICC_{I/B/E/S}$) and the $ICC_{Perfect\,Foresight}$. I provide explanations for the estimation of the independent variables in Section 4.2.3. I winsorize the dependent as well as the independent variables yearly at 1% and 99% levels. The Newey-West t-statistics are presented in brackets. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively. The sample covers the period from June 1985 to June 2012.

strongly differ. For instance, of the 27,786 observations of the OJ method, 16,791 have a positive bias, and 10,995 have a negative bias. The relative increase in negative-to-positive observations is due to the fact that many of the observations with a negative bias are dropped from the OJ and MPEG samples, either because the one- or two-year-ahead forecast is negative or because the short-term-growth is smaller than the assumed perpetual growth.

Table 4.6 shows that by including $ICC_{I/B/E/S}$ instead of book-to-market, the magnitude of the coefficients of the other risk proxies generally remains the same. However, most of the variables have lower t-statistics after this inclusion, due to the high correlation between $ICC_{I/B/E/S}$ and ICC absolute error. In terms of magnitude, in most cases, the higher $ICC_{I/B/E/S}$, the higher the ICC absolute error. Thus, the analysts are more likely to report inaccurate estimates for companies with high ICC. The strong relation between $ICC_{I/B/E/S}$ and ICC absolute error may also be inferred from the R-squared: for instance, in Panel A of Table 4.5, the R-squared ranges from 11.8% (MPEG) to 17.5% (GLS), while in Panel A of Table 4.6 (including the $ICC_{I/B/E/S}$), it ranges from 12,7%(MPEG) to 21,3% (GLS and CT).

4.7. The cross-sectional properties of ICC

4.7.1. Fama-Macbeth regression

In the literature, it is common to use the ICC in cross-sectional settings. However, the correlations between ICC and ex-post forward returns have shown weak significance (e.g., Guay et al. (2011); Easton and Monahan (2005)). In this setting, it is an unsolved puzzle whether the weak correlations are due to inaccuracy in earnings forecasts or due to the underlying assumptions of the valuation models. To gain a better understanding of these relations, I start with an FM regression, where these cross-sectional properties are analyzed not only with $ICC_{I/B/E/S}$ but also with $ICC_{Perfect\,Foresight}$.

Panel A of Table 4.7 reports the time-series average of slopes and the Newey-West t-statistics of FM regressions of firms' monthly returns on ICC premium estimated with analysts' earnings forecasts ($ICC_{I/B/E/S}$) or with perfect foresight earnings forecasts $ICC_{Perfect\,Foresight}$. I include the CT, GLS, OJ, and MPEG ICC approaches as well as the composite ICC. In Panel B, I carry out a similar setting to Panel A, but I control for market beta, size, gross profitability, asset growth, market leverage, and idiosyncratic volatility.[8] To calculate the ICC premiums, I use the yield on the U.S. 10-year government bond.

As can be seen on the LHS of Table 4.7, the $ICC_{I/B/E/S}$ has shown no significant coefficients, even at 0.10 significance level. The results are consistently insignificant for all ICC approaches and hold even when ICC premium is the only explanatory variable (see Panel of Table 4.7). These results tie in with previous literature findings (see e.g., Gebhardt et al. (2001); Gode and Mohanram (2003); Lee et al. (2009)). The weak correlation of $ICC_{I/B/E/S}$ and forward returns might indicate that I/B/E/S estimates are fully incorporated into the market; therefore it is not possible to generate arbitrage gains with this information.

When I substitute $ICC_{Perfect\,Foresight}$ for $ICC_{I/B/E/S}$, the respective coefficients become positive and highly significant in both settings. When ICC premium is the only explanatory variable, the coefficients range from 0.142 with t-statistic of 7.180 (Composite ICC) to 0.325 with t-statistic of 15.532. When ICC is regressed with other control variables, the coefficient for the GLS model is 0.331 with a t-statistic of 21.402, for the CT I find 0.234 with a t-statistic of 19.377, for the OJ I find 0.143 with a t-statistic of 21.446, for the MPEG I find 0.147 with a t-statistic of 22.535, and for the composite I find 0.255 with a t-statistic of 26.270. The results show that $ICC_{Perfect\,Foresight}$

[8] I do not include lnBeme in this regression due to the high correlation between this firm characteristic and some ICC approaches. Therefore, I ensure that the results are not driven by multicollinearity, though including this risk characteristic has little impact on ICC coefficients.

Table 4.7.: FM cross-sectional regression of monthly returns

Panel A: FM Monthly Regression

	$ICC_{I/B/E/S}$					$ICC_{Perfect\,Foresight}$				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
ICC Premium	0.030	0.005	0.005	0.007	0.022	0.325	0.238	0.156	0.161	0.142
	[1.151]	[0.201]	[0.308]	[0.452]	[0.996]	[15.532]***	[16.626]***	[18.279]***	[19.301]***	[7.180]***
Intercept	0.931	1.047	1.036	1.012	1.084	0.491	0.853	0.742	0.836	1.138
	[3.028]***	[3.531]***	[4.076]***	[4.051]***	[3.387]***	[1.446]	[2.823]***	[2.846]***	[3.215]***	[3.677]***
Observations	783,669	727,746	777,043	802,953	887,175	735,395	510,514	440,059	468,270	828,735
R-squared	0.70%	0.60%	0.80%	0.90%	0.80%	1.80%	1.50%	2.00%	2.10%	1.10%

Panel B: FM Monthly Extended Regression

	$ICC_{I/B/E/S}$					$ICC_{Perfect\,Foresight}$				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
Market Beta	0.131	0.110	0.048	0.062	0.108	0.115	0.091	0.219	0.201	0.131
	[0.891]	[0.763]	[0.368]	[0.472]	[0.755]	[0.769]	[0.626]	[1.607]	[1.465]	[0.890]
Size	-0.043	-0.041	-0.050	-0.050	-0.056	-0.042	-0.110	-0.050	-0.056	-0.047
	[-1.139]	[-1.048]	[-1.369]	[-1.398]	[-1.526]	[-1.125]	[-2.965]***	[-1.263]	[-1.453]	[-1.276]
Gross Profitability	0.554	0.518	0.534	0.544	0.567	0.426	0.455	0.971	0.934	0.442
	[3.319]***	[3.071]***	[3.218]***	[3.248]***	[3.460]***	[2.574]**	[2.814]***	[6.379]***	[6.166]***	[2.825]***
Asset Growth	-0.461	-0.435	-0.436	-0.428	-0.474	-0.254	-0.201	0.008	0.013	-0.190
	[-5.807]***	[-5.592]***	[-6.288]***	[-5.997]***	[-6.103]***	[-3.213]***	[-2.402]**	[0.091]	[0.151]	[-2.596]***
Market Leverage	0.021	0.019	0.012	0.014	0.027	-0.103	-0.037	-0.086	-0.090	-0.111
	[0.425]	[0.372]	[0.251]	[0.296]	[0.561]	[-2.205]**	[-0.839]	[-2.061]**	[-2.153]**	[-2.288]**
Idios. Volatility	0.000	0.001	-0.001	-0.001	0.000	0.063	0.054	0.073	0.068	0.044
	[0.019]	[0.044]	[-0.050]	[-0.046]	[-0.020]	[3.684]***	[3.127]***	[4.436]***	[4.124]***	[2.541]**
ICC Premium	0.009	0.002	0.000	0.001	0.004	0.331	0.234	0.143	0.147	0.255
	[0.443]	[0.087]	[0.024]	[0.050]	[0.360]	[21.402]***	[19.377]***	[21.446]***	[22.535]***	[26.270]***
Intercept	1.088	1.142	1.291	1.260	1.230	-0.050	0.894	-0.026	0.198	-0.074
	[3.240]***	[3.365]***	[3.671]***	[3.670]***	[3.693]***	[-0.151]	[2.549]**	[-0.074]	[0.568]	[-0.219]
Observations	656,073	611,452	641,388	663,885	739,468	622,706	443,489	368,199	392,333	657,356
R-squared	5.75%	5.70%	5.15%	5.31%	5.39%	6.93%	7.22%	7.30%	7.43%	7.34%

This table presents the time-series average of slope coefficients from cross-sectional FM regressions of monthly returns on risk factors. In Panel A, the independent variable is the ICC Premium. In Panel B, I add the following risk factors as control variables: market β, size, gross profits, asset growth, market leverage, and idiosyncratic volatility. On the left-hand side I use as a risk factor the ICC estimated with I/B/E/S earnings, and on the right-hand side, I include the ICC estimated with perfect foresight earnings. I estimate ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. I provide explanations for the estimation of the independent variables in Section 4.2.3. To compute the ICC premiums, I use the yield on the U.S. 10-year government bond. Following Novy-Marx (2013), I winsorize the independent variables yearly at the 1% and 99% levels. The Newey-West t-statistics are presented in brackets. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively. The sample covers the period from July 1985 to June 2013 (336 months).

has a robust explanatory power regarding the cross-section of expected returns, which indicates that the valuation models are in line with market expectations.

In order to evaluate whether the results of FM regressions based on monthly returns are also robust when yearly returns are used instead of monthly returns, Table 4.8 reports the time-series average of slopes and the Newey-West t-statistics of FM regressions of firms' yearly returns on ICC premium estimated with analysts' earnings forecasts ($ICC_{I/B/E/S}$) or with perfect foresight earnings forecasts $ICC_{Perfect\,Foresight}$ in univariate and multivariate regressions. The regressions are performed with the available information of June of each year, and the specifications of the other control variables are the same as in Table 4.7.

Regarding the univariate regressions (Panel A of Table 4.8) of yearly returns on ICC premium, the coefficients of $ICC_{I/B/E/S}$ are not statistically significant in all specifications. The t-statistics range from 0.199 (OJ approach) to 0.922 (GLS approach). When the regressions are based on the $ICC_{Perfect\,Foresight}$, all coefficients remain positive and highly significant. Another important result that illustrates the difference of explanatory power between the $ICC_{I/B/E/S}$ and the $ICC_{Perfect\,Foresight}$ is the R-squared. The R-squared coefficients of the regressions with $ICC_{I/B/E/S}$ range from 0.7% (OJ approach) to 1.4% (GLS approach), whereas the R-squared coefficients from the $ICC_{Perfect\,Foresight}$ regressions range from 11.9% (CT approach) to 20.4% (Composite ICC).

For the multivariate FM regressions (Panel B of Table 4.8) the inferences are also the same. The coefficients of the $ICC_{I/B/E/S}$ are not statistically significant and the coefficients of the $ICC_{Perfect\,Foresight}$ are positive and highly significant in all of the specifications. Concerning the R-squared coefficients, they range from 5.6% (MPEG approach) to 6.34% (GLS approach) in the regressions with $ICC_{I/B/E/S}$, and they range from 18% (CT approach) to 25.6% (Composite ICC) in the $ICC_{Perfect\,Foresight}$ specifications.

Table 4.8.: FM cross-sectional regression of yearly returns

Panel A: FM Yearly Regression

	$ICC_{I/B/E/S}$					$ICC_{Perfect\,Foresight}$				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
ICC premium	0.342	0.154	0.033	0.077	0.193	4.826	3.651	2.655	2.705	3.972
	[0.922]	[0.462]	[0.199]	[0.443]	[0.736]	[13.482]***	[13.670]***	[8.213]***	[8.611]***	[10.744]***
Intercept	10.650	11.656	12.279	11.882	11.473	2.968	7.837	2.987	4.958	-1.630
	[3.982]***	[4.512]***	[4.483]***	[4.527]***	[4.174]***	[0.822]	[3.103]***	[1.060]	[1.727]*	[-0.584]
Observations	64,903	60,283	64,373	66,520	74,402	61,088	42,428	36,583	38,928	65,199
R-squared	1.40%	1.10%	0.70%	0.70%	0.80%	13.50%	11.90%	17.70%	18.70%	20.40%

Panel B: FM Yearly Extended Regression

	$ICC_{I/B/E/S}$					$ICC_{Perfect\,Foresight}$				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
Market Beta	0.769	0.554	-0.200	0.001	0.487	0.514	0.055	2.176	1.839	0.819
	[0.498]	[0.387]	[-0.137]	[0.000]	[0.316]	[0.293]	[0.038]	[1.153]	[0.988]	[0.460]
Size	-0.474	-0.346	-0.633	-0.643	-0.706	-0.420	-1.469	-0.569	-0.669	-0.462
	[-0.611]	[-0.491]	[-0.962]	[-0.983]	[-0.962]	[-0.603]	[-2.189]**	[-0.668]	[-0.812]	[-0.628]
Gross Profitability	6.700	6.256	6.747	6.906	7.285	6.534	7.759	16.883	16.096	6.898
	[3.332]***	[3.102]***	[3.179]***	[3.201]***	[3.757]***	[3.126]***	[4.553]***	[7.059]***	[6.998]***	[3.888]***
Asset Growth	-6.005	-5.693	-5.878	-5.784	-6.330	-3.670	-3.454	-0.127	-0.063	-2.667
	[-5.693]***	[-5.097]***	[-6.495]***	[-6.229]***	[-6.036]***	[-3.202]***	[-3.168]***	[-0.131]	[-0.074]	[-2.729]**
Market Leverage	0.489	0.513	0.431	0.503	0.626	-1.765	-0.802	-1.451	-1.467	-1.894
	[0.726]	[0.740]	[0.680]	[0.784]	[0.926]	[-2.380]**	[-1.457]	[-1.969]*	[-1.948]*	[-2.321]**
Idios. Volatility	0.024	0.043	0.008	0.008	0.001	0.907	0.800	0.975	0.890	0.618
	[0.163]	[0.272]	[0.062]	[0.061]	[0.005]	[3.756]***	[4.387]***	[4.087]***	[4.121]***	[3.215]***
ICC premium	0.061	0.149	-0.016	-0.012	0.046	4.997	3.617	2.477	2.514	3.928
	[0.234]	[0.677]	[-0.143]	[-0.114]	[0.310]	[12.552]***	[14.704]***	[9.026]***	[9.344]***	[12.322]***
Intercept	13.196	12.287	16.240	15.801	15.349	-4.938	8.679	-7.798	-3.616	-6.089
	[2.370]**	[2.524]**	[3.021]***	[2.970]***	[2.791]***	[-1.216]	[1.923]*	[-1.331]	[-0.652]	[-1.348]
Observations	54,367	50,679	53,162	55,027	61,282	51,743	36,863	30,612	32,618	54,624
R-squared	6.34%	6.53%	5.62%	5.60%	5.89%	18.90%	18.00%	24.50%	25.20%	25.60%

This table presents the time-series average of slope coefficients from cross-sectional FM regressions of annual returns on risk factors. In Panel A, I use only ICC premium as an explanatory variable. In Panel B, I use as risk factors: market β, size, gross profits, asset growth, market leverage, idiosyncratic volatility, and ICC premium. On the left-hand side I use as a risk factor the ICC estimated with IBES earnings, and on the right-hand side, I include the ICC estimated with perfect foresight earnings. I estimate ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all above-mentioned approaches. I provide explanations for the estimation of the independent variables in Section 4.2.3. To compute the ICC premiums, I use the yield on the U.S. 10-year government bond. Following Novy-Marx (2013), I winsorize only the independent variables. The Newey-West t-statistics are presented in brackets. ***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively. The sample covers the period from June/1985 to June/2012.

4.7.2. Sorts on ICC

The FM regressions in Table 4.7 and Table 4.8 show that $ICC_{Perfect\,Foresight}$ explains average returns, while $ICC_{I/B/E/S}$ has no statistically significant power to explain average return. However, FM regressions are usually sensitive to outliers and in some cases can misspecify the parametric relation between the variables. In addition, FM regressions weight all observations equally. Consequently, results may be driven by small companies. I address these issues by considering the performance of value-weighted portfolios sorted on ICC in a nonparametric setting.

Table 4.9 shows the excess of returns of value-weighted portfolios sorted on ICC. To compute the excess of returns, I use the one-month Treasury bill rate. I sort stocks at the end of June yearly from 1985 to 2012 into quintiles, deciles, and percentiles based on the ICC. I report the results for each quintile as well as the long-short strategies of 5-1 (fifth quintile minus first quintile), 10-1 (tenth decile minus first decile), and 100-1 (hundredth percentile minus first percentile). On the LHS of the table, I sort the portfolios on $ICC_{I/B/E/S}$, and on the RHS, I sort them on $ICC_{Perfect\,Foresight}$. The sample covers the period July 1985 to June 2013.

By analyzing the long-short strategies of portfolios sorted on $ICC_{I/B/E/S}$, I find no significant excess returns. These results are in line with the ones from a Fama-Macbeth regression and confirm that the correlation between ICC and future returns is weak even before controlling for other risk factors. This result is evidence against the use of $ICC_{I/B/E/S}$ as a proxy of expected return in cross-sectional settings since the results may be driven by the inaccuracy of analysts' forecasts.

The results of sorts on $ICC_{Perfect\,Foresight}$ are completely different. All tested long-short strategies show strongly significant positive returns. In addition, in every ICC approach, average returns tend to increase from the low- to the high-ICC portfolios, which is another evidence of the strong correlation between $ICC_{Perfect\,Foresight}$ and returns.

Table 4.9.: Excess of returns in sorts on ICC portfolios

	$ICC_{I/B/E/S}$					$ICC_{Perfect\,Foresight}$				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
Low ICC	0.65	0.58	0.60	0.57	0.58	-0.32	-0.31	0.36	0.17	-0.98
	[2.523]**	[2.131]**	[2.459]**	[2.418]**	[2.314]**	[-1.129]	[-0.954]	[1.432]	[0.684]	[-3.127]***
2.00	0.64	0.66	0.68	0.71	0.70	0.35	0.22	1.11	1.00	0.11
	[2.652]***	[2.920]***	[2.886]***	[3.081]***	[3.071]***	[1.402]	[0.900]	[4.878]***	[4.460]***	[0.453]
3.00	0.64	0.73	0.56	0.56	0.61	0.84	0.74	1.57	1.55	0.85
	[2.502]**	[2.999]***	[2.126]**	[2.141]**	[2.375]**	[3.400]***	[3.145]***	[6.607]***	[6.533]***	[3.644]***
4.00	0.65	0.67	0.71	0.73	0.77	1.16	1.18	1.82	1.80	1.47
	[2.464]**	[2.622]***	[2.552]**	[2.634]***	[2.756]***	[4.842]***	[5.015]***	[6.924]***	[7.044]***	[6.049]***
High ICC	0.80	0.71	0.58	0.54	0.60	1.93	1.97	2.67	2.63	2.37
	[2.770]***	[2.346]**	[1.691]*	[1.588]	[1.788]*	[7.239]***	[7.060]***	[8.266]***	[8.159]***	[8.450]***
5-1	0.14	0.13	-0.02	-0.03	0.02	2.25	2.28	2.32	2.46	3.35
	[0.824]	[0.633]	[-0.088]	[-0.148]	[0.090]	[11.626]***	[9.872]***	[11.142]***	[12.001]***	[15.558]***
10-1	0.35	0.16	0.02	0.08	0.11	3.09	2.95	3.12	3.29	4.32
	[1.429]	[0.548]	[0.087]	[0.270]	[0.371]	[10.600]***	[10.119]***	[13.369]***	[13.910]***	[14.928]***
100-1	0.40	0.37	0.53	0.46	0.40	4.31	4.25	6.18	6.48	5.77
	[0.943]	[0.675]	[0.984]	[0.785]	[0.749]	[7.587]***	[8.306]***	[11.829]***	[12.760]***	[9.931]***

This table reports the excess returns of value-weighted portfolios sorted on ICC. I sort stocks at the end of June each year from 1985 to 2012 into quintiles, deciles, and percentiles based on ICC. I report the results for each quintile, as well as the long-short strategies of 5-1 (fifth quintile minus first quintile), 10-1 (tenth decile minus first decile), and 100-1 (hundredth percentile minus first percentile). On the left-hand side I sort the portfolios on ICC estimated with I/B/E/S earnings and on the right-hand side I sort on ICC estimated with perfect foresight earnings. I estimate ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. To compute the excess of returns, I use the one-month Treasury bill rate, which is downloaded at the Kenneth French's library. The OLS t-statistics are presented in brackets. ***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively. I sample covers the period from July 1985 to June 2013 (336 months).

Although the results of $ICC_{Perfect\,Foresight}$ are consistent in all specifications, it could be the case that the excess of returns in long-short strategies is positive due to some risk factors that are not taken into consideration. To ensure that these results hold even after controlling for risk-factors, I estimate the risk-adjusted return of these portfolios based on Fama and French (2015) five-factor model (F&F5).

Table 4.10 shows the risk-adjusted returns (α), i.e., the value-weighted excess of returns from portfolios sorted on ICC regressed on F&F5.[9] Stocks are sorted at the end of June yearly from 1985 to 2012 into quintiles, deciles, and percentiles based on the ICC. I show the results for each quintile as well as the long-short strategies of 5-1 (fifth quintile minus first quintile), 10-1 (tenth decile minus first decile), and 100-1 (hundredth percentile minus first percentile). On the LHS of the table, the portfolios are sorted on $ICC_{I/B/E/S}$, and on the RHS, I sort them on $ICC_{Perfect\,Foresight}$. The sample covers the period July 1985 to June 2013.

Starting the analysis with the $ICC_{I/B/E/S}$; the CT and GLS approaches have no significant α on the strategies of long-short 5-1, 10-1, or 100-1. The results for the OJ, MPEG, and Composite ICC are surprising. Generally, it is expected higher expected returns for companies with higher ICC. However, the results show negative risk-adjusted returns. In the strategy 5-1, the OJ approach has -0.40% risk-adjusted returns per month with t-statistic of 2.313, the MPEG has -0.48% per month as risk-adjusted returns with t-statistic of 2.794, and, finally, the Composite ICC has -0.33% with t-statistic of 1.880. The results not only confirm previous literature findings that the correlation

[9] Regarding the five-factor model (F&F5), Market is the value-weighted return on all NYSE, AMEX, and NASDAQ common stocks minus the one-month Treasury bill rate, SMB is the average return on three small portfolios minus the average return on three big portfolios, HML is the average return on two value portfolios minus the average return on two growth portfolios, RMW is the average return on two robust operating profitability portfolios minus the average return on two weak operating profitability portfolios, and CMA is the average return on two conservative investment portfolios minus the average return on two aggressive investment portfolios. The one-month Treasury bill rate, as well as the (F&F5), were downloaded at the Kenneth French's library. In order to save space, I report only the risk-adjusted returns (α), but the loadings on the factors are available by request.

