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Evaluating and Improving Methods to Estimate the Implied Cost of Capital and Return Decompositions

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Contents

List of Figures

List of Tables

Für Anke, Jona & meine Eltern

Chapter I

Introduction

1 Overview

The measurement of expected returns or cost of equity capital (I use the terms interchangeably) is a central topic in accounting and finance for both academics and practitioners. Questions like what determines firms' expected returns and what are the risk-factors that explain the variation of the rate across firms and over time have challenged the research community for decades. Yet, there is still no final conclusion to these questions. Moreover, researchers often assess economic outcomes for firms caused by legal or regulatory changes (e.g. reporting or disclosure standards, securities regulation, etc.) with regard to how such changes impact firms' cost of capital. The assessment of these effects is highly relevant for policy making especially in the context of recent attempts to foster securities market regulation following the financial crisis. Finally, companies must compute their cost of capital for financial planning and project appraisal, where a discount factor or hurdle rate is required when assessing the profitability of investment projects. It is crucial for companies to obtain proper cost of capital estimates as a misspecification of the rate might lead to a denial of profitable investments or, even worse, the approval of unprofitable investment projects.

The traditional approach to measure expected returns applies factor models (e.g. the capital asset pricing model (CAPM) or multi-factor models) that rely on realized returns. This practice might induce significant biases as evidence indicates that realized returns are a poor measure for expected returns, in particular, if the expected return estimation relies on short periods of time.[1] The more recent approach uses methods that estimate the implied cost of equity capital (ICC) to proxy for expected returns. The methods reverse-engineer a valuation model to back out the expected return as the internal rate of return that equates the current price of a stock to the present value of expected future cash-flows. Yet, while applied in several research studies that address questions associated with expected returns, the evaluation of the quality of ICC methods so far lacks direct evidence, since the required benchmark for the analysis, i.e. the expected return, is not observable.

The contribution of this dissertation is to analyze existing accounting-based methods to measure expected stock returns and to propose methodological advances to improve expected return estimation. The primary object of study are methods that estimate the implied cost of equity capital. Chapter II conducts a simulation study to provide direct evidence concerning the quality of existing ICC methods in capturing the true cost of capital. Following the evaluation, I propose a new approach to estimate the implied cost of equity capital that addresses specific problems of existing ICC methods (Chapter III). In Chapter IV I present a decomposition of realized stock returns based on implied cost of capital estimates and apply the return decomposition to shed light on the return anomaly that the quality of corporate governance helps to predict stock returns.

In this introductory chapter I will outline and present the main ideas of this dissertation. I will briefly review the common practice to approximate expected returns with realized returns and discuss likely problems associated with this approach. The discussion will be followed by a synopsis of the main results. I relegate the

[1] I defer the discussion of the evidence presented by Elton (1999); Davis, Fama, and French (2000); Lundblad (2007) to the next Section 2.

detailed discussion of methods and models applied in this dissertation as well as the relevant literature to the respective Chapters II to IV.

2 Expected return estimation

The capital asset pricing model of Sharpe (1964), Lintner (1965), and Black (1972) is one the most prominent and presumably the most-widely used model to measure expected returns. The model develops a framework, where the expected return is exclusively determined by the risk-free rate of interest, the market risk premium, and the variation of a stock with the market defined as a stock's market beta. Perhaps due to its simplicity, the CAPM has influenced an enormous strand of literature and is used in all areas of financial research. The website Google Scholar counts almost 15,000 citations jointly for the three papers of Sharpe, Lintner, and Black, while the Thomson ISI Web of Science reports approximately 4,000 citations. For comparison, the scores are more than double the citations of the path-breaking work of Modigliani and Miller (1958) on the irrelevance of capital structure.[2]

Even today, the model is still standard in every finance textbook and business or finance students around the world learn about the CAPM at some point during their education. Outside academia, practitioners apply the CAPM in every day business life. Graham and Harvey (2001) survey 392 US chief financial officers (CFOs) about their cost of capital. According to the survey, 73.5% of the CFOs always or almost always use the CAPM, while 39.4% of the CFOs work with average historical returns on common stock or a related multi-factor model (34.3%) to determine their cost of capital (multiple choices allowed). Multi-factor models rely on the arbitrage pricing theory (APT) of Ross (1976). The theory states that expected returns are a linear function of a set of economically meaningful factors. In this context, a one-factor APT model with the market beta as the single factor is identical to the CAPM.

[2]On April 15, 2011, Google Scholar (Thomson ISI Web of Science) reports 8,094 (2,175) citations of Sharpe (1964), 4,974 (1,388) citations of Lintner (1965), and 1,714 (441) citations of Black (1972). Modigliani and Miller (1958) obtain a citation score of 7,774 (1,629).

Despite its popularity, there exist ample empirical evidence that seems to contradict the main implications of the CAPM. The CAPM implies that market beta is the only priced risk factor and that beta suffices to explain the variation of expected returns. Black, Jensen, and Scholes (1972) as well as Fama and MacBeth (1973) test the second implication but find that market beta does not suffice to explain the variation of stock returns. Banz (1981) analyzes the relation between returns and the market value of NYSE stocks. His evidence for the period 1936 to 1975 documents a size effect that implies higher risk-adjusted returns for small than for large stocks. The size of the difference is considerable and equals almost 20% on an annualized basis. In a comparable study, Reinganum (1981) shows that portfolios build on size and the earnings-price (E/P) ratio earn average returns that systematically deviate from the returns predicted by the CAPM over a period of more than two years.[3] Fama and French (1992, 1993) extend the analysis of factors related to stock returns. Their analysis for the post-1963 period shows that the book-to-market equity ratio and size help to explain the cross-section and time-series of stock returns. Subsequently, Davis, Fama, and French (2000) find a book-to-market effect on average returns also for the period 1926 to 1963. In contrast, Ang and Chen (2007) argue that the book-to-market effect is due to an inconsistent estimation methodology and the use of time-constant betas. Ang and Chen control for both issues and obtain evidence that the CAPM captures the book-to-market effect over the period 1926 to 1963 as well as over the post-1963 period. Fama and French (2006b) reassess the evidence and document that over the early period high (low) book-to-market firms have high (low) market betas. The evidence implies that indeed the CAPM captures the book-to-market effect over this period. For the post-1963 period Fama and French, however, find that the relation between book-to-market and market beta reverses. The finding highlights that for the post-1963 period the CAPM market beta

[3] Reinganum also finds that controlling for size reduces abnormal returns of portfolios formed on the E/P ratio. He concludes that size and the E/P ratio likely proxy for the same underlying factor but that size is more closely related to this factor.

does not explain higher returns for high book-to-market stocks, even after controlling for time-varying betas.

Researchers put forward several explanations for the sources of risk that size and book-to-market capture. Cochrane (1999), for example, argues that small and high book-to-market stocks are often distressed and more likely to be exposed to recession risk. To the extent that human capital is also exposed to recession risk, investors require a premium for holding stocks that are sensitive to this risk. Related to this argument Vassalou and Xing (2004) provide evidence that size and book-to-market proxy for default risk. Moreover, size might be related to liquidity as common liquidity measures imply that large stocks are more liquid than small stocks. In line with this reasoning, Amihud and Mendelson (1986) find that average expected returns increase with the bid-ask spread and Pastor and Stambaugh (2003) show that market liquidity is priced. A further explanation for the observed size effect is opaqueness. The idea is that investors require a premium to hold stocks of firms, where they presume company information like earnings reports to be uninformative. Bhattacharya, Daouk, and Welker (2003) find supporting evidence at the country-level. Their findings imply that countries with a higher level of opaqueness have higher country-level cost of capital. Concerning the book-to-market factor Dechow, Sloan, and Soliman (2004) present evidence showing that the book-to-market factor proxies for firms equity duration.[4]

The return-related evidence raises the question whether the observed size and book-to-market effects proxy for underlying risk factors or whether they are simply a realization of market inefficiencies (anomalies). Given that a variation of returns with book-to-market and size has been documented in various research papers and for different time periods, researchers have mainly come to the conclusion that risk factors related to the variables are the more likely alternative. Above evidence, therefore, seems to contradict the implication of the CAPM that the market beta

[4]Equity duration measures the average maturity of a stocks's future cash flows. Stocks whose cash flows accrue in the more distant future have a larger equity duration.

is the only priced risk factor. As a consequence, financial research today often applies the three-factor model of Fama and French with market beta, size, and book-to-market when computing expected returns, while among practitioners the CAPM is still the most-widely applied model for expected returns (see Graham and Harvey, 2001).

The empirical evidence and the variety of explanations proposed in the literature highlight that the question concerning the correct model to estimate expected returns is still an open issue. The theoretical foundation favors the CAPM as it contains a clear identification of the priced risk factor. In contrast, multi-factor models commonly lack the foundation for the relevance of specific factors since the arbitrage pricing theory does not identify the relevant risk factors. The empirical evidence, in contrast, seems to support the claim that the CAPM is misspecified. There is, however, a further issue that has to be considered when assessing the empirical evidence. The CAPM is a model that explains the variation of expected returns. But, research studies that test pricing models and provide evidence for additional return-relevant factors almost exclusively rely on realized returns since expected returns are not observable.[5] The justification to transfer above research results obtained for realized returns on expected returns requires the assumption that on average realized returns provide an unbiased estimate of expected returns. The assumption implies that information surprises are not systematic but cancel out on average. However, if this assumption is not justified, it is unclear whether the identified factors are risk factors at all or whether they just explain the variation of average realized returns over specific time periods.

Elton (1999) contests the assumption. Elton analyzes empirical return findings and concludes that realized returns are a poor proxy for expected returns. His evidence shows that over long periods average realized returns on risky stocks and bonds range below the risk-free rate. An expected return measure that provides a

[5]The exception is the study of Brav, Lehavy, and Michaely (2005) who test the three-factor model of Fama and French based on expected returns derived from implied cost of capital estimates.

return on risky assets below the risk-free rate raises doubts concerning the reliability of the proxy. The problem with realized returns might be that the assumption that information surprises cancel out on average is not fulfilled or only applies for sufficiently large data samples or specific periods of time. The latter point would explain the evidence of Fama and French (2006b), who find that the CAPM holds over the pre-1963 period but not thereafter. Furthermore, the relationship between expected returns, prices, and realized returns implies that sufficiently large samples might be necessary to justify the assumption. Note that the expected return equals the discount factor in a fundamental valuation equation. Hence, an increase in the expected return is associated with higher discounting and a decrease in the stock price. The decrease induces a negative realized return so that in the short run the relation between expected and realized returns might even be negative.

But how many years of data are sufficient to make the assumption hold? Lundblad (2007) provides a possible answer to this question. He analyzes the relation between expected volatility (risk) and the market risk premium. Empirical evidence for the risk-return tradeoff commonly documents an insignificant or negative relationship. According to Lundblad, the evidence is due to the low explanatory power of volatility for realized returns. He claims that the detection of the relationship between volatility and expected return based on realized returns, requires large data samples. Using a simulation study, he shows that more than 100 years of data are required to obtain the risk-return tradeoff. Hence, the assessment of risk factors related to expected returns based on realized returns likely generates meaningful results only for large samples. Standard financial databases often provide data for about 50 years for the U.S. and less for the rest of the world. The common approach to apply realized returns as proxy for expected returns, therefore, likely suffers from significant problems. In line with this claim, Elton (1999) states:

"I believe that developing better measures of expected return and alternative ways of testing asset pricing theories that do not require using realized returns have a much

higher payoff than any additional development of statistical tests that continue to rely on realized returns as proxy for expected returns.”

Applying methods to estimate the implied cost of equity capital is the more recent approach to measure expected returns. Implied cost of capital estimates provide a forward-looking measure for expected returns and do not rely on realized returns or the identification of unknown risk factors. Common to above discussed factor models, there is, however, no direct evidence on the ability of ICC estimates to capture variation in expected returns, as the benchmark for the analysis, i.e. the expected return, is not observable.

Pastor, Sinha, and Swaminathan (2008) assess the risk-return tradeoff using ICC estimates as measure for expected returns. Their results imply that implied cost of capital help to detect the relation between risk and return. The evidence indicates that ICC estimates to some extent capture time-variation in expected returns. Other approaches assess the quality of ICC estimates by their association with potential risk factors or by their relation to realized stock returns (see Botosan and Plumlee, 2005; Brav, Lehavy, and Michaely, 2005; Guay, Kothari, and Shu, 2005; Easton and Monahan, 2005).[6] The first approach requires that the selection of the risk factors considered is correct and exhaustive, which is unlikely. The second approach is based on realized returns and therefore faces the previously discussed deficits associated with the approximation of expected returns from realized returns. Moreover, since the two approaches show distinct results, the question concerning the quality of ICC estimates remains unresolved.

Considering the problems of realized return models and the unsatisfactory evidence for ICC estimates Chapter II of this dissertation adds to this discussion by providing new evidence on the quality of implied cost of capital methods. The simulation approach applied analyzes the structure of ICC methods and derives diagnostics in an environment where the true cost of equity capital is known. I furthermore derive

[6]I provide a brief discussion of this literature in Chapter II of this dissertation.

suggestions for improving ICC methods and models to generate earnings forecasts utilized by the methods (Chapter III). Finally, I propose a setting that uses ICC estimates in the context of return decompositions (Chapter IV).

3 Outline of the thesis

Chapter II evaluates accounting-based methods to estimate the implied cost of capital using a simulation approach. The analysis rests on a simulated model economy in which the true cost of capital is known. The model economy is calibrated it to the CRSP-CompuStat universe to ensure that it reflects specific characteristics of real-world data. Since the true cost of capital is observed in the model economy, the simulation approach allows a direct evaluation of the quality of implied cost of capital estimates. The analysis then compares the true cost of capital to the implied cost of capital estimates from ten different methods proposed in the literature in terms of bias, accuracy, and their correlation with the true cost of equity capital. The results suggest that methods based on the residual income model perform better than those based on the abnormal earnings growth model. Moreover, methods that estimate the cost of capital and expected growth simultaneously work reasonably well if they rely on analyst forecasts instead of ex post realized values, even if analyst forecasts are biased. Finally, Chapter II explores improvements of implied cost of capital estimates by combining methods that are chosen so that the distortions from individual methods compensate each other. The analysis implies that some simple combinations outperform all individual methods.

Chapter III presents a new approach to measure the implied cost of equity capital that utilizes earnings forecasts from a vector autoregressive (VAR) model. The model allows to generate long-term earnings forecasts for an infinite horizon. I apply the model for annual portfolios of firms to obtain portfolio-specific coefficient estimates that I use to generate earnings forecasts (portfolio-level VAR model). This approach explicitly accounts for the possibility that growth dynamics defined by the portfolio-specific VAR coefficients vary across portfolios and over time. The results imply that – compared to short-term forecasts of existing earnings forecasting models – the portfolio-level VAR model delivers superior earnings forecasts over the short run (1-3 years). Moreover, the model allows to generate long-term earnings forecasts that are utilized within a long-horizon ICC method. The method is characterized by low data requirements and a reduced sensitivity to changes in the terminal value. It is, therefore, less dependent on the terminal growth rate assumption. By addressing the key issues associated existing ICC methods, the long-horizon method promises to deliver a more consistent measure for expected returns.

Chapter IV introduces a new approach to decompose realized stock returns. Following fundamental valuation, prices change due to changes in firms' expected future cash flows or expected returns. Accordingly, return decomposition models break down realized returns into expected returns, news about future cash flows, and news about future expected returns. The new approach to decompose returns relies on implied cost of equity capital as proxy for expected returns. The analysis shows that, in contrast to expected returns applied by the existing return decomposition approach, ICC estimates inherit specific characteristics that better reflect properties attributed to expected returns. To the extent that the implied cost of capital better capture the true expected returns, the ICC-based return decomposition also provides more consistent estimates of the return components. Finally, the chapter proposes an application of return decompositions that can be used to study well-known return anomalies. The application example is executed to assess the sources that underlie return differences related to the quality of firms' corporate governance.

Chapter II

Evaluating Methods to Estimate the Implied Cost of Equity Capital: A Simulation Study

1 Introduction

In this chapter we evaluate accounting-based methods to estimate the implied cost of equity capital (ICC) using a simulation approach in which the true cost of capital is known.[7] We show that ICC methods based on the residual income model perform better than those based on the abnormal earnings growth model. Combinations of several ICC methods outperform all individual methods if they average ICC estimates from firm-level calculations with estimates that simultaneously calculate the cost of equity capital and expected growth for a portfolio of firms.

[7]This chapter is based on joint work with Holger Daske and Ernst Maug, therefore I retain the personal pronoun "we", used in the original paper, throughout this chapter. All tables are gathered at the end of the chapter. We thank Inessa Love, The World Bank, for sharing her STATA code to estimate vector autoregressions using panel data sets. We also thank Alon Brav, Ingolf Dittmann, Günther Gebhardt, Eva Labro, Christian Leuz, Carsten Trenkler, and workshop participants at Maastricht University, the Campus for Finance Research Conference at WHU Vallendar, the 3rd FARS Midyear Conference San Diego, the EAA Annual Congress Istanbul, and the DGF Annual Meeting Hamburg for helpful comments and advice. We gratefully acknowledge financial support from the collaborative research center SFB TR 15 "Governance and the Efficiency of Economic Systems" and the Rudolph von Bennigsen-Foerder-foundation.

Previous work has addressed the same issue based on archival data (see Easton, 2009, Chapter 8 for a review). This approach faces limitations because the true cost of equity capital is unobservable, so empirical research can only compare the cost of capital from ICC methods with (1) the cost of capital generated by an asset pricing model (Lee, Ng, and Swaminathan, 2009), (2) its association with other firm-specific risk characteristics (Botosan and Plumlee, 2005; Brav, Lehavy, and Michaely, 2005), and (3) with realized stock returns (Guay, Kothari, and Shu, 2005; Easton and Monahan, 2005). The first approach encounters several well-known shortcomings outlined in the asset-pricing literature (e.g., Elton, 1999; Pastor and Stambaugh, 1999; Fama and French, 1997, Fama and French, 2002). The second approach requires that the selection of the risk factors considered is correct and exhaustive, which is unlikely (Easton and Monahan, 2005). The third method is based on realized returns and therefore relies on very noisy estimates (e.g., Lundblad, 2007; Pastor, Sinha, and Swaminathan, 2008). In the light of these limitations, it may not seem surprising that the rankings and overall evaluation of the ICC methods differ significantly across studies.[8]

We perform Monte Carlo simulations of a suitably calibrated economy to address these shortcomings. Monte Carlo simulations are a well-established scientific approach, and they have been applied to address a range of questions in accounting and finance where important aspects of the underlying environment are unobservable so that tests of theories with real-world data are impossible. In simulations we observe these otherwise unknown variables by construction.[9] The simulation model combines

[8]While research that focuses on the association of ICC methods with firm-specific risk characteristics concludes that some ICC approaches offer reliable estimates (Botosan and Plumlee, 2005), research that focuses on the association with realized returns is skeptical on the reliability of any of these estimates (Guay, Kothari, and Shu, 2005; Easton and Monahan, 2005; Easton, 2009). See also Botosan, Plumlee, and Wen (2010) for a more cautious conclusion.

[9]See e.g., Greenball (1968) for a classical example, and Labro and Vanhoucke (2007, 2008) for contemporary work. While Greenball's study is an example of studies in financial accounting evaluating different accounting methods and measurement rules (Francis, 1990; Rees and Sutcliffe, 1993; Healy, Myers, and Howe, 2002), the work of Labro and Vanhoucke is representative for the management accounting literature evaluating costing systems (Lambert and Larcker, 1989; Balachandran, Balakrishnan, and Sivaramakrishnan, 1997). Other prominent areas include evaluations of alternative testing procedures commonly used in accounting research (e.g., Barth and Kallapur,

an econometric forecasting model, a business planning model, and a DCF-based valuation model. The model parameters are calibrated to the CRSP-CompuStat universe. The valuation approach is designed so that it is neutral with respect to the specific assumptions of the ICC methods and therefore creates an appropriate benchmark for comparing and analyzing these methods.

In the next step of our analysis we use ten extant ICC methods that were proposed in the literature and calculate the cost of capital these methods generate for 20,000 firms from 100 industries in our simulated economy.[10] We distinguish three broad groups of ICC methods: (1) residual income methods, which calculate the ICC individually for each firm; (2) abnormal earnings growth methods, which also determine the ICC at the firm level, and (3) industry-level methods, which estimate the cost of capital and expected growth simultaneously for a portfolio of firms.[11] Finally, we compare the ICC from these methods with the true cost of capital, which is known for each firm in our simulated economy. The evaluation of the ICC methods follows Francis, Olsson, and Oswald (2000) and applies three criteria: (1) the bias of the method, which is particularly important for the correct estimation of the equity premium (e.g., Claus and Thomas, 2001); (2) the accuracy of the method, which is significant for all practical applications of these methods, where correct firm-specific estimates of the cost of capital are required (e.g., company valuation, project appraisal); (3) the explainability of the method, which refers to the correlation between the ICC and the true cost of capital; this criterion is particularly important in research applications that require a proxy for the cost of capital.

Residual income methods have a small negative bias, whereas abnormal earnings growth methods have a larger and positive bias. Industry-level methods also tend to

1996; Kothari, Sabino, and Zach, 2005), detecting audit effectiveness (e.g., Knechel, 1988), or detecting earnings management (e.g., Dechow, Sloan, and Sweeney, 1995).

[10] We use the term *model* for a generic modeling framework, for example the residual income model or the dividend discount model. By contrast, we use the term *method* for specific methods that parameterize these models to determine the cost of capital and refer to them as ICC methods.

[11] We do not further divide industry-level methods, which could also be grouped into these two categories according to the valuation model they use.

have a positive bias. Residual income methods tend to be the most accurate and industry-level methods that rely on analyst forecasts perform almost as well, even if analyst forecasts are biased. Industry-level methods that rely on ex post realized values tend to be inaccurate, as do abnormal earnings growth methods. Residual income methods also have a higher R-squared in regressions of the ICC estimates on the true cost of capital, where most industry-level methods and all abnormal earnings growth methods tend to perform poorly. We attribute the generally poor performance of abnormal earnings growth methods compared to residual income methods to their modeling of future earnings. Whereas residual income methods model the *level* of future abnormal earnings, abnormal earnings growth methods model the *changes* in abnormal earnings, which seems to produce less reliable forecasts.

All methods provide distorted estimates of the cost of capital, even if the average bias is small. Firm-level methods overestimate the cost of capital if the true cost of capital is high, and underestimate the cost of capital if the true cost of capital is low. By contrast, most industry-level methods generate the opposite result. We trace this distortion to the modeling of cash flow patterns by the ICC methods by applying the concept of equity duration developed in Dechow, Sloan, and Soliman (2004) and call it the *duration effect.* Thus, our study contributes by adding this effect to the theoretical discussions on ICC methods in the literature (e.g., Hughes, Liu, and Liu, 2009; Lambert, 2009; Pastor, Sinha, and Swaminathan, 2008).

Finally, we investigate the possibility that combinations of ICC methods may perform better than individual methods.[12] The analysis suggests that firm-level methods have a lower accuracy because they systematically overestimate the true cost of capital when it is high and vice versa, whereas industry-level methods do the opposite. Combining methods from each category should therefore lead to better estimates because the errors of the individual methods compensate each other. We find that this is indeed the case and we highlight two methods that combine

[12]The general argument for combinations is based on Hail and Leuz (2006) (Hail and Leuz, 2006, Hail and Leuz, 2009) and Dhaliwal, Krull, and Li (2007).

two, respectively four, individual methods and show that they tend to outperform all individual methods as well as prior ad hoc combinations. In particular, the combination of equally weighted estimates from Gebhardt, Lee, and Swaminathan (2001) and Easton, Taylor, Shroff, and Sougiannis (2002) provide a useful trade-off between simplicity and the ability to capture the true cost of equity capital in most circumstances. We conclude the chapter with a number of robustness checks that highlight various aspects of our simulation model and the valuation approach. Our main conclusions are robust to changing details of our research design.

A number of papers address the shortcomings of ICC methods or suggest improvements of existing methods. One area of improvements is the replacement of analyst forecasts with realized values (Easton and Sommers, 2007; O'Hanlon and Steele, 2000) or with a statistical forecasting model (Hou, Van Dijk, and Zhang, 2010). These analyses are complementary to ours because we derive the properties of ICC methods in a context in which unbiased forecasts are already available. Botosan and Plumlee (2005) and Easton and Monahan (2005) use different methodologies based on empirical data that reveal some shortcomings of existing ICC methods. By contrast, our simulation approach opens the black box, analyzes the structure of ICC methods and derives diagnostics in an environment where the true cost of equity capital is known. On this basis we can identify the errors that are systematically built into specific methods and can then suggest combinations of methods that benefit from compensating errors. Ours is not only the first study to evaluate industry-level ICC methods, but also contributes by showing how their specific properties add to the construction of combined methods.

The remainder of this chapter is structured as follows. The following Section 2 develops the simulation approach for our model economy. We discuss the different ICC methods and how we implement them in Section 3. Section 4 contains the main analysis. In Section 5 we evaluate how the individual methods may be combined. Section 6 presents robustness checks and Section 7 concludes with a discussion of the limitations of our approach and suggestions for future research.

2 Methodology: Simulating a model economy

We conduct our simulation by setting up a business planning model, where we forecast a complete set of financial statements (i.e. income statement, balance sheet, and statement of cash flows) for an economy of 20,000 firms for 50 years.[13] We calibrate the parameters of our model to those of a large sample of U.S. firms. As common in financial modeling and corporate valuation, we use sales growth and profitability (EBITDA-margin) as our main value drivers ("percentage-of-sales model").[14] We empirically estimate the parameters that describe the joint time series of these two variables. Sales growth rates and EBITDA-margins are then the random variables in our Monte Carlo simulation from which all other accounting and cash flow items in the projected financial statements are calculated, mostly as percentages of sales. In the final step, we draw each firm's cost of capital from a distribution and calculate the value of this firm in our simulated economy by discounting its future expected cash flows at this rate. Thus, we obtain for each firm in our simulation a complete set of financial statements, a cost of capital, realized and expected future cash flows and earnings, and an associated firm value.

The empirical basis for calibrating our model rests on an unbalanced panel of firms from 1970 to 2009, which we obtain from the CRSP-CompuStat Merged data file. We only use non-financial firms listed on the NYSE, AMEX, or NASDAQ. We derive balance sheet and income statement items from the CompuStat files, while returns, dividends, and market capitalization are obtained from CRSP. We are left with a sample of 96,719 firm-year observations for 8,036 firms. The median firm-year in our sample has sales of $170.2 million, total assets of $154.9 million, and a market capitalization of $143.28 million (these numbers are not tabulated).

[Insert Table II.1 about here.]

[13] All calculations for this Monte Carlo simulation are implemented using MATLAB.

[14] We use a simplified textbook approach, see, for example, Lundholm and Sloan (2006) or Penman (2009).

Table II.1 summarizes the salient financial ratios for our sample and the model parameters we use for our simulation. We typically use the median of the distribution of a ratio and round the model parameters (e.g., the median ratio of property, plant and equipment to sales is 21.5%, but we use 20%). We deviate from the median firm in some instances (e.g., the plowback rate) in order to achieve a better overall calibration, particularly of the valuation ratios (PE ratio and market-to-book ratio). We provide the reason for these decisions and an assessment of the quality of our calibrations below and later perform robustness checks to show that our modeling choices are inconsequential for our main results.

2.1 Forecasting sales growth and EBITDA-margins

Vector autoregressions. We model a firm's sales growth and EBITDA margins as a first-order vector autoregressive process (VAR(1)).[15] Unlike a univariate autoregressive (AR) model, vector autoregressions also model the cross-dependence of margins on sales growth and vice versa and therefore model also the dynamic behavior of the correlation between these key value drivers. Denote the rate of sales growth in period t (i.e., $\text{Sales}_t/\text{Sales}_{t-1} - 1$) for firm i by $g^S_{i,t}$ and the EBITDA margin (henceforth simply: margin) by $m_{i,t}$. We then estimate the following model:[16]

$$g^S_{i,t} = \alpha_{0,i} + \alpha_g g^S_{i,t-1} + \alpha_m m_{i,t-1} + \varepsilon_{i,t}, \tag{II.1}$$

$$m_{i,t} = \gamma_{0,i} + \gamma_g g^S_{i,t-1} + \gamma_m m_{i,t-1} + \eta_{i,t}. \tag{II.2}$$

We run the vector autoregression from (II.1) and (II.2) on our sample using panel VAR regression analysis. We winsorize the data for sales growth and EBITDA margins at the 1% level to reduce the impact of extreme outliers.

[15]For a review of vector autoregressive models, see Brooks (2008). We follow the approach used in Love and Zicchino (2006) or Dorn, Huberman, and Sengmueller (2008).

[16]In fact, we estimate this model after first demeaning (subtracting the time-series mean for each variable and for each firm) and then applying a so-called Helmert transformation (see Arellano and Bover (1995), pp. 41-43, for details). As a result, we do not obtain and therefore do not report intercepts or R-squareds.

[Insert Table II.2 about here.]

Panel A of Table II.2 reports the results for the panel vector autoregression of sales growth and EBITDA margins. Shocks to margins exhibit some persistence ($\gamma_m = 0.596$), whereas the impact of sales growth on past sales growth is rather weak ($\alpha_g = 0.166$). There is an economically meaningful and negative impact of past margins on sales growth ($\alpha_m = -0.166$). Also, there is a significant positive correlation of 0.354 between the contemporaneous shocks to margins $\eta_{i,t}$ and to cash flows $\varepsilon_{i,t}$ (panel B). We would miss these effects with univariate autoregressions. By contrast, the impact of past sales on profitability is statistically insignificant ($\gamma_g = -0.004$).

Our first-order VAR framework with two variables strikes a balance between simplicity and realism. We also experimented with second-order VAR processes, but found that second-order lags in equations (II.1) and (II.2) are only marginally significant and generate virtually identical impulse response functions. The key feature of the processes modeled here is the persistence of shocks, i.e., the length of time for which a shock to margins or sales growth has an impact on each of the value drivers. Whether the model captures the dynamic evolution of the value drivers more closely seems immaterial for valuation.

Simulations. In our Monte Carlo simulation, we generate 200 industries of 100 firms each, and for each industry we generate values for sales growth and margins from the processes (II.1) and (II.2). If $t = 0$ marks the beginning of our business planning model, then we start the processes at $t = -4$ because for some applications we need information about prior periods, and we end the process at $t = 1$ to obtain realized values for those methods that use ex post realizations.[17] We do not simulate values for periods later than $t = 1$ because for later periods we only need expected

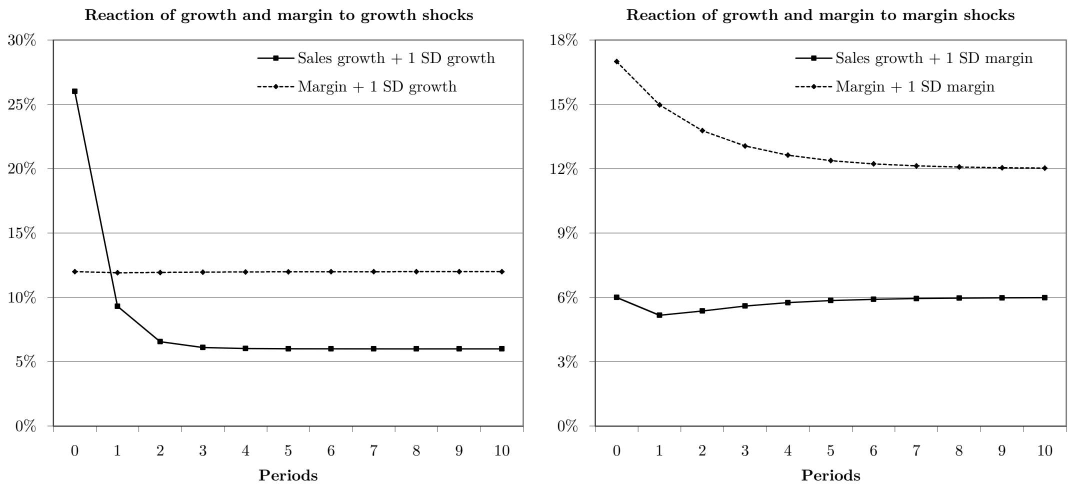
[17]The model by Gebhardt, Lee, and Swaminathan (2001) requires information about prior periods in order to calculate industry averages for the return on equity. Easton and Sommers (2007) use realizations of period $t = 1$.

values. Expected values are always generated for 50 periods. We use the parameters from panels A and B of Table II.2 with two modifications.

First, we draw the beginning values at $t = -4$ for sales growth and for the margin from normal distributions. The distribution of the beginning value for sales growth has a mean of 6.0% and a standard deviation of 20.0%. The median in the data from Table II.1 is 10.6% for sales growth and 19.9% for the time-series standard deviation of sales growth. The mean sales growth rate of 6% in the simulations differs from the median growth rate of 10.6% in our sample (see Table II.1), because we obtain better approximations for our valuation ratios for reasons we develop further below. Note that only the time-series variation and not the cross-sectional variation is relevant for calibrating the time series processes (II.1) and (II.2). The mean for the beginning value of the margin is 12% with a standard deviation of 5.0%, where the empirical values from Table II.1 are 11.4% and 4.7%, respectively. We apply the same standard deviations to the residuals $\varepsilon_{i,t}$ and $\eta_{i,t}$ in (II.1) and (II.2) as we use for the initial values. We model these using a joint distribution based on the empirical correlation of 0.354.

Second, we do not obtain estimates for the intercept coefficients α_0 and γ_0 from the panel VARs (see also footnote 16). Instead, we set these coefficients so that the long-term values for sales growth and the margin from processes (II.1) and (II.2) converge to firm-specific long-term values and report the average values in panel C of Table II.2. We draw long-term sales growth for each firm from a truncated normal distribution with a mean of 6% and a standard deviation of 2%. Similarly, long-term margins are drawn from a truncated normal distribution with a mean of 12% and a standard deviation of 1%. In both cases, the distribution is truncated to values within two standard deviations of the mean. Drawing long-term growth rates and margins from a distribution allows us to differentiate between different types of firms, particularly growth stocks and value stocks. We obtain the intercepts $\alpha_{0,i}$ and $\gamma_{0,i}$ for our simulations by substituting $\varepsilon_{i,t} = 0$, $\eta_{i,t} = 0$, and the firm-specific values for long-term sales growth and the long-term margin into equations (II.1) and (II.2)

Figure II.1: Impulse response functions – Sales growth and margin
This figure plots the impulse response function for the sales growth and margin equations (II.1) and (II.2). The left figure shows the reactions of sales growth and margins from a one standard deviation shock (20%) to the growth rate in $t = 0$. The right figure highlights the reactions for a one standard deviation shock (5%) to the margin in $t = 0$.



and then solving for the intercept values. For the average across the firm-specific intercepts we obtain $\alpha_0 = 0.070$ and $\gamma_0 = 0.049$.

Figure II.1 presents the impulse response functions of sales growth and margins for the first ten periods in response to a single positive, one standard deviation shock to growth (panel A) and a one standard deviation shock to the margin (panel B). We see that the processes converge relatively fast and are close to their original values after about 4 to 6 periods after the arrival of the shock if no further shocks arrive. Shocks to margins are more persistent, whereas shocks to growth have no impact on the margin.

Forecasting and expectations. For calculating firm values and for implementing the ICC methods, we have to generate market expectations as well as analyst forecasts about future earnings and cash flows. We generate forecasts for each firm from our VAR-estimates by first inserting the beginning values of margin and sales growth as well as the estimates for the coefficients in (II.1) and (II.2) to obtain expected sales growth and margins in period $t = 1$. We then use these forecasts iteratively to obtain forecasts for period $t = 2$ and repeat the exercise to estimate forecasts for all periods within the detailed planning horizon of 50 periods in our baseline simulation.

Our baseline approach assumes rational expectations. In particular, we assume that the forecasts of investors in the stock market and analyst forecasts are the same, and that both of them use the correct model of the economy when valuing the firm. This assumption is potentially a strong one because analyst forecast bias is a widely-documented phenomenon (e.g., Brown, 1993; Easton and Sommers, 2007). We therefore include a robustness check where we allow for optimism on the part of analysts.

Terminal values. For the terminal value after the detailed planning horizon we model terminal sales growth denoted by $g_{i,T}$ as a truncated normal random variable that varies for each firm on the interval [-3%;+3%] with a mean of 0% and a standard deviation of 1%. Hence terminal growth is equal to zero on average, but not equal to zero for every firm. We later check for the impact of our terminal value assumptions by shortening or extending the detailed planning period.

2.2 Generating company values from a business planning model

Income statements. We denote expectations for sales growth and margins from our forecasting model with $\hat{g}^S_{i,t} = E(g^S_{i,t})$ and $\hat{m}_{i,t} = E(m_{i,t})$, respectively. Based on these forecasts, we can then calculate expected sales and EBITDA from:

$$S_{i,t} = (1 + \hat{g}^S_{i,t})S_{i,t-1}, \tag{II.3}$$

$$EBITDA_{i,t} = \hat{m}_{i,t} \times S_{i,t}. \tag{II.4}$$

We set initial sales S_0 to 100. We calculate depreciation as a percentage of sales and deduct it from EBITDA to obtain EBIT, and then deduct taxes at a rate of 35%

of EBIT (if EBIT is positive) to obtain bottom-line net income.[18] Finally, retained earnings are equal to the plowback rate times net income; the remaining earnings are distributed as dividends. The plowback rate *pb* varies for each firm according to a truncated normal distribution on the interval [0.2;0.8] with mean equal 0.5 and a standard deviation of 0.1.

Balance sheets. We construct a highly simplified balance sheet that consists only of cash, current assets (*ca*) and property plant, and equipment (*ppe*) on the assets side, and current liabilities (*cl*) and shareholders' equity (book value of equity, *bv*) on the liabilities and equity side. Hence, we assume that firms are fully equity financed and abstract from debt financing. Including interest-paying debt would require modeling the cost of debt, debt issues, and the possibility of bankruptcy over time and would produce significantly more complexities without generating additional results. We therefore include only current liabilities.

Current assets, net PPE, and current liabilities are all calculated as percentages of contemporaneous sales using the ratios from Table II.1. The book value of equity bv_t always obeys the clean surplus condition:

$$bv_t = bv_{t-1} + e_t - d_t, \tag{II.5}$$

where e_t denotes total earnings (net income) and d_t denotes total dividends. Cash is the plug variable and therefore calculated as:

$$cash_t = cl_t + bv_t - ppe_t - ca_t. \tag{II.6}$$

Steady-state behavior. The assumptions about the model parameters, in particular the percentage-of-sales ratios, have direct implications for the long-term behavior

[18]We do not account for tax-loss carry-forwards or carry-backs.

of our business planning model. For each firm, each financial ratio converges to some steady-state value. In the appendix we show that the return on equity converges to (denote long-term steady state values by upper bars):

$$\overline{roe} = \frac{\overline{g}_i^S}{pb}. \tag{II.7}$$

In our model, the return on equity therefore results from the assumptions about the plowback ratio and the long-term growth rate. In the appendix we also show that the equity-sales ratio bv_t/S_t converges to:

$$\overline{\left(\frac{bv}{S}\right)} = \frac{\left(1+\overline{g}_i^S\right)(m-d)(1-T)\,pb}{\overline{g}_i^S}. \tag{II.8}$$

Given our baseline model parameters, the steady-state value of the equity-to-sales ratio from (II.8) equals 0.402 for the typical simulated firm, which has a plowback rate of 0.5, a long-term growth rate of 6%, and a long-term margin of 12%.

We calibrate the model so that the typical simulated firm is in a steady state, so that for this firm all financial ratios, including the ROE and the equity-sales ratio, start out in the steady state. We therefore set the initial book value bv_0 to 40, i.e., to 40% of initial sales. For the typical simulated firm we also obtain a steady-state value of 12% for the ROE from (II.7), which is equal to its starting value. However, given that the true cost of capital as well as the expected growth rates are stochastic, it is only the median firm that is in a steady state. Firms with higher growth have a higher ROE from (II.7) and converge to a lower equity-to-sales ratio from (II.8) and vice versa for low-growth firms.

Statements of cash flows. We obtain free cash flows (fcf_t) from earnings by adding back depreciation (dep_t) and subtracting investments in working capital and capital expenditures (changes in net PPE):

$$
\begin{aligned}
fcf_t &= e_t + dep_t - \Delta\text{Working capital} - \Delta\text{Net PPE} \\
&= e_t + dep_t - (ca_t - cl_t - (ca_{t-1} - cl_{t-1})) - (ppe_t - ppe_{t-1} + dep_t). \qquad \text{(II.9)}
\end{aligned}
$$

Cost of capital. We draw the cost of capital from a distribution that allows us to evaluate firm-level methods as well as industry-level ICC methods and that is also consistent with the notion that growth stocks have a lower cost of capital than value stocks, thus capture the insight that the CoEC are not independent from the cash flow risks of the firm (e.g. Beaver, Kettler, and Scholes, 1970). More specifically, the cost of equity capital $r_{E,i}$ of firm i are given by

$$r_{E,i} = r_{E,Ind} + a(\bar{g}_i^S - \bar{g}) + \varepsilon_i, \qquad \text{(II.10)}$$

where $r_{E,Ind}$ is the cost of equity capital (CoEC) of firm i's industry and $\left(\bar{g}_i^S - \bar{g}\right)$ is the deviation of firm i's long-term growth rate from the overall mean of 6%. We draw the industry cost of capital from a normal distribution with a mean of 10% and a standard deviation of 4%.[19] The distribution is winsorized at the risk-free rate r_f of 4.5%. Then we draw the firm-specific component ε_i of the CoEC from a distribution with a mean of zero and a standard deviation of 1%. Finally, we set $a = -0.5$, which generates a difference in mean expected equity returns between the highest book-to-market decile and the lowest book-to-market decile of 10.4% and introduces a link between cash flow shocks and shocks to expected returns. Fama and French (1992) find return differences between the highest and lowest book-to-market decile of around 16.7%, while Lettau and Wachter (2007) document a difference of only 4.9%.[20] We therefore use an intermediate value in our simulation. With these parameters, the overall standard deviation

[19]Easton and Monahan (2005), Table 2, report cost of equity capital in a range from 8.8% to 12.9%, depending on the ICC method used. Other studies comparing ICC methods report only average risk premia over time, and thus do not provide a suitable direct benchmark. Dechow, Sloan, and Soliman (2004) use $r_E = 12\%$ to calibrate their model.

[20]See Fama and French (1992), Table 4, which computes a difference of 1.4% for monthly returns, and Lettau and Wachter (2007), Table 1.

of the cost of capital in our economy is therefore $\sqrt{0.04^2 + 0.01^2 + (-0.5)^2\, 0.02^2} = 0.042$.

Research has identified a range of factors other than the book-to-market ratio and the value versus growth distinction that also affect the cost of capital, some for reasons that are not yet fully understood. Prominent examples are firm size, stock market liquidity, and disclosure quality.[21] We abstract from these variables, which are outside of our modeling framework. In many ways we see this aspect as an advantage of our more clinical approach. The features of the ICC methods that emerge from the simple model economy would in all likelihood also carry over to a more realistic model that would feature these additional effects. Similarly, we draw only one CoEC for each firm and assume that these CoEC do not change over time and are known to investors. The effects analyzed by Hughes, Liu, and Liu (2009) are therefore absent from our model.

Equity values. We construct forecasts for all free cash flows as explained above and then calculate the market value of the equity of each firm i using the firms' drawn cost of capital and a standard DCF-approach (e.g., Lundholm and Sloan, 2006; Penman, 2009). We denote these simulated firm values generated by the model by P_0^{DGP}, where DGP stands for "data generating process":

$$P_{i,0}^{DGP} = \sum_{t=1}^{50} \frac{E_0(fcf_{i,t})}{(1+r_{E,i})^t} + \frac{E_0(fcf_{i,50})(1+g_{i,T})}{(r_{E,i}-g_{i,T})(1+r_{E,i})^{50}}. \qquad \text{(II.11)}$$

Our results are robust if we use the dividend discount model instead of the DCF model (II.11) to generate firm values.

2.3 Comparison of the simulated economy to real data

We generate 200 industries of 100 firms each using the design described in the previous two sections. For 11 out of 20,000 firms (0.1%) the market value of equity

[21] See Hail and Leuz (2006) for a comprehensive set of factors that influence the CoEC empirically.

is smaller than or equal to zero.[22] We classify these firms as bankrupt and remove them from further analyses.

[Insert Table II.3 about here.]

Table II.3 compares the simulated values with the archival data in Table II.1 for key financial ratios. For each ratio, we calculate the difference between the quantiles for the simulated distribution and the respective quantile for the empirical distribution. We approximate the medians for sales growth, EBITDA-margin, the market-to-book ratio, and the PE-ratio very well. The market-to-book ratio is lower by 0.20 and the PE ratio is lower by 0.93 compared to the CompuStat sample. The median return on assets is 2.21% higher in the simulations than the corresponding figure in our sample, whereas the median return on equity is higher in the simulations by 0.08%. Since we do not model leverage, we can only calibrate one profitability ratio and therefore choose to calibrate the return on equity, which is more relevant for the valuation models. Overall, we have slightly lower valuation ratios and a higher profitability in our simulated economy relative to the empirical sample. We use a plowback rate of only 50% because a higher rate leads to large book equity values and correspondingly lower market-to-book ratios. The median plowback rate of firm-years in which cash is distributed is 65% in our empirical sample (see Table II.1). We show later that this decision is inconsequential for our results. Sales growth differs significantly from the empirical data because we obtain better calibrations with a rate of 6%. This choice is realistic for two reasons. First, the empirical sample suffers from survivorship bias and under represents firms with low growth rates, especially bankrupt firms. Second, growth in profits and growth in margins are closely linked in our model, but not in the data where firms also grow through zero-NPV projects like acquisitions that add to sales growth but much less to value growth.

[22] This may happen for firms with negative current margins in combination with high cost of capital. The negative margins generate negative free cash flows in the current periods. Later long-term positive free cash flows sometimes do not suffice to outweigh the earlier negative free cash flows if the discount rate is high, which then leads to market values below zero.

We match the tail behavior of the empirical distribution not as accurately as the median. These differences between the simulation and our sample come from a number of simplifications. We use normal distributions throughout, whereas the distributions of the data are skewed and have tails that are different from those of the normal distribution (compare means and medians for key ratios in Table II.1). Also, we model only the correlation between sales growth and margin in our VAR-estimations, but ignore correlations between other financial ratios. Finally, our simulations generate values based on a typical firm with key parameters (terminal growth, plowback rate) perturbed by random variables. Moreover, the medians in Table II.1 do not correspond to a typical firm, since the median of each parameter corresponds to a different firm.

In summary, our simulated values are more symmetric and more concentrated around the mean than our empirical sample. To some extent these differences are a cost we incur for the simplifications we make in our simulation. The corresponding benefit is that we do not need to winsorize or truncate to eliminate outliers, approaches commonly employed in empirical studies. Also, the results of our study are more representative for a typical firm. We run several robustness checks on our key modeling assumptions and show that our key results are not sensitive to the particular parameter values chosen here.

3 Implied cost of capital methods

In this section we develop the ten different Implied Cost of Capital (ICC) methods we compare in our subsequent analysis. The starting point of all these methods is the dividend discount model (DDM), which values the equity of a firm as:

$$P_0 = \sum_{t=1}^{t=\infty} \frac{d_t}{(1+r_E)^t}. \tag{II.12}$$

Assuming Modigliani and Miller (1961) dividend irrelevance, the dividend discount model (II.12) and the DCF model (II.11) generate the same equity value P_0.[23] We distinguish between three groups of methods, all of which can be derived from the DDM: (1) two firm-level methods based on the residual income model, which includes Claus and Thomas (2001) and Gebhardt, Lee, and Swaminathan (2001); (2) four firm-level methods based on the abnormal earnings growth model (AEG model), which includes Gode and Mohanram (2003) and a number of methods based on capitalization ratios, which are discussed in Easton (2004); (3) four industry-level methods, which rely also on either the residual income model or on the AEG model, but estimate the cost of equity capital at the industry-level rather than at the firm level and simultaneously infer a long-term growth rate. Table II.4 summarizes the key characteristics of these methods.[24] For all models we keep very closely to the assumptions in the respective original articles.

[Insert Table II.4 about here.]

Residual income methods. The generic equation of the residual income model can be written as:

$$P_0 = bv_0 + \sum_{t=1}^{T} \frac{ae_t}{(1+r_E)^t} + \frac{ae_{T+1}}{(r_E - g_{ae})(1+r_E)^T}, \tag{II.13}$$

where ae_t denotes residual income or abnormal earnings (we use both terms interchangeably) at time t and g_{ae} is the long-term growth of residual income. We implement the method of Claus and Thomas (2001) (henceforth CT) by using $T = 5$ and $g_{ae} = r_f - 3\% = 1.5\%$, since we assume $r_f = 4.5\%$ throughout. CT use analyst forecasts for expected future earnings for the first five periods, whereas we use the forecasts of earnings from the time-series forecasts and our business planning model.

[23]Note that our simulation model does *not* assume dividend irrelevance. In the model, retained earnings generate a return that is determined by the profitability implied by the EBITDA-process, which generally differs from the cost of equity of the firm.

[24]Easton (2009) provides a comprehensive survey of these methods. See also Table 1 in Easton and Monahan (2005).

As in CT, the book equity forecasts are obtained assuming a plow-back rate of 50%. The ICC is then obtained as an internal rate of return from (II.13).

We implement the method of Gebhardt, Lee, and Swaminathan (2001) (GLS) with $T = 12$ and $g_{ae} = 0$. Furthermore, we can rewrite $ae_t = (roe_t - r_E)\, bv_{t-1}$, where roe_t is the book return on equity. For the first three periods we use the explicit forecasts from our forecasting model. From $t = 3$ to $t = 12$ we use a linear interpolation between roe_3 and the industry median roe over all firms in the same industry during the last 5 years (periods $t = -4$ to $t = 0$, see above), where we exclude all firm-year observations of firms with negative net income.

We obtain the book equity forecasts for GLS using an endogenous payout ratio, which equals the current realized payout ratio if net income is positive; otherwise the payout ratio equals current dividends divided by 6% of total assets. Also, if the estimated payout ratio is larger than 1 or smaller than 0, the ratio is set equal the respective boundary values. The ICC is again obtained as an IRR from (II.13).

Abnormal earnings growth (AEG) methods. The AEG model rests on the definition of abnormal earnings growth $\Delta ae_t \equiv ae_t - ae_{t-1}$:

$$\begin{aligned} \Delta ae_t &= \Delta e_t - r_E\,(e_{t-1} - d_{t-1}) \\ &= \Delta e_t - r_E \Delta bv_{t-1}, \end{aligned} \tag{II.14}$$

where the second line assumes the clean surplus condition. Note that the AEG model does not generally assume clean surplus, but this condition always holds in our business planning model. With the clean surplus condition imposed, the residual income model and the AEG model are isomorphic. The generic valuation equation for the AEG model is:

$$P_0 = \frac{1}{r_e}\left[e_1 + \sum_{t=1}^{T-1} \frac{\Delta ae_{t+1}}{(1+r_E)^t} + \frac{\Delta ae_{T+1}}{(1+r_E)^{T-1}(r_E - g_{aeg})}\right], \tag{II.15}$$

which decomposes the value of equity into capitalized earnings and future earnings growth (see also Ohlson and Gao, 2006).

Gode and Mohanram (2003) (GM) use $T = 1$ (so the middle term in (II.15) drops out). Then:

$$P_0 = \frac{e_1}{r_e} + \frac{\Delta ae_2}{r_e\,(r_e - g_{aeg})}, \tag{II.16}$$

which can be rewritten as a quadratic equation. We obtain the CoEC as the larger square root of this quadratic equation. GM set $g_{aeg} = r_f - 3\%$. Dividend forecasts are obtained using the same procedure as for the GLS method.[25]

Easton (2004) uses $g_{aeg} = 0$, so that (II.16) simplifies to:

$$P_0 = \frac{\Delta e_2 + r_E d_1}{r_E^2}. \tag{II.17}$$

The CoEC is then obtained as $r_E = \sqrt{1/\text{MPEG}}$, where MPEG denotes the modified PEG ratio: $\text{MPEG} = P_0/(\Delta e_2 + r_E d_1)$. Similarly, with the additional assumption $d_1 = 0$ and the definition $\text{PEG} = P_0/\Delta e_2$, Easton (2004) obtains the CoEC as $r_E = \sqrt{1/\text{PEG}}$. Note that by construction, MPEG < PEG so that the MPEG ratio leads to a higher estimate of the cost of capital than the PEG ratio if dividends are positive. Finally, if we assume also that $\Delta ae_t = 0$ for all $t \geq 2$, then (II.16) simplifies to $P_0 = e_1/r_E$, so that $r_E = 1/\text{PE}$. We implement all four applications of the AEG model in the same way, by using forecasts of dividends, earnings, and book values from our business planning model and then inferring the cost of capital according to the formulae above. Like Easton (2004) we set $d_1 = d_0$ and apply the MPEG method only to firms where $\Delta e_2 \geq 0$. Note from (II.17) that this assumption imposes a stricter condition than necessary.

Industry-level methods. Industry-level methods infer the cost of capital and the growth rate *simultaneously* by rewriting the perpetual version of a valuation model

[25] Note that GM use the average of the two year growth and the I/B/E/S growth rate to avoid losing observations. We use the model in the original form in (II.16).

so that it resembles a linear regression equation. We describe the approach of Easton (2004) as an example. He uses the two-period AEG model and rearranges (II.16) to obtain:

$$\frac{e_2 + r_E d_1}{V_0} = r_E \left(r_E - g_{aeg}\right) + \left(1 + g_{aeg}\right) \frac{e_1}{P_0}. \tag{II.18}$$

We run a linear regression of $\frac{e_2+r_E d_1}{V_0}$ on the forward earnings-to-price ratio e_1/P_0 for all firms in the same industry. We begin by assuming a starting value of 12% for r_E and then recover one cost of capital estimate and one implied growth rate for each industry from the regression coefficients in (II.18). We recalculate the dependent variable $\frac{e_2+r_E d_1}{V_0}$ with the values obtained and then iterate regression (II.18) until the estimates of the cost of equity capital and of the implied growth rate converge.[26]

The other portfolio approaches follow a similar logic. O'Hanlon and Steele (2000) use the residual income equation (II.13) with $T = 1$ (hence, the middle term in (II.13) drops out) and obtain a regression equation with the realized book return on equity roe_1 as the dependent variable. Accordingly, we implement their regression approach and use realized instead of forecasted earnings to calculate roe_1.

Easton, Taylor, Shroff, and Sougiannis (2002) (ETSS) start with the two-stage formulation of the residual income model (II.13) with $T = 4$ and obtain a formulation similar to that of O'Hanlon and Steele after aggregating earnings and dividends for the first four years. We implement ETSS by running a linear regression of their measure of four-period cum-dividend earnings, scaled by the book value of equity, on the price-to-book ratio P_0/bv_0 for all firms in the same industry.

Easton and Sommers (2007) also start from the perpetual version of the residual income formula, but then assume that perpetual growth g_{ae} starts at $t = 0$. They therefore obtain a regression equation in terms of roe_0 instead of roe_1. With this modification the implementation of their approach is similar to that of O'Hanlon and Steele (2000).

[26] Convergence is achieved if both the change in the growth rate and the change in the cost of capital between two iterations is smaller than 10^{-10}.

4 Analysis

We start our analysis by comparing the ten individual methods for estimating the implied cost of capital. We follow Francis, Olsson, and Oswald (2000) and evaluate each method primarily in terms of its bias, accuracy, and explainability, where the latter refers to the correlation between the implied cost of capital and the true cost of capital. The importance of each of these criteria depends on the application, which we outline in the Introduction and discuss further in the Conclusion. We discuss the bias, accuracy, and feasibility in the next section 4.1 and defer the more involved analysis of explainability to Section 4.2.

4.1 Bias, accuracy, and feasibility

The starting point for each criterion is the difference $\delta_i^M \equiv r_{E,i}^M - r_{E,i}$ between the implied cost of capital $r_{E,i}^M$ estimated by method M and the true cost of capital $r_{E,i}$. Table II.5 reports the results for bias and accuracy.

[Insert Table II.5 about here.]

Bias. Bias is defined as the sample mean or median of δ_i^M. For all methods except GM and the MPEG ratio the mean and the median bias is below 2% in absolute value, which seems acceptably small. The residual income methods (CT and GLS) both slightly underestimate the cost of capital and have the lowest bias in absolute value. Three of the four methods based on the abnormal earnings growth model (GM, PEG ratio, MPEG ratio) overestimate the cost of capital, and the AEG methods have on average the largest bias in absolute value. All industry-level methods except Easton overestimate the cost of capital by about 1.1% on average.

We suspect that the firm-level methods generate biased ICC estimates because they rely on incorrect assumptions about the growth rate. Standard valuation analysis suggests that ICC methods should be more biased upward if they assume a growth rate that is too high. Then the upward bias in the growth rate would translate into higher model valuations, and, accordingly, a higher ICC. We analyze this point further by estimating implied long-term growth rates for each firm-level method in column (3) of Table II.5. This growth rate equates the true value of each firm with the model value given the true cost of capital. The bias in the growth rate in column (4) of Table II.5 is the difference between the implied growth rate and the growth rate assumed by the method. As expected, the biases are negative for the two residual income methods, but positive for GM. For all methods except ETSS the bias of the ICC is the same as the bias of the growth rate.

The positive bias of the three AEG methods follows from the fact that here the assumption is about the growth of abnormal earnings growth, i.e., about the growth of Δae, whereas the growth rate in residual income methods refers to ae itself.[27] For example, GM assumes growth of Δae of 1.5% per year, which implies much stronger earnings growth and therefore a higher valuation compared to the assumption of 1.5% of the *level* of abnormal earnings by Claus and Thomas (see Table II.4 for the model assumptions). In fact, we can have positive growth of residual income ($\Delta ae_t > 0$) even if abnormal earnings growth itself is constant or even negative. The negative implied growth rate of -17.4% for GM only implies that residual income will stop growing at some point, which does not rule out that it remains at a high level. A similar comment applies to MPEG, which assumes zero growth of abnormal earnings growth, which is still a much stronger assumption than the zero growth assumption of residual income made by GLS. We conclude from this discussion that the AEG methods with the standard growth assumptions in the literature are poorly calibrated.

The industry-level methods tend to display a low bias. Here the implied growth rates shown in column (3) are the growth rates predicted by these methods as part of the ICC estimation. While the bias for the implied growth rates is typically large, it does not translate one for one into a strong bias for the ICC.

[27] In some sense, g in residual income models refers to the first derivative of the valuation function $V(g)$, whereas in AEG models g refers to the second derivative of the valuation function.

Our results correspond broadly to those of Easton and Monahan (2005). We report their median ICC estimates for seven of their methods we also investigate in Table II.5.[28] Their ICC estimates are equal to the true CoEC, which is unknown in their setting, plus the bias of the methods. Like them, we find the lowest ICC estimate for the PE ratio and the highest for GM, and observe that the ordering of their estimates for empirical data corresponds broadly to the ordering we obtain for simulated data.

Accuracy. Accuracy refers to the typical error δ_i^M of the ICC estimates. We report the median absolute value and the standard deviation of δ_i^M in columns (6) and (7) of Table II.5. The accuracy of ICC methods is on average low with a median absolute deviation of 2.4% and a standard deviation of 3.9% across all methods, which is large relative to a median cost of equity capital of 10%. Both measures of accuracy vary significantly across methods, but are very consistent in terms of the implied rankings of the methods.[29] Accuracy tends to be higher for the residual income methods and for the industry-level methods, but is consistently poor for all AEG methods. CT has the highest accuracy (1.5% absolute deviation, 1.9% standard deviation), whereas the PEG ratio has the highest standard deviation (7.1%) and GM has the highest absolute deviation (3.7%).

We attribute the superiority of the residual income (RI) methods over the AEG methods to the modeling approach itself. In addition to the differences between the methods discussed above, RI methods make use of the information contained in the book value of equity, whereas AEG methods ignore this information, which leads to larger estimation errors for the ICC. We also suspect that RI methods perform better because they use longer forecasting horizons and therefore incorporate more information. In untabulated tests we develop a two-period version of the method

[28]See their Table 2, which reports results for CT, GLS, GM, PE, PEG, MPEG, and Easton (2004).

[29]We also calculate the root mean squared error (RMSE), which implies almost the same ranking of methods as the standard deviation and is therefore not tabulated.

of Claus and Thomas, which is more comparable to the AEG methods.[30] We find that such a modified method performs worse than the original CT method, but still outperforms all AEG methods. This observation supports the conclusion that it is the modeling approach and not just the length of the forecast horizon that explains the difference between the results for AEG methods and for RI methods.