Table 4.10.: Risk-adjusted returns of ICC portfolios on the F&F5

	$ICC_{I/B/E/S}$					$ICC_{Perfect\ Foresight}$				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
Small	0.07	0.02	0.05	0.07	0.06	-0.88	-0.77	-0.36	-0.50	-1.49
	[1.151]	[0.190]	[0.919]	[1.217]	[0.881]	[-10.243]***	[-7.568]***	[-4.915]***	[-7.218]***	[-13.613]***
2.00	-0.06	-0.04	-0.09	-0.05	-0.04	-0.38	-0.48	0.36	0.26	-0.62
	[-0.970]	[-0.648]	[-1.432]	[-0.794]	[-0.593]	[-5.536]***	[-5.955]***	[4.236]***	[3.324]***	[-8.598]***
3.00	-0.11	-0.07	-0.21	-0.24	-0.14	0.02	-0.05	0.80	0.78	0.13
	[-1.509]	[-0.994]	[-2.591]***	[-2.857]***	[-2.003]**	[0.299]	[-0.731]	[8.259]***	[7.935]***	[1.921]*
4.00	-0.20	-0.14	-0.15	-0.13	-0.17	0.33	0.30	0.96	0.93	0.63
	[-2.092]**	[-1.614]	[-1.833]*	[-1.525]	[-1.952]*	[3.897]***	[3.533]***	[8.455]***	[8.699]***	[8.004]***
Big	-0.04	-0.22	-0.35	-0.41	-0.27	1.07	0.96	1.77	1.72	1.48
	[-0.387]	[-1.940]*	[-2.404]**	[-2.923]***	[-1.953]*	[9.409]***	[8.010]***	[10.877]***	[10.813]***	[12.305]***
5-1	-0.11	-0.23	-0.40	-0.48	-0.33	1.94	1.73	2.13	2.22	2.97
	[-0.777]	[-1.360]	[-2.313]**	[-2.794]***	[-1.880]*	[11.550]***	[9.721]***	[11.834]***	[12.475]***	[15.034]***
10-1	0.06	-0.42	-0.38	-0.39	-0.40	2.49	2.24	2.72	2.86	3.73
	[0.263]	[-1.612]	[-1.645]	[-1.695]*	[-1.587]	[9.991]***	[9.409]***	[12.971]***	[13.298]***	[15.395]***
100-1	-0.24	-0.35	0.04	-0.32	-0.30	3.61	3.41	6.00	6.05	4.91
	[-0.571]	[-0.671]	[0.090]	[-0.610]	[-0.588]	[7.030]***	[7.081]***	[11.309]***	[11.757]***	[9.730]***

This table reports the risk-adjusted returns α of value-weighted excess of returns portfolios sorted on ICC regressed on the Fama and French (2015) five-factor model (F&F5). I sort stocks at the end of June each year from 1985 to 2012 into quintiles, deciles, and percentiles based on ICC. I report the results for each quintile, as well as the long-short strategies of 5-1 (fifth quintile minus first quintile), 10-1 (tenth decile minus first decile), and 100-1 (hundredth percentile minus first percentile). On the left-hand side I sort the portfolios on ICC estimated with I/B/E/S earnings and on the right-hand side I sort on ICC estimated with perfect foresight earnings. I estimate ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. Market is the value-weighted return on all NYSE, AMEX, and NASDAQ common stocks minus the one-month Treasury bill rate, SMB is the average return on three small portfolios minus the average return on three big portfolios, HML is the average return on two value portfolios minus the average return on two growth portfolios, RMW is the average return on two robust operating profitability portfolios minus the average return on two weak operating profitability portfolios, and CMA is the average return on two conservative investment portfolios minus the average return on two aggressive investment portfolios. To compute the excess of returns, I use the one-month Treasury bill rate. The one-month Treasury bill rate, as well as the (F&F5), were downloaded at the Kenneth French's library. The OLS t-statistics are presented in brackets. ***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively. The sample covers the period from July 1985 to June 2013 (336 months).

between ICC and ex-post realized return is weak, but also show that this relation can even be negative.

When I analyze the relation of $ICC_{Perfect\,Foresight}$ and ex-post realized returns, the figures are entirely different: all long-short strategies report positive and significant α on the Fama and French (2015) five-factor model (F&F5). In addition, the risk-adjusted returns are higher if extreme long-short strategies are used. For instance, for the strategy 100-1, the risk-adjusted returns and the t-statistics are 3.61% and 7.030, respectively, for the GLS, 3.41% and 7.081 for the CT, 6.00% and 11.309 for the OJ, 6.05% and 11.757 for the MPEG, and 4.91% and 9.730 for the Composite. Positive results are consistent with theoretical considerations, but the extent of the risk-adjusted returns captured by this strategy is tremendous. Accordingly, I can show that the valuation error in the market is huge. For instance, a 1 dollar investment in a 100-1 long-short strategy based on $MPEG_{Perfect\,Foresight}$ in July 1985, over 336 months, would have earned $372,894,586.44. Of course, this strategy assumes a hypothetical perfect foresight. The key finding, however, is that the earnings forecast inaccuracy has a great impact on investment strategies, while the valuation models used to estimate ICC work well empirically.

4.7.3. Predicting the ICC using risk factors

In the last section, I showed that the $ICC_{Perfect\,Foresight}$ is a very valuable proxy for detecting market mispricing. However, due to the fact that the $ICC_{Perfect\,Foresight}$ is estimated with up to five-year-ahead ex-post earnings, it can only be estimated it for lagged periods and accordingly this estimate cannot be used for ex-ante (out-of-sample) investment strategies. In this section, I estimate a fitted ICC that can be estimated with current data.

I follow an approach similar to Gode and Mohanram (2003) when estimating a fitted ICC. First, I run a rolling window pooled regression (in-sample) using the previous five years of data. In Equation 4.14, I show the respective regression model. I regress the dependent variable $ICC_{Perfect\,Foresight}$ for firm

Table 4.11.: FM yearly regressions of $ICC_{Perfect\,Foresight}$ on the Fitted ICC and $ICC_{I/B/E/S}$

	$ICC_{I/B/E/S}$					Fitted ICC				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
Coefficient	0.770	0.435	0.778	0.781	0.465	0.940	0.774	0.927	0.926	0.897
	[49.628]***	[13.035]***	[62.331]***	[79.259]***	[20.532]***	[32.915]***	[7.557]***	[49.986]***	[54.718]***	[9.869]***
Intercept	0.119	1.413	3.572	3.145	2.391	1.003	1.212	0.084	0.684	1.618
	[0.661]	[4.223]***	[40.781]***	[15.649]***	[8.133]***	[6.175]***	[4.857]***	[0.246]	[2.793]**	[6.638]***
Observations	33,103	23,316	21,109	22,227	37,894	33,103	23,316	21,109	22,227	37,894
R-squared	40.10%	7.45%	20.80%	20.40%	10.30%	42.50%	9.11%	24.50%	24.20%	14.20%

This table presents the time-series average of slope coefficients from cross-sectional FM regressions of $ICC_{Perfect\,Foresight}$ premium on $ICC_{I/B/E/S}$ premium (left-hand side) and on Fitted ICC premium (right-hand side). I estimate the ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. To compute the ICC premiums, I use the yield on the U.S. 10-year government bond. I winsorize the dependent as well as the independent variables yearly at the 1% and 99% levels. The Newey-West t-statistics are presented in brackets. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively. The sample covers the period from June 1994 to June 2012.

(i) in year (t) on a range of firm characteristics $(x1, x2, \cdots, xn)$ for firm (i) in the relevant years $(t - \tau$ with $\tau = 5)$. The independent variables, which show an influence on ICC in previous regressions, are $ICC_{I/B/E/S}$, size, lnbeme, gross profitability, asset growth, market leverage, and idiosyncratic volatility. $(\epsilon_{(i,t)})$ is the error term for period (t). I use τ= 5 years to ensure that I do not use any ex-post variables in any of the ICC approaches. In particular, the $CT_{Perfect\,Foresight}$ approach uses one- to five-year-ahead ex-post earnings forecasts.

$$ICC_{Perfect\,Foresight(i,t-\tau)} = \alpha_0 + \alpha_1 x1_{(i,t-\tau)} + \alpha_2 x2_{(i,t-\tau)} + \cdots + \alpha_n xn_{(i,t-\tau)} + \epsilon_{(i,t-\tau).} \quad (4.14)$$

Second, I calculate the fitted ICC for year (t) following the Equation 4.15. I obtain the fitted ICC by multiplying the independent variables for each firm (i) of year (t) with the coefficients $(\alpha_0, \alpha_1, \alpha_2, \cdots, \alpha_n)$ from the pooled regression from Equation 4.14. In this approach, there are no strict survivorship requirements, as I require firms only to have sufficient accounting data for year (t) to forecast $ICC_{Perfect\,Foresight}$.[10]

$$\widehat{Fitted\,ICC}_{(i,t)} = \alpha_0 + \alpha_1 x1_{(i,t)} + \alpha_2 x2_{(i,t)} + \cdots + \alpha_n xn_{(i,t).} \quad (4.15)$$

Table 4.11 shows the coefficients of FM regressions of $ICC_{Perfect\,Foresight}$ on $ICC_{I/B/E/S}$ as well as on fitted ICC. The results show that both ICC measures are highly significant at explaining the $ICC_{Perfect\,Foresight}$, having a positive and significant t-statistics in all specifications. However, the fitted ICC has a higher R-squared in all regressions. While the $ICC_{I/B/E/S}$ reports the R-squared of 0.401, 0.0745, 0.208, 0.204, and 0.103 consecutively for the GLS, CT, OJ, MPEG, and Composite approaches, the fitted ICC presents 0.425,

[10] Consider the following example. Assuming that the intention is to estimate the $ICC_{Perfect\,Foresight}$ for year 2010 (t). First, a pooled regression is carried out with the dependent variable and independent variables for the period 2001–2005 (from years $t - 9$ to year $t - 5$) and store the regression coefficients. Then, these coefficients $(\alpha_0, \alpha_1, \alpha_2, \cdots, \alpha_n)$ are multiplied by the independent variables $(x1, x2, ..., xn)$ from year 2010 (year $= t$) to estimate the $ICC_{Perfect\,Foresight}$ for 2010 (year $t + \tau$ with $\tau = 1$).

0.0911, 0.245, 0.242, and 0.142. Accordingly, the fitted ICC seemingly has a higher correlation to the $ICC_{Perfect\,Foresight}$ compared to the $ICC_{I/B/E/S}$.

Next, in order to evaluate whether the correlation between the fitted ICC and future returns is higher than the correlation between $ICC_{I/B/E/S}$ and future returns, I estimate the risk-adjusted returns of portfolios sorted on ICC estimates. I use a similar setting as in section 4.7.2, i.e., I report the α of value-weighted excess of returns portfolios sorted on ICC regressed on the Fama and French (2015) five-factor model (F&F5). On the left-hand side of the table, I show the results for sorting the portfolios on ICC estimated with I/B/E/S earnings and on the right-hand side, I sort them on fitted ICC. The sample covers July 1994 to June 2013, due to the regression methodology. The results are shown in Table 4.12.

The coefficients for $ICC_{I/B/E/S}$ once again confirm a low correlation to ex-post returns, since none of the αs is significant even at 0.10 level. However, the results of fitted ICC present a different picture. In particular, for the fitted ICC based on the abnormal earnings growth approaches, the results indicate positive and significant abnormal returns in the long-short strategies. For the strategy 5–1, the portfolio with high ICC outperforms the portfolio of low ICC in 0.515% per month with t-statistic of 2.504 for the OJ approach, and 0.532% with t-statistic of 2.662 for the MPEG approach. In the strategy 10–1 (tenth decile minus first decile), the abnormal returns are even higher, since they yield 0.858% per month for the OJ approach and 0.962% for the MPEG. The t-statistics are 3.006 and 3.292, respectively.

Although the long-short strategies sorted on the fitted ICC yield significant and positive α, I want to ensure that these results are robust even after considering the bid-ask spread. Thus, I estimate the portfolio returns assuming that the portfolios are bought by the ask price and sold by the bid price. Then, I run the returns of the long-short portfolios on the Fama and French (2015) five-factor model (F&F5).

Table 4.13 shows that the α of the 5–1 and the 10–1 long-short-strategies based on the fitted ICC are positive and significant for the OJ and MPEG

Table 4.12.: Abnormal returns of the Fitted ICC and $ICC_{I/B/E/S}$

	$ICC_{I/B/E/S}$					Fitted ICC				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
Low ICC	0.013	0.086	0.382	0.400	0.004	-0.021	0.023	0.412	0.374	0.039
	[0.176]	[0.764]	[3.468]***	[3.772]***	[0.048]	[-0.261]	[0.280]	[4.608]***	[4.437]***	[0.685]
2	0.025	-0.077	0.478	0.321	0.063	-0.006	0.068	0.380	0.335	-0.122
	[0.286]	[-0.785]	[3.892]***	[2.883]***	[0.794]	[-0.065]	[0.631]	[3.330]***	[2.872]***	[-1.221]
3	0.076	0.058	0.536	0.471	-0.085	-0.106	-0.172	0.539	0.523	-0.086
	[0.690]	[0.544]	[4.132]***	[3.590]***	[-0.779]	[-0.990]	[-1.363]	[4.353]***	[4.103]***	[-0.896]
4	-0.155	-0.123	0.445	0.421	0.009	-0.108	0.133	0.662	0.597	-0.054
	[-1.125]	[-0.922]	[3.389]***	[3.232]***	[0.074]	[-0.945]	[1.138]	[3.912]***	[3.823]***	[-0.522]
High ICC	-0.041	0.077	0.700	0.638	-0.356	-0.009	0.236	0.927	0.906	-0.016
	[-0.259]	[0.519]	[3.694]***	[3.561]***	[-1.881]*	[-0.070]	[1.504]	[4.756]***	[4.755]***	[-0.101]
5-1	-0.054	-0.009	0.318	0.239	-0.360	0.013	0.212	0.515	0.532	-0.054
	[-0.286]	[-0.041]	[1.443]	[1.136]	[-1.528]	[0.078]	[1.078]	[2.504]**	[2.662]***	[-0.306]
10-1	0.391	0.010	0.324	0.019	-0.400	-0.010	0.322	0.858	0.962	-0.069
	[1.524]	[0.035]	[1.201]	[0.066]	[-1.215]	[-0.040]	[1.282]	[3.006]***	[3.292]***	[-0.287]

This table reports pricing errors α of value-weighted excess of returns portfolios sorted on ICC regressed on the Fama and French (2015) five-factor model (F&F5). I sort stocks at the end of June each year from 1994 to 2012 into quintiles and deciles based on ICC. I report the results for each quintile, as well as the long-short strategies of 5-1 (fifth quintile minus first quintile) and 10-1 (tenth decile minus first decile). On the left-hand side I sort the portfolios on ICC estimated with I/B/E/S earnings and on the right-hand side I sort on ICC estimated with perfect foresight earnings. I estimate ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. Market is the value-weighted return on all NYSE, AMEX, and NASDAQ common stocks minus the one-month Treasury bill rate, SMB is the average return on three small portfolios minus the average return on three big portfolios, HML is the average return on two value portfolios minus the average return on two growth portfolios, RMW is the average return on two robust operating profitability portfolios minus the average return on two weak operating profitability portfolios, and CMA is the average return on two conservative investment portfolios minus the average return on two aggressive investment portfolios. To compute the excess of returns, I use the one-month Treasury bill rate. The one-month Treasury bill rate, as well as the (F&F5), were downloaded at the Kenneth French's library. The OLS t-statistics are presented in brackets. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively. The sample covers the period from July 1994 to June 2013.

Table 4.13.: Abnormal returns of the Fitted ICC and $ICC_{I/B/E/S}$ including Bid-Ask Spread

Panel A: Long-Short 5-1 Strategy

	IBES ICC					Perfect Foresight ICC				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
RMRF	0.094	0.097	0.185	0.225	0.190	0.048	0.151	0.216	0.232	0.153
	[1.919]*	[1.733]*	[3.183]***	[4.062]***	[3.083]***	[1.133]	[2.942]***	[4.015]***	[4.441]***	[3.302]***
SMB	0.274	0.219	0.458	0.432	0.487	0.220	0.243	0.598	0.630	0.528
	[4.408]***	[3.086]***	[6.206]***	[6.156]***	[6.217]***	[4.074]***	[3.721]***	[8.757]***	[9.502]***	[8.981]***
HML	0.541	0.663	0.629	0.618	0.533	0.734	0.785	0.846	0.825	0.884
	[6.704]***	[7.206]***	[6.580]***	[6.788]***	[5.252]***	[10.511]***	[9.294]***	[9.557]***	[9.598]***	[11.602]***
RMW	0.069	0.079	-0.161	-0.108	0.038	0.072	-0.168	-0.368	-0.337	-0.321
	[0.805]	[0.812]	[-1.595]	[-1.124]	[0.356]	[0.978]	[-1.880]*	[-3.932]***	[-3.704]***	[-3.985]***
CMA	0.056	0.053	0.052	0.139	0.189	0.185	0.006	-0.140	-0.132	0.255
	[0.503]	[0.417]	[0.396]	[1.114]	[1.357]	[1.934]*	[0.048]	[-1.154]	[-1.121]	[2.440]**
Intercept	-0.085	-0.047	0.264	0.190	-0.400	-0.017	0.172	0.469	0.486	-0.095
	[-0.452]	[-0.219]	[1.188]	[0.898]	[-1.695]*	[-0.107]	[0.874]	[2.278]**	[2.430]**	[-0.538]
R-squared	0.361	0.371	0.414	0.445	0.366	0.588	0.461	0.589	0.608	0.671

Panel B: Long-Short 10-1 Strategy

	IBES ICC					Perfect Foresight ICC				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
RMRF	0.013	0.126	0.176	0.260	0.223	0.039	0.138	0.151	0.177	0.149
	[0.187]	[1.624]	[2.486]**	[3.509]***	[2.580]**	[0.623]	[2.106]**	[2.012]**	[2.309]**	[2.375]**
SMB	0.291	0.349	0.426	0.523	0.553	0.100	0.527	0.759	0.811	0.580
	[3.408]***	[3.554]***	[4.748]***	[5.580]***	[5.054]***	[1.256]	[6.325]***	[7.991]***	[8.351]***	[7.281]***
HML	0.489	0.690	0.449	0.521	0.600	0.697	0.998	0.947	0.982	1.248
	[4.416]***	[5.425]***	[3.857]***	[4.285]***	[4.231]***	[6.752]***	[9.234]***	[7.694]***	[7.798]***	[12.087]***
RMW	-0.119	0.316	-0.170	-0.050	-0.086	0.015	-0.445	-0.622	-0.654	-0.616
	[-1.015]	[2.349]**	[-1.383]	[-0.392]	[-0.575]	[0.139]	[-3.890]***	[-4.775]***	[-4.911]***	[-5.640]***
CMA	0.309	0.219	0.227	0.288	0.338	0.515	0.091	-0.060	-0.165	0.124
	[2.035]**	[1.256]	[1.427]	[1.733]*	[1.740]*	[3.642]***	[0.618]	[-0.354]	[-0.959]	[0.874]
Intercept	0.360	-0.043	0.264	-0.043	-0.451	-0.046	0.263	0.809	0.905	-0.119
	[1.398]	[-0.144]	[0.975]	[-0.154]	[-1.368]	[-0.190]	[1.047]	[2.831]***	[3.095]***	[-0.498]
Observations	228	228	228	228	228	228	228	228	228	228
R-squared	0.261	0.339	0.282	0.335	0.302	0.459	0.522	0.527	0.542	0.641

This table reports the results of regressions of value-weighted excess of returns portfolios sorted on ICC on the Fama and French (2015) five-factor model (F&F5). I sort stocks at the end of June each year from 1994 to 2012 into quintiles and deciles based on ICC. I report the results of the long-short strategies of 5-1 (fifth quintile minus first quintile) and 10-1 (tenth decile minus first decile). To estimate the returns of the portfolios, I assume that the portfolios are bought by the ask price and sold by the bid price. On the left-hand side I sort the portfolios on ICC estimated with I/B/E/S earnings and on the right-hand side I sort on Fitted ICC. I estimate ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. Market is the value-weighted return on all NYSE, AMEX, and NASDAQ common stocks minus the one-month Treasury bill rate, SMB is the average return on three small portfolios minus the average return on three big portfolios, HML is the average return on two value portfolios minus the average return on two growth portfolios, RMW is the average return on two robust operating profitability portfolios minus the average return on two weak operating profitability portfolios, and CMA is the average return on two conservative investment portfolios minus the average return on two aggressive investment portfolios. To compute the excess of returns, I use the one-month Treasury bill rate. The one-month Treasury bill rate, as well as the (F&F5), were downloaded at the Kenneth French's library. The OLS t-statistics are presented in brackets. ***, **, and * denote significance at 0.01, 0.05, and 0.10 levels, respectively. The sample covers the period from July 1994 to June 2013.

approach even after considering the bid-ask spread. The fitted ICC based on the OJ approach yields abnormal returns (α) of 0.469% per month with t-statistic of 2.278 for the 5–1 long-short strategy, and 0.809% per month with t-statistic of 2.831 for the 10–1 long-short strategy. The fitted MPEG approach yields abnormal returns of 0.486% with t-statistic of 2.430 for the 5–1 strategy, and 0.905% with t-statistic of 3.095 for the 10–1 long-short strategy.

When I include the bid-ask spread in the long-short strategies sorted on $ICC_{I/B/E/S}$, most of the results are not statistically significant. However, the 5–1 long-short strategy based on the Composite ICC yields -0.40% per month with t-statistics 1.695, which is statistically significant at 0.10 level. Therefore, I confirm the weak or, in some cases, negative relation between $ICC_{I/B/E/S}$ and realized returns.

To sum up, these results show that the fitted ICC has a higher correlation, not only to $ICC_{Perfect\,Foresight}$ but also to ex-post realized returns. Accordingly, the fitted ICC may be a good alternative to $ICC_{I/B/E/S}$ as a proxy for expected returns.

4.8. Conclusion

The implied cost of capital (ICC) is widely used as a proxy for expected returns. However, many studies show that the cross-sectional correlation between ICC and ex-post realized returns is not statistically significant. An unsolved puzzle is whether this weak correlation is driven by the underlying assumptions of the valuation models or the inaccuracy of analysts' earnings forecasts, which is the most commonly used input for estimating the ICC.

To solve this puzzle, I evaluate the effect of analysts' earnings forecast errors on estimates of the ICC. For that purpose, I compare the properties of ICC estimated with analysts' forecasts ($ICC_{I/B/E/S}$) to $ICC_{Perfect\,Foresight}$, estimated with ex-post realized earnings. In order to determine the magnitude of inaccuracy in the ICC estimates due to the analysts' inaccuracy, I measure the ICC absolute error, which is defined as the absolute difference between $ICC_{I/B/E/S}$ and $ICC_{Perfect\,Foresight}$. To ensure that the results are not driven by wrong estimations of growth, the ICC absolute error is estimated at the portfolio level. I find that the magnitude of this error is 5.21% on average and, accordingly, conclude that the weak results of ICC explaining returns may be driven by inaccuracy in earnings forecasts.

Then, I compare the results of ($ICC_{I/B/E/S}$) and $ICC_{Perfect\,Foresight}$ by explaining ex-post realized returns. In line with previous literature, the $ICC_{I/B/E/S}$ has no significant relation to ex-post realized returns. However, the $ICC_{Perfect\,Foresight}$ has quite a strong relation to returns. The cross-sectional coefficients of $ICC_{Perfect\,Foresight}$ on returns are all positive and highly significant. Furthermore, a long-short strategy based on this proxy generates abnormal returns of up to 6.05% per month, in this setting. These results are in line with the hypothesis that the weak explanatory power of $ICC_{I/B/E/S}$ regarding returns is driven by analysts' inaccuracy. Furthermore, I find no evidence that this relation could be a valuation model specific issue.