Among the industry-level methods, those that use realized values (O'Hanlon and Steele, Easton and Sommers) rank below those based on analyst forecasts in terms of accuracy. However, our simulation approach may exaggerate the difference between methods based on analyst forecasts and those based on realized values because we assume rational expectations, i.e. we equate analyst forecasts with forecasts based on the correct model, an issue we address in our robustness checks. Similarly, reported earnings in practice might have more predictive ability for future earnings than in our simulated economy (e.g., by impounding managers' private information).

Feasibility. We note that the applicability of a method to the widest possible sample is also a quality criterion, particularly in empirical applications. Some methods cannot calculate the implied cost of capital for each firm in our sample. In particular, all two-period AEG methods can be applied only to about 61% of the firms in our model economy (column (8) of Table II.5), whereas the other methods generate estimates for the cost of capital in almost all cases.[31]

4.2 Explainability

We analyze explainability by running simple bivariate regressions of the implied cost of capital on the true cost of capital for each method and report the estimates for

[30] We acknowledge that the AEG methods were designed to reflect frequently used valuation heuristics, and in particular to utilize solely the next two periods' analyst forecasts because of their frequent availability in practice. See e.g. Bradshaw (2002) (Bradshaw, 2002, Bradshaw, 2004) and Easton (2004).

[31] We restrict the algorithm to search for the implied cost of capital in the unit interval, but in a small number of cases it can only find solutions that are either negative or higher than 100%. In these cases the algorithm returns a missing value.

the intercept and slope as well as the R-squared from these regressions in Table II.6. The table shows results for OLS (columns (1) to (3)) and for median regressions (columns (4) to (6)), which are more robust to outliers. The discussion below focuses on the OLS regressions.

[Insert Table II.6 here.]

R-squared. Our first measure of explainability is the R-squared, which displays a striking variation across methods from 27% (Easton and Sommers) to 89% (Easton). Firm-specific residual income methods perform best with R-squareds of 88% (CT) and 83% (GLS), respectively. AEG methods perform worst, with R-squareds between 32% and 65% and an average of 48%. Industry-level methods are in between with an average R-squared of 56%. Methods that work with realized values (O'Hanlon and Steele, Easton and Sommers) perform poorly, as realizations seem to introduce significant noise into cost of capital calculations. Note that the same caveat as in the case of accuracy with respect to analyst forecasts and the predictive power of realized earnings applies here as well. The ranking in terms of R-squared and the ranking in terms of median bias from Table II.5 tend to agree, i.e. a higher average bias (in absolute value) tends to correspond to lower explainability in terms of R-squared.

Regression-coefficient on CoEC. If the implied cost of capital methods were unbiased, then the univariate regressions should have an intercept of zero and a slope coefficient of one. Table II.5 reveals that this prediction is not borne out by the data. For all firm-level methods, the intercept is negative and the estimated CoEC-coefficient in the regression exceeds one significantly. For all industry-level methods except Easton the opposite conclusion holds.

Hence, while the average bias for most methods is small, many methods still have a low accuracy because they distort the estimates for companies with true CoEC that are either very low or very high. To illustrate this point, consider the ICC estimates for GLS when the true CoEC is five percentage points away from its mean of 10%. Then the ICC estimate is biased downward by 1.3% if the true cost of capital is only 5%, and the estimate is biased upward by 0.8% if the true cost of capital is 15%.[32] By contrast, for three of the four industry-level methods, the opposite bias obtains. For example, for ETSS we obtain a positive bias of 3.2% if the true CoEC is 5%, and a negative bias of -0.9% if the true CoEC is 15%. The effect is therefore economically large, even for those ICC methods where the average bias is small.

We label the deviation of the true CoEC from the ICC estimates *distortion* and refer to the regression coefficient on the true CoEC as the *distortion coefficient*. The effect differs for firm-level methods and for industry-level methods and we now investigate this phenomenon in more detail.

Distortion and the duration effect. In our model economy the DCF-value of each firm is a function of the true cost of capital: $P_0^{DGP} = P_0^{DGP}(r_E)$. (We suppress the reference to the firm index for notational convenience.) Similarly, each ICC method's valuation model implies a relationship between the implied cost of equity capital r_E^M and the equity value: $P_0^M = P_0^M(r_E^M)$, where M indexes the implied cost of capital methods. Hence, the model economy and each firm-level ICC method establish a relationship

$$P_0^{DGP}(r_E) = P_0^M(r_E^M). \tag{II.19}$$

From the implicit function theorem we then have:

$$\frac{dr_E^M}{dr_E} = \frac{dP_0^{DGP}(r_E)}{dr_E} \Big/ \frac{dP_0^M(r_E^M)}{dr_E^M}. \tag{II.20}$$

The bivariate regressions in Table II.6 simply estimate a linearized version of $\frac{dr_E^M}{dr_E}$ in (II.20). Hence, we obtain a large (small) slope coefficient in the regressions if the sensitivity of the firm value to the CoEC for the ICC's valuation model is smaller

[32] We use the OLS estimates from Table II.5, for example: $r_{GLS} = -2.3\% + 5\% * (1.2 - 1.0) = -1.3\%$.

(larger) than the same sensitivity for the data generating process. We therefore need to understand the sensitivities $\frac{dP_0^M(r_E^M)}{dr_E^M}$ of firm values with respect to the cost of capital for each ICC method and for the simulation model. However, this sensitivity is nothing but the sensitivity of a present value relationship with respect to the discount rate, and we know that these sensitivities depend critically on how soon the cash flows (or earnings or dividends) are expected to arrive: The present values of cash flows that will arrive in the immediate future are not sensitive to the discount rate, whereas the present values of more distant cash flows are more sensitive. In the Appendix, we formalize this intuition by relying on the notion of *equity duration* developed in Dechow, Sloan, and Soliman (2004). Here we summarize the three main features of equity duration, which we denote by DUR, and defer technical details to the Appendix:

- Equity duration measures the average maturity of future cash flows (or dividends) discounted in a present value relation. Firms whose cash flows or dividends are expected to arrive in the more distant future therefore have a larger equity duration.

- Duration increases with the expected future growth rate of the firm, i.e., growth stocks have larger equity durations compared to value stocks. This relationship is intuitive, because for faster growing firms, more of their value derives from cash flows that are expected to arrive in the distant future.

- The sensitivity of firm value with respect to the CoEC is proportional to the equity duration of the firm. In particular, the sensitivity from (II.20) is given by
$$\frac{dr_E^M}{dr_E} = \frac{DUR^{DGP}}{DUR^M}, \tag{II.21}$$
where DUR^{DGP} is the equity duration implied by the data generating process, and DUR^M is the duration implied by the ICC method for the same firm. Hence, $\frac{dr_E^M}{dr_E}$ is simply the ratio of the duration of the data generating process and that of the ICC method.

From the last property and the fact that DUR^{DGP} is the same for all methods, it follows immediately that the regression coefficient on the true CoEC in Table II.6 should be approximately equal to to DUR^{DGP}/DUR^{M}. We calculate the equity duration for each ICC method using equation (B.4) from the appendix, and report the median values in column (7) of Table II.6.[33] Our fitted DCF model generates a median equity duration of $DUR^{DGP} = 18.91$ years, i.e. the average cash flow in the model economy is almost 19 years away. By comparison, the median duration of the ICC methods ranges from 12.5 years (Easton) to 39.3 years (Easton and Sommers). These numbers compare to the estimate of 15 years of Dechow, Sloan, and Soliman (2004). However, their method is slightly different from ours and they assume a higher cost of capital.[34] Based on (II.21) we also calculate the ratio of DUR^{DGP} and DUR^{M} for each firm and report the mean and median of this ratio in columns (8) and (9) of Table II.6.

From comparing the distortion coefficients with the duration measures, and especially with the mean and median of the duration ratio, in Table II.6 we can observe that they are closely aligned.[35] We do not expect this relationship to be perfect because we are trying to capture the nonlinear relationship (II.20) with a linear regression and can safely conclude that (II.21) yields a very good approximation for our purposes. We can therefore attribute the pattern of distortion coefficients in Table II.6 to the fact that the equity duration measures implied by the firm-level ICC methods deviate from the equity duration in our fitted model economy. We refer to this effect, which relates the distortion of the cost of capital to the duration of the ICC method, as the *duration effect.*

[33] We calculate the derivative dP_0/dr_E numerically from (B.4) by evaluating the average change in the value implied by a one basis point change in r_E.

[34] Dechow, Sloan, and Soliman (2004) calculate equity durations implied by observed stock prices whereas we use rational forecasts of future cash flows to determine equity durations. Moreover, they assume a level perpetuity realized after ten years, which by construction leads to lower durations compared to our model with perpetual growth.

[35] The mean value of DUR^{DGP}/DUR^{MPEG} in Table II.6 is distorted by one single outlier for which the ratio exceeds 10,000. Removing this outlier leads to a value of 1.26, which is in line with the median value of 1.21.

From the discussion above we expect that the main driver of the disparities between the equity duration of the data generating process and that of the ICC methods are the different assumptions about growth. From comparing the implied growth rates in Table II.5 and the duration values in Table II.6 we can see that there is such a relationship, although the growth rates are only available for seven methods and not strictly comparable because, as we remarked in the discussion of the bias, the growth rates of residual income cannot be compared to those of abnormal earnings growth.

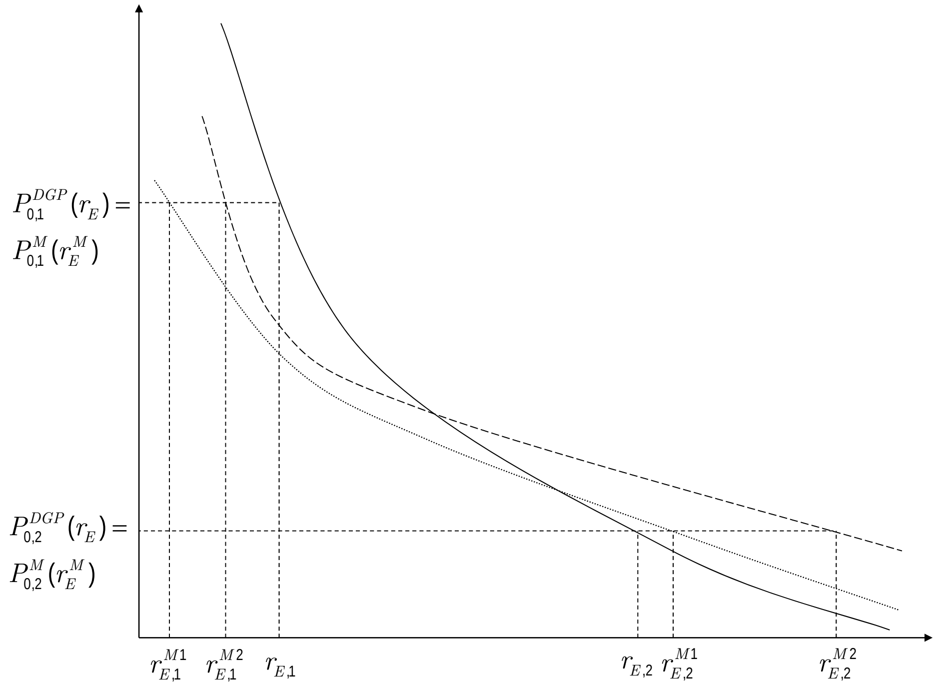
In addition to the duration effect, the distortion coefficient for the industry-level methods is also affected by a second feature of these methods. All industry-level methods assume that growth and the cost of capital are the same for all firms within an industry, which is not the case for our simulations. As a result, the variables in the regressions suffer from an errors-in-variables problem, which causes an attenuation bias for the slope coefficients and leads to a reduced sensitivity of the ICC to the true CoEC.[36] The bias decreases with the R-squared of the regression, which explains why the distortion coefficient and the R-squareds for the four industry-level methods are closely related and why the distortion coefficient for Easton's method is above one as it also has an R-squared of 89% and therefore little attenuation bias.

Finally, we note that the distortion effect is unrelated to other factors that may influence the cost of capital. As remarked above, our simulated economy neither features the effects of size, stock market liquidity, transparency, and other factors that may affect companies' cost of capital, nor does it model forecast bias on part of the analysts. These factors play an important role in practice and would have to be added as controls in regressions based on empirical observations.

Bias and distortion. Finally, we observe that the bias of the ICC methods is closely related to the distortion coefficient. The relationship between distortion and

[36]Easton (2004), Section IV discusses this problem. The attenuation bias moves the slope coefficients towards zero.

Figure II.2: Value sensitivity for high and low value firms
This figure shows the convexity effect by illustrating the deviations arising for firms with with high versus low firm values. The graphs highlight the value sensitivities with respect to changes in the CoEC of the underlying data generating process (solid line) and two representative firm-level ICC methods (dashed and dotted lines). We plot firms' cost of equity capital on the horizontal axis and the market equity value on the vertical axis.



bias can be understood from Figure II.2, which shows the relationship between firm value and the CoEC for the simulated values (solid line) and for two typical firm-level ICC valuation models (dotted line and dashed line). Now consider firm 1, which has a low true cost of capital $r_{E,1}$ and a high corresponding equity value $P_{0,1}^{DGP}$, which we can read off the function for the data generating process. Firm-level ICC method Mi now searches for a cost of equity capital $r_{E,1}^{Mi}$ for firm 1 that equates this equity value with that of the model from (II.19). The resulting error in the cost of capital estimate is then $r_{E,1}^{Mi} - r_{E,1}$, which is negative and equal in absolute value to the horizontal distance between the two curves. The same argument applies again to another firm 2, which has higher true cost of capital $r_{E,2}$, a low equity value $P_{0,2}^{DGP}$, and a positive error $r_{E,2}^{Mi} - r_{E,2}$. In this case, method 1 (dotted line), which exemplifies residual income methods, leads to a negative bias because the underestimation when the true cost of capital are low is much larger in absolute value than the overestimation when the true cost of capital is high. By contrast, method 2 (dashed line), which is more typical for AEG methods, leads to a positive bias because the overestimation is much larger. By experimenting with the functions for different methods we found that a longer forecasting horizon leads to a steeper function and therefore to a negative bias, whereas shorter forecasting horizons lead to shallower functions and a positive bias.

5 Combining ICC methods

In the previous section we diagnose the strengths and deficiencies of the ICC methods. In this section we turn to potential improvements in these methods. More specifically, we consider several different ways of combining individual ICC methods. The first method was suggested by Hail and Leuz (2006) (Hail and Leuz, 2006, Hail and Leuz, 2009), who use an equally weighted average of the methods of CT, GLS, GM, and the PEG ratio. In similar spirit, Dhaliwal, Krull, and Li (2007) use the mean of CT, GLS, and GM. The third combination weights all ten methods equally. The fourth approach applies principal component analysis and observes that the first component captures 71% of the variation in the ICC methods.[37] This observation supports the notion that the ICC methods measure one common factor. Also, the loadings of all methods on the first principal component are positive and vary in a narrow range from 0.25 to 0.36 (these results are not tabulated).

Next, we construct weights from regression analysis as follows. We run regressions of the true cost of capital r_E on each of the ICC measures. The results are reported in Table II.7.

[Insert Table II.7 here.]

[37] Hail and Leuz (2009) also use principal component analysis to extract a common factor from ICC estimates.

Specification (1) is a standard OLS-regression without any restrictions. The R-squared of this regression is 95.6%, so all ten methods combined leave only 4.4% of the true cost of capital unexplained. This observation reinforces the conclusion from principal component analysis that the ICC methods jointly capture a very large part of the variation in the cost of capital. If all ICC methods were unbiased and not distorted, then any combined method should result in regression coefficients that sum to one and in an intercept of zero and thereby generate the optimal weights for a combined method. However, combining the ICC measures in the way suggested by the coefficients from this regression implies that the weights sum to 0.70, whereas the intercept is 0.042. Regression (2) therefore restricts the regression coefficients to sum to one and sets the constant to zero. Regression (3) requires in addition that weights be non-negative. Note that several regression coefficients are close to zero now, in particular all the coefficients for the AEG methods, except for the industry-level method of Easton.

Finally, we consider two simple combinations that emanate from the regression analysis. Observe from regression (3) in Table II.7 that only four methods are given significant weights (CT, GLS, ETSS, and Easton) and that the weights are broadly similar. We therefore construct an equally weighted average of these four methods and label it "Equally weighted - top four" in the tables. Finally, we simplify even further and combine only GLS and ETSS, the best two methods, with equal weights and report it as "GLS & ETSS" in the tables. The reasoning for this combination is that we mainly need to remove the distortion effect in order to simultaneously improve bias, accuracy, and explainability. However, the distortion coefficient from firm-level methods is above one, resulting in a negative bias, whereas the distortion coefficient from industry-level methods is below one, resulting in a positive bias. Combining two methods, one from each category, should therefore suffice to address the main shortcomings we diagnose in Section 4.

[Insert Table II.8 here.]

Table II.8 reports the key evaluation criteria we used in Section 4 and applies them to the combined methods. With R-squareds up to 94.3%, many ICC combinations capture a significant portion of the true cost of capital and improve substantially relative to individual methods. Note that we have optimized the weights for the regression-based methods to match the characteristics of our simulated sample. We can therefore not legitimately compare the out-of-sample tests for ad hoc combinations with the in-sample tests for regression-based methods.

The improvement for some of the combined methods is significant relative to the individual methods. From the in-sample methods, the weighting scheme prescribed by regression (2) performs best, with a median bias of -0.1%, a standard deviation of 1.0%, a distortion coefficient of 0.99, and an R-squared of 93.6%. Hence, this method is practically unbiased and highly accurate and captures the true cost of capital almost perfectly. Specifically, it outperforms the method based on unrestricted regressions, which creates significant distortion, and the method based on principal components. However, the method based on regression (2) requires the input of all ten methods and can be computed only for the sample for which all these methods can be estimated.

From the ad hoc methods, “Equally weighted - top four” performs almost as well as the best regression-based method, with a bias of -0.3%, a standard deviation of 1.1%, and a distortion coefficient of 1.06. This combination outperforms all other ad hoc methods as well as all individual methods. Recall that the lowest standard deviation we observe among individual methods before is for CT (1.9%, see Table II.5), which then has substantially more bias and distortion. The “GLS-ETSS” combination performs only marginally worse on all dimensions in our economy. It provides a useful trade-off between simplicity and the ability to capture the true CoEC in most circumstances, and may therefore be recommendable for applications. By contrast, the ad hoc methods used in the prior literature (Hail and Leuz, Dahliwal et al.) perform significantly worse, mostly because they include firm-level AEG methods, which also limits their applicability.

6 Extensions and robustness checks

All our results in the previous two sections rely on the simulated model and on the parameterization we describe in Section 2 above. In this section we check to what extent the results we report above may reflect features of the simulation model rather than features of the ICC methods we wish to analyze. We want to make sure that the salient properties of the ICC methods pertain to these models and not to the simulation model.

[Insert Table II.9 here.]

Table II.9 summarizes the results for three different robustness checks (columns (2) to (4)). For convenience, we repeat the corresponding results for the baseline model in column (1). In panel A of the table we report the median of six key parameters for the simulated values. In the other panels we report the bias (median, panel B), accuracy (standard deviation, panel C) and explainability (distortion coefficient, panel D; R-squared, panel E) for the ten individual ICC methods and for two selected combined methods.

Alternative steady state model. In Section 2.2 above we justify the simulation parameters with reference to the empirical sample, but deviate from the empirical percentage-of-sales parameters in order to better match the valuation ratios. In the alternative scenario in column (2) of Table II.9 we use a parameterization that matches the empirical depreciation-to-sales ratio and the equity-to-sales ratio more closely by using 3.5% for the former (median in CompuStat sample: 3.6%) and 50% for the latter (sample median: 48.9%). With these parameters the steady-state value for the equity-to-sales ratio is 48.8% from (II.8).

As a result, valuations for this parameterizations are somewhat higher with a market-to-book ratio of 1.57 and a PE ratio of 14.09, where the latter now exceeds the empirical median by 2.3, which renders this parameterization somewhat worse in terms of valuation. The mean bias tends to become negative, but stays about the same in absolute value. Accuracy improves for all methods, but the ranking across methods stays the same as in the baseline case. Similarly, the distortion coefficient declines, but the patterns across methods is not affected. R-squareds also improve slightly. The two combined methods still improve significantly on each of the individual methods for all parameters except for the distortion coefficient, where the GLS-ETSS combination now overweighs ETSS. Overall, the general conclusions we derived above are not affected.

Analyst forecast bias. In our baseline model we generate forecasts from the vector autoregressive model (II.1) and (II.2) and the business planning model. This approach implicitly assumes rational expectations and unbiased forecasts. However, these forecasts from the VAR model take the place of analyst forecasts in the implementation of the ICC methods, and a large literature documents that analyst forecasts are biased (see e.g. Brown, 1993, Kothari, 2001). Moreover, Easton and Sommers (2007) argue that analyst forecasts bias ICC methods. We therefore repeat our analysis by creating an optimistic bias and report the results in column (3) of Table II.9. Starting from the baseline scenario, we calculate the ROE for each firm and each period for which the ICC methods require analyst forecasts, and then add 3% to this ROE value.[38] We then recalculate residual income and abnormal earnings growth with this increased ROE. Note that this modification does not change what really happens in our economy (hence, in panel A, the numbers in column (3) are the same as those in column (1)). Similarly, the results in panels B to E for the ICC methods that rely on realized returns are unaffected. As expected, analyst optimism leads to higher ICC estimates and generates a larger positive bias, in particular for the residual income methods, ETSS, and Easton. Whereas the average bias across

[38]Easton and Sommers (2007) find 3 percentage points CoEC bias. We use these 3 percentage points as an estimate for the bias of ROE forecasts. Although the magnitude of analysts' optimism reported in the literature varies considerably across studies (Kothari, 2001), and is typically expressed in percentage of stock price or per share, our 3 percentage points above ROE forecasts are in the upper range of reported optimism.

the eight methods that use analyst forecasts is 1.7% for the baseline model, it is 2.3% with the simulated analyst forecast bias. The results for accuracy are slightly worse with the analyst forecast bias and the distortion effect also gets somewhat worse. Overall, however, the analyst forecast bias erodes only a small part of the advantage of methods based on analyst forecasts relative to those based on realizations.

Dividend discount model. Finally, we also check for the impact of the valuation model we use to generate simulated firm values. In our baseline model we use a standard DCF model to generate firm values. Our business planning model also generates expectations for future dividends, based on the assumed values for the plowback rate and we therefore repeat the analysis with firm values generated by the dividend discount model. Column (4) panel A shows that this has a large impact on firm values. Firm values are now somewhat lower and also lower than in the CompuStat sample.[39] Otherwise, very little changes with respect to the analysis of the ICC methods. Whereas the estimates for bias and R-squared based on the dividend discount model are very similar to those obtained with the DCF model, those for accuracy and distortion are somewhat worse. However, all qualitative conclusions still hold.

Industry-level methods (not tabulated). In our simulated economy, industry-level methods have specific properties, which add to the construction of combined methods. We run two robustness checks addressing potential issues regarding the validity of these results.

First, our assumptions about the dispersion of the true cost of capital are somewhat ad hoc because little can be known about the parameters of the distribution of the true cost of capital. Our baseline specification assumes that the true cost of capital have

[39] Recall that Modigliani and Miller (1961) dividend irrelevance does not hold here. In their argument, cash that is distributed and cash that is retained both earn the cost of capital, whereas in our model cash retained in the firm is reinvested and generates the same return as all other capital invested in the firm.

an overall standard deviation of 4.2% from (II.10), where most of the variation comes from the variation between industries and very little comes from the variation between firms within the same industry. We change the parameterization so that the within-industry variation equals the between-industry variation, holding the overall standard deviation constant. As expected, the results are very similar for the firm-level methods, but industry-level methods perform worse in terms of accuracy and explainability, and the optimal weights when constructing combined methods would need to change. Nevertheless, even under this demanding scenario, the combined methods that give some weight to industry-level methods are generally at least at par with the individual methods in terms of accuracy and explainability (R-squared, distortion-coefficient).

Second, we perform a simulation where we draw 2,000 industries with only 10 firms each in order to investigate the performance of ICC methods for small industries, an issue regression-based methods face in real world applications. Unsurprisingly, the accuracy of industry-level methods that rely on realized values instead of forecasts declines substantially. Interestingly, ETSS and Easton are now less distorted, i.e., the distortion coefficient is closer to one. The combined methods we advocate still perform better than almost all other approaches.

Further checks (not tabulated). We perform several further robustness checks, but do not tabulate the results here. More specifically, we modify the parameters of the VAR process to generate more or less persistence in the response of EBITDA and sales growth to a shock, and we also change the length of the detailed planning period to 25 years and to 75 years, respectively. The change in the time series parameters has no discernible impact on our main inferences. We therefore do not pursue this avenue further and conclude that our results are robust to perturbations of the times series model we use.

Shortening the time horizon for the planning period in our model reduces valuations, whereas lengthening the time horizon increases valuations. This is simply a consequence of the fact that we assume zero growth for the horizon value, so that longer detailed planning periods also imply more growth. This modification has a corresponding impact on the bias, but only a very marginal impact on accuracy. The average distortion coefficient also does not change much with the horizon of the model, but the difference in distortion between firm-level methods and industry-level methods increases with the time horizon. Consequently, the assessment of the combined methods does not change.

Our assumption of a plowback rate of 50% differs from the empirical rate of 65% in our CompuStat sample. We performed an additional check where we set the plowback rate to 65% and found that its main impact is to reduce the market-to-book ratio to 1.33, significantly below the median empirical ratio of 1.61. All findings we discuss above are robust with respect to this change.

7 Conclusions

In this chapter we compare implied cost of capital methods by using a simulation approach. We calibrate a simulated economy to a large sample of real-world data. We obtain a number of robust conclusions with regard to the properties of the methods as well as to their application in empirical studies.

Within the group of firm-level methods, residual income methods uniformly dominate abnormal earnings growth methods. Abnormal earnings growth methods have a significant positive bias, whereas residual income methods have a negative bias that is less than half of that of abnormal earnings growth methods in absolute value. Similar conclusions also hold for accuracy, which we measure by the standard deviation of the estimation errors, and for the R-squared of regressions of the ICC estimates on the true cost of equity capital.

The essential difference between abnormal earnings growth methods and residual income methods is the modeling of abnormal earnings. Whereas residual income methods model the growth of future abnormal earnings, abnormal earnings growth methods model the *changes* in future abnormal earnings. Abnormal earnings growth methods therefore take an approach that focuses on the first derivative of abnormal earnings instead of abnormal earnings themselves, and this approach seems to lose information that is critical for valuation purposes and leads to less reliable forecasts.

The performance of industry-level methods that simultaneously estimate the cost of capital and expected growth is somewhere in between the two groups of firm-level methods. Especially those industry-level methods that rely on analyst forecasts perform remarkably well and in some cases come close to the performance of residual income methods, even if we allow for a 3% bias in analyst forecasts.

In addition to the average bias of each method we also consider whether the methods distort the true cost of capital by running regressions of the ICC estimates against the true cost of equity capital. If the methods are not distorted, then the slope coefficient in these regressions should be one, but it is in fact larger than one for all firm-level methods and smaller than one for three out of four industry-level methods. We attribute this finding to two factors. The first factor is the equity duration of the methods, i.e., how far earnings growth is projected into the future. The second factor is the errors-in-variables problem that arises in industry-level methods if the firms within the same industry do not all have the same growth rate and the same cost of capital.

We explore improvements of implied cost of capital estimates by aggregating several estimates through the calculation of averages of the individual methods. We identify weighting schemes based on regression analysis and principal components analysis as well as ad hoc, equally weighted methods that work well. The analysis of the individual methods suggests that residual income methods and industry-level methods based on forecasts provide good components for combined methods because they are biased and distorted in the opposite direction. Combinations that give equal weights to both classes of methods therefore benefit from compensating errors and outperform all individual methods.

Researchers have come to rely on ICC estimates as proxies for the cost of capital in a range of applications when testing related economic theories.[40] For these applications accuracy and bias are less relevant, because they mainly rely on estimates that capture a large part of the variation in the cost of capital. In our simulations, individual ICC methods capture up to 89% and one of the combined methods captures up to 94% of the variation in the true cost of equity capital, which provides an optimistic outlook on the use of ICC estimates in such research. As a note of caution, we add that some sources of noise that may be relevant in empirical settings are not included in our simulated economy.

All our conclusions are limited by the simulation approach we use here, which relies on a business planning model, the time-series modeling of the dynamics of profitability and sales growth, and its calibration towards median valuation ratios of the CRSP-CompuStat universe. We had little guidance from the literature on this effort, which has primarily focused on the short-term dynamics of key accounting variables (e.g. Bernard and Thomas, 1989). Little seems to be known about the long-term time-series properties of key accounting variables or the dynamics of the main value drivers (see Dechow, Kothari, and Watts (1998) for a short-term model) and more work is needed here.

[40]Examples include Botosan (1997) on voluntary disclosure; Hail and Leuz (2006) on the impact of legal institutions and securities regulation; Pastor, Sinha, and Swaminathan (2008) on the risk-return trade-off; Chen, Kacperczyk, and Ortiz-Molina (2011) on the influence of labor relations; Daske (2006) on voluntary and Daske, Hail, Leuz, and Verdi (2008) on mandatory IFRS adoption; Hail and Leuz (2009) on cross listings; and Hou and Van Dijk (2010) on the size effect.

Tables

Table II.1: Key financial ratios and model parameters

This table shows summary statistics for a CRSP-CompuStat sample of 8,036 firms with 96,917 firm-year observations between 1970 and 2009. The table includes univariate statistics for the main value drivers, percentages of sales and financial ratios of the sample firms using CRSP-CompuStat data. All variables are winsorized at the 1%-level. Payout consists of common dividends. Return on assets (equity) is defined as net income divided by the book value of total assets (equity). The price earnings ratio is computed as the share price divided by earnings per share (EPS), where EPS is net income divided by the number of common shares outstanding. Leverage is defined as book value of long term debt divided by total assets plus market capitalization minus book value of equity. The model parameters used later in the simulation framework are presented in the last column.

Variable	**25%**	**50%**	**75%**	**Mean**	**STD**	**Obs.**	**Model parameters**
Sales growth	1.0%	10.6%	23.8%	17.9%	39.6%	96,719	6.0%
EBITDA margin	5.8%	11.4%	18.6%	3.7%	60.8%	96,719	12.0%
Sales	48.2	170.2	689.2	1156.2	3176.3	96,719	100.0
Time-series std of sales growth	12.7%	19.9%	33.6%	28.2%	24.1%	96,031	20.0%
Time-series std of margin	2.8%	4.7%	9.1%	13.9%	32.6%	96,031	5.0%
Payout to net income	20.4%	34.8%	57.3%	41.4%	27.1%	43,601	N(0.5, 0.1)
Depreciation to sales	2.1%	3.6%	6.4%	6.2%	8.7%	96,719	5.0%
Current assets to sales	25.6%	37.4%	58.4%	106.1%	180.6%	96,719	35.0%
PPE to sales	11.4%	21.5%	46.3%	50.3%	78.2%	96,719	20.0%
Current liabilities to sales	13.8%	19.6%	29.4%	29.6%	36.4%	96,719	20.0%
Equity to sales	30.3%	48.9%	86.0%	104.4%	208.1%	96,719	40.0%
Market-to-book equity	0.94	1.61	2.99	2.99	4.21	96,719	
Return on assets	0.9%	5.1%	9.7%	3.0%	14.8%	96,719	
Book return on equity	2.4%	10.7%	18.0%	7.1%	30.1%	96,719	
PE-ratio	4.60	11.79	21.46	17.06	51.16	96,719	
Leverage	4.2%	19.5%	41.6%	25.6%	23.9%	96,719	

Table II.2: Estimates for panel vector autoregressions

This table shows estimates from panel vector autoregressions of equations (II.1) and (II.2). Panel A shows the results for the sample from Table 1. We regress sales growth and EBITDA margins on lagged sales and margins using panel vector autoregressions. The data for sales growth and margins is winsorized at the 1%-level. Standard errors are shown in parentheses. Panel B documents the correlation matrix of the residuals from the panel VAR. Panel C reports the modeling parameters for long-term sales growth and EBITDA margin used later in the simulation framework.

Panel A: Panel VAR results

Statistics	**Sales growth equation**	**Margin equation**
Sales growth(t-1)	0.166	-0.004
	(0.007)	(0.007)
Margin(t-1)	-0.166	0.596
	(0.017)	(0.022)
Obs.	81,036	81,036

Panel B: Residual correlation matrix

	Sales growth	**Margin**
Sales growth	1.000	
Margin	0.354***	1.000

Panel C: Long-term sales growth and margin

	Sales growth	**Margin**
Avg. firm-specific intercepts	0.070	0.049
Avg. long-term rates	6.0%	12.0%
STD of long-term rates	2.0%	1.0%

Table II.3: Comparison of simulated values vs. empirical data

This table shows the differences between the simulated data and the empirical data based on the CRSP-CompuStat sample. Differences are constructed by subtracting the corresponding quantiles of the empirical data from the simulated data.

	Difference: Simulated - real data				
Variable	**10%**	**25%**	**50%**	**75%**	**90%**
Sales growth	-9.13%	-8.56%	-4.80%	-3.84%	-16.21%
EBITDA margin	5.44%	2.00%	0.65%	-2.37%	-9.30%
Market-to-book equity	-0.12	-0.16	-0.20	-0.03	0.55
Return on assets	9.16%	1.80%	2.21%	3.29%	3.85%
Book return on equity	17.26%	1.50%	0.08%	1.73%	1.26%
PE-ratio	2.61	0.46	-0.93	5.96	28.94

Table II.4: Implied cost of equity capital methods

This table summarizes the salient features of the individual implied cost of equity capital methods analyzed in this study. Altogether, we test ten different methods suggested in prior literature. We classify each method according to the model type (RI=residual income, AEG=abnormal earnings growth), the level of estimation (firm-level or industry-level), the data input (analyst forecasts or realized values), and the time horizon of the detailed forecast period in years. Column (5) describes the modeling strategy for the terminal value, which is either a perpetuity or a model where values converge before the perpetual growth stage is reached. Column (6) shows the estimates for terminal growth.

					Terminal value modeling	
	Model	**Level**	**Input**	**Horizon**	**Method**	**Growth**
Method	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Claus and Thomas (2001)	RI	Firm	Forecasts	5	Perpetuity	$g_{RI} = r_f - 3\%$
Gebhardt et al. (2001)	RI	Firm	Forecasts	3	Fading to 12; Perp. after 12	$g_{RI} = 0\%$
Gode and Mohanram (2003)	AEG	Firm	Forecasts	2	Perpetuity	$g_{AEG} = r_f - 3\%$
PE ratio	AEG	Firm	Forecasts	1	Perpetuity	AGR(2) = 0
PEG ratio	AEG	Firm	Forecasts	2	Perpetuity	DIV(1) = 0; $g_{AEG} = 0\%$
MPEG ratio	AEG	Firm	Forecasts	2	Perpetuity	$g_{AEG} = 0\%$
Easton et al. (2002)	RI	Industry	Forecasts	4	Perpetuity	endogenous RI growth
Easton (2004)	AEG	Industry	Forecasts	2	Perpetuity	endogenous AE growth
O'Hanlon and Steele (2000)	RI	Industry	Realizations	0	Perpetuity	endogenous RI growth
Easton and Sommers (2007)	RI	Industry	Realizations	1 realized	Perpetuity	endogenous RI growth

Table II.5: Deviation between implied cost of equity capital and true cost of equity capital

This table shows univariate statistics for the deviation δ of implied cost of equity capital (ICC) estimates and the simulated firms' true cost of equity capital. Deviations are computed in percentage points. For methods that only allow ICC estimation at the industry-level we assign each firm the industry-level estimate. Columns (1) and (2) show the bias of ICC estimates. The growth rate that equates the true value of each firm with the model value given the true cost of capital is shown in column (3). Column (4) displays the deviation between the median growth rate assumed or estimated by the methods and the median implied growth rate. Column (5) contains the ICC estimates from Table 2 of Easton and Monahan (2005). Columns (6) and (7) measure accuracy as absolute deviation and standard deviation. Finally, column (8) shows the percentage of firms for which the ICC-value can be computed.

	Bias					Accuracy		Feasibility
Method	**Mean (1)**	**Median (2)**	**Median implied growth rate (3)**	**Bias in growth rate (4)**	**Estimates Easton & Monahan (5)**	**Median absolute deviation (6)**	**Standard deviation (7)**	**Possible (in %) (8)**
Claus and Thomas (2001)	-1.0%***	-1.4%***	4.0%	-2.5%	11.5%	1.5%	1.9%	99.0%
Gebhardt et al. (2001)	-0.1%***	-0.4%***	5.3%	-5.3%	10.7%	1.5%	2.3%	99.0%
Gode and Mohanram (2003)	4.0%***	3.0%***	-17.4%	18.9%	12.4%	3.7%	6.6%	60.8%
PE ratio	-1.3%***	-2.2%***	n.a.	n.a.	8.3%	3.4%	4.6%	96.6%
PEG ratio	1.8%***	0.8%***	n.a.	n.a.	10.6%	3.4%	7.1%	61.6%
MPEG ratio	3.2%***	2.0%***	n.a.	n.a.	11.6%	3.0%	6.3%	61.6%
Easton et al. (2002)	0.9%***	0.8%***	9.8%	-2.6%		1.7%	2.3%	100.0%
Easton (2004)	-1.0%***	-1.3%***	-15.5%	-16.5%	12.2%	1.8%	2.0%	100.0%
O'Hanlon and Steele (2000)	1.3%***	0.8%***	3.0%	3.8%		2.0%	3.4%	100.0%
Easton and Sommers (2007)	1.2%***	0.8%***	3.8%	4.0%		2.1%	3.7%	100.0%

Table II.6: Measures of explainability

This table displays the results from a regression of ICC estimates on firms' true cost of equity capital. For each method M we regress:

$$r_{E,i}^{M} = \theta_0^M + \theta_1^M r_{E,i} + \varepsilon_i^M,$$

where $r_{E,i}$ is the true cost of capital of firm i and $r_{E,i}^M$ is the ICC estimate of the cost of capital of firm i using method M. We use standard OLS regressions (columns (1)-(3)) as well as median regressions (columns (4)-(6)). The columns for θ_0 are labeled "Intercept" and those for θ_1 are labeled as CoEC. Column (7) shows the median durations obtained for each ICC method computed from (B.4), where the change in the cost of equity dr_E equals one basis point. Significance tests are for $\theta_0^M = 0$ and for $\theta_1^M = 1$.

	OLS regression			**Median regression**			**Duration**	$DUR(DGP)/DUR(M)$	
	Intercept	**CoEC**	**R^2**	**Intercept**	**CoEC**	**R^2**		**Mean**	**Median**
Method	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Claus and Thomas (2001)	-0.03***	1.18***	88.0%	-0.03***	1.13***	74.6%	15.09	1.13	1.09
Gebhardt et al. (2001)	-0.02***	1.20***	83.1%	-0.03***	1.20***	62.6%	15.55	1.16	1.15
Gode and Mohanram (2003)	-0.01***	1.48***	46.6%	-0.01***	1.45***	33.6%	17.78	1.22	1.10
PE ratio	-0.06***	1.45***	64.9%	-0.06***	1.42***	45.5%	13.34	1.35	1.37
PEG ratio	-0.01***	1.23***	32.4%	-0.01***	1.18***	21.9%	19.21	1.21	1.07
MPEG ratio	-0.02***	1.47***	48.6%	-0.02***	1.39***	36.0%	16.24	5.21	1.21
Easton et al. (2002)	0.05***	0.60***	68.3%	0.07***	0.43***	33.0%	36.01	0.74	0.45
Easton (2004)	-0.04***	1.24***	89.2%	-0.03***	1.20***	67.9%	12.50	1.49	1.40
O'Hanlon and Steele (2000)	0.05***	0.65***	40.0%	0.06***	0.46***	18.6%	21.91	0.80	0.53
Easton and Sommers (2007)	0.07***	0.47***	27.0%	0.08***	0.27***	8.4%	39.34	0.62	0.39

Table II.7: Construction of combined implied cost of capital methods

This table documents the regression analysis for the construction of combined methods, where we estimate the following regression:

$$r_{E,i} = \theta_0 + \sum_{M=1}^{M=10} \theta_M r_{E,i}^M,$$

where $r_{E,i}$ is the true cost of capital of firm i and $r_{E,i}^M$ is the ICC estimate of the cost of capital of firm i using method M. Hence, we jointly regress firms' true CoEC on all ten ICC method estimates. In model (1) we conduct an unrestricted OLS regression including an intercept. We apply restricted regressions in models (2) and (3). Model (2) requires coefficients to sum to one and excludes the intercept ($\theta = 0$, $\sum_{M=1}^{M=10} \theta_M = 1$). Model (3) requires in addition that coefficients lie within the unit interval ($0 \leq \theta_M \leq 1$).

Specification	**Unrestricted (1)**	**No constant, weights sum to one (2)**	**No negative weights (3)**
Intercept	0.042***		
Claus and Thomas (2001)	0.023**	0.14	0.17
Gebhardt et al. (2001)	0.123***	0.24	0.26
Gode and Mohanram (2003)	-0.195***	-0.13	0.00
PE-ratio	0.165***	0.02	0.01
PEG ratio	0.052***	0.00	0.02
MPEG ratio	0.269***	0.18	0.00
Easton et al. (2002)	-0.149***	0.47	0.36
Easton (2004)	0.412***	0.18	0.18
O'Hanlon and Steele (2000)	0.013***	-0.11	0.00
Easton and Sommers (2007)	-0.010***	0.01	0.00
R-Squared	95.6%		
Obs. (in % of total sample)	56.1%	56.1%	56.1%

Table II.8: Evaluation of combined implied cost of capital methods

This table shows results for the evaluation of combined implied cost of capital methods. As evaluation criteria we use a method's bias (mean, median deviation), accuracy (absolute deviation, standard deviation), feasibility, and explainability (intercept, CoEC coefficient, and R-squared from OLS regression). The combined methods differ with respect to their composition and weighting of methods. Combination (a) is used by Hail and Leuz (2006) (Hail and Leuz, 2006, Hail and Leuz, 2009) and equally weighs the estimates from Claus and Thomas, Gebhardt et al., Gode and Mohanram, and the PEG ratio. Combination (b) is used by Dhaliwal, Krull, and Li (2007) and equally weighs the estimates from Claus and Thomas, Gebhardt et al., and Gode and Mohanram. Combinations (c) and (d) include all ten methods but apply different weightings based on (c) equal weights and (d) the factor loading implied by the first principal component. The coefficients from models (1) and (2) in Table II.7 define the method weights for combinations (e) and (f), respectively. Combinations (g) and (h) assess the properties of two simple weighting schemes. Combination (g) equally weighs the estimates from Claus and Thomas, Gebhardt et al., Easton et al., and Easton. Finally, combination (h) equally weighs the estimates from Gebhardt et al. and Easton et al.

		Bias		Accuracy			OLS Regression		
				Median absolute		Possible			
		Mean	Median	deviation	STD	(in %)	Intercept	CoEC	R^2
	Method for weighting	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
(a)	Hail and Leuz	1.2%	0.5%	1.8%	3.9%	59.4%	-0.02	1.30	66.1%
(b)	Dahliwal et al.	1.0%	0.5%	1.5%	3.0%	59.6%	-0.02	1.32	78.8%
(c)	Equally weighted - all	0.4%	0.3%	0.9%	1.6%	56.1%	0.00	1.05	87.0%
(d)	Principal components	0.4%	0.3%	0.9%	1.6%	56.1%	0.00	1.07	87.5%
(e)	Unrestricted regression (1)	-4.2%	-4.2%	4.2%	0.8%	56.1%	-0.04	0.96	95.6%
(f)	No constant, weights sum to one (2)	-0.1%	-0.1%	0.6%	1.0%	56.1%	0.00	0.99	93.6%
(g)	Equally weighted - top four (3)	-0.3%	-0.5%	0.7%	1.1%	98.0%	-0.01	1.06	94.3%
(h)	GLS & ETSS (4)	0.4%	0.4%	0.9%	1.3%	99.0%	0.01	0.90	89.3%

Table II.9: Robustness checks

This table shows the results of several robustness checks, where we assess alternative specifications of our simulated model economy to see how the results are affected by the choice of the underlying model. We repeat results for the baseline model in column (1). The alternative specifications include (2) an adjusted steady-state model, where the equity- and depreciation-to-sales ratio is 50% and 3.5% to match the empirical parameters; (3) an analyst forecast bias model, where we assume that earnings forecasts are optimistic such that returns on equity forecasts are biased upward by 3 percentage points for every firm in every forecast period; (4) the use of a dividend discount model instead of a discounted cash flow model. Panel A shows the median values for key financial ratios from Table II.3. Panels B to E shows the results for the median bias, standard deviation, the distortion coefficient, and R-squared.

Panel A: Simulated data comparison

Median accounting item	Baseline model (1)	Adjusted steady-state model (2)	Analyst forecast bias (3)	Dividend discount model (4)
Sales growth	5.8%	5.8%	5.8%	5.8%
EBITDA margin	12.0%	12.0%	12.0%	12.0%
Market-to-book equity	1.42	1.57	1.42	1.25
PE-ratio	10.86	14.09	10.86	9.37
Duration	18.91	18.70	18.91	18.63
CoEC (HML)	10.39%	10.57%	10.39%	9.91%

Panel B: Median bias

	(1)	(2)	(3)	(4)
Claus and Thomas (2001)	-1.0%	-2.0%	1.7%	0.1%
Gebhardt et al. (2001)	-0.1%	-1.5%	1.0%	0.9%
Gode and Mohanram (2003)	4.0%	1.9%	4.6%	4.6%
PE ratio	-1.3%	-2.5%	1.3%	0.9%
PEG ratio	1.8%	-0.3%	1.7%	2.2%
MPEG ratio	3.2%	1.1%	3.2%	3.8%
Easton et al. (2002)	0.9%	0.3%	3.4%	1.2%
Easton (2004)	-1.0%	-2.1%	1.2%	0.5%
O'Hanlon and Steele (2000)	1.3%	0.4%	1.3%	1.3%
Easton and Sommers (2007)	1.2%	0.6%	1.2%	1.3%
Equally weighted - top four	-0.3%	-1.3%	1.8%	0.7%
GLS & ETSS	0.4%	-0.6%	2.2%	1.1%

Panel C: Method accuracy (standard deviation)

Method	(1)	(2)	(3)	(4)
Claus and Thomas (2001)	1.9%	1.0%	3.0%	2.7%
Gebhardt et al. (2001)	2.3%	1.9%	2.9%	3.5%
Gode and Mohanram (2003)	6.6%	4.6%	6.4%	6.3%
PE ratio	4.6%	3.5%	5.9%	7.9%
PEG ratio	7.1%	5.2%	7.0%	6.9%
MPEG ratio	6.3%	4.3%	6.1%	5.9%
Easton et al. (2002)	2.3%	2.6%	2.3%	2.5%
Easton (2004)	2.0%	1.5%	2.7%	2.2%
O'Hanlon and Steele (2000)	3.4%	2.8%	3.4%	3.4%
Easton and Sommers (2007)	3.7%	2.9%	3.7%	3.7%
Equally weighted - four	1.1%	0.8%	1.6%	1.3%
GLS & ETSS	1.3%	1.4%	1.4%	1.7%

Panel D: Method explainability (CoEC coefficient)

Claus and Thomas (2001)	1.18	1.05	1.55	1.37
Gebhardt et al. (2001)	1.20	1.10	1.36	1.34
Gode and Mohanram (2003)	1.48	1.24	1.58	1.53
PE ratio	1.45	1.28	1.90	1.85
PEG ratio	1.23	1.01	1.22	1.25
MPEG ratio	1.47	1.24	1.48	1.53
Easton et al. (2002)	0.60	0.45	0.58	0.44
Easton (2004)	1.24	1.06	1.46	1.32
O'Hanlon and Steele (2000)	0.65	0.54	0.65	0.29
Easton and Sommers (2007)	0.47	0.43	0.47	0.24
Equally weighted - top four	1.06	0.91	1.24	1.12
GLS & ETSS	0.90	0.77	0.97	0.89

Panel E: Method explainability (R-squared)

Claus and Thomas (2001)	88.0%	94.2%	89.1%	84.8%
Gebhardt et al. (2001)	83.1%	84.3%	81.8%	72.4%
Gode and Mohanram (2003)	46.6%	54.4%	52.2%	51.1%
PE ratio	64.9%	69.4%	72.2%	51.2%
PEG ratio	32.4%	37.2%	33.0%	34.9%
MPEG ratio	48.6%	57.4%	50.6%	54.2%
Easton et al. (2002)	68.3%	61.9%	68.0%	68.4%
Easton (2004)	89.2%	89.3%	89.0%	89.4%
O'Hanlon and Steele (2000)	40.0%	51.1%	40.0%	25.3%
Easton and Sommers (2007)	27.0%	44.7%	27.0%	15.4%
Equally weighted - top four	94.3%	96.3%	93.7%	93.4%
GLS & ETSS	89.3%	89.5%	93.7%	93.4%

Chapter III

Improving Implied Cost of Equity Capital Estimation Using Long-Term Forecasts from a VAR Framework

1 Introduction

In this chapter I propose a new approach to estimate expected returns based on a long-horizon implied cost of capital method that uses long-term earnings forecasts from a vector autoregressive (VAR) model.[41] There are two main approaches that are widely used as proxy for expected returns. The traditional approach, which still dominates the financial literature, applies factor models that rely on realized returns. This practice might induce significant biases as evidence indicates that realized returns are a poor measure for expected returns, in particular, if the expected return estimation relies on short periods of time (see Elton, 1999; Lundblad, 2007; Pastor,

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Sinha, and Swaminathan, 2008). The more recent approach estimates the implied cost of equity capital (ICC) based on earnings forecasts from financial analysts as proxy for expected returns. ICC methods reverse-engineer a valuation model to back out the expected return as the internal rate of return that equates the current price to the present value of future cash-flows.

There exist three main problems associated with ICC estimation based on analyst forecasts. First, analysts' forecast data is only available for a subset of firms and years (see Hou, Van Dijk, and Zhang, 2010). To the extent that analyst following is not random, this may give rise to a selection bias, as evidence concerning the implied cost of equity capital is only obtained for the specific group of firms that is followed by analysts. Second, ample evidence shows that analyst earnings expectations are biased and do not represent market expectations (see Easton and Monahan, 2005; Easton and Sommers, 2007). Third, analysts' forecast data is restricted to short horizons of maximum five years but for many firms not available beyond the second year. The non-availability of forecast data beyond the five-year period requires ICC methods to apply a horizon structure that is characterized by short detailed planning periods with uniformly low growth rates for all firms. The analysis in Chapter II shows that this particular method structure leads to a low value-sensitivity of existing ICC methods and results in distorted ICC estimates that are characterized by an overestimation (underestimation) of the true cost of equity capital when it is high (low).

To account for the described problems of existing ICC methods, I propose a new approach to estimate the implied cost of equity capital that utilizes earnings forecasts from a vector autoregressive model.[42] The VAR model links a vector of state variables – including a firms' book return on equity – to lags of these variables and uses the estimated coefficients to generate earnings forecasts. The persistence

[42]VAR models have been used to generate return expectations in the context of return decompositions (see Campbell, 1991; Vuolteenaho, 2002; Campbell, Polk, and Vuolteenaho, 2010). Callen, Segal, and Hope (2010) use the return decomposition to study the relation between conservatism and pricing.

and long-term rate for the earnings process is defined by the coefficients of the VAR model. I apply my earnings forecasting model for annual portfolios of firms to obtain portfolio-specific coefficient estimates (portfolio-level VAR model). This approach explicitly accounts for the possibility that growth dynamics defined by the portfolio-specific VAR coefficients vary across portfolios and over time.

The new forecasting methodology is subject to low data requirements. This feature makes the model applicable for a large sample that is not restricted to firm-years covered by analysts' forecast data. Since model-based earnings forecasts rely on the realized relationship between earnings and the state variables, they are less likely to be affected by potential biases documented for analyst forecasts. Compared to the short-term forecasts generated by existing earnings forecasting models, the portfolio-level VAR model delivers superior short-term earnings forecasts. More importantly, the portfolio-level VAR model also allows to generate long-term earnings forecasts and overcomes the non-availability of forecasts beyond the short- to medium-horizon (two to five years). This property enables me to apply a long-horizon ICC method that is – due to the length of the detailed planning period – less sensitive to changes in the terminal value and, hence, less dependent on the terminal growth rate assumption. The long-term forecasts generated by the VAR model indicate that the uniformly low growth rate assumption commonly applied to ICC estimation is not justified. Implied cost of capital estimates generated by the long-horizon method, therefore, promise to deliver a more consistent measure for expected returns.

Previous work has addressed the same issues by replacing analyst forecasts with earnings forecasts derived from a time-series model (see Allee, 2008) or a multivariate cross-sectional model (see Hou, Van Dijk, and Zhang, 2010). While both models improve on the limited data coverage of analysts' forecast data, the evidence regarding data quality of forecasts is mixed. Early evidence suggests that analyst forecasts outperform forecasts from simple time-series models with respect to forecast accuracy (e.g, Brown and Rozeff, 1978; O'Brien, 1988; Brown, Hagerman, Griffin, and Zmijewski, 1987). However, more recent papers by Bradshaw, Drake, Myers, and Myers (2010) and Hou, Van Dijk, and Zhang (2010) report that predictability is similar or even slightly better for model-based forecasts. The problem with existing time-series forecasting models is that they apply regressions on the individual firm-level. This methodology restricts the application of time-series models to firms with a sufficiently long horizon of available data. Following Fama and French (2000) this approach induces a severe survivorship bias. At the same time the statistical power of firm-level regressions is limited as regression coefficients based on about 20 observations likely provide noisy estimates.

By contrast, cross-sectional earnings forecasting models utilize a large cross-section of firms. The models link firms' realizations of future earnings to a set of ex-ante available variables and utilize the estimated relationship to build predictions about future earnings. This forecasting methodology raises a conceptual concern as it applies in-sample calibrations to form in-sample predictions. The problem is that the information set of market participants at the time they build their expectations about firms' future earnings does not include non-observable future earnings realizations. Moreover, the use of future realized earnings as dependent variable restricts model forecasts to a short or medium horizon. A five-year ahead earnings forecast, for example, requires realized earnings for period $t + 5$ that are linked to observable variables in t. Using data up to 2009, five-year ahead earnings forecasts cannot be obtained after 2004. Just as analysts' forecast data, existing models, therefore, do not account for the non-availability of long-term earnings forecasts.

An alternative approach to model-based earnings forecasting is to adjust analyst forecasts by removing the predictable forecast error (see Gode and Mohanram, 2008; Larocque, 2010). This approach tries to eliminate the bias component from analyst forecasts. The obtained forecasts, however, still cover firms followed by financial analysts, only, and are restricted short horizons. To the best of my knowledge, Nekrasov and Ogneva (2010) is the only study that implicitly addresses the non-availability of long-term forecasts. They apply a new ICC method that does not impose a uniformly low growth assumption but accounts for variation in firm-specific long-term growth. Their method is an adjusted version of the portfolio-level method of Easton, Taylor, Shroff, and Sougiannis (2002) that simultaneously computes firm-level ICC and growth. The authors obtain (perpetual) firm-level growth rates beyond the short-term horizon. The application of the method, however, requires to link cost of equity and growth to observable risk/growth factors. Given the variety of factors proposed in the literature, it is unclear to what extent the selection of factors impacts the firm-level ICC and growth estimates obtained.[43] Moreover, risk factors have been identified based on realized returns and it is an open question to what extent the evidence can be transferred to expected returns.

I start my analysis with the identification of variables that help to explain the variation of future realized returns on equity. My selections criterion is based on the incremental R-squared of a predictor variable. Among a set of 16 predictor variables proposed in the literature, I find that the current book return on equity, stock return, book-to-market ratio, and the ratio of total dividends to book equity explain most of the variation in future earnings. I use the identified variables and apply them to the portfolio-level VAR model. I test my model against other earnings forecasting models proposed in the literature. For the short horizon (one to three years), I find that the portfolio-level VAR model outperforms existing models with respect to tracking future realized earnings. In particular, the explanatory power of my model for variation in future earnings significantly exceeds that of existing approaches. To the extent that earnings realizations proxy for expectations in the short-run, my model promises to deliver superior short-term earnings forecasts. The fact that I compare out-of-sample forecasts from the VAR model with in-sample forecasts from existing approaches further supports the superiority of my model. Moreover,

[43]Besides the traditional CAPM-beta, return factors include size and book-to-market (Fama and French, 1992, 1993); growth (LaPorta, 1996); momentum (Carhart, 1997) liquidity (Pastor and Stambaugh, 2003); and equity duration (Dechow, Sloan, and Soliman, 2004).

since the VAR model, unlike existing approaches, also allows to generate long-term earnings forecasts it should be preferred to analyst and existing model-based forecasts when estimating the implied cost of equity capital.

Next, I use the generated long-term earnings forecasts from the portfolio-level VAR model to compute implied cost of capital from a long-horizon ICC method with a detailed planning period of 50 years. I also compute several other methods with varying forecast horizons to study how varying horizons affect ICC estimates. I can show that the long-horizon ICC method reduces the terminal value sensitivity of implied cost of capital estimates by shifting the terminal value further into the future, thereby making it less value-relevant. All in all, my ICC method overcomes important issues associated with ICC estimation. The improved data foundation and reduced sensitivity to exogenous growth rate assumptions favors the long-horizon ICC method and likely delivers a more consistent measure for expected returns.

In addition, I review some properties of the expected return measure obtained from long-horizon ICC estimates. I compute the annual market risk premium, which is positive throughout the data sample and varies between approximately 1-9% between 1970 and 2008. Over the same time, average annual realized excess returns vary between -46% and 55% and are negative in 15 years of the sample period. Looking at the periods of economic contraction and expansion, I obtain a consistent relation between the economic cycles and the market risk premium. Following Brav, Lehavy, and Michaely (2005) I analyze correlations of expected returns with size and the book-to-market ratio. I find that my measure for expected returns contains a significant and positive size effect. The effect is consistent across various specifications of my earnings forecasting model and contradicts the negative size effect that is commonly obtained for realized returns. For the book-to-market factor, I obtain a positive value premium on average, which is in line with evidence for realized returns. Computing the expected return difference between high and low book-to-market firms for different size groups, however, shows that the value effect is non-monotonic in size: while for small firms I observe a value premium, large firms are associated with a value discount.

The remainder of this chapter is structured as follows. The following Section 2 reviews the literature on earnings forecasts and describes the methodology to generate long-term earnings forecasts from a VAR framework. I present the sample selection and variable definition in Section 3. Section 4 contains the main analysis and evaluation of earnings forecasting models. In Section 5 I assess the expected return measure obtained from the long-horizon ICC method. Section 6 presents robustness checks and Section 7 concludes with a discussion of the limitations of my analysis and suggestions for future research.

2 Long-term earnings forecasting and ICC estimation

Compared to historical realized returns, the implied cost of equity capital (ICC) is a forward-looking measure for expected returns. ICC methods estimate expected returns based on a fundamental valuation relationship, e.g. as defined by a finite-horizon approximation of the residual income model:[44]

$$P_0 = bv_0 + \sum_{t=1}^{T} \mathrm{E}_0\left[\frac{ae_t}{(1+r_E)^t}\right] + \mathrm{E}_0\left[\frac{ae_T(1+g_{ae})}{(r_E - g_{ae})(1+r_E)^T}\right], \tag{III.1}$$

where P_0 and bv_0 describe the current market and book value of equity, respectively. Using market expectations (denoted by the expectations operator E_0) for future residual income or abnormal earnings ae_t (I use the terms interchangeably) and an assumption for the terminal growth rate g_{ae}, the valuation model (III.1) is reverse-engineered to back out the expected stock return r_E. It is obvious from (III.1) that

[44]I use the term *model* for a generic valuation model, e.g. residual income or dividend discount model and the models applied to generate earnings forecasts. By contrast, I use the term *method* for specific methods that parameterize the models to determine the ICC.

ICC estimation requires market expectations of future earnings as input data. Given that these expectations are not observable, the key issue for the application of ICC methods is to find suitable proxies for the market expectation of future earnings.

My analysis starts with a review of the problems associated with earnings forecast data from financial analysts. I proceed with a discussion of existing earnings forecasting models. Among the large set of predictors proposed in these models, I identify the variables that significantly explain the variation in firms' future earnings using an incremental R-squared analysis. I estimate a new earnings forecasting model that includes the identified variables based on the vector autoregressive (VAR) approach and evaluate all models concerning their ability to track future earnings.