Although the $ICC_{Perfect\,Foresight}$ seemingly has strong explanatory power in relation to returns, this proxy cannot be used in investment strategies because it requires ex-post earnings to be estimated. Thus, in order to determine a proxy for expected returns that can be estimated ex-ante, I calculate a fitted ICC, which is similar to an instrumental variable of the $ICC_{Perfect\,Foresight}$ but estimated ex-ante. I show that the fitted ICC has a higher correlation to $ICC_{Perfect\,Foresight}$ as well as to ex-post realized returns, making it a good alternative to $ICC_{I/B/E/S}$. In addition, a long-short strategy based on this proxy yields abnormal returns of up to 0.962% per month.

My findings are relevant for practitioners and academics who rely on ICC as a proxy for expected returns. I show that the ICC valuation models work in the real market but that earnings forecast accuracy plays a very important role in the estimation of ICC. I recommend using a fitted ICC as a proxy for expected returns. However, as the fitted ICC uses the $ICC_{I/B/E/S}$ as an input, further studies should also work on improving earnings forecast accuracy by using mechanical models, as suggested by Hou et al. (2012), or mixed data sampling regression methods, as proposed by Ball and Ghysels (2017).

5. Earnings Forecasts: A Combination of Analysts' Estimates with a Mechanical Model

This chapter is largely based on Azevedo et al. (2017).

I propose a novel method to forecast corporate earnings, which combines the accuracy of analysts' forecasts with the unbiasedness of a mechanical model. I build on recent insights from the earnings forecasts literature to select variables that have predictive power with respect to earnings. The model outperforms the most popular methods from the literature in terms of forecast accuracy, bias, and earnings response coefficient. Furthermore, using this model's estimates in the implied cost of capital calculation leads to a substantially stronger correlation with realized returns compared to extant mechanical earnings estimates.

5.1. Introduction

Earnings forecasts are a critical input in many academic studies in finance and accounting as well as in practical applications. They are central to firm valuation, are widely used in asset allocation decisions, and are the basis for calculating the Implied Cost of Capital (ICC). It is, therefore, crucial to have precise and unbiased estimates.

The most popular source for obtaining earnings forecasts are financial analysts. These forecasts are aggregated by data providers, such as the Institutional Brokers' Estimate System (I/B/E/S), and subsequently made available to academics and practitioners by these providers. Although analysts' forecasts are fairly accurate (O'Brien, 1988; Hou et al., 2012), researchers have found a significant optimism bias (Francis and Philbrick, 1993; McNichols and O'Brian, 1997; Easton and Sommers, 2007).

The alternative to analysts' earnings forecasts is a mechanical model, which can either solely be based on past realizations of earnings (time-series models) or on a combination of past earnings and other financial variables. The literature first developed time-series models. These models use past realizations of earnings in a linear or an exponential smoothing framework (Ball and Brown, 1968; Brown et al., 1987). The results are underwhelming; these forecasts are neither accurate nor unbiased. In addition, they suffer from survivorship bias as only firms with a long history of earnings can be included in the model. Fried and Givoly (1982) conclude that time-series models are worse than analysts' forecasts for predicting future earnings. This result was later confirmed by O'Brien (1988).

More recently, cross-sectional models to forecast earnings proliferated. Researchers have used accounting variables, such as assets, earnings, capital expenditure, as well as risk-factor variables, such as size (Banz, 1981; Fama and French, 1992), book-to-market ratio (Rosenberg et al., 1985), momentum (De Bondt and Thaler, 1985; Jegadeesh and Titman, 1993; Carhart, 1997), accruals (Sloan, 1996), dividends (Fama and French, 2000), and average returns (Haugen and Baker, 1996) to predict earnings. Fama and French (2006) create one of the first cross-sectional models that predict future profitability. Their empirical set-up comprises two different multiple regressions. The first one uses firm size and several accounting fundamentals. This model can be seen as a starting point for cross-sectional forecasting methods. The second model additionally includes the firm's stock return for fiscal year (t), analysts' earnings forecasts for $(t+1)$, the composite measure of Piotroski (2000) and Ohlson (1980) for firm's strength, and lagged returns. Average regression slopes change only slightly because of these new input parameters. The main outcome of these two models is that earnings as an independent variable are highly persistent in forecasting profitability.

Hou, van Dijk and Zhang (2012) develop a cross-sectional model (henceforth HVZ model) based on assets, earnings, and dividends, which outperforms analysts' forecasts in terms of coverage, Earnings Response Coefficients (ERC),[1] and forecast bias.[2] However, this model still trailed analysts' forecasts with respect to forecast accuracy.[3] Gerakos and Gramacy (2013) find that a simple Random Walk (RW) model, in which the previous period's value is used as a forecast, performs as well as other, more sophisticated, earnings forecast models. Finally, Li and Mohanram (2014) implement an Earnings Persistence (EP) and a Residual Income (RI) model to forecast earnings. They show that these models are superior to the HVZ and RW models in terms of bias, accuracy, and ERC.

Recently, Ball and Ghysels (2017) develop a model based on mixed data sampling regression methods (MIDAS), which combines various high-frequency time-series data to forecast earnings. Their model outperforms raw analysts' forecasts in some cases and also can be combined with analysts' forecasts to improve forecast accuracy. The findings from Ball and Ghysels (2017) tie in with mine as they show that mechanical models can be used to improve earnings forecasts. One important difference to this study is that the model from Ball and Ghysels (2017) is not suited to estimate ICCs as the focus is on quarterly forecasts (instead of yearly ones).

To summarize, it is still not clear whether there is a method which dominates other methods along both dimensions accuracy and bias. I contribute to the literature by proposing a parsimonious cross-sectional model which includes analysts' earnings forecasts, gross profits, and past stock performance.

[1] The ERC estimates the relationship between earnings surprises and stock returns.
[2] Bias is defined as the difference between the actual earnings and earnings forecast.
[3] Accuracy is defined as the absolute value of the forecast bias.

I aim for accurate and unbiased estimates that display a strong ERC. I include the accounting variable gross profits based on evidence from Novy-Marx (2013), who finds that gross profitability is able to explain many earnings-related anomalies, such as return on assets, earnings-to-price, asset turnover, gross margins, and standardized unexpected earnings. The rational for including past stock performance is based on Richardson et al. (2010) and Ashton and Wang (2012), who find that changes in stock prices drive earnings as well as evidence of Abarbanell (1991) that stock returns predict future forecast revisions. I term this method the combined model (CM), as it combines analysts' forecasts with a cross-sectional method.

I compare the combined model to the most popular methods in the literature, namely analysts' forecasts and the RW, EP, RI, and HVZ models. In addition, I estimate a cross-sectional analysts' forecasts (CSAF) model. This model is based on a cross-sectional regression including only analysts' earnings forecasts as an input. I show that the combined model delivers earnings forecasts that are slightly more accurate than analysts' forecasts and markedly more accurate than the mechanical models while beating all other tested methods in terms of bias and ERC. Concerning the CSAF model, the results show that this model underperforms not only the combined model but also the raw analysts' forecasts in terms of bias and accuracy. This evidence suggests that using the analysts' forecasts in a mechanical model is not sufficient to improve the accuracy of the forecasts nor to eliminate bias. However, the fact that the combined model outperforms all of the analyzed models, including the CSAF, shows that the variables gross profits and past performance substantially improve earnings forecasts.

One important application of earnings forecasts is the computation of the ICC. To further evaluate earnings forecasts estimated with the combined model, I employ them as inputs in computing the ICC. Then, I compare those estimates to ICC figures calculated by using the other tested earnings forecast methods. The results show that many of the benchmark models have a negative and significant relation to gross profits. This is in conflict with

Novy-Marx (2013) and Fama and French (2015) who derive theoretically and show empirically that firms with high gross profitability should have higher expected returns. In contrast, the ICC based on the combined model shows a positive and significant relation, in line with the theoretical derivation. In addition, the ICC based on the combined model displays a higher explanatory power on ex-post realized returns in both dimensions (cross-sectional and time-series) than the ICC based on the other benchmark models. A long-short strategy of buying the highest ICC decile and short-selling the lowest ICC decile based on the ICC estimated with the combined model yields a mean monthly return of up to 1.15%.

The paper is organized as follows. In Section 5.2, I describe my sample selection, the cross-sectional models, and provide details on the ICC estimation. In Section 5.3, I compare the performance of earnings forecast proxies in terms of bias, accuracy, and ERC. In Section 5.4, I evaluate the performance of ICC estimates calculated using different methods to forecast earnings. I conclude in Section 5.5.

5.2. Data and methodology

5.2.1. Sample selection

I select firms at the intersection of the Center for Research in Security Prices (CRSP), Compustat fundamentals annual, and I/B/E/S summary files. I filter for firms listed on NYSE, AMEX, and NASDAQ with share codes 10 and 11. My sample starts in June 1977, as this is the first year for which I/B/E/S provides analysts' forecasts, and ends on June 2015. At least five years of data are required for the 10-year pooled regressions of the cross-sectional forecasting models. To evaluate the earnings forecasts, I use data from the year after the forecast was made. Therefore, the forecasts cover the period from 1982 to 2014. I require non-missing one- and two-year-ahead earnings forecasts, price, and shares outstanding from I/B/E/S and book values, earnings, and dividends from Compustat to include a firm-year in the sample. My proxy for the risk-free rate is the yield on the U.S. 10-year government bond, which I obtained from Thomson Reuters Datastream. I use the following variables from Compustat: income before extraordinary items (Compustat IB), gross profits (Compustat items: $(REVT - COGS)$), total assets (Compustat AT), dividends (Compustat DVC), book value (Compustat CEQ), book value of the debt (Compustat items: $(DLC + DLTT)$), and capital expenditures (Compustat $CAPX$).

5.2.2. Earnings forecasts

I develop a model that combines analysts' earnings forecasts with a cross-sectional model to forecast earnings. This model is compared to popular methods from the literature, namely using only analysts' forecasts, the RW model,[4] and four cross-sectional models: the CSAF, Hou et al. (2012) (HVZ),[5] EP, and RI models.[6] Although one of the benefits of the cross-sectional models usually is the wider coverage since it requires only accounting variables and not analysts' forecasts, Li and Mohanram (2014) show that cross-sectional earnings forecasts in the sample without I/B/E/S coverage are substantially more inaccurate and biased than the sample with I/B/E/S coverage. This is intuitive as firms without analyst coverage tend to be smaller firms with a lower information environment (Hou et al., 2012), which makes it more difficult to forecast earnings mechanically.

I obtain analysts' forecasts and share prices from I/B/E/S as of June for each year in the sample period. To compare analysts' forecasts to the aforementioned models, I transform analysts' estimates from a per share level to

[4] I include the RW based on evidence that at a one-year horizon, the RW model performs as well as more sophisticated estimation methods (Gerakos and Gramacy, 2013).

[5] According to Hou et al. (2012), their cross-sectional model is superior to analysts' forecasts in terms of forecast bias and ERC.

[6] I include the Earnings Persistence and Residual Income models as a benchmark due to evidence of Li and Mohanram (2014) that these models outperform the HVZ model in terms of forecast bias, accuracy, earnings response coefficient, and correlation of ICCs with future earnings and risk factors.

a dollar level by multiplying the per share figures by the number of shares outstanding provided by I/B/E/S. For the RW model, following Gerakos and Gramacy (2013), I use income before extraordinary items from year (t) as earnings forecasts for year ($t+\tau$ with $\tau = 1$ to 3).

I follow the approach of Hou et al. (2012) when estimating the cross-sectional regressions. First, I run a rolling window pooled regression (in-sample) using the previous ten years of data. In Equation 5.1 I show the regression model. The dependent variable earnings ($E_{(i,t)}$) for firm (i) in year (t) are regressed on the independent variables ($x1, x2, \cdots, xn$) for firm (i) in the relevant year ($t - \tau$ with $\tau = 1$ to 3). ($\epsilon_{(i,t)}$) is the error term for period (t). I perform the regression at the dollar level with unscaled data.

$$E_{(i,t)} = \alpha_0 + \alpha_1 x1_{(i,t-\tau)} + \alpha_2 x2_{(i,t-\tau)} + \cdots + \alpha_n xn_{(i,t-\tau)} + \epsilon_{(i,t)}. \tag{5.1}$$

Second, I forecast earnings ($E_{(i,t+\tau)}$) (out-of-sample) for year ($t + \tau$) (see Equation 5.2). I obtain the forecast by multiplying the independent variables for each firm (i) of year (t) with the coefficients ($\alpha_0, \alpha_1, \alpha_2, \cdots, \alpha_n$) from the pooled regression from Equation 5.1. The advantage of this approach is that there are no strict survivorship requirements as firms are required only to have sufficient accounting data for year (t) to forecast earnings.

$$\tilde{E}_{(i,t+\tau)} = \alpha_0 + \alpha_1 x1_{(i,t)} + \alpha_2 x2_{(i,t)} + \cdots + \alpha_n xn_{(i,t)}. \tag{5.2}$$

Consider the following example. Assume that 2010 is year (t) and the objective is to to forecast the earnings for 2011 ($t+\tau$ with $\tau = 1$). First, a pooled regression is run with the dependent variable data for the period 2001–2010 (from year $t-9$ to year t) on the independent variables for the period 2000–2009 (from year ($t-9-\tau$) to year ($t-\tau$ with $\tau = 1$) and the regression coefficients are stored. Then, these coefficients ($\alpha_0, \alpha_1, \alpha_2, \cdots, \alpha_n$) are multiplied by the independent variables ($x1, x2, ..., xn$) from year 2010 (year $= t$) to estimate the earnings for 2011 (year $t+\tau$ with $\tau = 1$).

I forecast earnings in June of each year (t). I am mindful of avoiding the use of data that was not publicly available at the estimation dates. To this end, I collect accounting data only for companies with fiscal year end between April of year $(t-1)$ to March of year (t). To mitigate the influence of outliers, I winsorize earnings and other level variables each year at the first and last percentile as in Hou et al. (2012) and Li and Mohanram (2014).

Note that when evaluating forecast bias, accuracy, and ERC the researcher has to ensure that the definition of earnings forecasts and realized earnings are in line. More specifically, analysts typically forecast street earnings, which differ from earnings according to the Generally Accepted Accounting Principles (GAAP) in significant points (Bradshaw and Sloan, 2002). To account for this difference, I compare analysts' forecasts and the combined model forecasts to realized street earnings. For the other models (HVZ, RI, EP, RW), I perform the comparison based on realized income before extraordinary items, which is based on GAAP. This distinction is also made in other papers (e.g., Hou et al. (2012)). Furthermore, in order to report a fair comparison among the models, the sample of earnings forecast models is restricted to firm-year observations for which analysts' forecasts are available.

5.2.2.1. Combined model

The combined model aims to take advantage of the high accuracy of analysts' forecasts, while incorporating the low bias of the cross-sectional models. To include analysts' forecasts, I use the last available forecast from I/B/E/S. My cross-sectional model is a parsimonious approach that includes gross profits and two variables related to past stock returns. The use of gross profits is motivated by findings from Novy-Marx (2013), who shows that this variable explains most earnings related anomalies and a wide range of seemingly unrelated profitable trading strategies. I include two variables related to past stock returns because Ashton and Wang (2012) and Richardson et al. (2010) show that price changes drive earnings. The model is presented in Equation 5.3:

$$E_{(i,t)} = \alpha_0 + \alpha_1 eIBES1_{(i,t-\tau)} + \alpha_2 GP_{(i,t-\tau)} + \alpha_3 r10_{(i,t-\tau)} + \alpha_4 r122_{(i,t-\tau)} + \epsilon_{(i,t)}, \quad (5.3)$$

where $(E_{(i,t)})$ represents the street earnings of firm i in year (t), $(eIBES1_{(i,t-\tau)}$ with $\tau = 1 \; to \; 3)$ is the I/B/E/S one-year-ahead earnings forecast, $(GP_{(i,t-\tau)})$ is gross profits, $(r10_{(i,t-\tau)})$[7] is the change of market capitalization over the preceding month. $(r122_{(i,t-\tau)})$[8] is the change in market capitalization from $t-12$ to $t-2$ months. As the regression is carried out at the dollar level, the I/B/E/S one-year-ahead earnings per share forecast, as well as the realized street earnings per share, are multiplied by the number of shares provided by I/B/E/S.

5.2.2.2. Cross-Sectional Analysts' Forecasts

To show that the combined model benefits from the combination of analysts' forecast with a mechanical model (and that neither of its components drives the strong forecast performance), I include a model that uses analysts' forecast in a cross-sectional setting. I estimate the cross-sectional analysts' forecasts (CSAF) model with Equation 5.4:

$$E_{(i,t)} = \alpha_0 + \alpha_1 eIBES1_{(i,t-\tau)} + \epsilon_{(i,t)}, \quad (5.4)$$

where $(E_{(i,t)})$ represents the street earnings of firm (i) in year (t) and $(eIBES1_{(i,t-\tau)}$ with $\tau = 1 \; to \; 3)$ is the I/B/E/S one-year-ahead earnings forecasts. This regression is carried out at the dollar level. However, if the regression are performed at the per share level, it has no effect on inferences.

[7] I estimate $(r10_{(i,t-\tau)})$ by multiplying market equity of month $(t-1-\tau)$ with the total return (including dividends) from month $(t-1-\tau)$ to $(t-\tau)$.

[8] I compute $(r122_{(i,t-\tau)})$ by multiplying market equity of month $(t-12-\tau)$ with the total return (including dividends) from month $(t-12-\tau)$ to $(t-2-\tau)$.

5.2.2.3. The Hou, van Dijk and Zhang model

I estimate the Hou et al. (2012) model with Equation 5.5:

$$E_{(i,t)} = \alpha_0 + \alpha_1 eA_{(i,t-\tau)} + \alpha_2 D_{(i,t-\tau)} + \alpha_3 DD_{(i,t-\tau)} + \alpha_4 E_{(i,t-\tau)} + \alpha_5 NegE_{(i,t-\tau)} + \alpha_6 Ac_{(i,t-\tau)} + \epsilon_{(i,t)}, \quad (5.5)$$

where ($E_{(i,t)}$) represents income before extraordinary items of firm (i) in year (t), ($A_{(i,t-\tau)}$) represents total assets in year ($t-\tau$ with $\tau = 1$ to 3), ($D_{(i,t-\tau)}$) denotes paid dividends of firm (i) in year ($t-\tau$ with $\tau = 1$ to 3), ($DD_{(i,t-\tau)}$) is a dummy variable that equals 1 if firm (i) paid a dividend in year ($t-\tau$) and 0 otherwise, ($NegE_{(i,t-\tau)}$) is a dummy variable, which is set to 1 if company (i) reported negative earnings and 0 otherwise, and ($Ac_{(i,t-\tau)}$) is accruals for firm (i) in year ($t-\tau$ with $\tau = 1$ to 3). Accruals are estimated until 1987 as the change in non-cash current assets less the change in the current liabilities, excluding the change in short-term debt and the change in taxes payable minus depreciation and amortization expenses (Compustat items: $(ACT - CHE) - (LCT - DLC - TXP) - DP$). Starting in 1988, I estimate accruals as the difference between earnings and cash flows from operations (Compustat items: $IB - (OANCF - XIDOC)$).

5.2.2.4. The Earnings Persistence model

The Earnings Persistence (EP) model according to Li and Mohanram (2014) is specified as:

$$E_{(i,t)} = \alpha_0 + \alpha_1 eNegE_{(i,t-\tau)} + \alpha_2 E_{(i,t-\tau)} + \alpha_3 NegE * E_{(i,t-\tau)} + \epsilon_{(i,t)}, \quad (5.6)$$

where ($E_{(i,t)}$) represents income before extraordinary items for firm (i) in year (t),[9] ($NegE_{(i,t-\tau)}$) is a dummy variable, which is set to 1 if company

[9] Like Hou et al. (2012), I use income before extraordinary items as a proxy for earnings forecasts. I use the same proxy for the benchmark models in order to make the comparison consistent. The results are robust to using income before special and extraordinary

(i) reported negative earnings and 0 otherwise, and $(NegE * E_{(i,t-\tau)})$ is the interaction term of the latter two variables.

5.2.2.5. The Residual Income model

The Residual Income (RI) model was introduced by Edwards and Bell (1961) and Feltham and Ohlson (1996). The model was subsequently adjusted by Li and Mohanram (2014) to forecast earnings. The model is estimated by means of Equation 5.7:

$$E_{(i,t)} = \alpha_0 + \alpha_1 eNegE_{(i,t-\tau)} + \alpha_2 E_{(i,t-\tau)} + \alpha_3 NegE * E_{(i,t-\tau)} + \alpha_4 B_{(i,t-\tau)} + \alpha_5 Tacc_{(i,t-\tau)} + \epsilon_{(i,t)}, \quad (5.7)$$

where $(E_{(i,t)})$ represents income before extraordinary items for firm (i) in year (t), $(NegE_{(i,t-\tau)})$ is a dummy variable, which is set to 1 if company (i) reported negative earnings and 0 otherwise, $(NegE*E_{(i,t-\tau)})$ is the interaction term between the negative earnings dummy variable and earnings, $(B_{(i,t-\tau)})$ denotes book value for firm (i) in year $(t-\tau$ with $\tau = 1$ to 3), and $(Tacc_{(i,t-\tau)})$ is total accruals for firm (i) in year $(t - \tau$ with $\tau = 1$ to 3). Total accruals are based on Richardson et al. (2005), calculated as the sum of change in net working capital (Compustat items: $(ACT - CHE) - (LCT - DLC)$), the change in net non-current operating assets (Compustat items: $(AT - ACT - IVAO) - (LT - LCT - DLTT)$), and the change in net financial assets (Compustat items: $(IVST + IVAO) - (DLTT + DLC + PSTK)$).

5.2.3. Estimating the ICC

The ICC is defined as the interest rate that equates a stock's current price to the present value of its expected future free cash flows to equity. The cash flows are estimated using earnings forecasts and expected growth in earnings. There are many different approaches to estimate the ICC in the literature, so

items as proposed by Li and Mohanram (2014).

for the purpose of my tests, four common methods are chosen. I implement two methods that are based on a residual income model, namely Gebhardt et al. (2001) (GLS) and Claus and Thomas (2001) (CT).[10] In addition, I employ two methods that are based on an abnormal earnings growth model, namely Ohlson and Juettner-Nauroth (2005) (OJ) and Easton (2004) (modified price-earnings growth or MPEG). Last, I estimate a composite ICC, which is the average of the four aforementioned approaches. To maximize the coverage of the composite ICC, I only require a firm to have at least one non-missing individual ICC estimate (as in Hou et al. (2012))

For the calculation of ICC, I require each firm to have a one-year-ahead, a two-year-ahead, and a three-year-ahead earnings forecast. If the three-year-ahead forecast is not available, I estimate it by multiplying the two-year-ahead mean earnings forecast by one plus the consensus long-term growth rate. If neither the three-year-ahead earnings forecast nor the long-term growth rate is available, I compute the growth rate between the one-year and two-year-ahead earning forecasts and use this to estimate the three-year-ahead earnings forecast. Following Hou et al. (2012), I assume that the annual report becomes publicly available at the latest 90 days after the fiscal year-end. Like Gebhardt et al. (2001), I create a synthetic book value when this information is not yet public. Specifically, I estimate the synthetic book value using book value data for year $(t-1)$ plus earnings minus dividends ($B_t = B_{t-1} + EPS_t - D_t$). Regarding the payout ratio, I use the current payout ratio for firms with positive earnings. For firms with negative earnings, I compute the payout ratio as the ratio between dividends and 6% of total assets. In particular, for the residual income models, the book value is estimated in year[11] $t+\tau$ using the clean surplus relation $B_{(t+\tau)} = B_{(t+\tau-1)} + EPS_{(t+\tau)} * (1 - PayoutR)$. However, I set the payout ratio as zero, when the $EPS_{(t+\tau)}$ is negative. I do

[10] Although the CT and GLS approaches are both based on a residual income valuation model, the methods have an important difference. While the CT model is designed to compute the market-level cost of capital, the GLS model is made to compute the firm-level cost of capital.