2.1 Problems of analyst earnings forecasts

It has been common practice to approximate expected earnings by consensus earnings forecasts from financial analysts (e.g. I/B/E/S or Value Line). This approach, however, introduces several problems. First, analysts' consensus forecast data is only available for a subset of firms and years. Even for the US, data is not available before 1982 and an exhaustive coverage of firms is not obtained until the mid 1990s (see Hou, Van Dijk, and Zhang, 2010). This limited data coverage may introduce a sample selection bias as there is evidence that analyst following is not random, but depends on firm characteristics like ownership structure, size, return correlation with the market return, lines of business, governance, and recent performance (see Bhushan, 1989; McNichols and O'Brien, 1997; Hayes, 1998; Lang, Lins, and Miller, 2004). Consequently, not all firms are followed by analysts.[45] The problem is even more severe for non-US samples where analyst coverage varies considerably across countries.[46] Moreover, Lang, Lins, and Miller (2004) document that analyst following also depends on country-characteristics like the degree of investor protection.

[45]LaPorta (1996); Hong, Kubik, and Solomon (2000); Diether, Malloy, and Scherbina (2002) document that small and financially distressed firms are underrepresented in the I/B/E/S files.

[46]See Table 1 in Chan and Hameed (2006) for evidence about analyst coverage in 25 emerging market economies.

Second, financial analysts constitute a specific group of market participants and it is unclear to what extent their earnings forecasts reflect market expectations. In line with this reasoning, Easton and Monahan (2005) and Easton and Sommers (2007) present evidence that overly optimistic earnings forecasts lead to biased implied cost of capital estimates. Analyst optimism may arise from a behavioral bias documented in experimental studies (e.g., Maines and Hand, 1996; Sedor, 2002; Kadous, Krische, and Sedor, 2006) or may be incentive-driven through career concerns, investment-banking, underwriter, or management relationships (see Hong, Kubik, and Solomon, 2000; O'Brien, McNichols, and Lin, 2005; Lin and McNichols, 1998; Richardson, Teoh, and Wysocki, 2004; Francis and Philbrick, 1993).[47] Unless one assumes that investors in general share the analysts' optimism, the evidence raises concerns whether analyst forecasts qualify as a proxy for market expectations. However, at least for incentive-driven explanations this assumption is critical. For behavioral explanations the question to what extent investors share the analysts' optimism depends on whether the behavioral bias applies to specific groups (e.g. analysts) or to individuals in general (cognitive bias). To the extent that analyst consensus forecast data contains systematic forecast errors, ICC estimates derived from these earnings forecasts will also be biased.

Third, analyst forecast data is restricted to a short horizon of maximum five years but for many firms not available beyond the second year.[48] The short-horizon availability restricts existing ICC methods to rely on short detailed planning periods T of maximum five years.[49] As a consequence, the terminal value approximation in (III.1) is applied at an early stage, which makes firm-level ICC methods sensitive to the terminal growth rate assumption g_{ae}. Moreover, existing methods apply a uniform terminal growth rate to all firms in the sample implying that firms grow at

[47]An overview of papers addressing questions related to analyst incentives vs. behavioral biases is provided in Table 5 of Ramnath, Rock, and Shane (2008).

[48]Hou, Van Dijk, and Zhang (2010) document that between 1982 and 2006 analyst forecast data for one-, two, and three-year ahead earnings is available for approx. 90%, 80%, and 68% of their sample. Relative to their full sample from 1968-2006 the availability is 65%, 58%, and 50%.

[49]The exception is the method by Gebhardt, Lee, and Swaminathan (2001) that uses earnings forecasts data for the first three years followed by a fading of earnings towards the industry median until year 12.

the same rate after a short period of 2-5 years.[50] Finally, the terminal value restriction $(r_E - g_{ae}) > 0$ bounds the uniform terminal growth rate to the lowest ICC in the sample. Hence, existing methods apply a horizon structure that is characterized by short detailed planning periods with uniformly low growth rates for all firms. The simulation approach in Chapter II documents that these issues induce a low value sensitivity of firm-level ICC methods. The low value-sensitivity results in distorted ICC estimates that are characterized by an overestimation (underestimation) of the true cost of equity capital when it is high (low).

2.2 Earnings forecasting models

Existing studies that aim at predicting future earnings either exploit the cross-section or the time-series of earnings. Time-series evidence starts in the 1960s and 1970s with the analysis of univariate time-series properties of annual earnings.[51] Ball and Watts (1972) find that a random walk model adequately describes the time-series behavior of earnings. Subsequently, Watts and Leftwich (1977) and Albrecht, Lookabill, and McKeown (1977) test a simple random walk (or random walk with drift) model against a Box-Jenkins model. Their evidence confirms the random walk behavior of earnings. It is, however, possible that the supporting evidence for the random walk hypothesis of earnings is a consequence of the low statistical power of firm-level time-series regressions. In contrast to the early evidence, Freeman, Ohlson, and Penman (1982) find that the book return on equity has predictive power for future earnings changes, while O'Brien (1988) documents that time-series earnings forecasts predict future excess stock returns. Recently, Allee (2008) applies an exponential smoothing model to generate time-series earnings forecasts that he uses to estimate the implied cost of equity capital. However, due to the problems of univariate

[50] Exceptions are estimates based on the target price method (see Botosan and Plumlee, 2002), where a firm's terminal value beyond year 5 is approximated by the Value Line target price forecast. Nekrasov and Ogneva (2010) propose an approach to simultaneously estimate firm-level ICC estimates and growth rates.

[51] For a review of the literature that analyzes properties of quarterly earnings see Kothari (2001).

time-series earnings forecasting models applied on the individual firm-level described in the introduction, I disregard these models for my following analysis.

Cross-sectional earnings forecasting models. Existing cross-sectional earnings forecasting models link future earnings realizations to currently observable variables using multivariate regressions. In the following, I identify three models that are representative for the existing approaches of cross-sectional earnings forecasting. I estimate the models in each year t between 1970 and 2009 by running rolling-window pooled cross-sectional regressions using data over the preceding ten years (minimum eight years). I refer to this estimation methodology as the standard approach.[52]

My analysis starts with the model of Hou, Van Dijk, and Zhang (2010). Their model is the first attempt that uses cross-sectional forecasts to estimate implied cost of capital.[53] The forecasting model predicts the level of earnings before extraordinary items (henceforth: net income) $e_{i,t+\tau}$ for firm i in year $t+\tau$ ($\tau = 1, 2, 3$) by estimating the following model:

$$\begin{aligned} e_{i,t+\tau} &= \alpha_0 + \alpha_1 ev_{i,t} + \alpha_2 ta_{i,t} + \alpha_3 d_{i,t} + \alpha_4 dd_{i,t} + \alpha_5 e_{i,t} \\ &\quad + \alpha_6 nege_{i,t} + \alpha_7 acc_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{III.2}$$

where ev denotes the enterprise value (total assets plus market value of equity minus book value of equity), ta total assets, d total dividends, and acc operating accruals. The variables dd and $nege$ are dummy variables that equal one for non-dividend payers, respectively for firms with negative net income, and zero else. Hence, in each year the model computes a set of coefficients $\alpha^\tau = (\alpha_0, ..., \alpha_7)$ that are multiplied with the observable variables to generate one-, two-, and three-year ahead net income.

An alternative earnings forecasting model is proposed by Fama and French (2006a) and can be considered as the basis for the Hou, Van Dijk, and Zhang model. The

[52] Note that *model* refers to a specific earnings forecasting model (e.g. Hou, Van Dijk, and Zhang model), whereas *approach* refers the methodology used to estimate an earnings forecasting model (e.g. pooled cross-sectional regression or VAR approach).

[53] Their model relies on work of Fama and French (2000, 2006a) and Hou and Robinson (2006).

model forecasts one-, two-, and three-year ahead return on equity (*roe*) using the following specification:[54]

$$roe_{i,t+\tau} = \alpha_0 + \alpha_1 btm_{i,t} + \alpha_2 size_{i,t} + \alpha_3 dy_{i,t} + \alpha_4 dd_{i,t} + \alpha_5 roe_{i,t} + \alpha_6 nege_{i,t} + \alpha_7 \frac{acc_{i,t}}{ta_{i,t,}} + \varepsilon_{i,t}. \tag{III.3}$$

In (III.3), the predictor variables include the log book-to-market ratio *btm*, size (log of market capitalization), total dividends scaled by the book value of equity *dy* (henceforth: dividend yield), the current return on equity, and accruals scaled by total assets. The dividend and negative earnings dummy from the Hou, Van Dijk, and Zhang model are unchanged. Concerning the motivation of predictor variables, Beaver and Ryan (2000) and Fama and French (1995) find that the book-to-market ratio and size predict future returns on equity. Moreover, dividend-paying firms might be more profitable than non-dividend payers. Finally, Sloan (1996) is the starting point for a large literature on earnings components that documents a significant relation between accruals and future earnings and returns.

It is obvious from (III.2) and (III.3) that the Hou, Van Dijk, and Zhang model is an unscaled version of the forecasting model by Fama and French, where all variables, except size and the dummy variables for non-dividend payers and firms with negative earnings, are scaled by book equity or total assets.[55] Earnings forecasting approaches from prior studies often use scaled rather than unscaled variables (see Fama and French, 1995, 2000; Abarbanell and Bushee, 1997; Ou and Penman, 1989b). There is evidence that scaled earnings, i.e. book equity returns, are mean-reverting (see Brooks and Buckmaster, 1976; Lipe and Kormendi, 1994). Based on an initial shock, a mean-reverting variable is expected to converge to its historical average over time.

[54]Fama and French include separate variables for firms with positive and negative accruals scaled by the book value of equity rather than total assets. They also include asset growth which I drop to assure that the model only differs from the Hou, Van Dijk, and Zhang model with respect to scaling variables.

[55]Note that Fama and French use market capitalization rather than total assets to measure size.

This property is important, in particular, for generating long-term forecasts as it is more challenging to forecast a future level for a variable than a rate against which the variables converges. However, the analysis of Hou, Van Dijk, and Zhang (2010) aims at a comparison between model-based and analyst earnings forecasts. Given that forecasts of financial analysts commonly refer to the level of earnings, the approach by Hou, Van Dijk, and Zhang permits a more direct comparison. Moreover, it is interesting to see how scaling affects the evaluation of earnings forecasting models later in this chapter.

Besides the more recent papers on earnings forecasting, there is a long literature on financial statement analysis. This literature seeks to identify financial variables and ratios that help to predict future earnings changes. Ou and Penman (1989a,b) use a set of observable financial variables to estimate the likelihood of an earnings increase from a Logit model. They can show that their likelihood-measure is value-relevant with respect to predicting future stock returns. Lev and Thiagarajan (1993) screen financial publications, commentaries, and newsletters for comments about value-relevant financial information. They identify a set of financial variables (fundamental signals) and show that these are related to future stock returns in the predicted direction. Subsequently, Abarbanell and Bushee (1998) show that an investment strategy based on these fundamental signals earns significantly positive abnormal returns. Other papers report similar positive return findings using an investment strategy based on composite measures that combine specific financial variables and characteristics in a single score (see Beneish, 1999; Piotroski, 2000; Penman and Zhang, 2002).

Rather than forecasting future earnings, most of above papers try to categorize firms into high and low expected earnings portfolios. This categorization into high and low expected earnings portfolios is not surprising given that the main focus is to study the relation between financial variables and future returns using hedge-portfolio investment approaches. The study by Abarbanell and Bushee (1997), however, analyzes the set of financial signals from Lev and Thiagarajan (1993) regarding their relevance for future earnings changes. Given that some of the variables have been identified to predict future earnings changes, I test the ability of the financial signals to forecast future earnings using the following model for future return on equity:[56]

$$\begin{aligned} roe_{i,t+\tau} &= \alpha_0 + \alpha_1 inv_{i,t} + \alpha_2 ar_{i,t} + \alpha_3 gm_{i,t} + \alpha_4 capx_{i,t} + \alpha_5 s\&a_{i,t} \\ &\quad + \alpha_6 etr_{i,t} + \alpha_7 lf_{i,t} + \varepsilon_{i,t}. \end{aligned} \tag{III.4}$$

The financial signals include changes in inventory (inv), accounts receivable (ar), gross margin (gm), capital expenditures ($capx$), selling and administrative expenses ($s\&a$), the effective tax rate (etr), and the labor force (lf). For a motivation of these financial signals I refer to Lev and Thiagarajan (1993).

VAR based earnings forecasting models. Even if existing models to forecast future earnings have the potential to improve on analyst forecasts with respect to the quality of forecasts (bias) and the coverage of firms not followed by analysts, the non-availability of long-term forecasts is not addressed by these approaches. Hence, ICC methods applied with existing model-based earnings forecasts must still rely on short horizons leading to the low value-sensitivity of methods and the distortion of implied cost of capital estimates described above.

To overcome the problems of existing forecasting models, I propose an alternative forecasting methodology based on a vector autoregressive framework. My approach allows to generate earnings forecasts for an infinite number of periods. The VAR defines a system of equations that links currently observable variables to lags of these variables. More explicitly, I define a VAR(1) model that includes the return on equity (roe) and a vector of state variables x. The selection of state variables is

[56] Earnings and auditor quality are excluded from the analysis. The variables are not available for a significant fraction of my sample and auditor quality is not recorded in CompuStat before 1975. Including these variables reduces my sample by more than 30%.

based on an analysis to identify predictors that explain the variation in future return on equity. I defer the discussion of the analysis and the results to Section 4.1.

$$\begin{bmatrix} roe_{i,t} \\ x_{i,t} \end{bmatrix} = \underbrace{\begin{bmatrix} \alpha_{0,i} \\ \beta_{0,i} \end{bmatrix}}_{\phi_i} + \underbrace{\begin{bmatrix} \alpha_{roe,i} & \alpha_{x,i} \\ \beta_{roe,i} & \beta_{x,i} \end{bmatrix}}_{\mathbf{\Gamma}_i} \begin{bmatrix} roe_{i,t-1} \\ x_{i,t-1} \end{bmatrix} + u_{i,t}. \tag{III.5}$$

Unlike a univariate autoregressive (AR) approach, vector autoregressions also model the cross-dependence between return on equity and the state variables. I therefore also account for the dynamic behavior of the correlation between the variables.

In each year between 1970 and 2009 I estimate the VAR over rolling-windows of pooled cross-sectional data for the preceding ten years (pooled VAR approach).[57] I obtain an annual estimate for the intercept vector ϕ and the matrix $\mathbf{\Gamma}$ from these regressions, so that the index i in (III.5) drops. I then generate forecasts for each firm and year from my VAR estimates by first multiplying the current values of *roe* and the state variables with the coefficient matrix $\mathbf{\Gamma}$. Adding the intercept ϕ yields expected values for all state variables in period $t = 1$. I use these forecasts iteratively to obtain forecasts for period $t = 2$ and repeat the exercise to estimate forecasts for all periods within the detailed planning period of 50 years. Generally, the derivation of forecasts for the state variables in period $t + \tau$ follows:[58]

$$\mathrm{E}_t \begin{bmatrix} roe_{i,t+\tau} \\ x_{i,t+\tau} \end{bmatrix} = \phi\left(\mathbf{\Gamma}^{\tau} - \mathbf{I}\right)\left(\mathbf{\Gamma} - \mathbf{I}\right)^{-1} + \mathbf{\Gamma}^{-1} \begin{bmatrix} roe_{i,t} \\ x_{i,t} \end{bmatrix}. \tag{III.6}$$

One feature of the VAR approach is that it defines a mean-reverting process for each of the state variables. Based on the current observations the forecasts of each variable converge to a long-term average. The persistence of the processes is specified by the VAR coefficient matrix $\mathbf{\Gamma}$, while the long-term averages depend on the intercept

[57] In general, the system of equations (III.5) is estimated using seemingly unrelated regressions (SUR). Given that the right-hand side of (III.5) contains the same independent variables for each equation, SUR is equivalent to equation-by-equation OLS (see Hayashi, 2000, p. 282).

[58] See Petersen and Pedersen (2008), p.58.

vector ϕ. The annual rolling-window estimation of the pooled VAR model enables persistence and long-term rates to vary over time. However, so far it does not account for variation across firms. The latter would require a firm-level VAR estimation, which defines an individual time-series model that carries the above identified deficits. The estimation of the VAR approach for portfolios of firms (portfolio-level VAR approach) trades-off the benefit of a large cross-section to estimate the VAR and the demand for variation of VAR estimates across firms. In particular, a portfolio-level VAR allows for portfolio-specific growth dynamics (persistence) and long-term rates depending on the estimates Γ_i and ϕ_i, where i denotes the respective portfolio.

My portfolio definition is based on firm characteristics rather than industry classification.[59] The reason is that portfolios for earnings forecasting should group firms with comparable growth dynamics. In industries that contain both growth and value firms growth dynamics can differ considerably across firms. Growth firms, for example, are commonly characterized by small size, low book-to-market, and high beta. Firm characteristics like size, the book-to-market ratio, and beta might, therefore, better capture the differences in growth dynamics. Following this reasoning, the identification of portfolios based on firm characteristics yields more homogeneous portfolios, which promotes the portfolio-level VAR estimation.[60] For the portfolio formation, I assign firms into annual portfolios based on size, book-to-market, and beta. I use terciles for each variable as portfolio breakpoints (low / medium / high). The procedure results in 27 annual portfolios between 1970 and 2009 or 1,080 portfolio-year observations. The average portfolio-year contains 80 different firms (median: 73), while the smallest portfolio-year covers nine firms.

Finally, I do not use the estimated intercept coefficients ϕ_i from the portfolio-level VAR to generate forecasts based on (III.6). Instead, I set these coefficients

[59]Callen, Segal, and Hope (2010) use the VAR approach proposed by Vuolteenaho (2002) and apply it to industry portfolios of firms (Fama and French, 1997, industry classification). Their estimates, therefore, vary across industry portfolios but are constant over time.

[60]In addition, I provide a robust check for my portfolio-level VAR model based on industry classification later in the chapter.

so that the long-term values for the state variables converge to the median value over all firms in the same portfolio over the preceding ten years. The reason for this adjustment is that for the estimated intercepts ϕ_i the processes converge to their averages over the estimation period. Given that the mean is more sensitive to potential outliers, I prefer a convergence against the portfolio-specific median. I provide a robustness check later in the chapter showing that my result do not depend on this particular assumption. To obtain a convergence of the state variables against the portfolio-specific median I need to adjust the intercept vector that sets the long-term rates. I compute an adjusted intercept vector ϕ_i^* by substituting $u_{i,t} = 0$, and the portfolio-specific medians for *roe* and the other state variables x over the respective estimation period into the VAR from (III.5) and then solving for the intercept values.

2.3 Measuring implied cost of equity capital

Existing firm-level implied cost of capital methods reverse-engineer the finite-horizon approximation of a generic valuation model (e.g. residual income model). As an example, consider the method of Claus and Thomas (2001), which relies on a detailed planning period of 2-5 years and approximates the terminal value assuming perpetual residual income growth of 2-3%. The assumption implies that from period five on residual income is expected to grow at a rate of 3% on average for *all* firms. However, it is questionable whether this assumption adequately captures the growth dynamics of growth and value firms. The criticism is that there might still be considerable growth variation across firms at that time, which is not accounted for by the method.

To address this issue, I propose a long-horizon ICC method that utilizes the long-term earnings forecasts obtained from the VAR model. The benefit of such a model is that it shifts the terminal value to a period far in the future. Hence, the growth of a firm until that future period is specified by the empirical calibration of the underlying earnings forecasting model. Given that I generate portfolio-level earnings forecasts, I am able to account for portfolio-specific growth dynamics. Hence, growth firm portfolios will be characterized by a more persistent return on equity process that converges to an above average long-term rate. I therefore explicitly account for the variation in residual income growth in the long-run.

To estimate the implied cost of capital I rewrite the generic equation of the residual income model (III.1) by using $ae_t = (roe_t - r_E)\, bv_{t-1}$:

$$P_0 = bv_0 + \sum_{t=1}^{T} \mathrm{E}_0 \left[\frac{(roe_t - r_E)\, bv_{t-1}}{(1 + r_E)^t} \right] + \mathrm{E}_0 \left[\frac{(roe_T - r_E)\, bv_{T-1}(1 + g_{ae})}{(r_E - g_{ae})(1 + r_E)^T} \right]. \quad \text{(III.7)}$$

I use the return on equity forecasts from the VAR model to implement different versions of a long-horizon ICC method with a detailed planning period of $T =$ 20, 30, 40, and 50 years. For my baseline specification, I assume that there is no growth in residual income beyond the respective period T and set $g_{ae} = 0\%$. This assumption is ad hoc and I later assess the sensitivity of my ICC estimates to this particular assumption. However, I claim that for large T the variation of perpetual residual income growth across firms should be small. Moreover, due to the discounting effect, the impact of changes in g_{ae} on the ICC should be low for large T.

I obtain book equity forecasts using a payout ratio that equals the average historical five-year realized payout ratio. I define the realized payout ratio in each year as total dividends divided by net income if net income is positive; otherwise the payout ratio equals current dividends divided by 6% of total assets. Also, if the estimated payout ratio is larger than 1 or smaller than 0, the ratio is set equal the respective boundary value.

I compare my long-horizon implied cost of capital to estimates from existing ICC methods. I include the firm-level method of Gebhardt, Lee, and Swaminathan (2001) (GLS), the portfolio-level method of Easton, Taylor, Shroff, and Sougiannis (2002) (ETSS), and an equally weighted combination of both methods.[61] I include the

[61] Portfolio-level methods infer the cost of capital and the growth rate *simultaneously* by rewriting the perpetual version of a valuation model so that it resembles a linear regression equation.

method of GLS as it applies the longest detailed planning period among the existing firm-level ICC methods, thereby reducing concerns regarding the horizon structure. Moreover, the method also accounts for variation of long-term return on equity across portfolios. In line with this reasoning, Chapter II shows in a simulation setting that among six firm-level ICC methods, GLS shows the most reliable performance. Furthermore, the chapter highlights that a combined method that uses an equal weighting of the ICC estimates from GLS and ETSS provides a robust measure for firms' cost of capital under various specifications of the simulation environment.

I implement the method of GLS with $T = 12$ and $g_{ae} = 0$. For the first three periods I use the explicit forecasts from my VAR forecasting model. From $t = 3$ to $t = 12$ I use a linear interpolation between roe_3 and the median roe over all firms in the same portfolio during the last ten years.

I implement the method of ETSS using a two-stage formulation of the residual income model (III.1) with $T = 4$ and aggregate earnings and dividends for the first four years. Rearranging the obtained valuation equation yields,

$$\frac{X_c}{bv_0} = (R - 1) + (R - G)\,\frac{P_0}{bv_0}, \tag{III.8}$$

where $G = (1 + g_{ae})^4$ is one plus the expected growth in four-year residual income, $R = (1 + r_E)^4$ is one plus the four-year expected equity return, and X_c is the measure of four-period cum-dividend earnings. I run a linear regression of X_c, scaled by the book value of equity on the price-to-book ratio P_0/bv_0 for all firms in the same portfolio. I begin by assuming a starting value of 12% for r_E and then recover one cost of capital estimate and one implied growth rate for each portfolio from the regression coefficients in (III.8). I recalculate the dependent variable $\frac{X_c}{bv_0}$ with the values obtained and then iterate regression (III.8) until the estimates of the cost of equity capital and of the implied growth rate converge.[62]

[62]Convergence is achieved if both the change in the growth rate and the change in the cost of capital between two iterations is smaller than 10^{-10}.

3 Data and variable description

The empirical basis for this study is the CRSP-CompuStat intersection from 1962 to 2009. I only include non-financial firms that are listed on NYSE, AMEX, and NASDAQ.

Sample selection. My data set starts in 1962 as book equity data is generally not available before that date. To be included in the sample, I require a firm-year to have data on the return on equity, market and book equity, returns, dividends, total assets, and accruals. Furthermore, I require a firm-year to have a valid beta estimate that I compute from CRSP monthly return data. Applying these restrictions results in a data set with 88,767 firm-year observations that I use for the evaluation of the earnings forecasting models described in Section 2.2. Panel A of Table III.1 summarizes the sample selection criteria.

[Insert Table III.1 here.]

Starting in 1970, I run annual vector-autoregressions for each of the 27 portfolios and obtain a VAR coefficient matrix for 88,767 firm-year observations. The data set forms the basis to estimate the ICC methods described in Section 2.3. Applying my baseline ICC method with a 50-year horizon and zero terminal growth, results in 80,550 firm-year estimates of the implied cost of equity capital.[63] I compute one-year ahead realized returns from year t to $t+1$ based on monthly returns from 1st of July of year t to 30th of June of year $t+1$ and match them with ICC estimates for year t. This procedure reduces my final sample to 73,438 firm-year observations for 6,533 firms between 1970 and 2008.

Panel B of Table III.1 shows summary statistics for selected financial variables of the final data set. The average stock return in my data set 6.89%, while the

[63] I restrict the algorithm to search for the implied cost of capital in the unit interval, but in some cases it can only find solutions that are either negative or higher than 100%. In these cases the algorithm returns a missing value.

corresponding (book) return on equity is about 2.5% higher. The median firm-year has a book-to-market ratio of 0.66, which implies a market value that is 1.5 times above its book value for the median firm-year. Firm size shows the usual skewness with an average market capitalization of about 1.5 bn US-$ compared to a median of 153 mil. US-$. The distribution of firm-years shows that the average (median) firm survives 11.24 (8) years in my sample.

Variable definition. I measure all CRSP variables, i.e. prices, dividends, number of shares outstanding, and returns as of the end of June in year t. The variables are matched with the CompuStat data from the most recent fiscal year $t-1$. This procedure guarantees that all information from the annual financial statement is available at the time of the forecasts and impounded into prices and returns. Annual returns and dividends are compounded from monthly returns and dividends, recorded from the 1st of July to the 30th of June. The market capitalization equals the number of shares outstanding times the share price at the end of June. The proxy for firm size is defined as the log of market capitalization. In each June I compute (pre-)betas based on a regression of monthly stock returns on the CRSP value-weighted market index. I use regressions over the preceding 60 months and require a minimum of 24 months with valid data for the estimation. The estimation of post-betas follows a similar logic, but rather than the preceding 60 months I use the 60 months following June of year t to estimate post-betas. I use annually compounded T-Bill returns from Ibbotson Associates as the risk-free rate.

For book equity, I use CompuStat common equity and, if common equity is unavailable, the liquidation value of common equity. If available, I add income taxes payable and deferred taxes and investment tax credit to common equity. I treat common equity as missing if it is negative. Data on net income is obtained from CompuStat earnings before extraordinary items. I compute return on equity as net income dividend book equity from the previous fiscal year. The book-to-market ratio equals book equity from fiscal year $t-1$ divided by the market capitalization as of the end of June in year t. The enterprise value is defined as total assets minus book equity plus market capitalization.

The calculation of accruals follows the indirect balance sheet method defined as the change in current assets excluding cash and short-term investments less the change in current liabilities net of the change in debt in current liabilities and income taxes payable minus depreciation and amortization. I divide accruals by total assets to obtain my scaled accruals variable. The (book) dividend yield equals total dividends scaled by book equity. The P/E ratio is computed as market capitalization divided by net income. I define leverage as debt divided by debt plus market capitalization, where debt equals long-term debt plus debt in current liabilities plus preferred stock from CompuStat.

The definition of the financial signals (*inv*, *ar*, etc.) follows Abarbanell and Bushee (1997). They compute most of the signals as the percentage change in a variable, e.g. inventory, minus the percentage change in sales.[64] I provide a detailed description of the signals in Appendix C and refer to Lev and Thiagarajan (1993) for a motivation of these signals. I winsorize each variable at the 1% level to reduce the impact of extreme outliers.

4 Analysis

I start my analysis by estimating and evaluating the various earnings forecasting models discussed in Section 2.2. I follow Francis, Olsson, and Oswald (2000) and evaluate each forecasting model primarily in terms of its bias, accuracy, and explainability, where the latter refers to the correlation between the future realized and expected return on equity derived from the model. I discuss the results from the earnings forecasting regressions in the next section 4.1 and defer the model evaluation to Section 4.2.

[64] Changes are defined as the actual value divided by the average value over the last two years minus one.

4.1 Earnings forecasting models and variable selection

Properties of existing forecasting approaches. I begin with the analysis of the existing earnings forecasting models based on Hou, Van Dijk, and Zhang (2010), Fama and French (2006a), and Abarbanell and Bushee (1997) (Models 1-3). Table III.2 shows estimates from rolling-window pooled cross-sectional regressions (standard approach) for these models. The coefficients and (adjusted) R-squareds equal the average estimates from annual regressions. I calculate t-statistics from time-series standard errors.

[Insert Table III.2 here.]

Panel A of Table III.2 shows results for the model of Hou, Van Dijk, and Zhang. Overall, the estimates are consistent with those reported in Hou, Van Dijk, and Zhang (2010). The autocorrelation coefficient is slightly lower (around 0.5 compared to 0.6 in their paper) but like in their paper the most significant variable (highest t-statistic). Enterprise value and total dividends show a consistently positive relation to future net income, while the model predicts that non-dividend payers gain lower future net income. Accruals have the correct sign but are not significant for my sample. Like Hou, Van Dijk, and Zhang (2010), I also find that the variables altogether explain a large part of the variation in level net income, which is highlighted by R-squared values of 88%, 82%, and 79% for one, two, and three-year ahead net income compared to 87%, 81%, and 77% in their paper.

The results for the model of Fama and French are documented in Panel B. As explained above, the model is a scaled version of the previous Model 1, where the dependent and independent variables – despite size and dummy variables – are scaled by either book equity or total assets. Again, I find results that closely match the results obtained by Fama and French (2006a). Moreover, the signs for the coefficient estimates of unscaled variables from Model 1 and scaled variables from Model 2 are the same. Given that the book-to-market ratio is basically the inverse of the enterprise value scaled by book equity, a negative coefficient for book-to-market is in line with the positive coefficient for the enterprise value in Model 1. This finding highlights that scaling variables does not alter the observed relationship between future earnings and the predictor variables.

Interestingly, the R-squared estimates for the Fama and French model are significantly lower and vary between 13% and 39% (compared to 79% to 88% for Model 1). The effect is a consequence of using scaled variables for the regression. Ultimately, the large R-squared from Model 1 captures that large firms have high levels of net income, while small firms are associated with low levels. Excluding the size component from the variables, reduces the explained variation of future earnings significantly. This effect is even more important for two- and three year-ahead forecasts. While for Model 1 the R-squared in period $t + 3$ compared to $t + 1$ decreases by less than 10% (from 88% to 79%), R-squared estimates from Model 2 decrease by two-third from 39% to 13%. The evidence shows that current realizations of the predictor variables explain much of the variation in next-periods return on equity. Their explanatory power for the profitability in later periods is, however, considerably lower. Nevertheless, a model that predicts on average approximately 25% of the variation in one-, two-, and three-year ahead return on equity is supporting evidence for the quality of earnings prediction models.