[11] The CT (GLS) ICC approach requires the calculation of book value from the year t to year $t+\tau$ with $\tau = 4$ ($\tau = 11$).

that in order to ensure that the model does not assume a negative dividend yield. Finally, I exclude all observations with negative book value per share, and I winsorize growth rates below 2% and above 100%. See Sections 2.2 and 2.3 for a detailed description of the ICC methodologies.

5.3. Empirical results of earnings forecasts methods

5.3.1. Coefficient estimates of cross-sectional regressions

In this section, I present the first step of the procedure to forecast earnings, i.e., the pooled (in-sample) regression using lagged ten years of data. I report the average coefficients, the respective t-statistics with Newey and West (1987) adjustment and the Adjusted R-squared. The earnings are estimated yearly from 1983 to 2015 for one-year-ahead forecasts, from 1985 to 2015 for two-year-ahead forecasts, and from 1987 to 2015 for three-year-ahead forecasts. I regress earnings at time (t) on lagged independent variables. ($\tau = 1$), ($\tau = 2$), and ($\tau = 3$) indicate that the independent variables are lagged by one, two and three years, respectively.

Panel A of Table 5.1 reports the results for the combined model. First, the results show that lagged analysts' earnings forecasts ($eIBES1_{i,t-\tau}$ with $\tau = 1$ to 3) are highly significant in explaining earnings even when controlling for other variables from the earnings forecasts literature. Various studies have documented the accuracy of analysts' earnings forecasts (e.g., Fried and Givoly (1982); O'Brien (1988); Hou et al. (2012)) and this finding corroborates the choice of including analysts' forecasts in the combined model. In terms of magnitude, the average coefficient for analysts' earnings forecasts is less than 1 (0.957 for one-year-lagged regression, 0.872 in two-year-lagged regression, and 0.774 in the three-year-lagged regression), which confirms the result from the literature that analysts' forecasts tend to be too optimistic.

Table 5.1.: Coefficient estimates from the pooled (in-sample) regressions

Panel A: Combined Model

	Intercept	$eIBES1_{(t-\tau)}$	$GP_{(t-\tau)}$	$r10_{(t-\tau)}$	$r122_{(t-\tau)}$	Adj. R-squared
$\tau = 1$	-1.550	0.957	-0.006	0.057	0.013	0.94
	[4.33]**	[33.31]**	[2.62]*	[4.74]**	[2.02]	
$\tau = 2$	0.914	0.872	0.026	0.086	0.014	0.86
	[0.53]	[21.37]**	[7.32]**	[4.24]**	[2.25]*	
$\tau = 3$	3.947	0.774	0.057	0.054	0.037	0.81
	[1.08]	[13.08]**	[12.53]**	[3.13]**	[1.18]	

Panel B: Cross-Sectional Analysts' Forecasts (CSAF)

	Intercept	$eIBES1_{(t-\tau)}$	Adj. R-squared
$\tau = 1$	-1.675	0.953	0.94
	[3.85]**	[35.87]**	
$\tau = 2$	5.941	0.971	0.85
	[1.74]	[22.08]**	
$\tau = 3$	15.343	0.992	0.78
	[2.6]*	[20.38]**	

Panel C: Hou et al. (2012) Model

	Intercept	$E_{(t-\tau)}$	$A_{(t-\tau)}$	$D_{(t-\tau)}$	$Acc_{(t-\tau)}$	$DD_{(t-\tau)}$	$NegE_{(t-\tau)}$	Adj. R-squared
$\tau = 1$	-2.202	0.733	0.002	0.339	-0.086	5.572	4.258	0.77
	[1.85]	[42.69]**	[3.80]**	[9.49]**	[-0.86]	[8.56]**	[1.15]	
$\tau = 2$	-1.675	0.641	0.004	0.460	-0.135	7.848	6.972	0.69
	[-1.09]	[27.86]**	[3.4]**	[8.01]**	[-0.49]	[6.63]**	[1.40]	
$\tau = 3$	1.249	0.668	0.004	0.411	-0.168	6.905	16.315	0.66
	[1.16]	[10.85]**	[5.05]**	[8.04]**	[2.03]	[6.63]**	[2.37]*	

Panel D: Earnings Persistence

	Intercept	$E_{(t-\tau)}$	$NegE * E_{(t-\tau)}$	$NegE_{(t-\tau)}$	Adj. R-squared
$\tau = 1$	2.380	0.968	-0.980	-9.728	0.77
	[6.05]**	[77.46]**	[6.41]**	[3.26]**	
$\tau = 2$	6.046	0.993	-1.394	-11.644	0.68
	[4.64]**	[34.54]**	[7.57]**	[2.46]*	
$\tau = 3$	10.411	1.038	-1.990	-19.516	0.63
	[2.63]*	[23.05]**	[7.37]**	[3.47]**	

Panel E: Residual Income

	Intercept	$E_{(t-\tau)}$	$NegE * E_{(t-\tau)}$	$B_{(t-\tau)}$	$Tacc_{(t-\tau)}$	$NegE_{(t-\tau)}$	Adj. R-squared
$\tau = 1$	-0.362	0.767	-0.502	0.035	-0.049	-8.476	0.78
	[-0.30]	[18.80]**	[6.17]**	[8.81]**	[-1.14]	[2.70]*	
$\tau = 2$	1.346	0.688	-0.661	0.053	-0.072	-10.737	0.70
	[0.91]	[25.59]**	[5.62]**	[9.68]**	[-1.35]	[2.23]*	
$\tau = 3$	3.128	0.679	-1.108	0.062	-0.055	-15.394	0.66
	[1.42]	[12.72]**	[7.21]**	[7.40]**	[1.81]	[2.23]*	

This table shows the average coefficients, the respective t-statistics with Newey and West (1987) adjustment (in brackets) and the Adjusted R-squared from pooled regressions using 10 years of data. I regress Earnings from year t on lagged independent variables from year ($t - \tau$ with $\tau = 1$ to 3 years). The regressions are performed from 1982 to 2014 for $\tau = 1$, from 1983 to 2013 for $\tau = 2$, and from 1984 to 2012 for $\tau = 3$.** and * denote significance at 0.01 and 0.05 level, respectively. Panel A reports the coefficients from the Combined Model, Panel B from the Cross-sectional Analysts' Forecasts, Panel C from HVZ model, Panel D from Earnings Persistence, and Panel E from Residual Income. Details of the variables estimation are provided in section 5.2.2.

Although the one-year-lagged gross profits variable ($GP_{i,t-1}$) is negative and slight significant in explaining earnings, the two-, and three-year-lagged coefficients of gross profits are positive and significant with a t-statistic of 7.32 and 12.53 and coefficients of 0.026 and 0.057, respectively. The low significance and the negative coefficients in the one-year-lagged ($\tau = 1$) regression are likely due to the large explanatory power of analysts' one-year-ahead earnings forecasts, leaving one-year-lagged gross profits redundant. The positive and significant coefficients of gross profits in the two and three-year-lagged regressions confirm the results of Novy-Marx (2013) that this variable is a good proxy for future earnings.

The coefficients of the one-month past stock return ($r10_{(t-\tau)}$) are all positive (0.057, 0.086, and 0.054, for τ= 1 to 3, respectively) and significant at the 1% level in all analyzed periods. Finally, past stock return from -12 to -2 months ($r122_{(t-\tau)}$) is significant at the 5% significance level for two-year-lagged period (t-statistics of 2.25) having positive coefficient (0.014 for $\tau =$ 2). These results confirm the findings from Ashton and Wang (2012) and Richardson et al. (2010) that stock price changes have a positive correlation with forward earnings and they tie in with the evidence from Abarbanell (1991) that analysts' forecasts do not fully reflect the information in prior stock price changes. These results are also in line with Guay et al. (2011) who find that analysts tend to react slowly to information contained in recent stock price changes.

Panel B of Table 5.1 reports the results regarding the CSAF model. In particular, the coefficients of analysts' earnings forecasts in the one-year-lagged regressions are quite close to the CM (coefficient of 0.953 with t-statistics of 35.87 for the CSAF comparing to the coefficient of 0.957 and t-statistics of 33.31 for the CM). However, the two- and three-year-lagged regressions have shown a different picture. While the coefficients of analysts' earnings forecasts on the CSAF regression are closer to one (0.971 in the two-year-lagged regression and 0.992 in the three-year-lagged regression), the coefficients of the CM are lower (0.872 in the two-year-lagged regression and 0.74 in the three-year-lagged regression). This is evidence that the additional variables gross profits and lagged returns of the CM should have a stronger impact on the two- and three-year-ahead earnings forecasts rather than on one-year-ahead. This results are in line with Bradshaw et al. (2012) who show that analysts' forecasts are accurate for one-year-ahead, but the two- and three-year-ahead forecasts can underperform even a random walk estimation.

The results regarding the HVZ model are shown in Panel C of Table 5.1. The model proposed by Hou et al. (2012) shows a positive and significant relation between earnings ($E_{(t)}$) and one-, two-, and three-year-lagged ($\tau = 1$ to 3) earnings ($E_{(t-\tau)}$), lagged dividends ($D_{(t-\tau)}$), lagged assets ($A_{(t-\tau)}$) and the dummy of lagged dividends ($DD_{(t-\tau)}$). The coefficient of the dummy variable indicating lagged negative earnings ($NegE_{(t-\tau)}$) is positive and statistically significant in three-year-lagged regression and accruals ($Ac_{(t-\tau)}$) variable is significant in none of the regressions. The magnitude and the sign of the coefficients are similar to Hou et al. (2012) and Li and Mohanram (2014), even though the sample period is different.[12]

For the EP model (see Panel D of Table 5.1), the lagged dummy variable of negative earnings ($NegE_{(t-\tau)}$) is negative and significant, lagged earnings ($E_{(t-\tau)}$) is positive and significant, and the interaction term (Neg E * $E_{(t-\tau)}$) is negative and significant in all analyzed regressions ($\tau = 1$ to 3).

For the RI model (see Panel E of Table 5.1), the lagged dummy of negative earnings ($NegE_{(t-\tau)}$) is negative and significant, lagged earnings ($E_{(t-\tau)}$) is positive and significant, the interaction term (Neg E * $E_{(t-\tau)}$) is negative, and lagged book value ($B_{(t-\tau)}$) is positive and significant. All these results are similar to Li and Mohanram (2014) with the only difference being that ($Tacc_{(t-\tau)}$) is negative but not significant in my regression. This difference is probably due to the different estimation period and a possibly different calculation method of standard errors for the t-statistics.

When one compares the adjusted R-squared estimates, the combined model and the CSAF present the highest values for all analyzed periods. For the one-year-lagged regression, the adjusted R-squared of the combined model is 0.94, compared to 0.94 (CSAF), 0.77 (HVZ model), 0.77 (EP model), and 0.78 (RI model). For the two-year-lagged regression, the combined model has

[12] Hou et al. (2012) perform the regression yearly from 1968 to 2008 using ten years of lagged data, while Li and Mohanram (2014) use the period from 1968 to 2012.

an adjusted R-squared of 0.86, which is higher than the CSAF(0.85) HVZ (0.69), EP (0.68), and RI (0.70) models. For the three-year-lagged regression, the adjusted R-squared values are 0.81 (combined model), 0.78 (CSAF), 0.66 (HVZ model), 0.63 (EP model), and 0.66 (RI model). The adjusted R-squared values for the EP and RI models are higher than in Li and Mohanram (2014) as I estimate these models at the dollar level so that the heteroskedasticity of the dollar level data inflates the adjusted R-squared. Although a high in-sample R-squared value is not a sufficient condition for high out-of-sample performance, it is a necessary one (Welch and Goyal, 2008). These in-sample results bode well for the combined model. The forecast bias is analyzed in the next section.

5.3.2. Bias comparison

There is ample evidence that analysts' forecasts tend to be too optimistic (see, e.g., Lin and McNichols (1998); Hong and Kubik (2003); Merkley et al. (2017)) with one of the reasons being that they face a conflict of interest. In a survey of 365 analysts, Brown et al. (2015) find that 44% of respondents say their success in generating underwriting business or trading commissions is very important for their compensation. There is also empirical evidence for the conflict of interest hypothesis. Hong and Kubik (2003) find that controlling for accuracy, analysts who are optimistic compared to the consensus are more likely to have favorable job separations. In particular, for analysts who cover stocks underwritten by their houses, optimism becomes more relevant than accuracy for favorable job separations. This optimism bias carries over into many applications that use these forecasts as an input. Easton and Sommers (2007) estimate that overly-optimistic analysts' earnings forecasts lead to an upward bias in the ICC of 2.84%. This bias becomes even more relevant if one takes into account that the equity risk premium based on analysts' forecasts is roughly 3% for the U.S. market (Claus and Thomas, 2001). Given the importance of bias, I now compare the mean and median biases of all tested earnings forecast models. Bias is defined as the difference between actual earnings and earnings forecasts, scaled by the firm's end-of-June market equity. I estimate bias out-of-sample for one-, two-, and three-year-ahead forecasts ($\tau = 1$ to 3).

$$Bias_{(i,t+\tau)} = \frac{(Actual\,Earnings_{(i,t+\tau)} - Earnings\,Forecast_{(i,t+\tau)})}{Market\,Equity_{(i,t)}} \tag{5.8}$$

Table 5.2.: Earnings forecast bias

Panel A: Bias of earnings forecasts						
	Bias Et+1		Bias Et+2		Bias Et+3	
	Mean	Median	Mean	Median	Mean	Median
CM	-0.006	0.005	-0.009	0.000	-0.005	-0.001
	[-1.08]	[1.99]	[-1.06]	[0.09]	[-0.38]	[-0.33]
AF	-0.033	-0.002	-0.036	-0.009	-0.028	-0.013
	[2.79]**	[2.62]*	[4.77]**	[5.29]**	[3.23]**	[3.84]**
CSAF	-0.008	0.005	-0.035	-0.010	-0.047	-0.018
	[-1.21]	[2.03]	[3.10]**	[2.58]*	[1.88]	[2.04]
HVZ	-0.038	0.002	-0.040	-0.004	-0.053	-0.008
	[3.49]**	[0.92]	[2.23]*	[-0.84]	[2.29]*	[-1.15]
EP	-0.048	-0.003	-0.073	-0.013	-0.078	-0.016
	[3.44]**	[-1.16]	[4.69]**	[3.08]**	[7.41]**	[2.42]*
RI	-0.026	0.003	-0.040	-0.005	-0.051	-0.010
	[2.06]*	[1.10]	[2.61]*	[-1.46]	[3.41]**	[1.72]
RW	0.004	0.006	0.029	0.010	0.036	0.014
	[0.49]	[5.32]**	[1.65]	[3.13]**	[1.53]	[2.73]*
Panel B : Difference of bias of earnings forecasts						
	Bias Et+1		Bias Et+2		Bias Et+3	
	Mean	Median	Mean	Median	Mean	Median
CM-AF	0.027	0.007	0.027	0.009	0.023	0.012
	[2.50]*	[2.31]*	[3.33]**	[2.83]**	[6.60]**	[5.13]**
CM-CSAF	0.003	0.000	0.026	0.011	0.042	0.016
	[1.00]	[0.48]	[4.73]**	[3.96]**	[2.99]**	[2.67]*
CM-HVZ	0.032	0.003	0.032	0.004	0.049	0.006
	[2.42]*	[0.86]	[1.51]	[0.80]	[2.19]*	[1.05]
CM-EP	0.042	0.008	0.065	0.013	0.074	0.015
	[2.80]**	[2.24]*	[4.10]**	[3.16]**	[4.48]**	[3.44]**
CM-RI	0.02	0.00	0.03	0.01	0.05	0.01
	[1.44]	[0.78]	[1.88]	[1.51]	[2.55]*	[2.06]*
CM-RW	-0.010	-0.001	-0.037	-0.009	-0.041	-0.015
	[0.96]	[0.45]	[2.34]*	[3.26]**	[1.91]	[7.50]**

This table summarizes the mean and median bias for the Combined Model (CM), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW). In addition, the bias of analysts' forecasts (AF) is also included. The Newey-West t-statistics are presented in brackets. Results are shown for one-, two-, and three-year ahead earnings forecasts. I estimate one, two, three-year ahead forecast bias for the periods 1985–2015, 1987–2015, and 1989–2015, respectively. The bias is defined as the difference between earnings forecasts and actual earnings, scaled by the firm's end-of-June market equity. ** and * denote significance at 0.01 and 0.05 levels, respectively.

As one can see in Equation 5.8, a negative (positive) bias means overly-optimistic (pessimistic) earnings forecasts. A bias of zero means unbiased forecasts. Bias is computed at the end of June of each year[13] for each firm. Then, I estimate the yearly mean and median forecast biases. In Panel A of Table 5.2, I report the average of the yearly mean and median biases and the respective t-statistics with the Newey-West adjustment for all tested models.[14]

Panel A of Table 5.2 shows that the combined model is the only model that has no statistically significant bias at the 0.05 significance level. This result also holds when analyzing the mean and median biases and when testing one-, two- or three-year-ahead forecasts. My results confirm the positive bias of analysts' forecasts, as the mean and median biases are negative and statistically significant for one-, two, and three-year-ahead forecasts. The one-year-ahead median bias is small in magnitude (-0.002), i.e., it overestimates earnings by an amount of 0.2% of market equity. However, the median bias increases in two and three-year ahead forecasts to -0.009 and -0.013, respectively. My results do not confirm the findings from Abarbanell and Lehavy (2003), who show that the median bias is zero in analysts' forecasts. This is possibly due to the different sample period (Abarbanell and Lehavy (2003) analyze the period from 1985 to 1998) and the different forecast periodicity (the authors use quarterly forecasts while I use yearly forecasts).

Moving to the benchmark models, the HVZ and RI models present an optimistic mean bias in the one-, two-, and three-year-ahead forecasts. The EP model presents an optimistic bias in the mean one-year-ahead forecasts as well as in the median two- and three-year-ahead regressions. The forecasts based on the RW model show a positive bias which means that they are overly pessimistic. This is intuitive as this model does not take growth in earnings into account. Finally, although the CSAF model seems to perform well since the model presents significant bias only in the two-year-ahead earnings forecasts, the CSAF model presents a way greater bias in terms of magnitude for

[13] I estimate one, two, three-year-ahead forecast bias for the periods 1985–2015, 1987–2015, and 1989-2015, respectively.

[14] In Appendix A.2, I provide the year-by-year mean and median bias from each of the analyzed models.

three-year-ahead earnings forecasts than the raw analysts' forecasts and similar for two-year-ahead forecasts. This is evidence that the usage of analysts' forecasts as an input in mechanical earnings may not be sufficient to eliminate the analysts' overly-optimistic bias. Note that the CSAF model, as well as any other cross-sectional model, use the coefficients from the in-the-sample regression to forecast earnings out-of-sample and, accordingly, the mechanical models may have a bias because the in-the-sample estimates in many cases do not perform well out-of-sample.

Panel B of Table 5.2 shows whether the bias of the combined model is statistically different in comparison to other models. The first row presents the difference between the combined model and analysts' forecasts, and one sees that in all periods, for the mean and the median, the biases are statistically different. Thus, the results show that the combined model is not as overly-optimistic as raw analysts' forecasts. By comparing the CM to the CSAF (In the second row), one can see that the bias is statistically different for two- and three-year-ahead mean and median forecasts. These results show that the additional variables of the CM (compared to the CSAF) are important to keep the forecasts unbiased, in particular for long-term earnings. When the combined model is compared to the RI model, one sees differences only for the three-year-ahead forecast. In addition, the CM is statistically less optimistic than the HVZ for one- and three-year-ahead forecasts and less pessimistic than the RW for two- and three-year-ahead forecasts. Last, I show that the combined model is not as overly-optimistic as the EP model at a statistically significant margin for all analyzed periods. In short, the combined model displays the lowest bias of all tested models for all forecast horizons.

In order to analyze forecast bias over time, Figures 1 to 6 show the mean and median forecast bias for one-, two-, and three-year-ahead earnings forecasts. For the sake of clarity, I only include the raw analysts' forecasts, the combined model, and the benchmark model with forecast bias closest to zero in the figure. The optimism bias of the raw analysts' forecasts is immediately apparent. The corresponding graph is almost always below zero for different

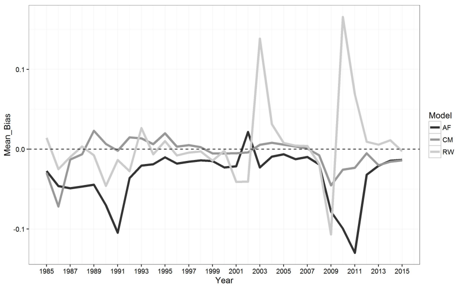

Figure 5.1.: One-year-ahead Mean Bias

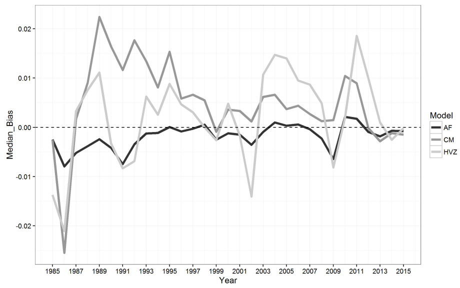

Figure 5.2.: One-year-ahead Median Bias

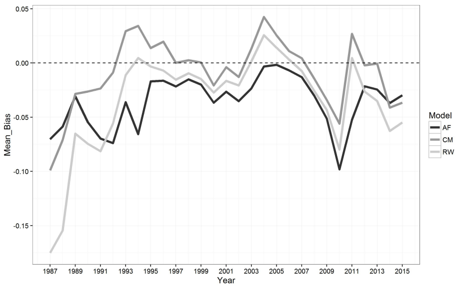

Figure 5.3.: Two-year-ahead Mean Bias

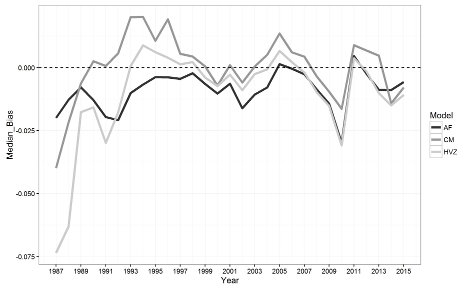

Figure 5.4.: Two-year-ahead Median Bias

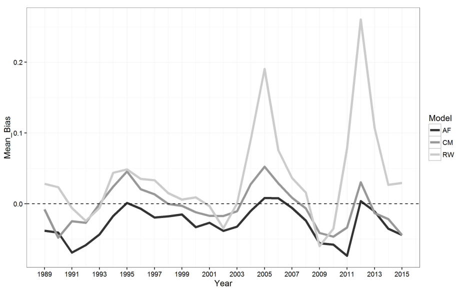

Figure 5.5.: Three-year-ahead Mean Bias

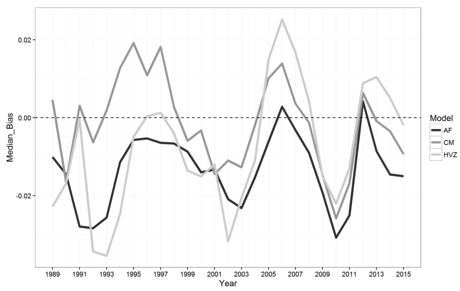

Figure 5.6.: Three-year-ahead Median Bias

forecast horizons and aggregation methods (mean and median). The spikes in the bias for the RW model correspond to economic shocks. For example, the burst of the Internet bubble in 2001 results in an overly-optimistic estimate as the previous (high) level of earnings is used as a forecast.

5.3.3. Accuracy comparison

There is substantial evidence that analysts' forecasts are more accurate than mechanical models (e.g., Fried and Givoly (1982); O'Brien (1988); Hou et al. (2012)). Researchers argue that the higher accuracy of analysts' forecasts is due to their "innate ability and task-specific experience"[15] (e.g., Clement et al. (2007)), industry related experience obtained before becoming an analyst (e.g., Bradley et al. (2017)), and the number of analysts covering each industry (e.g., Merkley et al. (2017)).

In this section, I compare the forecast accuracy of all tested models. I use absolute error as a proxy for accuracy. Following Bradley et al. (2017), I estimate the absolute error as the absolute difference between actual earnings and earnings forecasts, scaled by the firm's end-of-June market equity. The lower the value of the absolute error, the more accurate the forecast.

$$Absolute\,error_{(i,t+\tau)} = \left| \frac{(E\,Forecasts_{(i,t+\tau)} - Actual\,E_{(i,t+\tau)})}{Market\,Equity_{(i,t)}} \right| \tag{5.9}$$

I estimate the out-of-sample absolute error at the end of June of each year,[16] based on Equation 5.9, for one-, two-, and three-year-ahead time horizons (τ = 1 to 3) for each firm. In Panel A of Table 5.3, I report the yearly average of the mean and median absolute errors (accuracy) and the respective t-statistics with the Newey-West adjustment for all tested models.[17]

[15] According to Clement et al. (2007), task-specific experience is defined as the analyst's experience in forecasting around a particular type of situation or event, such as forecasting earnings when restructurings occur or forecasting earnings around an acquisition.

[16] I estimate one-, two-, and three-year-ahead forecast accuracy for the periods 1985–2015, 1987–2015, and 1989–2015, respectively.

[17] In Appendix A.3, I provide the year-by-year mean and median accuracy from each of the analyzed models.

Table 5.3.: Earnings forecast accuracy

Panel A: Accuracy of earnings forecasts

	Accuracy Et+1		Accuracy Et+2		Accuracy Et+3	
	Mean	Median	Mean	Median	Mean	Median
CM	0.046	0.015	0.063	0.026	0.070	0.033
AF	0.057	0.011	0.070	0.024	0.076	0.033
CSAF	0.050	0.016	0.076	0.030	0.099	0.042
HVZ	0.109	0.033	0.119	0.045	0.128	0.048
EP	0.112	0.029	0.135	0.045	0.135	0.050
RI	0.104	0.028	0.117	0.041	0.120	0.046
RW	0.114	0.025	0.124	0.037	0.127	0.044

Panel B : Difference of accuracy of earnings forecasts

	Accuracy Et+1		Accuracy Et+2		Accuracy Et+3	
	Mean	Median	Mean	Median	Mean	Median
CM-AF	-0.010	0.005	-0.007	0.002	-0.006	-0.001
	[1.48]	[3.68]**	[2.07]*	[1.67]	[3.61]**	[0.84]
CM-CSAF	-0.004	-0.001	-0.013	-0.004	-0.029	-0.009
	[3.50]**	[1.10]	[2.46]*	[1.89]	[2.38]*	[3.22]**
CM-HVZ	-0.062	-0.018	-0.056	-0.019	-0.058	-0.015
	[5.41]**	[8.30]**	[6.94]**	[16.60]**	[6.71]**	[13.65]**
CM-EP	-0.065	-0.013	-0.072	-0.019	-0.064	-0.017
	[5.90]**	[4.29]**	[7.85]**	[13.00]**	[7.64]**	[12.76]**
CM-RI	-0.058	-0.013	-0.054	-0.014	-0.050	-0.014
	[4.49]**	[3.05]**	[8.19]**	[11.54]**	[10.06]**	[16.02]**
CM-RW	-0.067	-0.010	-0.061	-0.011	-0.056	-0.011
	[4.02]**	[2.73]*	[4.21]**	[6.97]**	[4.52]**	[6.40]**

This table summarizes the mean and median forecast accuracy for the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models. I show Newey-West t-statistics in brackets. I estimate one-, two-, and three-year ahead forecast accuracy for the periods 1985–2015, 1987–2015, and 1989–2015, respectively. I define accuracy as the absolute difference between actual earnings and earnings forecasts, scaled by the firm's end-of-June market equity. ** and * denote significance at 0.01 and 0.05 levels, respectively.

As one sees in Panel A of Table 5.3, the combined model is slightly superior to the raw analysts' forecasts and the CSAF model and markedly superior to the benchmark models in terms of mean accuracy. By comparing the three most accurate models, the CM has the best accuracy (0.046), followed by CSAF (0.050), and AF (0.057). The mean absolute error of the benchmark models is roughly twice as high (inaccurate) as the CSAF model, raw analysts' forecasts or the combined model for the one-year-ahead forecast. For two- and three-year ahead mean absolute error, the combined model again is more accurate than the other models but the difference to analysts' forecasts is smaller (the combined model has a mean absolute error of 0.63 and 0.070 for two- and three-year-ahead forecasts, in comparison, the mean absolute error of analysts' forecasts is 0.070 and 0.076). Regarding the CSAF model, the difference regarding accuracy to the CM becomes higher for long-term forecasts since the absolute error for the CSAF model is 0.076 for two-year-ahead and 0.099 for three-year-ahead forecasts. Comparing the CSAF model to the raw analysts' forecasts in terms of mean absolute error, the CSAF model outperforms the analysts in one-year-ahead, but the analysts are more accurate in two- and three-year-ahead forecasts. Finally, the mean absolute error of the other benchmark models is on average five percentage points higher than the combined model.

With regard to median absolute error, the results of analysts' forecasts are slightly superior to the combined model for one- and two-year-ahead horizons (0.011 and 0.024 for raw analysts' forecasts and 0.015 and 0.026 for the combined model for one-year and two-year forecasts, respectively). For three-year-ahead forecasts, the median absolute error is 0.033 for both models. The third best model in terms of median accuracy is the CSAF, with absolute errors of 0.016, 0.030, and 0.042 for one-, two-, and three-year-ahead forecasts. Concerning the other benchmark models, the median absolute error is substantially higher (more inaccurate) compared to analysts' forecasts, and the CSAF and combined models since for one-year-ahead horizons, the lowest value is 0.025 (the RW model), for two-year-ahead it is 0.041 (the RI model), and for three-year-ahead it is 0.044 (the RW model). I also highlight that the analysts' forecasts are more accurate than the ones estimated with the CSAF model in one-, two-, and three-year-ahead forecasts. This is evidence that only including the analysts' forecasts in a cross-sectional model is not sufficient to improve the forecasts.

In Panel B of Table 5.3, I test whether the differences are statistically significant. The combined shows superior accuracy compared to all cross-sectional models and the RW model. Like Gerakos and Gramacy (2013), I find that the RW model is as accurate as the cross-sectional models. Comparing the combined model to analysts' forecasts, the combined model outperforms the analysts in the medium and long-term (two- and three-year-ahead) forecasts.

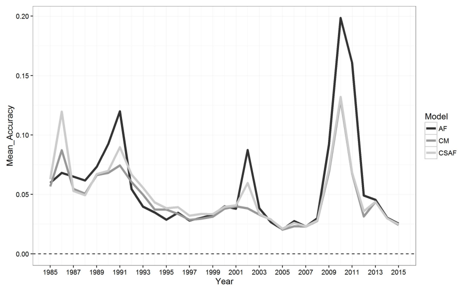

Figure 5.7.: One-year-ahead Mean Accuracy

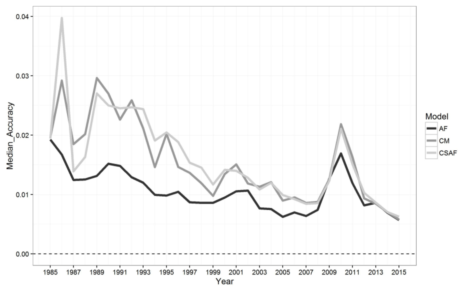

Figure 5.8.: One-year-ahead Median Accuracy

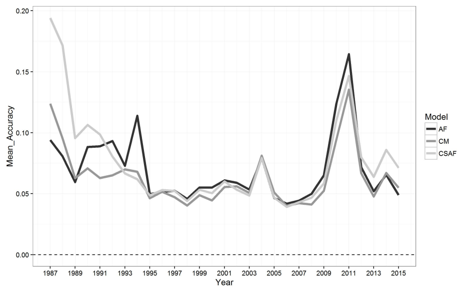

Figure 5.9.: Two-year-ahead Mean Accuracy

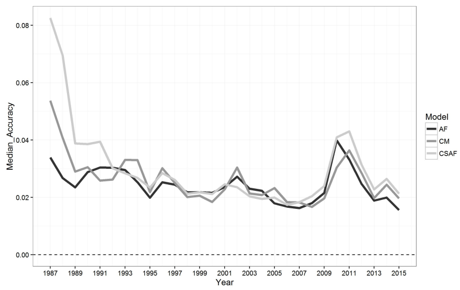

Figure 5.10.: Two-year-ahead Median Accuracy

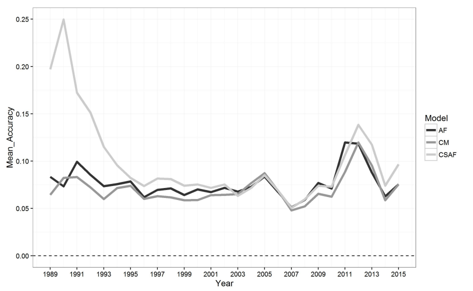

Figure 5.11.: Three-year-ahead Mean Accuracy

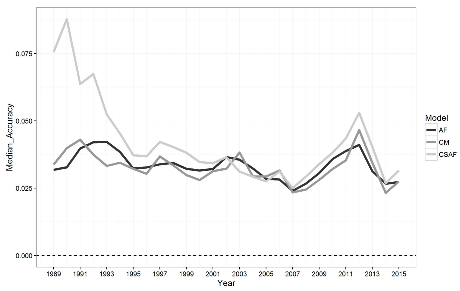

Figure 5.12.: Three-year-ahead Median Accuracy

However, the results for one-year-ahead are mixed since the analysts' forecasts have a better median accuracy, while the mean accuracy is not statistically different between both models.

In Figures 7 to 12, I plot the forecast accuracy over time for the tested methods. The raw analysts' forecasts are superior to the combined model in terms one-year-ahead median accuracy, in particular for the first years of the sample period. When I split the analyzed period into two equal-length subperiods, one sees that the difference in median accuracy during the period 1985–2000 is 0.0073, while in the period 2001–2015 it decreases to 0.0022. The same pattern can be seen in two-year-ahead median accuracy; here the difference falls from 0.0032 (earlier period) to 0.0000 (later period), which indicates that the combined model has improved the accuracy compared to the raw analysts' forecasts over the years. Last, note that the raw analysts' forecasts and the combined model outperform the benchmark models in all periods.

5.3.4. Earnings response coefficient

According to Easton and Zmijewski (1989), the ERC is the coefficient that measures the response of stock prices to surprises (new information) in accounting earnings announcements. Li and Mohanram (2014) clarify that a higher ERC suggests that the market reacts more strongly to the unexpected earnings from a model that represents a better approximation of market expectations. I estimate the ERC using the sum of the quarterly earnings announcement returns (market-adjusted, from day -1 to day $+1$) on one-, two-, and three-year-ahead firm-specific unexpected earnings (i.e., the forecast bias) measured over the same horizon. The unexpected earnings, as well as the returns, are standardized to make the ERC comparable among all models. Panel A of Table 5.4 shows the time-series average of the ERCs, the respective t-statistics, and the time-series average of adjusted R-squared for all tested models. Panel B of Table 5.4 shows the pairwise comparison between the combined model and the other models.

Table 5.4.: Earnings response coefficient

Panel A: Earnings Response Coefficient (ERC)						
	Et+1		Et+2		Et+3	
	ERC	Adj. R-squared	ERC	Adj. R-squared	ERC	Adj. R-squared
CM	0.132	0.016	0.130	0.017	0.098	0.009
	[13.12]**		[5.72]**		[6.75]**	
AF	0.104	0.011	0.097	0.011	0.087	0.008
	[9.25]**		[5.15]**		[6.60]**	
CSAF	0.129	0.016	0.109	0.013	0.061	0.005
	[12.66]**		[4.96]**		[4.09]**	
HVZ	0.120	0.015	0.081	0.010	0.057	0.006
	[10.75]**		[5.30]**		[3.25]**	
EP	0.114	0.015	0.069	0.007	0.068	0.006
	[9.03]**		[4.53]**		[5.85]**	
RI	0.124	0.017	0.082	0.008	0.072	0.006
	[11.03]**		[7.83]**		[5.94]**	
RW	0.120	0.015	0.088	0.009	0.061	0.005
	[7.37]**		[6.80]**		[4.38]**	

Panel B: Comparison of the difference						
	Et+1		Et+2		Et+3	
	ERC	Adj. R-squared	ERC	Adj. R-squared	ERC	Adj. R-squared
CM-AF	0.028	0.005	0.033	0.007	0.011	0.002
	[3.76]**	[4.27]**	[1.21]	[1.47]	[1.32]	[1.51]
CM-CSAF	0.003	0.000	0.021	0.004	0.037	0.004
	[0.59]	[0.23]	[3.16]**	[3.08]**	[2.45]*	[2.88]**
CM-HVZ	0.011	0.000	0.049	0.007	0.041	0.003
	[0.95]	[0.15]	[2.12]*	[2.12]*	[1.98]	[1.64]
CM-EP	0.018	0.000	0.060	0.010	0.030	0.003
	[1.72]	[0.14]	[2.42]*	[2.02]	[1.51]	[1.83]
CM-RI	0.007	-0.001	0.047	0.010	0.027	0.003
	[0.70]	[0.35]	[2.63]*	[2.21]*	[1.34]	[1.82]
CM-RW	0.012	0.001	0.042	0.008	0.037	0.004
	[0.68]	[0.26]	[1.88]	[2.02]	[3.69]**	[2.53]*

This table reports the time-series averages of the earnings response coefficients (ERC) for forecasts from the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models, as well as their pairwise comparisons. The Newey-West t-statistics are reported in brackets. The ERC is estimated by regressing the sum of the quarterly earnings announcement returns (market-adjusted, from day -1 to day $+1$) over the next one-, two-, and three-years on firm-specific unexpected earnings (i.e., the forecast bias) measured over the same horizon. I standardize the unexpected earnings and the returns to make the ERC comparable among all models. ** and * denote significance at 0.01, and 0.05 levels, respectively.

As one sees in Panel B of Table 5.4, for one-year-ahead forecasts, the combined model outperforms raw analysts' forecasts in terms of ERC coefficient and adjusted R-squared. The difference in the ERC coefficient is also highly statistically significant (t-statistic of 3.76). For the same forecast horizon, the combined model does not significantly outperform the other benchmark models. When analyzing two-year-ahead forecasts, the combined model shows a higher ERC coefficient than the CSAF, HVZ, EP, RI, models and a higher adjusted R-squared than the CSAF, HVZ and RI models at a statistically significant margin. Finally, for three-year-ahead forecasts, the results are statistically different when comparing the combined model to the RW or the CSAF models.

In summary, I find that the combined model is not just the less biased and more accurate but also represents market expectations most consistently among all tested models. In the next section, I evaluate the impact of different computation of earnings forecasts on estimates of the implied cost of capital.

5.4. Implied Cost of Capital

In this section, I analyze the performance of ICC estimates using proxies for earnings forecasts based on the combined model, analysts' forecasts, and the benchmark models. First, I compute the ICC on an aggregate level and evaluate its ability to predict realized returns over time. Then, I analyze the cross-sectional correlation between ICC and ex-post forward returns. Last, I carry out a cross-sectional analysis of the relation between firm characteristics and expected returns.

5.4.1. Relation between ICC and returns on an aggregate level

There is evidence that the ICC at an aggregate level is a good proxy for time-varying expected returns (e.g., Pástor et al. (2008); Li et al. (2013)). Due to the fact that one of the main inputs for the ICC estimation are earnings forecasts, I believe that this input can strongly influence the ICC's performance as a proxy for expected returns. In this section, I compare the performance of the ICC calculated using different proxies for earnings forecasts in predicting future market returns. To do so, I perform univariate (in-sample) forecast regressions. I regress ex-post, one-year-forward value-weighted (VW) excess market returns on market ICC equity premiums. For each earnings forecast method, I estimate five different ICC models (GLS, CT, OJ, MPEG, and a composite of the four previous models). I employ the following proxies for earnings forecasts: the combined model, analysts' forecasts, the HVZ model, the EP model, and the RI model.[18] To compute the ICC premiums and excess returns, I use the yield on the U.S. 10-year government bond. Panel A of Table 5.5 presents the results.

For the one-year-forward return predictive regressions, the coefficients of interest are only significant at the 0.10 level. This low level of significance is probably due to the low power of these tests. As I use yearly observations for this test, the sample size is small and therefore, the power to reject the null hypothesis is low. However, I document that the ICC estimated with earnings from the combined model offers the most substantial number of significant regression slopes. For three ICC methods (CT, OJ, and MPEG) the coefficients are significant at the 0.10 level. In contrast, the HVZ and raw analysts' forecasts methods only produce two significant coefficients, and the CSAF method only has one significant regression slope. My t-statistics are not as high as in Li et al. (2013) probably because of the lower sample size; these authors use monthly overlapping observations while I use yearly observations.

5.4.2. Relation between ICC and returns cross-sectionally

In the previous section, I compared the predictive power of the ICC over time. Now, I analyze whether the ICC can explain forward returns cross-sectionally. To this end, I perform univariate Fama and Macbeth (1973) (FM) cross-

[18] I do not include the RW model because this method does not allow for earnings growth and is, therefore, not suitable for estimating the ICC.

Table 5.5.: Regressions of ICC and ex-post realized returns

Panel A: Forecasting at the aggregate level												
Model	CM		AF		CSAF		HVZ		EF		RI	
	Interc.	Coeff.	Interc.	Coeff.	Interc.	Coeff.	Interc.	Coeff.	Interc.	Coeff.	Interc.	Coeff.
GLS	2.671	1.473	0.523	1.519	0.523	1.379	2.780	1.242	3.667	1.172	3.575	1.145
	[0.586]	[1.071]	[0.086]	[1.127]	[0.086]	[0.970]	[0.596]	[0.796]	[0.878]	[0.744]	[0.842]	[0.722]
CT	3.640	3.858	-1.927	3.096	-1.927	3.753	-7.429	2.245	-1.968	1.338	3.197	1.782
	[0.853]	[1.901]	[-0.364]	[1.865]	[-0.364]	[1.677]	[-0.904]	[0.988]	[-0.322]	[0.453]	[0.721]	[0.688]
OJ	3.807	2.763	3.182	2.648	3.182	2.192	-4.092	1.950	-11.531	0.081	-2.401	1.734
	[0.875]	[1.908]	[0.666]	[1.614]	[0.666]	[1.905]	[-0.692]	[1.873]	[-0.949]	[0.063]	[-0.420]	[1.593]
MPEG	-0.046	1.275	4.639	1.715	4.639	0.799	0.592	1.298	1.113	0.465	-5.116	1.110
	[-0.009]	[1.761]	[1.197]	[1.798]	[1.197]	[1.666]	[0.117]	[1.712]	[0.261]	[0.538]	[-0.664]	[1.582]
Composite	2.989	2.329	2.546	2.298	2.546	1.459	4.337	1.775	2.628	0.737	0.706	1.443
	[0.759]	[1.591]	[0.585]	[1.491]	[0.585]	[0.805]	[1.190]	[0.983]	[0.612]	[0.313]	[0.143]	[0.723]
Panel B: Fama-Macbeth regression												
Model	CM		AF		CSAF		HVZ		EF		RI	
	Interc.	Coeff.	Interc.	Coeff.	Interc.	Coeff.	Interc.	Coeff.	Interc.	Coeff.	Interc.	Coeff.
GLS	1.019	0.016	1.019	0.008	1.019	0.013	1.019	0.003	1.019	0.006	1.019	0.005
	[3.091]**	[0.673]	[3.091]**	[0.320]	[3.091]**	[0.771]	[3.091]**	[0.229]	[3.091]**	[0.393]	[3.091]**	[0.316]
CT	1.039	0.021	1.039	-0.001	1.039	0.007	1.039	0.000	1.039	0.000	1.039	0.000
	[3.164]**	[1.599]	[3.164]**	[-0.036]	[3.164]**	[0.967]	[3.164]**	[-0.056]	[3.164]**	[-0.020]	[3.164]**	[0.000]
OJ	1.081	0.018	1.081	0.008	1.081	0.015	1.081	0.001	1.081	0.004	1.081	0.009
	[3.587]**	[1.240]	[3.587]**	[0.379]	[3.587]**	[0.988]	[3.587]**	[0.086]	[3.587]**	[0.296]	[3.587]**	[0.879]
MPEG	1.093	0.012	1.093	0.001	1.093	0.010	1.093	0.000	1.093	0.005	1.093	0.009
	[3.584]**	[1.077]	[3.584]**	[0.083]	[3.584]**	[0.925]	[3.584]**	[-0.023]	[3.584]**	[0.358]	[3.584]**	[0.741]
Composite	1.019	0.017	1.019	-0.005	1.019	0.010	1.019	0.002	1.019	0.001	1.019	0.003
	[3.415]**	[1.098]	[3.702]**	[-0.261]	[3.702]**	[1.000]	[3.507]**	[0.274]	[3.495]**	[0.124]	[3.023]**	[0.229]

Panel A presents univariate OLS regressions of ex-post excess realized returns on ICC premium based on five proxies of earnings forecasts: Combined Model (CM), Analysts' Forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou et al. (2012) (HVZ), Earnings Persistence (EP), and Residual Income (RI). I show the results based on the following ICC approaches: GLS, CT, OJ, MPEG and the composition of the mentioned ICC approaches. The dependent variables are the value-weighted market risk premium. Panel B presents the average coefficients of Fama-Macbeth regressions of realized returns on ICC premium. To compute the ICC premiums and excess returns, I use the yield on the U.S. 10-year government bond. The table provides the intercepts (interc.), and coefficients (coeff), and Newey-West t-statistics, which are presented in brackets. ** and * denote significance at 0.01 and 0.05 levels, respectively. The sample is from June 1986 to June 2012.

sectional regressions of ex-post-forward return premium on four individual ICC premium estimates (I use the GLS, CT, OJ, and MPEG approaches) and on the Composite ICC premium at the firm level. To estimate earnings' forecasts for the ICC computation, I use the following proxies: the combined model, analysts' forecasts, the CSAF model, the HVZ model, the EP model, and the RI model. The results are reported in Panel B of Table 5.5.