Finally, Panel C of Table III.2 shows the results for the model of Abarbanell and Bushee (1997). The results document that the autocorrelation term and the change in CapEx, inventory, and labor force show a consistently significant relation to future realized return on equity for at least 2 periods. The signs of the coefficients indicate that capital expenditures below the industry average as well as a reduction in labor force increase future return on equity, whereas inventory investments that exceed the change in revenues decrease future earnings. The average number of observations per annual regression is significantly lower for the Abarbanell and Bushee model. The reason is that the variable calculation for this model is much more demanding which results in a significant reduction of the sample size.[65] The average R-squared is also lower, but still the model explains about 19% of the variation in return on equity over the following three years. For the one- and three-year ahead profitability I again obtain the sharp decline in R-squared from 33% to 9%.

Selection of predictor variables. In the following, I run an analysis to identify predictor variables that explain a significant part of the variation in future return on equity. My analysis includes all variables from Models 2 and 3. I use the scaled variables from Model 2 rather than their unscaled counterparts from Model 1, since the purpose of the analysis is the identification of variables for my VAR-based forecasting model. The VAR approach requires that all state variables are stationary to guarantee that forecasts converge over time. Therefore, my analysis focuses on the return on equity rather than the level of earnings and excludes the level variables from Model 1. I also add a firm's stock return and P/E ratio as predictor variables. Vuolteenaho (2002) and Fama and French (2006a) find that stock returns significantly impact future return on equity. Moreover, Ou and Penman (1989a) document a significant relation between the P/E ratio and future earnings.

Removing less relevant predictors is required for the portfolio-level VAR estimation. According to equation (III.5) for a VAR model with K state variables $K(K+1)$ coefficient estimates need to be obtained. To consistently estimate the set of coefficients a sufficient number of observations is required. Hence, including too many predictor variables introduces estimation problems for the portfolio-level VAR as for small portfolios a consistent estimation of the coefficients cannot be guaranteed.

I run forward stepwise regressions to select variables (see Hastie, Tibshirani, and Friedman, 2001) and apply the incremental adjusted R-squared as selection criterion. I use adjusted R-squared to account for the increasing number of explanatory variables in each step. The procedure results in a selection of predictors based on

[65] The variables capture the change relative to the average value over the preceding two years and require more lags, which reduces the data set.

their explanatory power for variation in future earnings. In the first step, I run annual cross-sectional regressions of one-year ahead return on equity separately on each of the predictor variables and select the variable with the highest average (adjusted) R-squared from these regressions. In the second step, I repeat the annual cross-sectional regressions but change the right-hand side such that it includes the predictor identified in step 1 plus each of the remaining variables separately (right-hand side now includes two variables). I now select the variable with the highest incremental R-squared (additional R-squared that adds to the R-squared from step 1) and add it to the set of selected right-hand side variables. I repeat this exercise until all predictors are selected. Table 3 shows the results of the analysis. Each line of the table corresponds to one step in the analysis. I display the incremental R-squareds in column (17).

[Insert Table III.3 here.]

Line (1) in Table III.3 indicates that the current return on equity (*roe*) explains most of the variation in one-year ahead return on equity when each of the predictors is considered separately. The R-squared equals 33.7% and confirms the evidence from Table III.2 documenting the high significance of the autocorrelation term. Comparing the R-squared estimates from step 2 (line (2)) shows that the maximum R-squared is obtained for the regression that includes current return on equity together with stock returns (*ret*). The R-squared increases by 5.2% so that after adding the return to the set of independent variables 38.9% of the variation in future realized earnings is explained. I continue this exercise and find that the book-to-market ratio (*btm*) and the dividend yield (*dy*) increase the R-squared by another 1.5% and 0.8%, respectively. Beyond step (4), none of the predictors raises the R-squared by more than 0.5%. Moreover, I find that the sum of incremental R-squareds from the variables following the dividend yield in line(4) is only 1.2% (excluding variables from lines (14)-(16)). The changes in inventory, accounts receivable, and S&A even reduce the R-squared. The reason is that the availability of these variables is much lower. The regressions that account for these variables show a reduced sample size and are associated with lower R-squareds.[66]

I repeat the analysis but replace the one-year ahead with the two- and three-year ahead return on equity as dependent variable (results not tabulated). My findings are generally consistent to this change. The variables selected in steps (1)-(4) always include current return on equity, stock return and dividend yield. Only for the three-year ahead return on equity the capital expenditures signal (*capx*) is selected in step 4 rather than the book-to-market ratio that drops to the 5th step of the selection procedure. With 0.1%, the incremental R-squared difference between the two variables is, however, marginal.

I also experiment with a backward selection of variables using the Bayesian information criterion (BIC) (see Frank and Goyal, 2009). In principle, both approaches yield comparable results with respect to the ranking of predictor variables (results not tabulated). A selection of predictors based on the information criterion, however, identifies eight variables to be included in the model.[67] This selection requires the estimation of 72 coefficients for each portfolio-year. Since the average portfolio contains 82 observations, a consistent estimation of the portfolio-level VAR coefficients could not be obtained for a large fraction of the sample. Hence, I stick to the results of my forward stepwise selection analysis and select the earnings forecasting model with the reduced number of predictors including the current return on equity, stock returns, the book-to-market ratio, and the dividend yield (reduced form model).

Properties of VAR-based forecasting models. Similar to the previous analysis of existing earnings forecasting models, I now estimate the reduced form earnings

[66]Using a constant sample with full data for all financial signals reduces my sample by 28,699 observations (32%). I also run the analysis for the constant sample and find that that my results are robust to the choice of the sample.

[67]The minimum BIC value is obtained for the model that includes the current return on equity, stock return, book-to-market ratio, dividend yield, dividend dummy, negative earnings dummy, scaled accruals, and size.

forecasting model. The new model has the benefit that it induces low data requirements as it only requires data on net income, book equity, returns, market capitalization (price and shares outstanding), and total dividends. The data is easily available from CRSP-CompuStat for a large universe of firms, which minimizes concerns about data coverage.

I first estimate the model with the standard approach from Models 1 to 3 that runs rolling-window pooled cross-sectional regressions of one-, two-, and three-year ahead earnings on the four predictor variables (Model 4). I subsequently use rolling-window regressions to estimate the reduced form model using the pooled VAR approach (Model 5) and the portfolio-level VAR approach (Model 6) described in Section 2.2.

[Insert Table III.4 here.]

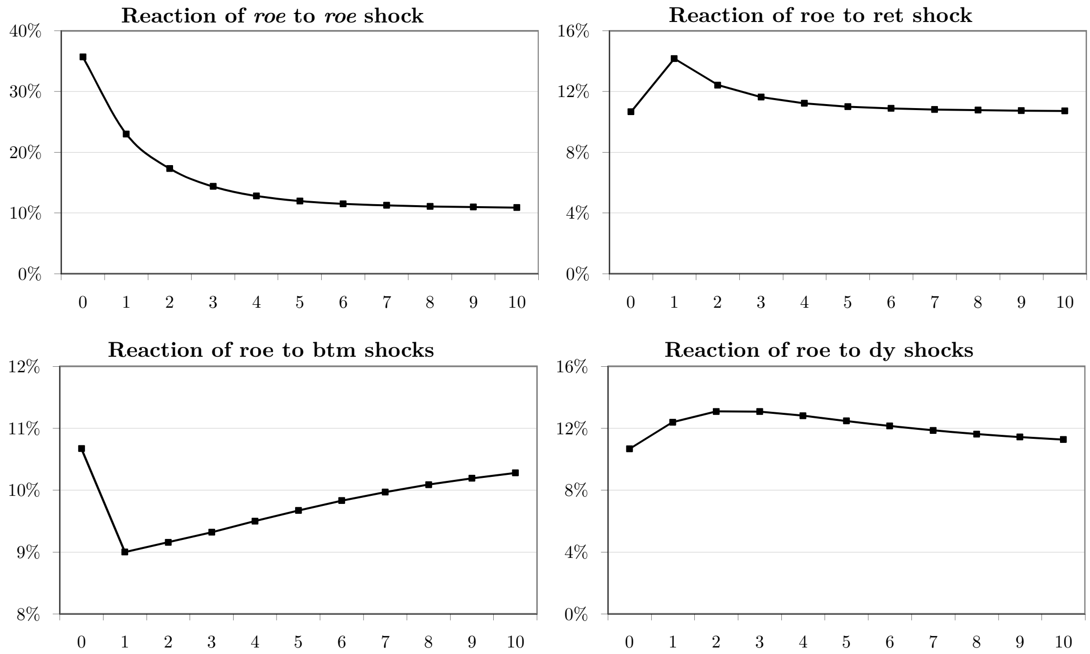
In Table 4 coefficients and R-squareds equal the average estimates from rolling-window regressions for Models 4 and 5. The t-statistics are calculated from time-series standard errors. For the portfolio-level VAR (Model 6) I include univariate statistics highlighting the distribution of VAR coefficients across portfolios.

Panel A of Table III.4 indicates that all of the four identified variables explain a significant part of the variation in one-, two-, and three-year ahead earnings. The sign of the predictor variables is consistent for each future return on equity. While a high current return and dividend yield imply a high future return on equity, a high book-to-market ratio forecasts a low profitability.

Panel B of Table III.4 shows the coefficient matrix $\mathbf{\Gamma}$ and the intercept vector ϕ for the reduced form model obtained from the pooled VAR approach. The results indicate that all lagged variables explain a significant portion of the variation in current return on equity. The signs of the coefficients for the return on equity equation are in line with the effects observed for Model 4. With 41.9% the R-squared for the return on equity equation slightly exceeds the R-squared from the standard approach. Looking at the cross-correlations, I find that – despite the effect of lagged return on equity and returns on the book-to-market ratio – all correlations are highly significant at the 1%

Figure III.1: Impulse response functions – Return on equity

This figure plots the impulse response function for the return on equity. The upper left (right) figure shows the reactions of return on equity from a one standard deviation shock to return on equity (stock return) in $t = 0$. The lower left (right) figure highlights the reactions for a one standard deviation shock to the book-to-market ratio (dividend yield) in $t = 0$.



level. Using only the return on equity equation would disregard the cross-dependence of the variables when forecasting expected future return on equity.

Figure III.1 presents the impulse response functions of return on equity for the first ten periods in response to a single positive, one standard deviation shock to return on equity (upper left), returns (upper right), the book-to-market ratio (lower left), and the dividend yield (lower right). I observe that the processes converge relatively fast and are close to their original values after about 4 to 6 periods after the arrival of the shock if no further shocks arrive. Shocks to the book-to-market ratio and the dividend yield are more persistent though. Panel B of Table III.4 indicates autocorrelation coefficients of 0.755 and 0.719 for the book-to-market ratio and the dividend yield, respectively. The values indicate that shocks to these variables are persistent and carry over on the return on equity over several periods.

Panel C of Table III.4 shows univariate statistics for the 1,080 portfolio-year estimates of the coefficient matrix $\mathbf{\Gamma}_i$. The mean estimates (column (1)) of the four state variable equations are in line with the pooled estimates from Panel B. More interestingly, the standard deviation of the coefficients (column (2)) and the quartile range (columns (3) and (4)) indicate a considerable variation of estimates across portfolio-years. I also assess to what extent the numbers result from variation across time or across portfolios (results not tabulated). The annual coefficient estimates for the portfolios show that most of the variation is indeed due to variation across portfolios rather than variation over time.

In addition, I report univariate statistics for the portfolio-level long-term rates of the four state variables at the bottom of Panel C. For each portfolio-year the four state variables are expected to converge against this long-term rate over time. The long-term rate for the return on equity, for example, indicates that it converges to a rate of 10.7% for the median portfolio-year. More importantly, with a standard deviation of 6.35% long-term return on equity shows a considerable variation across portfolios. The fact that the persistence and long-term rates of the processes vary across portfolios, emphasizes the use of the portfolio-level VAR approach to capture the differences in portfolio-specific long-term growth dynamics. Furthermore, the variation indicates that a uniform (terminal) residual income growth rate of 3% for all firms is a poor approximation. To see this consider the following example: Regard a firm with a constant return on equity that exceeds its cost of equity in each period. For this firm residual income growth equals the return on equity times the plow-back rate. Considering the average long-term return on equity of approximately 10% and a plow-back rate of about 0.65 (see Table III.1 Panel B) leads to a residual income growth of 6.5% constant over all periods. Accounting for the fact that there is return on equity (and plow-back rate) variation across firms in the medium- and long-term (quartile range for long-term return on equity equals 4.9%), residual income growth should also vary considerably.

4.2 Evaluation of earnings forecasting models

The starting point for my evaluation of the six earnings forecasting models discussed in the previous section is the difference $\delta^M_{i,t+\tau} \equiv roe_{i,t+\tau} - \mathrm{E}_t\left[roe^M_{i,t+\tau}\right]$ (for $\tau = 1,\ 2,\ 3$) between the one-, two-, and three-year ahead return on equity $roe_{i,t+\tau}$ and the earnings forecast $\mathrm{E}_t\left[roe^M_{i,t+\tau}\right]$ estimated by model M.[68] Table III.5 reports the results for bias, accuracy and explainability.

[Insert Table III.5 about here.]

I define the bias as the sample mean or median of $\delta^M_{i,t+\tau}$ and report the results in columns (1) and (2) of Table III.5. Panel A shows the results for the existing models by Hou, Van Dijk, and Zhang, Fama and French, and Abarbanell and Bushee (Models 1-3). I find that, compared to Models 2 and 3, the model estimates of Hou, Van Dijk, and Zhang contain a considerable bias. The negative mean (median) bias indicates that earnings forecasts from this model are too optimistic and exceed the corresponding realizations by 7.84% (1.97%) on average. In contrast, the bias for the models that include the scaled earnings variable is below 1% in absolute value, which seems acceptably small.

A similar picture can be obtained for the accuracy of the models. Accuracy refers to the typical error $\delta^M_{i,t+\tau}$ of the earnings forecast. I report the median absolute value and the standard deviation of $\delta^M_{i,t+\tau}$ in columns (3) and (4) of Table III.5. Both measures of accuracy are considerably worse for Model 1, indicating a lower precision of earnings forecasts obtained from this model. In particular, the standard deviation of 26% by far exceeds the standard deviation of Models 2 and 3.

Finally, I analyze the explainability of the models by running annual cross-sectional regressions of one-, two-, and three-year ahead earnings on the respective forecast. Explainability is an important criterion as for an unbiased forecast the

[68] Hou, Van Dijk, and Zhang define the bias as the difference between realized and forecasted net income scaled by market capitalization. Applying their measure does not impact my results with respect to the obtained ranking of earnings forecasting models.

slope coefficient should not deviate from 1. I report the average slope coefficient as well as the average (adjusted) R-squared from these regressions in columns (5) and (6). I also test for the difference of the time-series slope coefficients from 1. My results show that estimates from Model 1 are heavily distorted. With an average value of 0.271 the coefficient is significantly smaller than 1 and comes along with a low R-squared of 8.15% on average only. Contrary to Model 1, the explainability for Models 2 and 3 is good. The average time-series coefficients do not differ significantly from 1 and the models obtain R-squared estimates of 24.37% and 18.07% on average.

The weak performance of Model 1 is caused by the conversion of net income forecasts into return on equity forecast. To obtain the return on equity forecasts assessed in Table III.5, I scale the net income forecasts by the book equity of the previous period. This conversion requires book equity forecasts that I obtain from the earnings forecasts and the plowback rate assuming clean-surplus accounting. Hence, return on equity forecasts from Model 1 combine the forecasts for two variables: net income and book equity. Compared to the direct return on equity forecasts from Models 2 and 3, this procedure creates additional noise and leads to the observed deviations for Model 1.[69]

Panel B of Table 5 repeats the evaluation criteria for the reduced form model estimated using the standard approach (Model 4), the pooled VAR approach (Model 5), and the portfolio-level VAR approach (Model 6). Using the reduced model with four state variables under the standard estimation approach leads to results that are comparable to those of Models 2 and 3. The slope coefficient for Model 4 is significantly different from 1 but the deviation is economically small. At the same time, I observe a slight improvement in average R-squared (25.75%) for Model 4.

Looking at the performance of the pooled VAR approach (Model 5), I find that the results are significantly worse compared to those from Models 2-4. While bias

[69]Since Hou, Van Dijk, and Zhang (2010) use net income rather than return on equity to estimate the ICC, their estimation does not suffer from the noise created by scaling forecasts.

and accuracy are only slightly worse, the slope coefficient is significantly distorted. In particular, the forecasts for period $t+3$ show a slope coefficient of 1.416 compared to 1.070 for $t+1$. The reason for the distortion is that according to the pooled VAR, the persistence and long-term rate for return on equity only vary over time but are similar for each firm within one year. This uniform treatment of all firms, however, leads to significant deviations for firms with growth dynamics that differ from those implied by pooled VAR coefficients. The effect can be observed even for the short-horizon as the overall persistence of the processes is commonly low and deviations in long-term rates materialize after few periods.

Turning to the results for the portfolio-level VAR (Model 6), I find a high explainability of the forecasts for future return on equity. The slope coefficient is close to one for each forecast period and only in one case marginally significant. The R-squareds of 43.7%, 22.1%, and 13.6% indicate that the reduced form model estimated using the portfolio-level VAR approach has the greatest explanatory power for one-, two-, and three-year ahead return on equity. I also test for the significance of the differences in R-squared between Model 6 and Models 1-5. I find that the R-squareds for the portfolio-level VAR-based forecasting model significantly exceed the estimates from all other models at least on the 5%-level.[70] The accuracy of Model 6 is in line with the other models, while results for the bias imply that forecasts obtained from the portfolio-level VAR are on average optimistic. However, looking at the median bias I find that the optimism of the model is not larger than the pessimism obtained for the other forecasting models. The evidence shows that over the short-horizon the portfolio-level VAR model significantly improves on existing models. In particular, the explanatory power of my model for variation in future earnings significantly exceeds that of existing approaches. To the extent that earnings realizations proxy for expectations in the

[70]For Models 2 and 4 the R-squared for the three-year ahead return on equity is higher than that of the portfolio-level VAR, but statistically insignificant. I test for the significance of the difference in the (time-series) R-squareds using a non-parametric Wilcoxon test.

short-run, my model promises to deliver superior short-term earnings forecasts. The superiority of my model is further promoted by the fact that I compare out-of-sample forecasts from the VAR model with in-sample forecasts from existing approaches.

Unlike existing approaches, my VAR model allows to generate long-term earnings forecasts. Assessing the quality of long-term forecasts is, however, problematic due to the missing benchmark problem. While the approximation of earnings expectations by realizations is justified in the short-run, this is unlikely the case over the medium- and long-term. My portfolio-level VAR model implies that earnings in the long-run mean-revert to the median return on equity of the firm's respective portfolio over the last ten years. Empirical evidence shows that realized return on equity is mean-reverting over time (see Brooks and Buckmaster, 1976; Lipe and Kormendi, 1994) so that the modeling of forecasts is consistent with this property. To what extent the modeling approach, however, captures long-term market expectations is still an open issue that I leave to future research.

Like Hou, Van Dijk, and Zhang (2010), I also assess the earnings response coefficients (ERC) associated with the model-based earnings forecasts (results not tabulated). I compute the ERCs by running annual cross-sectional regressions of one-, two-, and three-year ahead stock returns on the forecast error $\delta^{M}_{i,t+\tau}$ ($\tau = 1,\ 2,\ 3$) of model M (unexpected earnings).[71] My evidence is in line with the findings obtained by Hou, Van Dijk, and Zhang (2010). Most importantly, I find that my portfolio-level VAR approach slightly improves on all other models as it provides on average higher coefficient estimates and R-squareds.

All in all, I conclude from my evaluation that forecasts from a portfolio-level VAR estimation of the identified reduced form model outperform forecasts of existing models as measure for the market's earnings expectations in the short-run ($t + 1$ to $t + 3$). Moreover, unlike existing approaches, the new model also allows to generate

[71] I standardize the unexpected earnings to have unit variance for each cross-section to make the ERCs comparable between models.

long-term earnings forecasts. Forecasts generated by the portfolio-level VAR should, therefore, be preferred to existing model-based forecasts when estimating the implied cost of equity capital.

5 Evidence from long-horizon ICC

In the previous section I diagnose the strengths and deficiencies of earnings forecasting models. In this section I apply the portfolio-level VAR approach to generate long-term earnings forecasts and use the forecasts to estimate the implied cost of capital. I analyze the sensitivity and univariate statistics of expected returns and risk premia obtained from ICC in the next section and defer the assessment of the risk-factor related evidence of expected returns to Section 5.2.

5.1 ICC sensitivity and expected return evidence

As a staring point, I assess the sensitivity of ICC estimates with respect to changes in the terminal growth rate assumption and the length of the detailed planning period. I derive implied cost of equity capital for the seven ICC methods described in Section 2.3. Earnings forecasts for the detailed planning period of each method are obtained from the portfolio-level VAR. Following the detailed planning period each method applies a terminal value approximation using a terminal growth assumption of $g_{ae} = 0\%,\ 2.5\%,$ and 5%. I report the average equally- and value weighted ICC estimates in Table III.6.

[Insert Table III.6 here.]

Table III.6 documents the variation of ICC estimates due to changes in the growth rate or the horizon structure of the methods. Note that the method of ETSS is not affected by the growth rate assumption since the method estimates the ICC and terminal growth simultaneously. For a medium terminal growth rate of $g_{ae} = 2.5\%$ the ICC methods obtain value-weighted estimates between 9.2% (GLS) and 11.6%

(ETSS). The average (value-weighted) implied cost of capital across all seven methods is 10.7% and 11.1% for a terminal growth rate of 0% and 5%, respectively. Of course, this is a mechanical outcome as the higher numerator arising from a higher growth rate translates into an increased ICC to equate the current price.

Nevertheless, the last two columns (numbers in bold shape) show that the seven ICC methods are differently affected by the changed growth assumption. While ETSS, which computes an endogenous growth rate is not affected at all, ICC estimates obtained from GLS change by about 1% depending on the assumption of either 0% or 5% terminal growth. I later show that a 1% change in the ICC can result in considerable price changes. For the long horizon ICC methods ($r_{20},\ r_{30},\ r_{40},$ and r_{50}), I find that – as expected – the terminal growth sensitivity decreases with the length of the detailed planning period. When going from 0% to 5% growth, the value-weighted ICC from the method with the 50-year forecast horizon only changes by 0.2% and hence 50 basis points less than the change for 20-year horizon method. The numbers indicate that increasing the length of the detailed planning period and shifting the terminal value further into the future effectively reduces the sensitivity of ICC estimates to changes in the terminal growth assumption.

The last two rows of Table III.6 highlight how the length of the detailed planning period affects the average ICC estimates. I compute the difference for the longest-horizon method r_{50} on the one hand and the "short" horizon method of GLS (12-year horizon) and the 40-year horizon method r_{40} on the other hand. The numbers show that ICC estimates converge with the length of the forecast horizon. While implied cost of capital between the 50-year horizon method (r_{50}) and GLS differ by 1.7% for the scenario with 2.5% terminal growth, the difference is only 0.2% for the 40-year horizon method (r_{40}). In principle, one could extent the detailed planning period of the methods to the point where convergence of ICC estimates is achieved and no further terminal value approximation of the infinite horizon is required. However, the difference between ICC estimates from 40- and 50-year horizon method of only

0.2% already indicates that the long-horizon ICC method with 50 years detailed planning period almost achieves convergence of ICC estimates.

Another interesting finding emerges from the differences between average ICC estimates for methods with long and short horizon. The 20-year horizon method, for example, utilizes empirical residual income growth based on the earnings forecasts from the VAR model over the detailed planning period from $t+1$ to $t+20$. In the following residual income is assumed to grow at a rate g_{ae} in perpetuity. The long-horizon ICC method r_{50}, in contrast, utilizes empirical residual growth over the 50-year horizon and applies a similar terminal growth assumption from period $t+51$ onwards. Since both methods rely on the same earnings forecasts, they only differ with respect to residual income growth between periods $t+21$ to $t+50$. The positive difference between ICC estimates of the 50- and 20-year horizon method shows that on average the empirical residual income growth from $t+21$ to $t+50$ utilized by r_{50} exceeds the assumed terminal growth rate g_{ae} utilized by r_{20}.

Overall, the evidence indicates that on average even in the medium- and long-term, there is still considerable growth beyond the terminal growth rate commonly applied by existing short-horizon ICC methods. It, therefore, seems reasonable to apply a long-horizon residual income method when estimating the implied cost of equity capital. The method utilizes the empirically calibrated earnings dynamics over a long-period of time and can therefore effectively reduce the sensitivity of ICC estimates to changes in the exogenous terminal growth assumption.

In the following, I assess the properties of expected returns obtained from the long-horizon implied cost of capital method with a detailed planning period of $T = 50$ years and terminal growth $g_{ae} = 0\%$. Table III.7 shows univariate statistics for annual expected and realized returns.

[Insert Table III.7 here.]

Panel A of Table III.7 shows that the average equally- and value-weighted expected return (columns (1) and (2)) for the sample period 1970-2008 equal 10% and 11.3%, respectively, implying a risk premium between 4.4% and 5.7%. Over the same time, realized returns are about 6%, which indicates that firms on average did not earn their expected returns. The value-weighted excess return over the expected return amounts -5.3%.

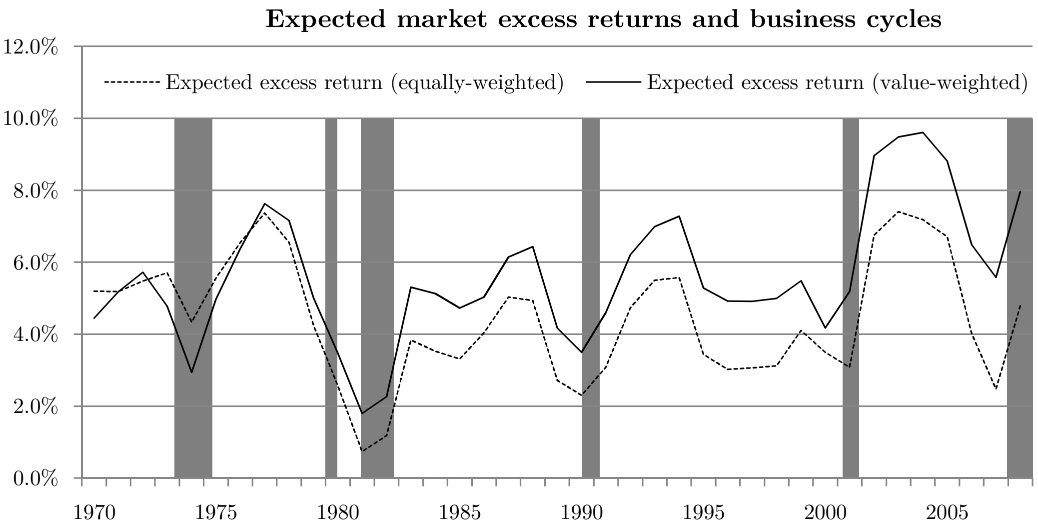
The standard deviation (column (3)) for expected and realized returns highlights considerable differences. While annual realized returns are highly volatile (standard deviation of about 44%), expected returns vary in a narrow range with a standard deviation of only 3.4%.[72] However, the effects on firm-value that can arise from these rather small changes in expected returns are huge. I calculate the value-impact caused by a 1% decline of the expected return for a medium-sized firm in 2008 and find that ceteris paribus this decline is associated with a realized return of 34%. The number highlights that small changes in firms' expected return can cause considerable price effects and contribute substantially to the observed variation in realized returns. Moreover, the numbers emphasize the relevance of the differences in average ICC estimates obtained from Table III.6.

Panels B and C of Table III.7 break down the sample into an early and a late subperiod. Overall, results for expected returns do not vary much across subperiods. Realized returns are, however, smaller for the period 1990-2008. Accordingly, over this period the excess return over the risk-free rate is even slightly negative. Realized returns during this time fall short of expected returns by 7.5% on average (value-weighted).

Figure III.2 shows the time-series variation of the equally- and value-weighted expected market excess returns (market risk premium) over the sample period. First of all, the market risk premium is positive in each year, which is not the case for risk premia obtained from historical realized returns (e.g., see Elton, 1999), but should be a necessary condition for a valid expected return measure. Furthermore, expected market excess returns show a considerable variation with a minimum of about 1% obtained in the early 80s and a maximum of 9% reached in the early years of this century.

[72] The results are in line with the standard deviations for the ICC estimates reported in Easton and Monahan (2005).

Figure III.2: Time-series variation of expected market excess returns
This figure shows the time-series variation of equally-weighted (dotted line) and value-weighted (solid line) expected market excess returns (market risk premium) from 1970 to 2008. Annual expected market excess returns are calculated from estimates of the long-horizon ICC method for all sample firms minus the annualized return on monthly T-Bills from Ibbotson. The gray-shaded areas highlight periods of economic contraction obtained from the National Bureau of Economic Research (NBER).



The gray-shaded areas show business cycle contraction periods identified by the National Bureau of Economic Research (NBER).[73] Accordingly, the periods between the gray bars are times of economic expansion. Interestingly, the market risk premium shows a time-series behavior that seems to be consistently related to the economic business cycles. Figure III.2 documents that the risk premium always obtains its local minimum close to or during periods of economic contraction. The subsequent increase of the risk premium is accompanied by a period of economic expansion. However, in each of the boom periods, the risk premium only increases in the first half of the expansion cycle. Thereafter, the risk premium starts declining until it again obtains its minimum shortly before the contraction period sets in.

An explanation for the observed coincidence might be that stock or financial markets lead product markets. Shortly before or during periods of economic contraction

[73]The NBER defines a recession as a significant decline in economic activity spread across the economy and lasting more than a few months. According to NBER, a recession is normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales.

the market risk premium and hence firms' financing costs are low on average. The low financing costs enable firms to finance (new) investment projects that have been unaffordable beforehand. To the extent that increased investment activity promotes future product market and economic activity, it is the opener for the subsequent expansion period. Then approximately in the middle of the expansion cycle expected market excess returns reach their maximum. Following the financing cost rationale, firms might be forced to reduce their investment activity which harms future product market and economic activity.

I do not further comment on this point but leave the investigation of the connection between market excess returns and economic activity for future research. This also applies to the question concerning the identification of factors that drive the observed variation of the risk premium, which might even be more important.