When I regress cross-sectional monthly returns on the ICC, I observe that none of the ICC approaches present significant coefficients at any conventional significance levels. However, the combined model ICC shows the highest t-statistic (1.599) among all tested models. The results are in line with previous studies which document the low correlation between ICC and ex-post returns in cross-sectional settings (e.g., Guay et al. (2011)).

5.4.3. Portfolio strategies

As shown in Table 5.5, the ICC exhibits weak explanatory power in FM regressions. However, this finding might be driven by small and micro-cap stocks as the FM regressions weight the observations equally (Novy-Marx, 2013). An additional shortcoming of FM regressions is that it is sensitive to outliers. To address these potential issues, I analyze the performance of value-weighted portfolios sorted on their ICC.

Table 5.6.: Returns of portfolios formed on ICC

	Combined Model					Analysts' Forecasts				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
Low	0.54	0.54	0.55	0.61	0.52	0.57	0.57	0.62	0.55	0.57
	[2.145]*	[2.151]*	[2.229]*	[2.377]*	[2.061]*	[2.151]*	[2.026]*	[2.494]*	[2.242]*	[2.178]*
2.00	0.63	0.65	0.70	0.69	0.63	0.55	0.62	0.58	0.57	0.67
	[2.353]*	[2.541]*	[2.641]**	[2.520]*	[2.409]*	[2.114]*	[2.642]**	[2.385]*	[2.339]*	[2.792]**
3.00	0.64	0.65	0.71	0.71	0.67	0.76	0.69	0.59	0.66	0.63
	[2.283]*	[2.303]*	[2.373]*	[2.414]*	[2.260]*	[2.791]**	[2.668]**	[2.157]*	[2.380]*	[2.271]*
4.00	0.66	0.90	0.78	0.70	0.82	0.67	0.75	0.67	0.71	0.70
	[2.148]*	[2.792]**	[2.264]*	[2.053]*	[2.459]*	[2.382]*	[2.628]**	[2.253]*	[2.310]*	[2.359]*
High	0.84	0.74	0.75	0.78	0.78	0.79	0.64	0.61	0.60	0.60
	[2.467]*	[1.980]*	[2.145]*	[2.181]*	[2.096]*	[2.331]*	[1.774]	[1.629]	[1.592]	[1.554]
5-1	0.30	0.20	0.19	0.17	0.26	0.22	0.07	-0.01	0.05	0.02
	[1.442]	[0.849]	[0.907]	[0.804]	[1.072]	[1.009]	[0.308]	[-0.049]	[0.182]	[0.091]
10-1	0.40	1.15	0.92	1.05	0.98	0.39	0.79	0.78	0.84	0.70
	[1.517]	[4.067]**	[3.155]**	[3.672]**	[3.168]**	[1.236]	[2.204]*	[2.520]*	[2.569]*	[2.118]*

	CSAF Model					HVZ Model				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
Low	0.53	0.55	0.54	0.57	0.52	0.56	0.54	0.53	0.50	0.51
	[2.085]*	[2.119]*	[2.107]*	[2.131]*	[2.009]*	[2.111]*	[2.026]*	[2.137]*	[1.982]*	[1.913]
2.00	0.64	0.59	0.67	0.67	0.65	0.64	0.60	0.59	0.61	0.58
	[2.409]*	[2.199]*	[2.419]*	[2.461]*	[2.333]*	[2.433]*	[2.314]*	[2.385]*	[2.365]*	[2.180]*
3.00	0.69	0.71	0.64	0.71	0.68	0.61	0.66	0.61	0.58	0.68
	[2.295]*	[2.294]*	[2.077]*	[2.420]*	[2.159]*	[2.363]*	[2.657]**	[2.433]*	[2.362]*	[2.680]**
4.00	0.69	0.74	0.71	0.82	0.79	0.72	0.68	0.55	0.61	0.69
	[2.103]*	[2.156]*	[2.185]*	[2.469]*	[2.264]*	[2.537]*	[2.311]*	[2.055]*	[2.326]*	[2.464]*
High	0.78	0.83	0.71	0.80	0.79	0.69	0.65	0.68	0.65	0.55
	[2.093]*	[2.163]*	[1.970]*	[2.295]*	[2.023]*	[1.826]	[1.562]	[1.884]	[1.783]	[1.438]
5-1	0.25	0.28	0.17	0.23	0.27	0.13	0.11	0.15	0.15	0.04
	[0.984]	[1.079]	[0.714]	[1.025]	[1.041]	[0.536]	[0.392]	[0.633]	[0.611]	[0.166]
10-1	0.25	0.96	0.93	0.89	0.83	-0.02	0.84	0.72	0.76	0.87
	[0.782]	[3.631]**	[3.379]**	[3.150]**	[3.038]**	[-0.057]	[2.791]**	[2.536]*	[2.586]*	[2.738]**

	EP Model					RI Model				
	GLS	CT	OJ	MPEG	Composite	GLS	CT	OJ	MPEG	Composite
Low	0.54	0.56	0.55	0.55	0.55	0.56	0.55	0.47	0.47	0.51
	[2.107]*	[2.132]*	[2.113]*	[2.116]*	[2.143]*	[2.177]*	[2.134]*	[1.880]	[1.831]	[1.945]
2.00	0.66	0.65	0.67	0.69	0.65	0.64	0.55	0.52	0.58	0.64
	[2.473]*	[2.537]*	[2.526]*	[2.596]**	[2.465]*	[2.413]*	[2.067]*	[1.934]	[2.126]*	[2.449]*
3.00	0.71	0.78	0.81	0.80	0.77	0.71	0.76	0.70	0.72	0.69
	[2.564]*	[2.803]**	[2.891]**	[2.898]**	[2.824]**	[2.682]**	[2.848]**	[2.567]*	[2.803]**	[2.502]*
4.00	0.67	0.65	0.69	0.73	0.71	0.65	0.79	0.71	0.70	0.78
	[2.061]*	[1.895]	[2.219]*	[2.372]*	[2.134]*	[2.068]*	[2.545]*	[2.518]*	[2.444]*	[2.644]**
High	0.79	0.67	0.52	0.46	0.63	0.68	0.50	0.77	0.72	0.63
	[1.983]*	[1.501]	[1.398]	[1.236]	[1.420]	[1.824]	[1.254]	[2.286]*	[2.091]*	[1.634]
5-1	0.26	0.11	-0.03	-0.09	0.08	0.11	-0.05	0.30	0.25	0.12
	[0.966]	[0.389]	[-0.134]	[-0.404]	[0.257]	[0.517]	[-0.203]	[1.461]	[1.196]	[0.512]
10-1	-0.01	0.94	0.91	0.86	0.88	0.18	0.91	0.77	0.78	0.85
	[-0.027]	[3.145]**	[3.209]**	[3.025]**	[2.807]**	[0.584]	[2.851]**	[2.511]*	[2.583]*	[2.663]**

This table reports the value-weighted excess of returns of portfolios sorted on ICC. I sort stocks at the end of June each year from 1985 to 2012 into quintiles and deciles based on ICC. I report the results for each quintile, as well as the long-short strategies of 5-1 (fifth quintile minus first quintile), and 10-1 (tenth decile minus first decile). I sort the portfolios on ICC estimated with earnings estimated by the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models. I estimate ICC based on Claus and Thomas (2001) (CT), Easton (2004) (MPEG), Gebhardt et al. (2001) (GLS), and Ohlson and Juettner-Nauroth (2005) (OJ). In addition, I include a Composite ICC, which is the average of all of the above-mentioned approaches. To compute the excess of returns, I use the one-month Treasury bill rate. The one-month Treasury bill rate was downloaded at the Kenneth French's library. The Newey-West t-statistics are presented in brackets. ** and * denote significance at 0.01 and 0.05 levels, respectively. The sample covers the period from July 1986 to June 2013.

Table 5.6 presents the results. The stocks are sorted into quintiles and deciles based on their respective ICC at the end of June each year from 1985 to 2012. I report the performance for each quintile and for the long-short strategies of 5-1 (fifth quintile minus first quintile) and 10-1 (tenth decile minus first decile). I estimate ICCs based on earnings from the following models: the CM, AF, CSAF, HVZ, RI, and EP. The portfolios are sorted by the following ICC approaches CT, GLS, OJ, and MPEG. In addition, I include a Composite ICC, which is the average of the aforementioned approaches. To compute the excess returns, I use the one-month Treasury bill rate.

The results of the long-short strategies show that in most cases the ICC based on the combined model outperforms the other models. In particular, for the CT, OJ, MPEG, and Composite ICC approaches the strategy is profitable regardless of earnings forecast model is used. However, in three (CT, MPEG, and Composite) of these four approaches, the ICC estimated with the combined model yields the highest excess returns. This is evidence that the ICC estimated with the combined model has the highest correlation with future returns among the analyzed models.

5.4.4. Firm characteristics and expected returns

I evaluate whether a set of firm characteristics that have been used to explain the cross-sectional variation of expected returns proxied by average realized returns also have the same relation when the ICC is used as a proxy for expected returns. I perform Fama and Macbeth (1973) (FM) cross-sectional regressions with ex-post excess realized returns from July (year t) to June (year $t+1$) and excess ICC estimated with different proxies for earnings forecasts as dependent variables. The independent variables are firm characteristics available prior to the end of June of year (t). I estimate the ICC[19] based on different proxies of earnings forecasts at the end of June of each year.

[19] For the sake of brevity, following Hou et al. (2012), I provide the results based only on the Composite ICC, which is the average of the CT, GLS, OJ, and MPEG approaches.

I use the following firm characteristics. I estimate market β at the end of June for each stock and for each year using the stock's previous 60 monthly excess returns (I require a minimum of 24 months and excess returns are in excess of the one-month Treasury bill rate taken from Kenneth French's data library). Idiosyncratic volatility is estimated as the standard deviation of the residuals from the regression of the stock's returns in excess of the one-month Treasury bill rate on the three Fama and French (1993) factors[20] estimated yearly at the end of June using the previous 60 monthly returns (I require a minimum of 24 months) (e.g., Ang et al. (2006); Hou et al. (2015)). Asset growth is the change in total assets from the fiscal year ending in year $(t-1)$ to the fiscal year ending in (t), divided by $(t-1)$ total assets (e.g., Fama and French (2015)). Size is estimated as the natural logarithm of market equity at the end of June in year (t). Gross profitability is the ratio of gross profits to total assets (e.g., Novy-Marx (2013)). Leverage is book value of debt divided by book equity. CapEx is capital expenditures divided by total assets from year $(t-1)$. $ln(beme)$ is the natural logarithm of the ratio of book equity to market equity at the previous fiscal year-end. In Table 5.7, I provide the average of the FM regression coefficients estimated yearly for the period from June 1986 to June 2012 and the respective t-statistics with Newey-West adjustment.

For market β the results are mixed. While one sees negative and significant coefficients for the ICC with earnings forecasts from the combined model, as well as from the cross-sectional (CSAF, HVZ, EP, and RI) models, the ICC using analysts' earnings forecasts has a positive relation with market β. The relation between market β and forward returns is not statistically significant. These results are similar to Hou et al. (2012), as their ICC model has a negative and significant relation to market β and the relation to realized returns are not statistically significant. The ICC based on the combined model, analysts' forecasts, EP, and HVZ earnings forecasts has a positive and significant relation with leverage, but forward returns and ICC with CSAF

[20] I download the three Fama-French factor returns from Kenneth French's website.

and RI earnings forecasts have no significant coefficients for leverage.

All proxies of expected returns have positive coefficients for idiosyncratic volatility. However, the coefficients are statistically significant only for the ICC with earnings forecasts derived from the combined model (t-statistic of 2.514), analysts' forecasts (t-statistic of 4.446), the CSAF model (t-statistics of 2.518), and the EP model (t-statistic of 3.218). The results for asset growth are interesting since I can to confirm the negative cross-sectional relation of asset growth and returns, also shown in Aharoni et al. (2013). Although, the ICC estimated with most proxies of earnings forecasts shows a negative and significant relation with asset growth (the ICC with the combined model earnings forecasts has a coefficient of -0.497 and t-statistic of 5.386, the ICC with HVZ model has a coefficient of -1.637 and t-statistic of 5.687, the ICC with the EP model has a coefficient of -0.417 and t-statistics of 3.521, and the ICC with the RI model has a coefficient of -0.769 and a t-statistic of 4.986), the ICC with analysts' forecasts has a positive and significant relation with a coefficient of 0.181 and a t-statistic of 3.076. These findings provide evidence against using ICC based on analysts' forecasts earnings as a proxy for expected returns.

The size effect is stronger when I use the ICC as a proxy for expected returns than when realized returns are used. The ICCs based on any of the tested earnings forecasts methods show significant coefficients at the 0.01 level. When I analyze the relation of size and forward returns, the coefficient is not statistically significant. Concerning the value effect, the coefficients of ln(BEME) are positive and statistically significant for all proxies of expected returns, but the t-statistics are higher when the ICC is used as a proxy for expected returns than when the ex-post realized returns are used.

According to Novy-Marx (2013), gross profitability has a positive and significant relation to returns. These results are confirmed since the t-statistic of returns is 3.181, and the coefficient is 5.627. The results for the ICC based on the combined model (a positive coefficient of 3.013 and a t-statistic of 8.492) are also similar to the one from returns. However, when the ICCs

Table 5.7.: Implied Cost of Capital and risk factors

	Realized Returns	CM	AF	CSAF	HVZ	EP	RI
Market β	0.180	-0.467	0.503	-0.703	-1.428	-0.455	-0.495
	[0.106]	[-2.669]*	[2.170]*	[-2.119]*	[-3.605]**	[-2.306]*	[-1.888]
Idios. Volatility	-0.126	0.161	0.184	0.636	0.262	0.533	0.417
	[-0.792]	[2.514]*	[4.446]**	[2.518]*	[1.496]	[3.218]**	[1.793]
Asset Growth	-4.871	-0.497	0.181	0.143	-1.637	-0.417	-0.769
	[-5.563]**	[-5.386]**	[3.076]**	[0.906]	[-5.687]**	[-3.521]**	[-4.986]**
Ln(Size)	0.057	-1.331	-0.781	-3.736	-2.411	-3.236	-2.465
	[0.084]	[-5.863]**	[-10.407]**	[-5.168]**	[-4.326]**	[-6.518]**	[-3.515]**
Gross Profitability	5.627	3.013	-0.461	1.439	-5.151	-0.209	-3.012
	[3.181]**	[8.492]**	[-1.518]	[1.881]	[-6.657]**	[-0.315]	[-3.280]**
Leverage	-0.065	0.107	0.064	0.032	0.132	0.059	0.057
	[-0.507]	[4.738]**	[5.936]**	[1.136]	[4.599]**	[2.078]*	[1.472]
CapEX	-5.660	-3.527	0.105	-2.412	-4.845	-2.680	-3.659
	[-0.731]	[-5.016]**	[0.151]	[-1.799]	[-4.032]**	[-2.384]*	[-3.458]**
Ln(BEME)	2.086	1.951	1.212	2.585	4.263	3.262	3.961
	[1.925]	[16.141]**	[10.602]**	[11.665]**	[10.974]**	[13.213]**	[37.946]**

This table presents the time-series average of slope coefficients from cross-sectional FM regressions of annual Composite ICC premium and ex-post realized returns premium on the following risk factors: market β, idiosyncratic volatility, asset growth, size, gross profitability, leverage, CapEx and ln(beme) (book-to-market). I estimate market β at the end of June for each stock and for each year using the stock's previous 60 monthly excess returns (I require a minimum of 24 months and excess returns are in excess of the one-month Treasury bill rate taken from Kenneth French's data library). Idiosyncratic volatility is the standard deviation of the residuals from regressing the stock's returns in excess of the one-month Treasury bill rate on the three Fama and French (1993) factors estimated yearly at the end of June using the previous 60 monthly returns (I require a minimum of 24 months). Asset Growth is the change in total assets from the fiscal year ending in year $(t-1)$ for the fiscal year ending in (t), divided by $(t-1)$ total assets. Size is the natural logarithm of market equity at the end of June in year (t). Gross profitability is the ratio of gross profits to total assets. Leverage is book value of debt divided by book equity. CapEx is capital expenditures divided by total assets from year $(t-1)$. $ln(beme)$ is the natural logarithm of the ratio of book equity to market equity at the previous fiscal year-end. I estimate ICC with earnings forecasts from the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models. To compute the ICC premiums and the excess returns, I use the yield on the U.S. 10-year government bond. The Newey-West t-statistics are presented in parentheses. ** and * denote significance at 0.01 and 0.05 level, respectively. The sample covers the period from June 1986 to June 2012.

are estimated with earnings forecasts from the HVZ model and the RI model, the results show a negative and significant relation, with a t-statistic of 6.657, and 3.280, respectively. Finally, CapEx has a negative and significant relation with the ICC based on the combined model, HVZ, EP, and RI models and insignificant with the other proxies of expected returns analyzed in this study.

5.5. Conclusion

In this study, I develop a new method to forecast corporate earnings. I build upon analysts' earnings forecasts, which are known to be accurate, yet upwardly biased. To improve these analysts' forecasts, I combine them with variables that have proven to be good predictors of earnings. First, I include gross profits, as Novy-Marx (2013) finds a strong association with earnings. Second, I follow Ashton and Wang (2012), who show that stock price changes drive earnings, by including recent stock market performance.

I compare this new approach to several methods from the literature, namely raw analyst forecasts, the model by Hou et al. (2012), the earnings persistent model (Li and Mohanram, 2014), and the residual income model (Li and Mohanram, 2014). In addition, I add an alternative benchmark, the CSAF model, which is based on a cross-sectional regression including only analysts' earnings forecasts as an input. I find that the combined model has the lowest bias and highest accuracy, so that the raw analysts' forecasts as well as the CSAF, HVZ, EP, and RI models, lag behind for those two metrics. Regarding market expectations, I show that the combined model also perform better than the other benchmark models. Furthermore, I compute the ICC based on the different earnings forecast models and find that the combined model leads to ICC estimates that have the strongest ability to predict realized earnings.

This new method makes a strong case for combining two different approaches to forecast earnings, that is, human forecasts made by financial analysts and mechanical forecasts based purely on financial data. These two approaches have distinct advantages and disadvantages, analysts' forecasts are known to be accurate, yet upwardly biased. On the other hand, mechanical forecasts are unbiased, but not as accurate. Combining them into one model may mitigate both disadvantages while conserving the advantages.

My findings are relevant for practitioners who work with earnings forecasts, as well as academics who use earnings forecasts as inputs for other models such as the ICC. I recommend the use of the combined model to improve the accuracy and unbiasedness of earnings forecasts, which benefits methods that build on these forecasts and applications thereof.

6. Conclusion

This chapter summarizes the main findings. Further, the contribution to the existing literature and the respective implications are discussed. Then, the limitations are addressed. Finally, avenues for future research are provided.

6.1. Summary of results

The ICC is the discount rate (or internal rate of return) that equates the asset's market value to the present value of its expected future cash flows. This estimate has been used in many studies as a proxy for expected returns. This dissertation focuses on the impact earnings forecast estimates have on different estimates of Implied Cost of Capital. In **Chapter 1**, I explained the reason why ICC plays an important role in Finance and Accounting and why earnings forecasts may drive the estimation of ICC. Then, I showed important gaps in the ICC literature.

Chapter 2 explained the valuation models, in which the ICC are estimated. I presented the derivations of the dividend discount model, residual income model, and the abnormal earnings growth model, which are the base models for the ICC approaches used in this dissertation. Then, I discussed some underlying assumptions of the ICC models, and I reviewed the most common estimates of earnings forecasts in the literature: analysts' forecasts and mechanical earnings.

As this dissertation focuses on ICC in an asset pricing context, in **Chapter 3**, I analyzed the joint roles of ICC estimated with analysts' forecasts and the risk proxies used in the recent Fama-French five-factor model on returns across firms, over time, and both dimensions at the same time. I found that ICC predicts stock returns over time and over both dimensions (across firms and over time) together. These results are robust not only at the aggregate level but also at the firm level. In other words, I presented evidence that ICC can be used to perform time-varying tests at the firm level. This result is relevant, especially because at the firm level realized returns are even noisier, and the literature previously lacked tests of alternative proxies of expected returns at the firm level.

Another important contribution of this dissertation to the literature is the time-series Fama-Macbeth approach. The asset pricing literature lacked regression methods to estimate the relationship of risk characteristics and returns at the firm level. In this dissertation, I adapted the cross-sectional Fama-Macbeth regression, which is widely used in cross-sectional tests, to perform asset pricing tests over time. Finally, confirming previous literature, I found no evidence of a positive relation between ICC and returns cross-sectionally since none of the ICC approaches yielded significant slopes to explain cross-sectional returns. To sum up, the results confirm that ICC has a positive relation to returns over-time, which suggests that ICC can replace realized returns in time-series settings. However, the fact that ICC has no significant relationship with returns cross-sectionally sheds light on an important weakness of ICC. Furthermore, given that many studies have used ICC to test relationships with risk proxies cross-sectionally, an unsolved puzzle is whether this weak correlation is driven by the underlying assumptions of the valuation models or the inaccuracy of analysts' earnings forecasts, which is the most commonly used input for estimating ICC.

To solve this puzzle, in **Chapter 4** I evaluate the effect of analysts' earnings forecast errors on estimates of ICC. To this end, I compare the properties of ICC estimated with analysts' forecasts ($ICC_{I/B/E/S}$) to $ICC_{Perfect\,Foresight}$, which is estimated with ex-post realized earnings. Although the effect of analysts' forecast bias on ICC has been documented, the literature lacked a measure of the magnitude of analysts' forecast errors on ICC. To the best of my knowledge, I am the first to measure the ICC absolute error, which is defined as the absolute difference between $ICC_{I/B/E/S}$ and $ICC_{Perfect\,Foresight}$. I measured the ICC absolute error at the firm level as well as at the portfolio level. The advantage of the estimation at the portfolio level is that the results are not driven by incorrect estimations of growth. The magnitude of the ICC absolute error at the firm level is 5.21% on average, which shows that the magnitude is huge. These results have two implications. First, the analysts' forecasts seem to be too poor in terms of accuracy to be used to estimate the cost of capital. Secondly, the analysts' forecast errors could be the reason for the weak results of ICC explaining returns across firms.

Then, I examined the relation between $ICC_{Perfect\,Foresight}$ and ex-post realized returns cross-sectionally. Interestingly, the $ICC_{Perfect\,Foresight}$ has quite a strong relation to returns. The cross-sectional coefficients of FM regressions of $ICC_{Perfect\,Foresight}$ on returns are all positive and highly significant. The results are also robust in portfolio analyses since all long-short portfolios sorted on ICC have shown positive and significant normal and abnormal excess returns. The magnitude of the abnormal returns is another important point; a long-short strategy based on this proxy generates abnormal returns of up to 6.05% per month. As I found no evidence that this relation could be a valuation model specific issue, these results confirm the hypothesis that the weak explanatory power of $ICC_{I/B/E/S}$ regarding returns is driven by analysts' inaccuracy. In addition, these results show that by improving the accuracy of earnings forecasts it is still possible to beat the market with very profitable strategies. On the one hand, the $ICC_{I/B/E/S}$ has a weak correlation with returns due to the inaccuracy of the analysts' forecasts. On the other hand, the $ICC_{Perfect\,Foresight}$ has strong power to explain returns, but the estimation of such a proxy requires ex-post earnings. Accordingly, this estimate cannot be used in investment strategies or any ex-ante analysis.

In order to find an accurate proxy for the cost of capital that can be estimated ex-ante, I analyze whether the ICC absolute errors can be explained by firms' characteristics. I found that the ICC absolute error in most cases relates positively to $ICC_{I/B/E/S}$, market beta, book-to-market, market leverage, and idiosyncratic volatility, and negatively to size and gross profitability. Based on this finding, I used these variables, which are correlated to ICC absolute error, to estimate an ex-ante Fitted ICC. The calculation of this estimate is similar to an instrumental variable of the $ICC_{Perfect\,Foresight}$. The results show that the Fitted $ICC_{I/B/E/S}$ has a higher correlation to $ICC_{Perfect\,Foresight}$ as well as to ex-post realized returns compared to $ICC_{I/B/E/S}$, making it a good alternative for estimation of the implied cost of capital. Interestingly, a long-short strategy based on this proxy yields abnormal returns of up to 0.962% per month. Thus, another important contribution of the dissertation is the introduction of the Fitted ICC since it gets closer to the perfect foresight ICC.

However, the Fitted ICC should not be seen as the only alternative to estimate the cost of capital accurately. Another possibility could be to improve the analysts' forecasts. To this end, I had to find an alternative to earnings forecasts with better results, not only in terms of accuracy but also in terms of bias since the analysts' forecasts are upwardly biased.

In **Chapter 5**, I developed a new method to forecast corporate earnings, namely the combined model. This model combines analysts' forecasts with variables that have proven to be good predictors of earnings in a mechanical forecast setting. I included gross profits, as Novy-Marx (2013) finds a strong association with earnings, and recent stock market performance, based on evidence from Ashton and Wang (2012), who show that stock price changes drive earnings.

In order to analyze the properties of this new estimate of earnings forecasts, I compared these results to several methods from the literature: analysts' forecasts, random walk, the model from Hou et al. (2012), the earnings persistent model (Li and Mohanram, 2014), and the residual income model (Li and Mohanram, 2014). Furthermore, I proposed a cross-sectional analysts' forecasts (CSAF) model, as a benchmark, based on a cross-sectional regression including only analysts' earnings forecasts as input. The results show that the combined model has the lowest bias and highest accuracy among all methods analyzed.

Another important measure for earnings forecasts is the Earnings Response Coefficients (ERC), which aim to determine which earnings forecast method has a better approximation of market expectations. I showed that even in terms of ERC the combined model outperforms the other benchmark models. In addition, by finding that the estimates from the CSAF model underperform the combined model and the raw analysts' forecasts in all metrics, I showed that to include analysts' forecasts in mechanical models is not sufficient to improve the accuracy of the forecasts nor to eliminate bias.

Given that the combined model has outperformed the benchmark models in terms of bias, accuracy, and ERC, the next step is to test the properties of ICC calculated using different estimates of earnings forecasts. By comparing results of different ICC estimates on portfolio and Fama-Macbeth regressions, the combined model has shown the strongest correlation with future returns. Furthermore, in contrast to ICC estimated using other benchmark methods, the ICC estimated using the combined model earnings forecasts have shown similar patterns with firms' characteristics compared to future returns. These results have important implications. First, a method that has higher accuracy, lower bias, and higher ERC reports higher correlation with future returns. Second, the estimates of earnings from the combined model are a good alternative to analysts' forecasts as well as to mechanical models. These results are relevant for practitioners who intend to implement trading strategies with ICC, and for academics because the ICC is commonly used as a proxy for expected returns.

6.2. Limitations

The first limitation of my dissertation is that I focus on four ICC approaches (GLS, CT, MPEG, and OJ) and a composite ICC based on the average of these four methods. Although analyzing the results with other ICC approaches could be interesting, I employ the most common approaches in the literature. In addition, all the results of this dissertation were robust for all ICC approaches, and I found no evidence that the results were driven by the specific ICC approach employed.

Another important limitation is the database of analysts' forecasts. In terms of time sample, the coverage of I/B/E/S started in 1977, and the sample was very restricted until 1985. In addition, the analysts do not cover all the firms. Hou et al. (2012) show that due to these two constraints, the ICC based on the I/B/E/S analysts' forecasts can be estimated for roughly 50% of the sample compared to ICC using mechanical earnings. The decision of which estimates of earnings forecasts used is an important tradeoff between coverage and reliability. If I had used mechanical earnings forecasts in the entire dissertation, the sample would definitely have been larger. However, the analysis would have had other shortcomings. The first one is the lack of monthly estimates of earnings forecasts based on cross-sectional mechanical models. Due to that, most of the analysis of **Chapter 3** could not have been carried out because monthly ICC estimates were required. Moreover, the literature has shown that the earnings forecasts based on mechanical models are poor in the sample not covered by I/B/E/S. Thus, the results could be driven by noisy estimates of earnings forecasts. Consequently, I decided to use analysts' forecasts as the main input to estimate ICC in the dissertation, and the properties of the mechanical models were tested in **Chapter 5**.

The analysts' forecasts are reported in different databases, such as First Call, I/B/E/S, Value Line, and Zacks. Although the I/B/E/S has the aforementioned limitations, I have chosen the I/B/E/S as a source for analysts' forecasts because this database offers the largest coverage. Moreover, due to the fact that most of the ICC literature use I/B/E/S, using this database is an advantage since it improves comparability. The next section offers some recommendations for further research.

6.3. Recommendations for further research

Based on the results of **Chapter 3**, it could be relevant to determine whether the predictive power of ICC explaining returns at the firm level remains strong not only for the U.S. sample but also for an international sample. An international sample could also be useful to analyze the properties of ICC and the risk-proxies of the Fama and French (2015) five-factor model in other dimensions. Furthermore, conditional CAPM models (see, e.g., Jagannathan and Wang (1996)) usually make use of the same variables that help predict the business cycle to forecast the market risk premium. Thus, analyzing whether ICC could be such a proxy could also be relevant. Finally, other ICC approaches, such as the Gordon and Gordon (1997) approach based on the earnings-to-price ratio, and the Pástor et al. (2008) based on the DDM, could be used to confirm whether the relation between ICC and a firm's characteristics also holds for different ICC approaches.

Concerning **Chapter 4**, estimating the ICC absolute error based on mechanical models could be informative. The errors would likely be even larger compared to analysts' forecasts since the mechanical models are not as accurate as analysts' forecasts, but the extent of this error is still unknown. In addition, estimating the Fitted ICC using other ICC approaches or based on mechanical earnings forecasts could improve the results in terms of correlation with future returns and with $ICC_{Perfect\,Foresight}$. Finally, the impact of analysts' forecast errors in an international sample could be analyzed in further research to determine the extent of the difference among countries.

With regard to the comparison of earnings forecast estimates in **Chapter 5**, other methods could be included in the comparison. In terms of cross-sectional settings, the model from Ashton and Wang (2012) allows for simultaneous estimation of the cost of capital and implied growth rate, and could contribute to the comparison. In the time-series dimension, I recommend the comparison with the recent model based on mixed data sampling regression methods (MIDAS) from Ball and Ghysels (2017). In addition, applying analysts' forecasts after removing predictable analyst forecast errors (see, e.g., Gode and Mohanram (2003); Larocque (2013)) could be a useful benchmark for the combined model.

A. Appendix

A.1. Yearly ICC absolute error

Table A. 1.: ICC absolute error based on the GLS approach

Year	Firm-Years	Mean Absolute Error	Median Absolute Error	Value-Weighted Absolute Error
1985	1,352	2.56%	1.71%	1.82%
1986	1,368	1.97%	1.18%	1.28%
1987	1,466	2.02%	1.22%	1.25%
1988	1,427	2.15%	1.38%	1.35%
1989	1,545	2.20%	1.41%	1.57%
1990	1,595	2.21%	1.45%	1.50%
1991	1,681	1.93%	1.26%	1.27%
1992	1,758	1.71%	1.01%	1.00%
1993	1,877	1.71%	0.98%	0.90%
1994	2,072	1.72%	0.97%	1.03%
1995	2,056	1.68%	0.98%	1.02%
1996	2,167	1.73%	0.95%	1.00%
1997	2,214	1.90%	1.06%	1.03%
1998	2,094	2.00%	1.14%	1.01%
1999	1,940	2.07%	1.33%	1.17%
2000	1,953	2.13%	1.49%	1.45%
2001	1,997	1.86%	1.22%	1.17%
2002	2,071	1.63%	0.94%	0.94%
2003	2,066	1.61%	0.87%	1.06%
2004	2,068	1.61%	0.85%	1.03%
2005	2,054	1.59%	0.90%	1.20%
2006	2,053	2.01%	1.15%	1.58%
2007	2,055	2.10%	1.38%	1.60%
2008	2,045	2.10%	1.33%	1.53%
2009	1,911	1.88%	1.12%	1.28%
2010	1,938	1.56%	0.83%	1.00%
2011	1,962	1.57%	0.84%	0.90%
2012	1,904	1.49%	0.76%	0.90%

This table reports the mean, median, and value-weighted annual ICC absolute error. The ICC absolute error is measured as the absolute difference between ($ICC_{I/B/E/S}$) and the $ICC_{Perfect\,Foresight}$ estimated with the GLS approach. The sample covers the period from 1985 to 2012.

Table A. 2.: ICC absolute error based on the CT approach

Year	Firm-Years	Mean Absolute Error	Median Absolute Error	Value-Weighted Absolute Error
1985	829	3.25%	2.46%	2.95%
1986	878	2.88%	2.29%	2.35%
1987	943	2.89%	2.42%	2.00%
1988	931	3.25%	2.68%	2.53%
1989	1,078	3.20%	2.59%	2.43%
1990	1,170	3.19%	2.50%	2.51%
1991	1,199	3.06%	2.17%	2.06%
1992	1,281	2.96%	2.11%	1.97%
1993	1,372	2.78%	1.99%	1.98%
1994	1,348	2.82%	2.11%	2.08%
1995	1,341	3.11%	2.31%	2.24%
1996	1,314	2.85%	2.14%	2.11%
1997	1,227	3.00%	2.44%	2.05%
1998	1,341	3.22%	2.55%	1.96%
1999	1,342	3.18%	2.50%	1.89%
2000	1,445	3.56%	2.68%	1.95%
2001	1,446	3.10%	2.04%	2.01%
2002	1,517	3.05%	2.07%	2.13%
2003	1,505	3.30%	2.33%	2.40%
2004	1,343	2.99%	2.27%	2.58%
2005	1,320	2.85%	2.28%	2.28%
2006	1,390	2.90%	2.31%	2.29%
2007	1,418	2.59%	2.00%	2.05%
2008	1,484	3.23%	2.50%	2.73%
2009	1,349	3.30%	2.36%	2.31%
2010	1,378	2.63%	1.85%	2.15%
2011	1,472	3.93%	2.42%	2.83%
2012	1,516	5.68%	3.00%	3.23%

This table reports the mean, median, and value-weighted annual ICC absolute error. The ICC absolute error is measured as the absolute difference between ($ICC_{I/B/E/S}$) and the $ICC_{Perfect\,Foresight}$ estimated with the CT approach. The sample covers the period from 1985 to 2012.

Table A. 3.: ICC absolute error based on the OJ approach

Year	Firm-Years	Mean Absolute Error	Median Absolute Error	Value-Weighted Absolute Error
1985	661	5.60%	3.70%	3.90%
1986	806	5.45%	3.88%	4.21%
1987	958	5.78%	3.84%	5.21%
1988	739	5.67%	3.61%	3.92%
1989	741	5.07%	3.43%	3.60%
1990	748	5.62%	3.76%	3.25%
1991	1,053	5.50%	3.49%	2.84%
1992	1,176	5.18%	3.83%	3.51%
1993	1,413	4.26%	3.05%	2.96%
1994	1,461	4.91%	3.43%	3.87%
1995	1,668	4.73%	3.32%	2.94%
1996	1,672	4.29%	2.96%	2.80%
1997	1,480	4.17%	2.76%	2.38%
1998	1,522	3.96%	2.78%	2.50%
1999	1,369	4.98%	3.07%	2.87%
2000	921	4.84%	3.37%	2.29%
2001	1,138	4.76%	3.61%	2.69%
2002	1,272	4.48%	3.03%	3.22%
2003	1,499	4.76%	3.31%	3.16%
2004	1,501	4.66%	3.28%	2.77%
2005	1,444	4.75%	3.46%	3.76%
2006	1,246	4.29%	3.23%	2.75%
2007	1,006	4.28%	3.02%	3.05%
2008	762	5.07%	3.43%	2.88%
2009	1,175	6.61%	4.87%	4.70%
2010	1,364	4.95%	3.61%	4.07%
2011	1,297	4.71%	3.30%	3.61%
2012	1,338	4.94%	3.35%	2.96%

This table reports the mean, median, and value-weighted annual ICC absolute error. The ICC absolute error is measured as the absolute difference between ($ICC_{I/B/E/S}$) and the $ICC_{Perfect\,Foresight}$ estimated with the OJ approach. The sample covers the period from 1985 to 2012.

Table A. 4.: ICC absolute error based on the MPEG approach

Year	Firm-Years	Mean Absolute Error	Median Absolute Error	Value-Weighted Absolute Error
1985	865	5.38%	3.98%	3.88%
1986	929	5.38%	3.76%	4.07%
1987	1,121	5.75%	3.96%	4.94%
1988	952	5.54%	3.71%	4.01%
1989	928	5.03%	3.67%	3.75%
1990	948	5.38%	3.89%	3.61%
1991	1,208	5.37%	3.47%	3.14%
1992	1,343	5.16%	3.78%	3.63%
1993	1,520	4.19%	3.04%	2.96%
1994	1,637	4.80%	3.43%	3.85%
1995	1,798	4.68%	3.28%	3.00%
1996	1,830	4.23%	2.92%	2.90%
1997	1,627	4.17%	2.73%	2.64%
1998	1,602	3.96%	2.80%	2.52%
1999	1,455	4.96%	3.14%	2.94%
2000	996	4.76%	3.32%	2.29%
2001	1,191	4.72%	3.56%	2.85%
2002	1,324	4.49%	3.07%	3.33%
2003	1,529	4.81%	3.35%	3.23%
2004	1,572	4.63%	3.27%	2.77%
2005	1,495	4.78%	3.44%	3.69%
2006	1,317	4.28%	3.18%	2.82%
2007	1,080	4.32%	3.14%	3.14%
2008	791	5.05%	3.49%	2.96%
2009	1,195	6.58%	4.82%	4.65%
2010	1,383	4.97%	3.64%	4.05%
2011	1,282	4.59%	3.24%	3.57%
2012	1,323	4.84%	3.29%	2.95%

This table reports the mean, median, and value-weighted annual ICC absolute error. The ICC absolute error is measured as the absolute difference between ($ICC_{I/B/E/S}$) and the $ICC_{Perfect\,Foresight}$ estimated with the MPEG approach. The sample covers the period from 1985 to 2012.

Table A. 5.: ICC absolute error based on the Composite ICC

Year	Firm-Years	Mean Absolute Error	Median Absolute Error	Value-Weighted Absolute Error
1985	1,569	5.08%	3.76%	3.47%
1986	1,586	4.36%	3.05%	2.99%
1987	1,700	4.56%	3.46%	3.44%
1988	1,694	4.50%	3.27%	2.84%
1989	1,811	4.15%	3.13%	2.78%
1990	1,871	4.75%	3.51%	3.18%
1991	1,953	4.49%	3.16%	2.66%
1992	2,064	4.40%	3.28%	2.95%
1993	2,249	3.69%	2.59%	2.24%
1994	2,475	4.12%	2.95%	2.78%
1995	2,563	4.06%	2.91%	2.51%
1996	2,609	3.77%	2.63%	2.36%
1997	2,663	3.89%	2.80%	2.31%
1998	2,512	3.90%	2.77%	2.24%
1999	2,274	4.11%	2.96%	2.30%
2000	2,184	4.11%	3.20%	2.45%
2001	2,237	3.84%	2.88%	2.45%
2002	2,311	3.64%	2.50%	2.42%
2003	2,329	3.70%	2.48%	2.69%
2004	2,398	3.68%	2.52%	2.64%
2005	2,373	3.55%	2.61%	2.65%
2006	2,366	3.73%	2.71%	2.63%
2007	2,370	3.74%	2.87%	2.86%
2008	2,365	4.14%	3.02%	3.03%
2009	2,188	4.61%	3.16%	3.05%
2010	2,239	3.90%	2.67%	2.74%
2011	2,287	4.31%	2.98%	2.74%
2012	2,258	4.85%	3.18%	2.77%

This table reports the mean, median, and value-weighted annual ICC absolute error. The ICC absolute error is measured as the absolute difference between ($ICC_{I/B/E/S}$) and the $ICC_{Perfect\,Foresight}$ estimated with the Composite approach. The sample covers the period from 1985 to 2012.

A.2. Yearly earnings forecast bias

Table A. 6.: Yearly One-year-ahead Bias

	CM		AF		CSAF		HVZ		EP		RI		RW	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1985	-0.030	-0.003	-0.027	-0.002	-0.033	-0.009	-0.090	-0.014	-0.144	-0.015	-0.106	-0.011	0.014	0.020
1986	-0.072	-0.025	-0.046	-0.008	-0.104	-0.034	-0.089	-0.021	-0.203	-0.048	-0.154	-0.039	-0.025	0.003
1987	-0.013	0.002	-0.049	-0.005	-0.028	0.004	-0.030	0.003	-0.048	-0.002	-0.047	-0.002	-0.010	0.005
1988	-0.006	0.009	-0.047	-0.004	-0.021	0.006	-0.020	0.008	-0.028	0.005	-0.013	0.009	0.003	0.008
1989	0.023	0.022	-0.044	-0.002	0.017	0.017	-0.044	0.011	-0.029	0.006	-0.009	0.012	-0.008	0.012
1990	0.007	0.016	-0.070	-0.004	-0.001	0.012	-0.084	-0.003	-0.055	-0.005	-0.026	0.006	-0.046	0.006
1991	-0.002	0.012	-0.105	-0.007	-0.018	0.010	-0.106	-0.008	-0.121	-0.013	-0.061	0.002	-0.014	0.002
1992	0.015	0.018	-0.036	-0.003	0.012	0.014	-0.101	-0.007	-0.099	-0.011	-0.063	0.002	-0.028	0.002
1993	0.014	0.013	-0.021	-0.001	0.018	0.015	-0.032	0.006	-0.059	0.002	-0.032	0.008	0.027	0.010
1994	0.006	0.008	-0.019	-0.001	0.011	0.012	-0.047	0.003	-0.051	-0.001	-0.032	0.006	-0.006	0.009
1995	0.020	0.015	-0.010	0.000	0.018	0.014	-0.033	0.009	-0.038	-0.001	-0.017	0.006	0.010	0.010
1996	0.003	0.006	-0.018	-0.001	0.009	0.011	-0.044	0.005	-0.042	-0.002	-0.021	0.007	-0.008	0.008
1997	0.005	0.007	-0.016	0.000	0.008	0.009	-0.043	0.003	-0.041	-0.003	-0.021	0.006	-0.004	0.007
1998	0.003	0.005	-0.014	0.001	0.005	0.008	-0.055	0.000	-0.043	-0.001	-0.019	0.007	-0.003	0.008
1999	-0.005	-0.001	-0.015	-0.003	-0.001	0.003	-0.049	-0.003	-0.047	-0.006	-0.028	0.002	-0.014	0.004
2000	-0.005	0.004	-0.023	-0.001	-0.001	0.005	-0.036	0.005	-0.040	0.000	-0.020	0.006	-0.002	0.006
2001	-0.005	0.003	-0.021	-0.001	-0.002	0.004	-0.073	-0.002	-0.069	-0.005	-0.052	0.004	-0.041	0.003
2002	-0.004	0.001	0.022	-0.004	0.014	0.001	-0.109	-0.014	-0.171	-0.016	-0.124	-0.011	-0.041	-0.006
2003	0.006	0.006	-0.023	-0.001	0.002	0.004	0.046	0.011	-0.009	-0.001	0.003	-0.004	0.139	0.010
2004	0.008	0.007	-0.009	0.001	0.006	0.006	0.015	0.015	-0.013	0.004	-0.017	0.001	0.031	0.009
2005	0.006	0.004	-0.006	0.000	0.006	0.005	0.013	0.014	0.001	0.007	0.002	0.006	0.008	0.010
2006	0.003	0.004	-0.013	0.001	-0.002	0.004	0.002	0.009	-0.010	0.004	0.003	0.007	0.005	0.008
2007	0.001	0.003	-0.010	0.000	-0.001	0.002	0.003	0.009	-0.005	0.004	0.004	0.008	0.004	0.006
2008	-0.008	0.001	-0.019	-0.002	-0.010	0.001	-0.016	0.005	-0.021	0.002	-0.010	0.005	-0.019	0.002
2009	-0.045	0.001	-0.078	-0.006	-0.052	-0.002	-0.128	-0.008	-0.150	-0.017	-0.128	-0.010	-0.107	-0.012
2010	-0.026	0.010	-0.099	0.002	-0.037	0.008	0.029	0.002	-0.013	-0.006	0.014	-0.002	0.166	0.002
2011	-0.023	0.009	-0.130	0.002	-0.028	0.007	0.044	0.019	0.072	0.018	0.088	0.020	0.069	0.016
2012	-0.005	0.000	-0.032	-0.001	-0.003	0.003	0.002	0.010	0.016	0.008	0.038	0.013	0.009	0.007
2013	-0.020	-0.003	-0.021	-0.002	-0.018	0.000	-0.037	0.001	-0.017	-0.001	0.015	0.007	0.006	0.003
2014	-0.016	-0.001	-0.014	-0.001	-0.013	0.001	-0.031	-0.003	-0.002	0.000	0.020	0.006	0.011	0.003
2015	-0.014	-0.001	-0.013	-0.001	-0.011	0.001	-0.022	0.000	-0.006	0.002	0.013	0.006	-0.003	0.003

This table shows the yearly one-year-ahead mean and median forecast bias for the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models. The bias is defined as the difference between earnings forecasts and actual earnings, scaled by the firm's end-of-June market equity.