5.2 Expected returns and common risk factors

I now turn the focus to the analysis of the relationship between expected returns and firm characteristics. In particular, I assess to what extent expected returns covary with the two common factors that have been found to explain the variation in realized returns, i.e. size and the book-to-market ratio. Other papers also assess this relationship for different ICC methods and found mixed evidence (e.g., see Botosan and Plumlee, 2005; Brav, Lehavy, and Michaely, 2005). Some ICC estimates show a relation consistent with that for realized returns while others do not. Interestingly, this evidence is often used to judge the quality of ICC estimates, following the implicit assumption that the observed relation between the common factors and realized returns also holds for expected returns. Ample evidence, however, implies that this assumption is highly debatable (see Elton, 1999; Lundblad, 2007; Pastor, Sinha, and Swaminathan, 2008). A consistent ICC-based measure for expected returns might simply deviate from the realized return evidence because the underlying expected return itself shows a different relation.

The long-horizon ICC method that I propose in this chapter addresses many of the concerns that have been raised against existing ICC approaches. ICC estimates from this method are promising to deliver a more consistent measure for expected returns. It is, therefore, interesting to assess if and how the new expected return measure is affected by the two common firm characteristics.[74] Table III.8 shows average equally- and value-weighted (bold) returns for 25 portfolios sorted on book-to-market and size. The last column (line) documents the difference between the high and low book-to-market (large and small size) portfolios.

[Insert Table 8 here.]

Panel A of Table III.8 contains the results for realized excess returns. The difference between the high and low book-to-market portfolios supports the value premium associated with realized returns. Value firms (high book-to-market) on average earn significantly higher returns than growth firms (low book-to-market) across all size portfolios. Different from the evidence of Fama and French (1992), the univariate statistics do not show a negative size effect.[75] Evidence for the lowest book-to-market portfolio even indicates a positive size effect.

I repeat the analysis for expected returns in Panel B of Table III.8. The positive return differences between the large and small firm portfolios indicate a significant and economically large size effect for expected returns. This finding contradicts the negative size premium for realized returns observed in the literature. The average value-weighted expected return premium for large stocks equals 1.8% (2.4% equally-weighted). The return difference for book-to-market firms indicates a non-monotonic relationship. For small firms the expected return difference between high and low book-to-market portfolios is significantly positive and indicates a value premium. For large firms, however, there seems to be a value discount.

[74]I provide a robustness check that analyzes whether the observed effects also apply to ICC estimates from different methods later in the chapter.

[75]Note that Fama and French (1992) use monthly returns, while my results rely upon annual returns.

To further assess the univariate relationships obtained from Table III.8, I run multivariate annual cross-sectional Fama-McBeth regressions of annual realized and expected excess returns on (post-)beta, size, and the book-to-market ratio. Table III.9 reports the regression coefficients and t-statistics (in brackets).

[Insert Table 9 here.]

Concerning the beta factor the results verify earlier findings of Fama and French (1992) that beta does not explain the cross-section of stock returns for more recent periods. The coefficient for beta is not significant for both realized and expected excess returns. For the size and book-to-market effects, the multivariate regressions support the univariate results. I find a positive and significant relation between realized excess returns and the book-to-market ratio and a negative but insignificant relation to size. In contrast, expected returns show a highly significant positive size effect. Notwithstanding the non-monotonic book-to-market effect observed in Table III.8, the coefficient for this factor is positive and significant. This result is due to the fact that small firms for which the effect is positive make up a larger fraction of the data set. All results also hold separately for the early and late subperiod.

In the following, I briefly review possible explanations for the observed correlation between expected returns and firm characteristics. However, given the scope of my analysis, I leave the detailed analysis for future research. There are mainly three explanations that have been put forward to explain the observed relation between the common risk-factors and realized returns: liquidity, opacity, and equity duration.

Based on the finding that liquidity is a priced factor for realized returns (see Pastor and Stambaugh, 2003), the liquidity explanation states that illiquid stocks should trade at a premium compared to liquid stocks. However, empirical evidence suggests that the large firms are commonly more liquid than small firms and contradicts the size-factor evidence for expected returns. Liquidity could, however, play a role for the obtained value premium. To the extent that glamor stocks (low book-to-market) are more frequently traded than value stocks, investors might demand a liquidity premium for holding value stocks implying higher expected returns for value stocks. Nevertheless, this complexity does not explain the observed non-monotonicity in the value premium.

If investors regard large firms as more opaque than small firms, the opacity argument would qualify as an explanation for the observed size effect. Large firms overall seem to be more public but the question is whether publicity reduces opaqueness. Ultimately, it is the quality and relevance of the published information that is important. To the extent that large firms have even more possibilities to camouflage negative information, large firms might indeed be more opaque.

Finally, Dechow, Sloan, and Soliman (2004) find that the book-to-market effect for realized returns stems from variation in firms equity duration. They present evidence that low duration firms (high book-to-market) trade at a premium relative to high duration firms (low book-to-market). In principle, this effect might also play a role for expected returns, even though it is not completely clear, why investors demand a premium for holding stocks with a low equity duration. Dechow, Sloan, and Soliman (2004) argue that investors might have preferences for holding long duration stocks and require a premium for holding short-duration stocks, accordingly. The underlying rationale for such a preference, however, remains unclear.

6 Robustness checks

In this section I check to what extent the results I report in sections 4 and 5 are robust to alternative specifications of the earnings forecasting model or ICC method. First, I assess how the evaluation of earnings forecasting models from Table III.5 is affected by changes in the underlying methodology. Second, I review how the changes impact the expected return evidence from the previous section.

Robustness of VAR-based earnings forecasting. Table III.10 summarizes the results for four different robustness checks (Panel B to E). For convenience, I repeat the corresponding results for the portfolio-level VAR model in Panel A.

[Insert Table III.10 here.]

In Panel B of Table III.10 I show results for the earnings forecasting model of Fama and French, when applied using the pooled VAR approach. I find that this model only improves on the portfolio-level VAR model with respect to the mean bias. For all other categories, the baseline model obtains a better performance. The difference in R-squared estimates between the models are significant at the 1%-level.

Panel C of Table III.10 contains estimates for an alternative portfolio-level VAR model, where I define portfolios based on the industry classification (2-digit SIC). Overall, the results for the alternative portfolio formation are very similar. The differences in R-squared for one- and two-year ahead earnings are not significant. For the three-year ahead earnings the forecasts from the baseline model have significantly higher explanatory power.

Panel D and E of Table III.10 include specifications of the portfolio-level VAR model, where I replace the intercept vector ϕ_i^* that I have utilized so far.[76] I use the estimated intercepts from the portfolio-level VAR model ϕ_i in Panel D and find that the bias, accuracy, and explainability slightly improve for this specification. R-squared estimates are significantly larger at the 1%-level. The routine that computes the ICC estimates, however, more frequently obtains invalid solutions based on the forecasts from this model. The ICC sample size resulting from the VAR model with empirical intercepts is, therefore, 7.3% lower (more than 5,000 firm-year observations less). I therefore stick to the VAR model that utilizes the intercept vector ϕ_i^* as my baseline model.

Panel E utilizes adjusted intercepts $\phi_i^{\#}$ that imply a convergence of the VAR state variables against the historical 25% quartile rather than the median. The

[76]Recall that the intercept vector ϕ_i^* provides that long-term forecasts of the state variables converge against their median values computed over the estimation period of the VAR. Changing the intercept vector implies different long-term rates for the state variables.

latter scenario should account for concerns that using historical medians as long-term rates might be too optimistic. Panel E documents that this adjusted VAR model produces significantly higher forecast deviations as documented by all three evaluation criteria. This finding is expected since the use of the low long-term rates incorporates deviations from the empirically measured average rates for the state variables by construction.

Robustness of expected return evidence. I diagnose the robustness of ICC estimates to changes in the earnings forecasting model and the ICC method applied. Table III.11 summarizes results for expected excess returns and standard deviations (Panel A) and for the size- and book-to-market related evidence (Panel B and C) from Tables III.8 and III.9. For convenience, I repeat the results for the baseline specification in column (1).

[Insert Table III.11 here.]

Column (2) reports the ICC evidence obtained for the earnings forecasting model that uses the estimated intercepts ϕ_i. The results are robust to those obtained from my baseline VAR model. The average excess returns are slightly lower, while the standard deviation increases by 50 basis points. Also I find the significantly positive value premium and the non-monotonic book-to-market effect.

I report results for the model, where I use adjusted intercepts $\phi_i^{\#}$ (convergence of long-term rates against the historical 25% quartile) in column (3). As expected, the lower long-term rates for the return on equity imply lower average expected returns. The size effect evidence also holds for this low-growth specification. The non-monotonicity of the book-to-market premium persists, but the average positive value premium from Panel C is no longer significant.

In columns (4)-(6) I apply alternative methods to estimate the implied cost of capital. The methods include the combination that equally weights estimates from GLS and ETSS (column (4)) as well as estimates obtained from the two methods, separately (columns (5) and (6)). Using ICC estimates from ETSS and the combined method leads to comparable average expected excess returns. Estimates of GLS are lower consistent with previous evidence from Table III.6. The positive size premium obtained for the long-horizon ICC method persists for all alternative ICC estimates and is highly significant. Evidence for the book-to-market factor is mixed. For ETSS and the combined method I observe a consistently negative value effect from univariate (Panel B) and multivariate results (Panel C). In line with the evidence for realized returns, estimates from GLS document a significant and positive value premium. The non-monotonicity of the value effect cannot be obtained for any of the alternative ICC methods. The results indicate that the evidence concerning the book-to-market factor highly depends on the ICC estimates applied and that more research on the association between expected returns and this particular firm characteristic is required. The evidence concerning the size effect, in contrast, is robust to all alternative specifications and methods applied.

All in all, the evidence shows that my long-horizon ICC estimates are robust to alternative specifications of the earnings forecasting model. The portfolio-level VAR approach shows reasonable performance against various alternative models assessed in Tables III.5 and III.10. The input data generated from alternative specifications does not alter the main findings for my long-horizon ICC method.

7 Conclusions

In this chapter I present a new approach to generate long-term earnings forecasts from a vector autoregressive (VAR) model. I am the first to apply model-based earnings forecasting on the portfolio-level to account for differences of long-term growth dynamics across groups of firms. I test my model against other earnings forecasting models proposed in the literature and find that, in particular, the explanatory power of the model for variation in future earnings significantly outperforms existing approaches. Moreover, since the VAR model unlike the existing approaches allows to generate long-term earnings forecasts it should be the preferable model when it comes to measuring the market's earnings expectations.

I subsequently use long-term earnings forecasts obtained from the rolling-window portfolio VAR model to compute implied cost of capital from a long-horizon ICC method. The method utilizes firms' empirical growth dynamics over a long-horizon and therefore better captures the variation of growth rates across firms in the medium and long-run than a uniform terminal growth assumption. Furthermore, the long-horizon ICC method reduces the terminal value sensitivity of implied cost of capital estimates by shifting the terminal value to a future period, thereby making it less value-relevant. The method overcomes important issues associated with ICC estimation, so that implied cost of capital estimates derived from my approach promise to deliver a more consistent measure for expected returns.

In addition, I review some properties of the expected return measure obtained from long-horizon ICC estimates. I find that my measure for expected returns, while hardly related to realized returns, contains a significantly positive size effect. The effect is consistent throughout various specifications of my earnings forecasting model and contradicts the negative size effect that is commonly obtained for realized returns. For the book-to-market factor, I obtain on average a positive value premium, which is in line with evidence for realized returns. Breaking up the average effect, however, shows that the value effect is non-monotonic, resulting in a value premium for small firms and a value discount for large firms. Finding consistent explanations for the expected return effects is an interesting question for further research.

All my conclusions for the evaluation of earnings forecasting models rely on the underlying assumption that, in the short-run, future earnings realizations are on average an unbiased proxy for the market's earnings expectations. The assumption allows me to assess the performance of the models based on their ability to track future earnings realizations. Since earnings expectations, like return expectations, are unobservable, I follow the prior literature and apply the comparison based on short-term earnings realizations, which seem to be the best proxy available.

Moreover, I cannot present direct evidence for my conclusion that long-horizon ICC estimates promise to provide a better measure for expected returns. To the extent that my approach overcomes input data and methodological issues, estimates derived from this approach should be a more consistent proxy for return expectations. I do not follow the previous literature and evaluate ICC estimates based on realized return (see Easton and Monahan, 2005; Botosan and Plumlee, 2005; Botosan, Plumlee, and Wen, 2010). Following Elton (1999), the underlying assumption for the evaluation that return realizations are an unbiased estimator for earnings expectations is highly debatable. Developing expected return tests that do not rely on realized return correlations, e.g. the identification and testing of properties that characterize expected returns, is an important issue for future research.

Tables

Table III.1: Sample selection and summary statistics

This table shows the sample selection criteria and sample characteristics for the data set used in this chapter. Panel A lists the sample selection criteria applied to estimate earnings forecasting models and implied cost of equity capital (ICC). The final data set covers the time period 1970-2008. Panel B contains univariate statistics for selected financial variables that characterize the data set. For the payout ratio I only consider firm-years with a positive payout.

Panel A: Sample selection

Step	**Adjustment**	**Firm-year obs.**
(1)	CRSP-CompuStat Merged universe (1962 - 2009)	133,884
(2)	Drop financial institutions (SIC 6000-6999)	110,338
(3)	Variable availability for earnings forecasting models (1962-2009)	88,767
	Compute forecasting parameters for 27 annual portfolios from 1970-2009	
(4)	Delete observation pre-1970 observations	85,676
	Compute ICC using long-horizon RI model with 50 periods & g=0%	
(5)	Drop firms with no valid ICC estimate	80,550
(6)	Compute one-year ahead returns	73,438
	Final data set: period 1970-2008	**73,438**

Panel B: Sample characteristics

		Quartiles				
	Mean	**25%**	**50%**	**75%**	**SD**	**N**
Return	6.89%	-16.51%	8.35%	31.71%	44.26%	73,438
Return on equity	9.38%	4.45%	11.02%	17.49%	21.02%	73,438
Book-to-Market	0.84	0.38	0.66	1.10	0.66	73,438
Market capitalization	1,494.53	35.49	153.37	735.53	5,536.00	73,438
Leverage	24.73%	4.82%	19.43%	39.89%	22.28%	73,296
Sales growth	16.43%	1.48%	10.57%	22.48%	35.51%	73,438
Beta	1.12	0.68	1.07	1.48	0.65	73,438
Payout ratio	36.17%	19.03%	33.60%	51.42%	22.07%	43,556
Firm-years	11.24	3.00	8.00	15.00	9.87	6,533

Table III.2: Estimates for existing earnings forecasting models

This table shows regression results for three existing earnings prediction models that regress one-, two-, and three-year ahead earnings on selected predictor variables. Panel A documents the estimates for Model 1 by Hou, Van Dijk, and Zhang (2010) that uses a firm's level of net income as dependent earnings variable. Panel B contains the estimates for Model 2 by Fama and French (2006a), who apply a scaled version of Model 1, where the dependent variable is a firm's future return on equity. Panel C shows the results for Model 3, where I regress return on equity on a set of predictor variables motivated by Abarbanell and Bushee (1997). All models are estimated using rolling-window pooled cross-sectional regressions between 1970 and 2009 including data over the preceding ten years. t-values are shown in brackets.

Panel A: Model 1 – Hou et al. (2010)

Independent variable	**Intercept**	**Enterprise value**	**Total assets**	**Total Dividend**	**Dividend dummy**	**Net income**	**Neg. earnings dummy**	**Accruals**	**N**	**R^2**
Net income (t+1)	3.565	0.016	-0.005	0.132	-5.058	0.605	0.961	-0.029	19,272	87.7%
	[3.405]	[10.106]	[-2.534]	[2.740]	[-4.636]	[13.531]	[0.675]	[-1.080]		
Net income (t+2)	4.817	0.022	-0.003	0.111	-6.197	0.492	2.545	-0.037	18,012	82.1%
	[2.828]	[9.637]	[-0.908]	[1.574]	[-3.338]	[8.612]	[1.311]	[-1.151]		
Net income (t+3)	6.053	0.026	-0.001	0.028	-6.820	0.469	3.285	-0.037	16,870	78.5%
	[2.616]	[9.395]	[-0.275]	[0.302]	[-2.720]	[6.870]	[1.403]	[-0.995]		

Panel B: Model 2 – Fama & French (2006) model / Scaled Model 1

Independent variable	**Intercept**	**Book-to-market**	**Size**	**Dividend yield**	**Dividend dummy**	**Return on equity**	**Neg. earnings dummy**	**Accruals / Total assets**	**N**	**R^2**
Return on equity (t+1)	0.075	-0.044	0.000	0.319	-0.013	0.504	-0.020	-0.127	19,272	38.8%
	[11.474]	[-14.385]	[0.549]	[7.503]	[-4.450]	[24.999]	[-2.972]	[-6.007]		
Return on equity (t+2)	0.079	-0.031	0.000	0.463	-0.012	0.322	-0.014	-0.156	18,012	20.0%
	[9.444]	[-9.013]	[-0.269]	[8.208]	[-2.944]	[14.476]	[-1.780]	[-6.567]		
Return on equity (t+3)	0.070	-0.016	0.000	0.504	-0.010	0.256	-0.004	-0.159	16,870	13.0%
	[7.433]	[-4.369]	[-0.170]	[7.440]	[-2.112]	[10.480]	[-0.439]	[-6.371]		

Panel C: Model 3 – Ababarnell & Bushee (1997)

Independent variable	Intercept	Return on equity	Inventory	Accounts receivable	Gross margin	CapEx	S&A	Effective tax rate	Labor force	N	R^2
Return on equity (t+1)	0.041	0.569	-0.018	0.005	-0.008	0.004	-0.006	-0.041	0.012	13,167	32.5%
	[16.200]	[28.914]	[-3.354]	[0.840]	[-0.760]	[2.307]	[-0.564]	[-0.601]	[1.268]		
Return on equity (t+2)	0.062	0.389	-0.018	-0.004	0.010	0.008	0.014	-0.019	0.031	12,336	14.5%
	[19.137]	[16.984]	[-2.733]	[-0.517]	[0.967]	[4.257]	[1.239]	[-0.242]	[3.149]		
Return on equity (t+3)	0.070	0.309	-0.010	-0.008	0.021	0.009	0.024	-0.037	0.024	11,572	9.1%
	[19.428]	[12.182]	[-1.450]	[-1.182]	[1.772]	[4.544]	[2.147]	[-0.463]	[2.135]		

Table III.3: Selection of forecasting variables

This table shows results for the analysis, where I identify predictor variables to forecast future realized return on equity. The variables that I test include the predictor variables from Model 2 (columns (1)-(7)) and 3 (columns (8)-(14)) of Table III.2. A firm's P/E ratio (15) and stock return (16) complete my set of variables. I start the analysis with simple bivariate regressions of one-year ahead return on equity on each of the variables and an intercept (step 1). I show the R^2 estimates from the regressions in line (1). In the second step I regress one-year ahead return on equity on the variable with the largest explainability (R^2) for future return on equity from step 1 and separately on each of the remaining variables. Line (2) documents the R^2 estimates from the regressions that include two predictor variables (and the intercept). I select the variable with the largest incremental R^2 in this step. I repeat this procedure until all variables are selected. I display the largest R^2 estimate in each step in bold shape. Column (17) contains the incremental R^2 estimates. All regressions are estimated using pooled annual cross-sectional regressions between 1970 and 2009 including data over the preceding ten years. R^2 estimates are simple averages of the annual cross-sectional estimates. Note that the last three variables selected (line (14)-(16)) lead to lower R^2 estimates as they include fewer observations due to data availability of these variables.

	Average R^2 estimates from annual pooled cross-sectional regressions of next-period's return on equity on																
	btm	***size***	***nege***	***roe***	***sc_acc***	***dd***	***dy***	***inv***	***ar***	***gm***	***capex***	***s&a***	***etr***	***lf***	***pe***	***ret***	**ΔR^2**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13**	**(14)**	**(15)**	**(16)**	**(17)**
(1)	11.80%	5.48%	13.94%	**33.65%**	1.22%	3.58%	7.33%	0.29%	0.03%	1.91%	0.34%	1.10%	1.07%	0.34%	0.70%	9.81%	
(2)	37.17%	34.54%	34.04%		34.20%	34.19%	35.06%	32.86%	33.42%	33.72%	34.04%	31.17%	33.50%	33.99%	33.71%	**38.86%**	5.21%
(3)	**40.38%**	39.24%	39.19%		39.10%	39.25%	39.96%	38.51%	38.72%	38.93%	39.12%	37.37%	38.77%	39.15%	38.87%		1.52%
(4)		40.54%	40.64%		40.64%	40.87%	**41.21%**	40.35%	40.40%	40.60%	40.87%	39.41%	40.57%	40.77%	40.46%		0.83%
(5)		41.28%	41.44%		41.40%	41.30%		41.14%	41.19%	41.39%	**41.60%**	40.23%	41.40%	41.53%	41.27%		0.39%
(6)		41.67%	**41.84%**		41.79%	41.70%		41.45%	41.47%	41.67%		40.57%	41.66%	41.73%	41.66%		0.24%
(7)		41.89%			**42.04%**	41.89%		41.66%	41.69%	41.90%		40.79%	41.91%	41.99%	41.87%		0.20%
(8)		42.09%				42.08%		41.79%	41.90%	42.09%		40.96%	42.08%	**42.22%**	42.07%		0.18%
(9)		**42.29%**				42.27%		42.03%	42.08%	42.26%		41.19%	42.30%		42.25%		0.08%
(10)						**42.33%**		42.11%	42.16%	42.34%		41.27%	42.35%		42.33%		0.05%
(11)								42.15%	42.20%	**42.38%**		41.30%	42.39%		42.37%		0.04%
(12)								42.18%	42.24%			41.32%	42.41%		**42.41%**		0.02%
(13)								42.21%	42.27%			41.36%	**42.44%**				0.03%
(14)								42.35%	42.32%			41.55%					-0.09%
(15)									42.32%			42.13%					-0.03%
(16)												42.14%					-0.17%

Table III.4: Estimates for alternative earnings forecasting approaches

In this table I repeat the forecasting regressions from Table III.2 for a reduced form model containing only variables that have been identified to significantly explain the variation in future realized return on equity based on the analysis from Table III.3. The variables include the return on equity (autocorrelation term), stock return, book-to-market ratio, and the dividend yield. Panel A shows regression results for the reduced form model using the standard approach from Table III.2, where I regress one-, two-, and three-year ahead return on equity on the predictor variables (Model 4). Panel B documents the results for the pooled vector autoregressive (VAR) approach, where I regresses the current return on equity, the stock return, the book-to-market ratio, and the dividend yield on lags of each variable (Model 5). Models 4 and 5 are estimated between 1970 and 2009 over rolling-windows including data for the preceding ten years. Panel C applies the VAR approach from Panel B for portfolios of firms (portfolio-level VAR approach – Model 6). Firms are annually assigned into 27 portfolios based on firms beta, size and book-to-market ratio (tercile breakpoints). Panel C shows univariate statistics for the 1,080 portfolio-year coefficient estimates and the rates against which for the state variables are expected to converge in the long-run. t-values are displayed in brackets.

Panel A: Model 4 – Reduced form model (standard approach)

Independent variable	**Int.**	***roe(t)***	***ret(t)***	***btm(t)***	***dy(t)***	**N**	**R^2**
Return on equity (t+1)	0.049	0.493	0.075	-0.024	0.440	19,272	41.2%
	[12.098]	[29.577]	[19.068]	[-9.422]	[12.742]		
Return on equity (t+2)	0.058	0.307	0.052	-0.016	0.565	18,012	20.7%
	[11.309]	[15.891]	[13.088]	[-5.024]	[12.299]		
Return on equity (t+3)	0.059	0.233	0.031	-0.007	0.587	16,870	12.7%
	[10.167]	[10.998]	[7.502]	[-1.991]	[10.724]		

Panel B: Model 5 – Reduced form model (pooled VAR approach)

	Int.	***roe(t-1)***	***ret(t-1)***	***btm(t-1)***	***dy(t-1)***	**N**	**R^2**
Return on equity (t)	0.050	0.493	0.074	-0.025	0.430	18,711	41.9%
	[21.682]	[71.204]	[29.270]	[-12.403]	[15.504]		
Stock return (t)	-0.094	0.212	0.003	0.125	0.752	18,711	4.9%
	[-9.361]	[5.725]	[0.358]	[17.184]	[7.123]		
Book-to-market (t)	0.270	-0.032	0.018	0.755	-0.875	18,711	56.8%
	[24.986]	[-0.785]	[1.862]	[103.268]	[-7.620]		
Dividend yield (t)	0.008	0.013	0.002	-0.002	0.729	18,711	57.1%
	[14.484]	[6.871]	[3.583]	[-4.691]	[129.724]		

Panel C: Model 6 – Reduced form model (portfolio-level VAR approach)

	Mean	SD	Quartiles 25%	50%	75%	N
	(1)	(2)	(3)	(4)	(5)	(6)
Return on equity equation						
roe (t-1)	0.440	0.099	0.373	0.439	0.505	1,080
ret (t-1)	0.083	0.029	0.063	0.082	0.101	1,080
btm (t-1)	-0.042	0.040	-0.057	-0.037	-0.023	1,080
dy (t-1)	0.368	0.353	0.187	0.328	0.504	1,080
Return equation						
roe(t-1)	0.090	0.146	-0.001	0.078	0.168	1,080
ret(t-1)	0.016	0.059	-0.022	0.016	0.053	1,080
btm(t-1)	0.153	0.058	0.114	0.143	0.188	1,080
dy(t-1)	0.189	0.662	-0.087	0.208	0.526	1,080
Book-to-market equation						
roe(t-1)	0.060	0.134	-0.020	0.059	0.127	1,080
ret(t-1)	0.014	0.070	-0.028	0.011	0.054	1,080
btm(t-1)	0.704	0.085	0.660	0.717	0.762	1,080
dy(t-1)	-0.427	0.716	-0.697	-0.392	-0.171	1,080
Dividend yield equation						
roe(t-1)	0.017	0.017	0.005	0.011	0.022	1,080
ret(t-1)	0.000	0.003	-0.001	0.001	0.002	1,080
btm(t-1)	-0.004	0.004	-0.006	-0.003	-0.001	1,080
dy(t-1)	0.554	0.166	0.436	0.559	0.679	1,080
Long-term (convergence) rates						
roe	10.16%	6.35%	8.33%	10.72%	13.22%	1,080
ret	7.12%	9.07%	1.59%	8.40%	12.75%	1,080
btm	0.735	0.368	0.440	0.665	0.961	1,080
dy	1.90%	2.04%	0.00%	1.43%	3.40%	1,080

Table III.5: Evaluation of existing forecasting approaches

This table shows the evaluation of the earnings forecasting models 1-3 from Table III.2 (Panel A) and models 4-6 from Table III.4 (Panel B). The evaluation criteria include the bias, accuracy and explainability of a forecasting model. The bias (columns (1) and (2)) refers to the mean and median deviation between the forecasted one-, two-, and three-year ahead return on equity and the respective future realized return on equity. Columns (3) and (4) document the accuracy of the models defined as the median and standard deviation of the absolute deviation. Columns (5) and (6) show the average coefficient and R^2 estimates from annual cross-sectional regressions of future realized return on equity on the respective one-, two-, and three-year ahead earnings forecast. The stars in column (5) indicate whether the average coefficient significantly differs from 1 at the 1%, 5%, and 10% level.