Table A. 7.: Yearly Two-year-ahead Bias

	CM		AF		CSAF		HVZ		EP		RI		RW	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1987	-0.099	-0.040	-0.070	-0.020	-0.175	-0.074	-0.151	-0.064	-0.332	-0.088	-0.242	-0.072	-0.024	0.004
1988	-0.071	-0.022	-0.059	-0.013	-0.155	-0.063	-0.126	-0.040	-0.293	-0.054	-0.244	-0.048	0.014	0.010
1989	-0.028	-0.006	-0.031	-0.008	-0.065	-0.018	0.005	0.014	-0.054	-0.009	-0.035	-0.003	0.031	0.018
1990	-0.026	0.003	-0.055	-0.013	-0.075	-0.016	-0.068	0.004	-0.064	-0.006	-0.038	0.001	-0.007	0.016
1991	-0.024	0.001	-0.070	-0.020	-0.081	-0.030	-0.117	-0.021	-0.093	-0.028	-0.065	-0.016	-0.030	0.003
1992	-0.009	0.006	-0.074	-0.021	-0.056	-0.018	-0.131	-0.030	-0.151	-0.028	-0.100	-0.018	0.019	-0.001
1993	0.029	0.020	-0.036	-0.010	-0.011	0.001	-0.099	-0.015	-0.081	-0.018	-0.032	-0.004	0.027	0.008
1994	0.034	0.020	-0.066	-0.007	0.005	0.009	-0.050	-0.003	-0.088	-0.005	-0.046	0.002	0.038	0.015
1995	0.014	0.011	-0.017	-0.004	-0.003	0.006	-0.051	0.005	-0.056	-0.002	-0.031	0.005	0.013	0.016
1996	0.020	0.019	-0.016	-0.004	-0.007	0.004	-0.045	0.004	-0.051	-0.009	-0.027	0.001	0.024	0.017
1997	0.000	0.005	-0.022	-0.004	-0.015	0.001	-0.046	0.003	-0.049	-0.007	-0.024	0.003	0.010	0.016
1998	0.002	0.004	-0.015	-0.002	-0.009	0.002	-0.047	-0.001	-0.042	-0.006	-0.019	0.003	0.003	0.014
1999	0.001	0.001	-0.020	-0.006	-0.015	-0.004	-0.066	-0.009	-0.054	-0.011	-0.030	0.000	-0.005	0.010
2000	-0.021	-0.007	-0.037	-0.010	-0.027	-0.007	-0.060	-0.009	-0.053	-0.012	-0.028	-0.004	-0.001	0.008
2001	-0.004	0.001	-0.026	-0.006	-0.017	-0.003	-0.051	-0.004	-0.064	-0.011	-0.037	-0.002	-0.002	0.008
2002	-0.013	-0.006	-0.035	-0.016	-0.021	-0.009	-0.080	-0.025	-0.079	-0.025	-0.063	-0.016	-0.038	-0.007
2003	0.013	0.000	-0.023	-0.011	0.002	-0.003	-0.026	-0.013	-0.107	-0.018	-0.064	-0.013	0.054	0.001
2004	0.042	0.005	-0.003	-0.008	0.026	-0.001	0.092	0.014	-0.081	-0.001	-0.020	-0.001	0.228	0.019
2005	0.026	0.014	-0.002	0.001	0.014	0.007	0.040	0.027	-0.008	0.008	-0.012	0.006	0.070	0.023
2006	0.011	0.006	-0.007	0.000	0.003	0.002	0.014	0.019	-0.010	0.007	-0.005	0.007	0.026	0.017
2007	0.004	0.004	-0.013	-0.003	-0.007	-0.002	0.003	0.010	-0.015	0.003	0.002	0.007	0.020	0.013
2008	-0.015	-0.004	-0.030	-0.009	-0.026	-0.010	-0.013	0.006	-0.029	-0.002	-0.013	0.005	-0.002	0.007
2009	-0.034	-0.010	-0.051	-0.014	-0.043	-0.015	-0.071	-0.013	-0.082	-0.019	-0.063	-0.011	-0.065	-0.010
2010	-0.056	-0.016	-0.098	-0.030	-0.080	-0.031	-0.072	-0.022	-0.107	-0.031	-0.070	-0.020	-0.004	-0.016
2011	0.027	0.009	-0.052	0.005	0.005	0.004	0.065	0.014	-0.040	-0.007	0.039	0.006	0.272	0.017
2012	-0.002	0.007	-0.021	-0.002	-0.026	-0.001	0.038	0.023	0.024	0.017	0.060	0.020	0.106	0.028
2013	-0.001	0.005	-0.024	-0.009	-0.035	-0.010	0.001	0.010	-0.001	0.005	0.027	0.009	0.010	0.010
2014	-0.041	-0.014	-0.037	-0.009	-0.063	-0.015	-0.025	-0.001	-0.033	-0.007	0.018	0.002	0.028	0.006
2015	-0.037	-0.008	-0.030	-0.006	-0.055	-0.011	-0.035	-0.004	-0.034	-0.007	0.005	0.000	0.012	0.007

This table shows the yearly two-year-ahead mean and median forecast bias for the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models. The bias is defined as the difference between earnings forecasts and actual earnings, scaled by the firm's end-of-June market equity.

Table A. 8.: Yearly Three-year-ahead Bias

	CM		AF		CSAF		HVZ		EP		RI		RW	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1989	-0.008	0.005	-0.038	-0.010	-0.155	-0.048	-0.144	-0.023	-0.065	-0.018	-0.160	-0.032	0.028	0.021
1990	-0.048	-0.016	-0.041	-0.014	-0.220	-0.072	-0.149	-0.017	-0.080	-0.016	-0.152	-0.032	0.023	0.021
1991	-0.025	0.003	-0.069	-0.028	-0.146	-0.045	-0.090	0.000	-0.100	-0.024	-0.094	-0.022	-0.006	0.012
1992	-0.027	-0.006	-0.058	-0.028	-0.133	-0.056	-0.146	-0.034	-0.104	-0.045	-0.083	-0.037	-0.024	0.000
1993	0.000	0.002	-0.043	-0.026	-0.091	-0.039	-0.119	-0.035	-0.097	-0.038	-0.074	-0.028	-0.006	0.006
1994	0.024	0.013	-0.017	-0.011	-0.035	-0.012	-0.090	-0.025	-0.082	-0.023	-0.050	-0.015	0.044	0.015
1995	0.046	0.019	0.001	-0.006	0.002	0.004	-0.050	-0.005	-0.086	-0.005	-0.042	-0.001	0.049	0.025
1996	0.021	0.011	-0.007	-0.005	-0.008	0.004	-0.037	0.000	-0.061	-0.006	-0.032	0.001	0.035	0.022
1997	0.013	0.018	-0.019	-0.006	-0.027	-0.002	-0.058	0.001	-0.075	-0.013	-0.045	-0.004	0.033	0.025
1998	0.000	0.003	-0.018	-0.007	-0.030	-0.006	-0.057	-0.004	-0.064	-0.011	-0.034	-0.001	0.015	0.022
1999	-0.003	-0.006	-0.015	-0.009	-0.029	-0.013	-0.061	-0.014	-0.066	-0.023	-0.037	-0.010	0.006	0.014
2000	-0.012	-0.003	-0.033	-0.014	-0.039	-0.015	-0.073	-0.015	-0.070	-0.019	-0.034	-0.007	0.009	0.014
2001	-0.017	-0.014	-0.027	-0.013	-0.029	-0.012	-0.072	-0.012	-0.075	-0.021	-0.044	-0.011	-0.003	0.009
2002	-0.017	-0.011	-0.038	-0.021	-0.038	-0.019	-0.105	-0.032	-0.116	-0.037	-0.082	-0.026	-0.035	-0.004
2003	-0.011	-0.013	-0.032	-0.023	-0.025	-0.016	-0.059	-0.021	-0.065	-0.025	-0.044	-0.018	0.000	0.001
2004	0.028	-0.002	-0.010	-0.015	0.010	-0.008	-0.014	-0.011	-0.153	-0.021	-0.087	-0.015	0.090	0.008
2005	0.052	0.010	0.008	-0.006	0.037	0.003	0.018	0.015	-0.224	0.001	-0.121	0.003	0.191	0.031
2006	0.029	0.014	0.008	0.003	0.013	0.005	0.026	0.025	-0.027	0.008	-0.012	0.008	0.076	0.032
2007	0.008	0.004	-0.006	-0.003	0.001	0.000	0.009	0.017	-0.015	0.006	-0.007	0.005	0.037	0.024
2008	-0.007	-0.001	-0.024	-0.009	-0.021	-0.010	-0.011	0.004	-0.036	-0.004	-0.016	0.002	0.016	0.014
2009	-0.041	-0.015	-0.056	-0.019	-0.053	-0.023	-0.077	-0.015	-0.097	-0.029	-0.081	-0.020	-0.060	-0.006
2010	-0.046	-0.026	-0.058	-0.031	-0.058	-0.033	-0.051	-0.022	-0.071	-0.032	-0.050	-0.022	-0.035	-0.013
2011	-0.034	-0.017	-0.073	-0.025	-0.054	-0.028	-0.028	-0.013	-0.083	-0.024	-0.031	-0.012	0.078	0.003
2012	0.030	0.006	0.004	0.004	0.010	0.001	0.019	0.009	-0.088	-0.011	0.025	0.009	0.260	0.028
2013	-0.013	-0.001	-0.011	-0.009	-0.038	-0.011	0.015	0.010	-0.028	0.003	0.035	0.010	0.107	0.029
2014	-0.022	-0.003	-0.035	-0.015	-0.042	-0.011	-0.004	0.005	-0.028	-0.001	0.003	0.002	0.027	0.013
2015	-0.044	-0.009	-0.044	-0.015	-0.072	-0.017	-0.033	-0.002	-0.057	-0.008	-0.018	-0.003	0.030	0.011

This table shows the yearly three-year-ahead mean and median forecast bias for the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models. The bias is defined as the difference between earnings forecasts and actual earnings, scaled by the firm's end-of-June market equity.

A.3. Yearly earnings forecast accuracy

Table A. 9.: Yearly One-year-ahead Accuracy

	CM		AF		CSAF		HVZ		EP		RI		RW	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1985	0.057	0.020	0.060	0.019	0.063	0.019	0.106	0.025	0.165	0.030	0.128	0.027	0.081	0.029
1986	0.087	0.029	0.068	0.017	0.120	0.040	0.113	0.035	0.214	0.053	0.170	0.046	0.101	0.025
1987	0.055	0.018	0.065	0.012	0.053	0.014	0.093	0.034	0.079	0.023	0.078	0.023	0.091	0.022
1988	0.051	0.020	0.062	0.013	0.049	0.016	0.090	0.036	0.081	0.024	0.077	0.024	0.099	0.023
1989	0.066	0.030	0.073	0.013	0.067	0.027	0.111	0.039	0.101	0.028	0.092	0.026	0.116	0.026
1990	0.068	0.027	0.092	0.015	0.070	0.025	0.126	0.038	0.106	0.026	0.098	0.026	0.125	0.023
1991	0.074	0.023	0.120	0.015	0.090	0.025	0.160	0.038	0.177	0.032	0.138	0.027	0.173	0.025
1992	0.060	0.026	0.055	0.013	0.067	0.025	0.150	0.040	0.148	0.032	0.126	0.028	0.122	0.026
1993	0.050	0.021	0.040	0.012	0.056	0.024	0.112	0.039	0.101	0.028	0.083	0.027	0.096	0.026
1994	0.037	0.015	0.035	0.010	0.043	0.019	0.094	0.033	0.085	0.025	0.074	0.024	0.080	0.023
1995	0.037	0.020	0.029	0.010	0.038	0.020	0.088	0.037	0.078	0.028	0.069	0.026	0.077	0.024
1996	0.033	0.015	0.035	0.010	0.039	0.019	0.086	0.032	0.077	0.026	0.068	0.025	0.074	0.023
1997	0.028	0.014	0.028	0.009	0.032	0.015	0.085	0.030	0.073	0.025	0.064	0.022	0.071	0.022
1998	0.030	0.012	0.030	0.009	0.034	0.015	0.091	0.030	0.081	0.024	0.069	0.024	0.069	0.023
1999	0.031	0.010	0.033	0.009	0.033	0.012	0.083	0.029	0.079	0.024	0.070	0.022	0.070	0.022
2000	0.038	0.013	0.040	0.009	0.040	0.014	0.096	0.035	0.093	0.028	0.085	0.026	0.091	0.026
2001	0.040	0.015	0.038	0.011	0.041	0.014	0.122	0.035	0.122	0.031	0.115	0.030	0.106	0.028
2002	0.038	0.012	0.087	0.011	0.060	0.013	0.201	0.040	0.214	0.035	0.189	0.035	0.214	0.032
2003	0.033	0.011	0.038	0.008	0.034	0.011	0.166	0.036	0.144	0.034	0.152	0.035	0.242	0.030
2004	0.029	0.012	0.027	0.008	0.029	0.012	0.085	0.032	0.072	0.026	0.077	0.030	0.092	0.023
2005	0.020	0.009	0.021	0.006	0.021	0.010	0.058	0.024	0.054	0.020	0.055	0.021	0.058	0.019
2006	0.023	0.009	0.028	0.007	0.026	0.009	0.056	0.022	0.056	0.019	0.057	0.021	0.061	0.019
2007	0.023	0.009	0.023	0.006	0.023	0.008	0.052	0.022	0.054	0.019	0.056	0.021	0.059	0.018
2008	0.028	0.009	0.030	0.007	0.028	0.009	0.061	0.022	0.061	0.018	0.064	0.022	0.065	0.017
2009	0.069	0.013	0.092	0.013	0.071	0.012	0.186	0.040	0.202	0.041	0.204	0.041	0.207	0.035
2010	0.130	0.022	0.198	0.017	0.132	0.021	0.275	0.060	0.251	0.060	0.258	0.054	0.398	0.053
2011	0.068	0.016	0.161	0.012	0.068	0.015	0.112	0.039	0.153	0.040	0.158	0.040	0.145	0.036
2012	0.031	0.009	0.049	0.008	0.036	0.010	0.077	0.028	0.097	0.025	0.104	0.027	0.087	0.023
2013	0.044	0.008	0.045	0.009	0.044	0.009	0.100	0.029	0.105	0.026	0.111	0.028	0.117	0.024
2014	0.030	0.007	0.030	0.007	0.030	0.007	0.076	0.024	0.079	0.021	0.084	0.021	0.081	0.019
2015	0.024	0.006	0.025	0.006	0.025	0.006	0.058	0.021	0.058	0.017	0.063	0.020	0.054	0.016

This table shows the yearly one-year-ahead mean and median forecast accuracy for the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models. We define accuracy as the absolute difference between actual earnings and earnings forecasts, scaled by the firm's end-of-June market equity.

Table A. 10.: Yearly Two-year-ahead Accuracy

	CM		AF		CSAF		HVZ		EP		RI		RW	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1987	0.124	0.054	0.094	0.034	0.194	0.083	0.164	0.071	0.349	0.098	0.261	0.084	0.111	0.039
1988	0.095	0.041	0.081	0.027	0.172	0.069	0.153	0.055	0.329	0.071	0.285	0.066	0.104	0.033
1989	0.063	0.029	0.060	0.023	0.095	0.039	0.087	0.044	0.097	0.040	0.086	0.037	0.091	0.035
1990	0.071	0.030	0.088	0.029	0.106	0.039	0.134	0.051	0.132	0.047	0.117	0.042	0.110	0.041
1991	0.063	0.026	0.089	0.030	0.099	0.039	0.148	0.044	0.125	0.047	0.108	0.041	0.116	0.035
1992	0.065	0.026	0.093	0.030	0.081	0.030	0.166	0.048	0.193	0.049	0.154	0.040	0.169	0.039
1993	0.070	0.033	0.073	0.030	0.067	0.028	0.166	0.049	0.156	0.049	0.125	0.041	0.128	0.042
1994	0.068	0.033	0.114	0.025	0.062	0.027	0.131	0.051	0.142	0.048	0.107	0.042	0.124	0.044
1995	0.046	0.022	0.050	0.020	0.049	0.023	0.109	0.043	0.100	0.036	0.082	0.032	0.084	0.035
1996	0.052	0.030	0.052	0.025	0.053	0.028	0.111	0.050	0.103	0.047	0.087	0.042	0.095	0.040
1997	0.047	0.025	0.052	0.024	0.052	0.026	0.099	0.042	0.097	0.040	0.082	0.036	0.083	0.037
1998	0.040	0.020	0.046	0.022	0.044	0.021	0.093	0.040	0.086	0.037	0.073	0.033	0.075	0.034
1999	0.049	0.021	0.055	0.022	0.053	0.022	0.107	0.042	0.094	0.037	0.079	0.033	0.083	0.035
2000	0.044	0.018	0.055	0.022	0.050	0.021	0.102	0.038	0.096	0.038	0.079	0.031	0.080	0.031
2001	0.055	0.023	0.061	0.024	0.060	0.025	0.121	0.049	0.120	0.047	0.103	0.040	0.113	0.039
2002	0.056	0.030	0.059	0.027	0.053	0.024	0.119	0.047	0.123	0.047	0.111	0.042	0.105	0.039
2003	0.051	0.021	0.053	0.023	0.049	0.020	0.115	0.042	0.147	0.041	0.112	0.039	0.150	0.036
2004	0.081	0.021	0.079	0.022	0.079	0.019	0.168	0.040	0.176	0.037	0.130	0.037	0.286	0.037
2005	0.051	0.023	0.046	0.018	0.047	0.020	0.096	0.044	0.089	0.038	0.093	0.041	0.121	0.038
2006	0.040	0.018	0.042	0.017	0.039	0.017	0.071	0.036	0.070	0.030	0.069	0.031	0.074	0.030
2007	0.042	0.018	0.044	0.016	0.043	0.018	0.066	0.033	0.069	0.030	0.066	0.030	0.072	0.029
2008	0.041	0.017	0.050	0.018	0.047	0.020	0.071	0.034	0.076	0.029	0.075	0.029	0.080	0.028
2009	0.052	0.020	0.065	0.022	0.058	0.024	0.107	0.040	0.110	0.038	0.109	0.038	0.110	0.035
2010	0.094	0.030	0.124	0.040	0.110	0.041	0.145	0.049	0.157	0.052	0.152	0.052	0.186	0.046
2011	0.135	0.036	0.164	0.033	0.147	0.043	0.208	0.062	0.190	0.063	0.182	0.054	0.377	0.057
2012	0.067	0.028	0.072	0.025	0.080	0.031	0.129	0.056	0.150	0.058	0.151	0.051	0.176	0.053
2013	0.048	0.020	0.052	0.019	0.064	0.023	0.086	0.035	0.111	0.035	0.110	0.033	0.097	0.032
2014	0.067	0.024	0.065	0.020	0.086	0.026	0.098	0.036	0.126	0.037	0.121	0.033	0.121	0.031
2015	0.055	0.020	0.049	0.016	0.071	0.021	0.077	0.029	0.094	0.031	0.088	0.027	0.082	0.026

This table shows the yearly two-year-ahead mean and median forecast accuracy for the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models. We define accuracy as the absolute difference between actual earnings and earnings forecasts, scaled by the firm's end-of-June market equity.

Table A. 11.: Yearly Three-year-ahead Accuracy

	CM		AF		CSAF		HVZ		EP		RI		RW	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1989	0.064	0.034	0.083	0.032	0.197	0.076	0.194	0.055	0.112	0.053	0.207	0.062	0.103	0.041
1990	0.082	0.040	0.073	0.033	0.250	0.088	0.194	0.048	0.125	0.049	0.189	0.058	0.103	0.041
1991	0.083	0.043	0.099	0.040	0.172	0.064	0.172	0.054	0.138	0.051	0.133	0.050	0.127	0.044
1992	0.072	0.037	0.086	0.042	0.151	0.067	0.177	0.054	0.141	0.062	0.128	0.057	0.106	0.043
1993	0.060	0.033	0.073	0.042	0.115	0.052	0.154	0.055	0.143	0.061	0.125	0.054	0.104	0.044
1994	0.072	0.034	0.076	0.039	0.095	0.045	0.150	0.053	0.148	0.057	0.124	0.053	0.135	0.050
1995	0.074	0.032	0.078	0.032	0.082	0.037	0.120	0.050	0.150	0.051	0.114	0.046	0.106	0.048
1996	0.060	0.030	0.062	0.033	0.074	0.037	0.112	0.051	0.122	0.050	0.100	0.046	0.099	0.044
1997	0.063	0.037	0.070	0.034	0.082	0.042	0.131	0.055	0.131	0.058	0.108	0.052	0.106	0.048
1998	0.062	0.034	0.071	0.034	0.081	0.040	0.116	0.050	0.120	0.051	0.100	0.047	0.094	0.045
1999	0.059	0.030	0.064	0.032	0.074	0.038	0.107	0.047	0.108	0.053	0.089	0.045	0.086	0.045
2000	0.059	0.028	0.070	0.032	0.075	0.035	0.125	0.049	0.119	0.047	0.095	0.042	0.091	0.043
2001	0.064	0.031	0.067	0.032	0.072	0.034	0.129	0.049	0.122	0.051	0.101	0.042	0.103	0.041
2002	0.064	0.032	0.072	0.037	0.075	0.037	0.144	0.056	0.150	0.056	0.124	0.050	0.121	0.045
2003	0.065	0.038	0.068	0.036	0.063	0.031	0.107	0.044	0.112	0.047	0.097	0.043	0.091	0.039
2004	0.077	0.029	0.073	0.032	0.072	0.029	0.110	0.041	0.193	0.045	0.133	0.041	0.163	0.040
2005	0.087	0.029	0.084	0.028	0.085	0.028	0.166	0.044	0.292	0.045	0.194	0.040	0.255	0.048
2006	0.069	0.032	0.068	0.028	0.069	0.031	0.102	0.049	0.119	0.046	0.103	0.043	0.129	0.049
2007	0.048	0.023	0.051	0.024	0.051	0.025	0.074	0.040	0.082	0.039	0.075	0.037	0.082	0.040
2008	0.052	0.025	0.059	0.027	0.060	0.029	0.077	0.038	0.086	0.038	0.076	0.036	0.088	0.036
2009	0.065	0.028	0.077	0.031	0.074	0.034	0.116	0.046	0.126	0.049	0.120	0.045	0.118	0.043
2010	0.062	0.032	0.071	0.036	0.073	0.038	0.080	0.038	0.089	0.042	0.083	0.041	0.085	0.036
2011	0.089	0.035	0.120	0.039	0.106	0.043	0.130	0.044	0.150	0.045	0.128	0.045	0.182	0.039
2012	0.120	0.047	0.119	0.041	0.138	0.053	0.158	0.059	0.197	0.061	0.163	0.054	0.345	0.061
2013	0.095	0.034	0.088	0.031	0.117	0.040	0.128	0.054	0.147	0.058	0.144	0.049	0.180	0.053
2014	0.059	0.023	0.063	0.027	0.074	0.027	0.082	0.035	0.100	0.037	0.090	0.032	0.099	0.034
2015	0.076	0.028	0.076	0.027	0.097	0.032	0.103	0.037	0.118	0.039	0.104	0.035	0.118	0.034

This table shows the yearly three-year-ahead mean and median forecast accuracy for the Combined Model (CM), raw analysts' forecasts (AF), Cross-Sectional Analysts' Forecasts (CSAF), Hou, van Dijk and Zhang (HVZ, 2012), Residual Income (RI), Earnings Persistence (EP), and Random Walk (RW) models. We define accuracy as the absolute difference between actual earnings and earnings forecasts, scaled by the firm's end-of-June market equity.

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