Panel A: Evaluation of existing earnings forecasting models

	Bias		**Accuracy**		**Explainability**	
	Mean	**Median**	**Median**	**SD**	**Coefficient**	**R^2**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Model 1 – Hou et al. (2010)						
roe(t+1) - E_t[roe(t+1)]	-3.06%	-0.44%	5.73%	20.76%	0.507***	19.16%
roe(t+2) - E_t[roe(t+2)]	-8.38%	-1.89%	7.06%	27.60%	0.197***	3.95%
roe(t+3) - E_t[roe(t+3)]	-12.07%	-3.59%	7.92%	29.68%	0.108***	1.32%
Average values	**-7.84%**	**-1.97%**	**6.90%**	**26.01%**	**0.271**	**8.15%**
Model 2 – Fama & French (2006) / Scaled Model 1						
roe(t+1) - E_t[roe(t+1)]	-0.73%	0.58%	4.54%	16.36%	1.041	38.77%
roe(t+2) - E_t[roe(t+2)]	-0.63%	0.91%	5.60%	16.85%	1.078	20.52%
roe(t+3) - E_t[roe(t+3)]	-0.52%	0.92%	5.94%	17.05%	1.120	13.82%
Average values	**-0.63%**	**0.80%**	**5.36%**	**16.75%**	**1.080**	**24.37%**
Model 3 – Abarbanell & Bushee (1997)						
roe(t+1) - E_t[roe(t+1)]	-0.43%	0.87%	4.68%	14.56%	0.977	30.87%
roe(t+2) - E_t[roe(t+2)]	-0.46%	0.91%	5.73%	14.94%	0.989	14.06%
roe(t+3) - E_t[roe(t+3)]	-0.44%	0.86%	6.06%	14.82%	1.012	9.26%
Average values	**-0.44%**	**0.88%**	**5.49%**	**14.77%**	**0.993**	**18.07%**

Panel B: Evaluation of alternative earnings forecasting models

	Bias		Accuracy		Explainability	
	Mean	**Median**	**Median**	**SD**	**Coefficient**	**R^2**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Model 4 – Reduced form model (standard approach)						
roe(t+1) - E_t[roe(t+1)]	-0.56%	0.82%	4.51%	16.19%	1.070**	42.04%
roe(t+2) - E_t[roe(t+2)]	-0.59%	1.01%	5.59%	16.85%	1.107**	21.51%
roe(t+3) - E_t[roe(t+3)]	-0.46%	0.98%	5.95%	17.11%	1.146*	13.70%
Average values	**-0.54%**	**0.94%**	**5.35%**	**16.72%**	**1.107**	**25.75%**
Model 5 – Reduced form model (pooled VAR approach)						
roe(t+1) - E_t[roe(t+1)]	-0.69%	0.76%	4.63%	16.40%	1.070**	41.66%
roe(t+2) - E_t[roe(t+2)]	-0.60%	1.30%	5.94%	17.10%	1.213***	20.50%
roe(t+3) - E_t[roe(t+3)]	-0.42%	1.52%	6.53%	17.53%	1.416***	12.38%
Average values	**-0.57%**	**1.19%**	**5.70%**	**17.01%**	**1.233**	**24.85%**
Model 6 – Reduced form model (portfolio-level VAR approach)						
roe(t+1) - E_t[roe(t+1)]	-1.82%	-0.33%	4.23%	16.05%	1.053*	43.73%
roe(t+2) - E_t[roe(t+2)]	-2.57%	-0.67%	5.14%	17.09%	1.075	22.11%
roe(t+3) - E_t[roe(t+3)]	-2.77%	-0.87%	5.65%	17.55%	1.035	13.63%
Average values	**-2.39%**	**-0.62%**	**5.01%**	**16.90%**	**1.054**	**26.49%**

Table III.6: Sensitivity of ICC estimates

This table shows the averages of annual equally- and value-weighted ICC estimates obtained from ICC methods with varying detailed planning periods and terminal growth rates ($g = 0\%$, 2.5%, and 5%). I include ICC estimates based on Gebhardt, Lee, and Swaminathan (2001) (GLS), Easton, Taylor, Shroff, and Sougiannis (2002) (ETSS), a simple average of the two methods proposed in Chapter II (COMB), and four residual income methods comparable to Claus and Thomas (2001) with a 20-, 30-, 40-, and 50-year horizon. The last two columns of Panel A document the average difference between the method estimates under the assumption of 5% vs. 0% terminal growth. The last two lines of Panel A display the difference of average method estimates for the 50- vs. 40-year horizon method and the 50-year vs. GLS method.

	g = 0%		**g = 2.5%**		**g = 5%**		**[g = 5%] - [g = 0%]**	
ICC method	**Equally-weighted**	**Value-weighted**	**Equally-weighted**	**Value-weighted**	**Equally-weighted**	**Value-weighted**	**Equally-weighted**	**Value-weighted**
r_{GLS}	8.85%	9.22%	9.29%	9.74%	9.84%	10.37%	**0.99%**	**1.15%**
r_{ETSS}	9.90%	11.63%	9.90%	11.63%	9.90%	11.63%	**0.00%**	**0.00%**
r_{COMB}	9.50%	10.44%	9.69%	10.69%	9.98%	11.02%	**0.48%**	**0.58%**
r_{20}	9.34%	10.12%	9.65%	10.44%	10.10%	10.85%	**0.76%**	**0.73%**
r_{30}	9.68%	10.72%	9.95%	10.92%	10.33%	11.19%	**0.65%**	**0.47%**
r_{40}	9.91%	11.11%	10.15%	11.20%	10.49%	11.42%	**0.58%**	**0.32%**
r_{50}	10.08%	11.32%	10.30%	11.40%	10.63%	11.53%	**0.55%**	**0.21%**
$r_{50} - r_{GLS}$	**1.23%**	**2.10%**	**1.01%**	**1.66%**	**0.79%**	**1.16%**		
$r_{50} - r_{40}$	**0.16%**	**0.21%**	**0.15%**	**0.21%**	**0.13%**	**0.11%**		

Table III.7: Evidence on expected and realized returns

This table shows univariate statistics for realized (excess) returns and my main measure of expected (excess) returns based on implied cost of equity capital estimates from a long-horizon valuation model with a detailed planning period of 50 years. Statistics include the averages of the annual equally- and value-weighted returns (columns (1) and (2)), the standard deviation (column (3)), the quartiles (columns (4)-(6)), and the number of observations (column (7)). Panel A documents the results for the full sample from 1970-2008. Panel B and C show a breakdown of the results for the early (1970-1989) and late (1990-2008) sample period.

Panel A: Full sample

	Average return			Quartiles			
	Equally-weighted	Value-weighted	SD	25%	50%	75%	N
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Expected return (ICC)	10.00%	11.31%	3.41%	7.96%	10.18%	12.37%	73,438
Realized return	6.46%	6.00%	44.27%	-16.59%	8.14%	31.38%	73,438
Expected excess return (ICC - rf)	4.41%	5.72%	3.32%	2.44%	4.47%	6.49%	73,438
Realized excess return	1.03%	0.58%	44.12%	-22.01%	2.60%	25.85%	73,438
Realized excess return over ICC	-3.55%	-5.31%	44.02%	-26.56%	-2.25%	20.94%	73,438

Panel B: Early period (1970-1989)

Expected return (ICC)	11.80%	12.40%	2.52%	10.18%	11.91%	13.49%	32,354
Realized return	10.43%	9.85%	40.43%	-12.37%	10.86%	34.09%	32,354
Expected excess return (ICC - rf)	4.38%	4.98%	2.84%	2.59%	4.51%	6.34%	32,354
Realized excess return	2.92%	2.34%	40.50%	-20.09%	3.29%	26.78%	32,354
Realized excess return over ICC	-1.37%	-2.56%	40.06%	-23.97%	-1.19%	21.93%	32,354

Panel C: Late period (1990-2008)

Expected return (ICC)	8.59%	10.46%	3.35%	6.77%	8.67%	10.65%	41,084
Realized return	3.33%	2.97%	46.85%	-20.14%	6.03%	28.91%	41,084
Expected excess return (ICC - rf)	4.43%	6.29%	3.66%	2.32%	4.45%	6.62%	41,084
Realized excess return	-0.46%	-0.81%	46.72%	-23.85%	2.06%	25.17%	41,084
Realized excess return over ICC	-5.26%	-7.48%	46.83%	-28.92%	-3.05%	20.16%	41,084

Table III.8: Evaluation of size and book-to-market effects

This table shows a breakdown of average annual realized (Panel A) and expected returns (Panel B) for 25 portfolios formed on size and book-to-market. The numbers for equally-weighted (value-weighted) returns are in regular (bold) shape. The columns "High - Low" document the difference between the low and high book-to-market portfolio. The lines "Large - Small" the difference between the large and small size portfolio. Stars indicate significance at the 10%, 5%, and 1% significance level using a two-sided Wilcoxon rank test.

Panel A: Average annual realized excess returns on size and book-to-market portfolios

		Book-to-market					
		Low	**2**	**3**	**4**	**High**	**High - Low**
Size	**Small**	-6.37%	-0.18%	0.99%	2.04%	6.67%	13.04%***
		-13.53%	**-5.84%**	**-3.20%**	**-4.65%**	**-2.29%**	**11.24%*** **
	2	-6.57%	-1.18%	1.95%	4.10%	4.30%	10.87%***
		-9.62%	**-4.59%**	**-1.14%**	**-0.15%**	**-0.87%**	**8.75%*** **
	3	-4.74%	0.72%	1.14%	3.24%	6.51%	11.25%***
		-9.06%	**-3.23%**	**-2.26%**	**-1.37%**	**3.51%**	**12.57%*** **
	4	-3.20%	0.70%	2.94%	2.29%	5.27%	8.47%***
		-6.41%	**-2.86%**	**-0.60%**	**-3.06%**	**0.43%**	**6.85%*** **
	Large	-1.83%	0.98%	2.76%	2.40%	4.52%	6.36%***
		-5.88%	**-2.83%**	**0.73%**	**0.53%**	**-0.82%**	**5.06%*** **
Large		4.54%***	1.16%	1.77%	0.36%	-2.14%	
- Small		**7.65%*** **	**3.00%**	**3.93%*** **	**5.18%**	**1.47%**	

Panel B: Average annual expected excess returns on size and book-to-market portfolios

		Book-to-market					
		Low	**2**	**3**	**4**	**High**	**High - Low**
Size	**Small**	1.29%	2.71%	3.14%	2.66%	2.93%	1.64%***
		1.73%	**3.34%**	**3.83%**	**3.26%**	**3.54%**	**1.81%*** **
	2	3.92%	4.62%	4.74%	4.39%	4.81%	0.88%***
		4.35%	**4.81%**	**4.93%**	**4.40%**	**4.80%**	**0.45%*** **
	3	6.64%	6.32%	5.16%	4.48%	4.98%	-1.66%***
		7.52%	**6.97%**	**5.63%**	**4.53%**	**4.91%**	**-2.60%*** **
	4	6.41%	6.14%	5.19%	4.41%	5.00%	-1.42%***
		7.42%	**6.84%**	**5.62%**	**4.39%**	**4.87%**	**-2.56%*** **
	Large	5.93%	5.64%	4.46%	4.05%	4.47%	-1.46%***
		6.65%	**6.41%**	**4.29%**	**3.65%**	**3.83%**	**-2.81%*** **
Large		4.64%***	2.93%***	1.32%***	1.39%***	1.54%***	
- Small		**4.91%*** **	**3.07%*** **	**0.46%*** **	**0.38%*** **	**0.29%*** **	

Table III.9: The relation between returns and firm characteristics

This table shows regression results from annual cross-sectional regressions of realized and expected excess returns on firm characteristics, i.e. post-ranking betas, book-to-market, and size. Columns (1)-(3) document the results for realized returns in excess of the risk-free rate for the full, early, and late sample period. Columns (4)-(6) cover the results for expected excess returns. t-values are displayed in brackets.

	Realized excess returns			**Expected excess returns**		
	Full sample	**1970-1989**	**1989-2008**	**Full sample**	**1970-1989**	**1989-2008**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Intercept	4.667	0.027	9.822	-0.743	1.038	-2.721
	[1.06]	[0.01]	[1.97]	[-3.05]	[5.18]	[-9.49]
Beta	0.718	1.537	-0.191	-0.108	-0.039	-0.183
	[0.39]	[0.73]	[-0.13]	[-1.15]	[-0.38]	[-2.29]
Book-to-Market	4.428	4.785	4.032	0.268	0.332	0.196
	[3.02]	[3.21]	[2.79]	[2.72]	[3.40]	[1.98]
Size	-0.494	1.283	-2.469	3.356	2.412	4.404
	[-0.20]	[0.64]	[-0.87]	[23.48]	[21.45]	[25.83]
Avg. Adj. R^2	9.1%	10.0%	8.2%	30.9%	29.0%	33.1%
Avg. N	1,758	1,540	2,000	1,758	1,540	2,000

Table III.10: Robustness of earnings forecasting model estimates

This table shows the results of several robustness checks, where I assess alternative specifications to see how the results regarding the performance of earnings forecasting models from Table III.5 are affected by the choice of the underlying methodology. I repeat results for the baseline specification (Model 6) in Panel A. The alternative specifications include a version of Model 2 when applied using the pooled VAR approach (Panel B); a portfolio-level VAR, where I assign firms to portfolios based on the 2-digit SIC industry classification (Panel C); a model that utilizes the empirical intercepts from the portfolio-level VAR regressions (Panel D); and a VAR model with adjusted intercepts so that the long-term rates converge to the historical 25%-quartile rather than the median (Panel E). The evaluation criteria include the bias (1)-(2), accuracy (3)-(4), and explainability (5)-(6).

	Bias		**Accuracy**		**Explainability**	
	Mean	**Median**	**Median**	**SD**	**Coefficient**	**R^2**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Panel A – Reduced form model – portfolio-level VAR approach						
roe(t+1) - E_t[roe(t+1)]	-1.82%	-0.33%	4.23%	16.05%	1.053*	43.73%
roe(t+2) - E_t[roe(t+2)]	-2.57%	-0.67%	5.14%	17.09%	1.075	22.11%
roe(t+3) - E_t[roe(t+3)]	-2.77%	-0.87%	5.65%	17.55%	1.035	13.63%
Average values	**-2.39%**	**-0.62%**	**5.01%**	**16.90%**	**1.054**	**26.49%**
Panel B – Fama & French (2006) model – pooled VAR approach						
roe(t+1) - E_t[roe(t+1)]	-0.79%	0.58%	4.60%	16.54%	1.042127	38.62%
roe(t+2) - E_t[roe(t+2)]	-0.70%	0.99%	5.93%	17.10%	1.0763	19.58%
roe(t+3) - E_t[roe(t+3)]	-0.48%	1.24%	6.52%	17.53%	1.096025	11.51%
Average values	**-0.65%**	**0.94%**	**5.69%**	**17.06%**	**1.071**	**23.24%**
Panel C – Reduced form model – portfolio-level VAR approach (2-digit SIC)						
roe(t+1) - E_t[roe(t+1)]	-1.94%	-0.27%	4.39%	16.08%	1.028	43.93%
roe(t+2) - E_t[roe(t+2)]	-2.77%	-0.54%	5.29%	17.13%	1.093*	22.15%
roe(t+3) - E_t[roe(t+3)]	-3.03%	-0.74%	5.80%	17.91%	1.045	12.37%
Average values	**-2.58%**	**-0.52%**	**5.16%**	**17.04%**	**1.055**	**26.15%**
Panel D – Reduced form model – portfolio-level VAR approach (empirical intercepts)						
roe(t+1) - E_t[roe(t+1)]	-0.36%	0.73%	4.45%	15.84%	1.030	44.08%
roe(t+2) - E_t[roe(t+2)]	-0.26%	1.06%	5.38%	16.67%	1.058	22.76%
roe(t+3) - E_t[roe(t+3)]	-0.12%	1.16%	5.88%	17.07%	1.031	14.56%
Average values	**-0.25%**	**0.99%**	**5.24%**	**16.53%**	**1.040**	**27.13%**
Panel E – Reduced form model – portfolio-level VAR approach (adjusted intercepts)						
roe(t+1) - E_t[roe(t+1)]	0.87%	1.44%	4.79%	15.88%	0.994	42.55%
roe(t+2) - E_t[roe(t+2)]	2.96%	3.21%	6.45%	16.86%	0.866***	19.74%
roe(t+3) - E_t[roe(t+3)]	3.94%	3.91%	7.24%	17.38%	0.739***	11.68%
Average values	**2.59%**	**2.85%**	**6.16%**	**16.71%**	**0.867**	**24.66%**

Table III.11: Robustness of ICC estimates

This table shows the results of several robustness checks, where I assess alternative specifications to see how the results regarding the ICC estimates are affected by the choice of the earnings forecasting model and ICC method. I repeat results for the baseline specification in column (1). The alternative specifications include (2) ICC estimates based on an earnings forecasting model that uses the empirical intercepts from the portfolio-level VAR regressions; (3) ICC estimates obtained from earnings forecasts that utilize an alternative intercept adjustment where intercepts are recalculated such that long-term ratios converge against the historical 25%-quartile; and (4)-(6) ICC estimates based on the methods of GLS, ETSS, and the combination (simple average) of the two. Panel A shows key univariate results. Panel B and C show a summary of the results for book-to-market and size effects associated with expected returns from Tables III.8 and III.9.

Panel A: Univariate results

	Baseline specification (1)	**Empirical intercepts (2)**	**Adjusted intercepts (Q25%) (3)**	**Combined ICC method (4)**	**ICC based on GLS (5)**	**ICC based on ETSS (6)**
Excess return (EW)	4.41%	2.51%	0.33%	3.93%	3.20%	4.09%
Excess return (VW)	5.72%	4.32%	2.09%	5.03%	3.60%	5.97%
SD	3.32%	3.81%	3.42%	2.96%	3.22%	4.36%

Panel B: Expected return differences

	(1)	(2)	(3)	(4)	(5)	(6)
High - Low (small firms)	1.81%***	1.76%***	2.01%***	-1.36%	4.45%***	-5.15%***
High - Low (large firms)	-2.81%***	-3.52%***	-1.32%***	-3.33%***	0.46%***	-6.37%***
Large - Small (low firms)	4.91%***	5.82%***	4.90%***	2.53%***	3.74%***	2.99%***
Large - Small (high firms)	0.29%***	0.54%***	1.57%***	0.55%***	-0.25%***	1.77%***

Panel C: Cross-sectional relation to firm characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Beta	-0.108	-0.625	-0.560	-0.248	-0.272	-0.344
	[-1.15]	[-6.13]	[-5.36]	[-3.17]	[-3.42]	[-2.90]
Book-to-market	0.268	0.390	0.157	-0.170	2.193	-1.897
	[2.72]	[3.61]	[1.49]	[-2.41]	[28.71]	[-18.03]
Size	3.36	3.683	4.537	2.221	2.868	1.907
	[23.48]	[22.42]	[27.19]	[18.55]	[23.73]	[10.74]

EW: equally-weighted; VW: value-weighted

Chapter IV

A New Approach to Decompose Stock Returns Using the Implied Cost of Equity Capital

1 Introduction

In this chapter I propose a new approach to decompose realized stock returns using the implied cost of equity capital (ICC).[77] The common decomposition approach relies on expected returns from a model calibrated to realized returns. Ample evidence, however, shows that realized returns might be a poor proxy for expected returns (see Elton, 1999; Lundblad, 2007). By contrast, the ICC-based return decomposition utilizes the implied cost of capital as measure for expected returns. Pastor, Sinha, and Swaminathan (2008) argue that the ICC estimates help to detect time-variation in expected returns. This feature is of special interest for the dynamic nature of return decompositions so that the ICC-based return decomposition delivers new insights about the components of realized stock returns.

[77]I thank Ernst Maug for helpful comments and advice. I gratefully acknowledge financial support from the collaborative research center SFB TR 15 "Governance and the Efficiency of Economic Systems" and the Rudolph von Bennigsen-Foerder-foundation.

The common approach to decompose realized returns is based on the early work of Campbell (1991). Utilizing the dividend ratio model of Campbell and Shiller (1988a,b), Campbell applies an aggregate vector autoregressive (VAR) model to decompose market excess returns into news about future cash flows and news about discount rates. Vuolteenaho (2002) is the first study to apply a return decomposition to the level of individual firms/stocks using an accounting-based VAR model. To estimate the components of realized returns the common approach applies a VAR model to generate expected returns required to compute the return news component. Cash flow news are then either backed out as a residual or estimated directly from the VAR model or from future clean-surplus return on equity values (see Vuolteenaho, 2002; Campbell, Polk, and Vuolteenaho, 2010; Callen, Segal, and Hope, 2010; Cohen, Polk, and Vuolteenaho, 2003, 2009). The advantage of the VAR model is that it allows the researcher to measure the discounted effect of current shocks to cash flows (cash flow news) and expected returns (return news) over the infinite horizon.

The crucial assumption behind the VAR approach is that the VAR model correctly specifies the evolution of return and cash flow expectations over time. For expected return on equity used to calculate the cash flow news the assumption might be less serious. The explanatory power of specific financial variables for the return on equity is commonly high. Moreover, the evidence in Chapter III indicates that model-based earnings forecasts obtained from a VAR model almost similar to the model of Vuolteenaho (2002) explain a considerable part of future earnings. Finally, in line with the mean-reversion property of the VAR approach, Brooks and Buckmaster (1976) and Lipe and Kormendi (1994) find that the return on equity is mean-reverting over time. If investors are rational and incorporate the observed mean-reversion when forming earnings expectations, the VAR model would account for this characteristic.

Concerning expected stock returns, above assumption might, however, be more problematic as it is completely unclear to what extent a VAR model calibrated for realized returns captures future stock return expectations. Elton (1999) argues that empirical evidence suggests that realized returns are a poor measure for expected returns. The necessary assumption that information surprises cancel out over time might not be fulfilled at all or at least not for comparably small samples covering US data over about 40 to 50 years. One issue is the relation between expected and realized returns in the short run. Suppose the expected return (discount factor) of a stock increases resulting in higher discounting of expected future cash flows. The corresponding realized return is negative and might induces a negative connection between realized and expected returns in the short run.

Of course, in the long-run these effects should wash out. But how many years of data are required for this? The main problem is that realized returns are highly volatile and the explanatory power of commonly applied variables for future realized returns is low. Lundblad (2007) argues that the low explanatory power makes it hard to detect a relationship between expected returns and the variable of interest based on realized returns. In line with this reasoning, he finds that an extremely large sample covering more than 100 years is required to detect the risk return relation. The same argument applies to the standard approach to infer expected returns from realized return models, since the explanatory power of these models commonly ranges between 1-3%. The latter point is supported by Chen and Zhao (2009). They argue that the estimation of return news suffers from a small predictive power that might introduce a considerable measurement error of the return news component. It is, therefore, unclear to what extent the realized return could be used to infer future return expectations and how this procedure affects the return news estimate obtained from the existing return decomposition model. If cash flow news are backed out as a residual, this error can, furthermore, result in a mismeasurement of cash flow news, which absorb the misspecification of the return news estimation.

To address these concerns I propose a new approach to decompose stock returns using the implied cost of equity capital. Implied cost of capital equal the internal rate of return that equates the current stock price to the sum of discounted future earnings or cash flows. ICC estimates deliver a forward-looking measure for expected returns that rely on a solid conceptual foundation (fundamental valuation) rather than an ad hoc realized return relationship.

I analyze the expected return measures obtained from the ICC and the standard Vuolteenaho VAR approach. On the market-level I find that ICC-based market risk premia are positive over the whole sample period (1972-2009) and considerably increase during the recent years of the financial crisis. By contrast, market risk premia from the standard approach are negative in 12 out of 38 years and decline over recent years. On the firm-level my findings highlight that the Vuolteenaho VAR model computes negative expected excess returns (firm-level risk premia) for almost 40% of the sample. In contrast, risk premia obtained from the long-horizon ICC method are positive for more than 90% of the sample and generate a much more convincing expected return pattern, both in the cross-section and over time.

Overall, the firm- and market-level evidence implies that ICC estimates much better reflect specific properties one would attribute to a consistent expected return measure. Compared to expected return estimates that rely on realized returns, implied cost of equity capital estimates provide a superior measure for expected returns. Ultimately, applying a more consistent expected return measure also promotes the estimation of return news obtained from the ICC-based return decomposition. The application of implied cost of capital could, therefore, help to reduce likely measurement errors associated with the common decomposition approach. To avoid the problems related to the indirect estimation of cash flow news as a residual, I directly estimate the cash flow news component from earnings forecasts required to compute the ICC. The earnings forecasts are derived from the portfolio-level VAR approach proposed in Chapter III. I then follow Cohen, Polk, and Vuolteenaho (2003, 2009) and directly estimate cash flow news as the discounted sum of changes in expected return on equity values.[78]

[78] Cohen, Polk, and Vuolteenaho (2003, 2009) only include earnings over 2-5 periods, whereas my cash flow news include expected return on equity for an infinite horizon.

My return decomposition documents remarkable differences for return components obtained from the Vuolteenaho and ICC-based return decomposition. In particular, the return news components obtained from the two decomposition approaches show significant differences. The analysis documents that the two return news measures, which should capture the same underlying variable, are in principle unrelated. For the cash flow news components obtained from the two decomposition models I observe a positive and significant correlation. The correlation is, however, considerably smaller than one. The findings highlights that the alternative modeling approach that applies implied cost of capital as measure for expected returns leads to considerable differences in the obtained return decomposition and the relationship among the return components. Given the evidence that the implied cost of capital better capture the true expected returns, the ICC-based return decomposition should also provide more consistent estimates of the return components.

In a second step, I propose an application of return decompositions for the controversial question from the corporate governance literature whether the quality of corporate governance helps to predict returns. The discussion was initiated by Gompers, Ishii, and Metrick (2003), who claim that firms with good governance persistently earn higher returns.[79] Core, Guay, and Rusticus (2006) investigate whether the market is surprised by negative cash flow information for firms with weak corporate governance inducing the inferior return performance of these firms. They find that operating performance of firms with weak governance is poor, but that the market is not surprised by the information since analysts anticipate the weak performance. Johnson, Moorman, and Sorescu (2009) claim that return differences for firms with good and weak governance are due to insufficient industry controls. Cremers and Ferrell (2010) find that the superior performance of good governance firms persists even after controlling for industry in a larger data set going back to 1978. They argue that return differences are much more important in the 1980s when

[79] Bebchuk, Cohen, and Ferrell (2009) support the evidence using an alternative, but related governance index (E-index).

many of the relevant governance provisions have been enacted. Giroud and Mueller (2010) find that the effect found by Gompers, Ishii, and Metrick is concentrated in industries with weak product market competition. They conclude that product market competition is a substitute for corporate governance such that in industries with high product market competition stock market performance does not depend on the quality of governance at the corporate level.

I use the G-index of Gompers, Ishii, and Metrick (2003) to assess whether returns and return components, i.e. cash flow news and return news, vary for firms with high and low G-index. Indeed, I find that returns are significantly lower for firms with weak corporate governance (high G-index) over the sample period prior to the publication of the Gompers, Ishii, and Metrick results (1990-2003). Afterwards (2003-2008), I do no longer find return differences for firms with high and low G-index. The result support previous evidence of Giroud and Mueller (2010), who also find that return differences do not persist until recent years. Furthermore, the finding is in line with the argument of Schwert (2003), who claims that many so called return anomalies seem to have weakened or disappeared after the papers that highlighted them were published. Following Schwert the identification of anomalies leads investors to trade on the anomalous return behavior, which causes anomalies to disappear following their detection.

I analyze the sources of the observed return differences and find that differences arise from lower cash flow news and higher return news of firms with weak governance. Over recent years differences in cash flow and return news, however, become insignificant and return differences disappear, accordingly. The evidence indicates that during the 1990s and early 2000s investors were surprised by the weak operating performance of high G-index firms. As a consequence investors reduced their cash flow expectations and applied higher expected returns for high G-index firms resulting in lower cash flow and higher return news. Both effects jointly explain the poor return performance of firms with good corporate governance over this period.[80] Investors

[80]Note that higher cash flow news increase realized returns, whereas higher return news decrease realized returns.

subsequently learned about the weak operating performance of high G-index firms, which leads to the decline of the effects during recent years.

Return decompositions have previously been applied to study the covariation of stock returns. Campbell (1991) and Campbell and Ammer (1993) decompose aggregate excess stock and bond returns and find that returns are mainly driven by news about future excess stock returns and inflation. Vuolteenaho (2002) supports the finding that overall stock market return variation mainly arises from variation of discount rates (return news). On the individual firm level, however, the variation of cash flow news seems to be the main driver for return variation. Campbell and Mei (1993) apply a decomposition of portfolio returns for size and industry portfolios to check whether the covariance of portfolio and market returns is determined by portfolios' cash flow or return news. In contrast, Campbell and Vuolteenaho (2004) decompose the returns on the market portfolio and test whether return on portfolios covary stronger with the market's cash flow or return news. Campbell and Vuolteenaho identify that systematic risk comes along with a "good" and "bad" beta, where the good beta captures risk associated with shocks to the market discount factor while bad beta is associated with aggregate cash flow shocks. Following the evidence, the return premium for value stocks documented by Fama and French (1992) arises from a higher bad beta of value stocks.

Campbell, Polk, and Vuolteenaho (2010) combine the analysis of Campbell and Mei (1993) and Campbell and Vuolteenaho (2004). They compute cash flow and return news on the level of individual stocks and the market portfolio to assess how cash flow and returns news on the aggregate and individual level covary with each other. They find that the higher good betas of growth stocks and bad betas of value stocks mainly arise from the cash flow fundamentals of these companies. They conclude that growth stocks are characterized by a high equity duration (see Dechow, Sloan, and Soliman, 2004; Lettau and Wachter, 2007) meaning that cash flows are expected to arise later in the future. This pattern makes aggregate discount factor news more important for growth stocks. By contrast, cash flows of value stocks are expected to arise in the near future, making aggregate cash flow shocks more important for these companies.

In a different context Easton and Monahan (2005) use an alternative return decomposition to assess the quality of implied cost of equity capital methods. Callen and Segal (2004) extend the Vuolteenaho (2002) return decomposition by a component that captures accruals news. They show that accruals news build a significant part of the overall return variation that is even more important than expected return news. Analyzing the importance of domestic and foreign earnings, Callen, Hope, and Segal (2005) find that return variation more heavily depends on domestic earnings rather than foreign earnings variation. Callen, Segal, and Hope (2010) utilize the standard return decomposition model to study the relation between equity prices and accounting conservatism.

Overall, this chapter adds to the return decomposition literature by introducing an alternative model to decompose stock returns that relies on expected returns obtained from implied cost of capital estimation. The application of cash flow and return news to assess the superior return performance of firms with good corporate governance adds to the governance return literature. Moreover, the analysis opens the field for further research concerning the sources of other return anomalies by means of return decompositions.

The remainder of this chapter is structured as follows. The following Section 2 describes the estimation of the Vuolteenaho (2002) and ICC-based return decomposition models. I present the sample selection and variable definition in Section 3. Section 4 contains the main analysis of return decomposition models. In Section 5 I use the return decomposition to assess the relation between corporate governance and returns. Section 6 presents robustness checks and Section 7 concludes with a discussion of the limitations of my analysis and suggestions for future research.

2 The decomposition of realized returns

The analysis starts with the presentation of two approaches to decompose realized (excess) stock returns. I review the Vuolteenaho (2002) return decomposition model in the next Section 2.1 and defer the presentation of my return decomposition approach based on expected returns from implied cost of capital estimation to Section 2.2.

2.1 The Vuolteenaho (2002) return decomposition model

The literature on return decomposition starts with the early work of Campbell (1991) and Campbell and Ammer (1993). They use the general dividend discount model to decompose aggregate stock returns. The intuition behind the return decomposition is straightforward. Assume that stock prices (P) are obtained from a general present value relation so that the price equals the discounted value of expected future dividends or cash flows (fcf):

$$P_t = \mathrm{E}_t \sum_{j=1}^{\infty} \frac{fcf_{t+j}}{(1+r_E)^j}, \tag{IV.1}$$

where r_E equals the expected future stock return. Following the model, prices only change if either the expected future cash flows in the numerator or the expected future returns (discount rate) in the denominator change. The first effect is known as cash flow news as it captures revisions in future cash flow expectations. The second effect is called return news (or discount rate news) and captures revisions in future expected returns. Since returns represent changes in prices (plus dividends) between two periods, it follows that realized returns can be decomposed into a cash flow news and a return news component.

Vuolteenaho (2002) uses the clean-surplus relation to extent the return decomposition from the dividend representation previously applied by Campbell (1991) and Campbell and Ammer (1993) to earnings in general. Following his model, the unexpected excess return, i.e. the return above the expected return, is defined as:[81]

$$er_t - \mathrm{E}_{t-1}er_t = \underbrace{\Delta \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j \left(roe_{t+j} - f_{t+j}\right)}_{=Ncf_t} - \underbrace{\Delta \mathrm{E}_t \sum_{j=1}^{\infty} \rho^j \left(er_{t+j}\right)}_{=Nr_t} + \kappa_t, \quad \text{(IV.2)}$$

where er_t is the log of one plus the stock return in excess of the risk-free rate, roe_t the log of one plus the book return on equity, and f_t the log of one plus the risk-free rate. E_t refers to expectations at time t. The difference operator Δ describes a change from $t-1$ to t (e.g. $\mathrm{E}_t - \mathrm{E}_{t-1}$). The parameter ρ is a number smaller but close to one and can be interpreted as a discount factor. I describe the estimation of ρ later in this chapter. κ_t captures an approximation error accounting for the fact that (IV.2) is obtained from a linear Taylor approximation (see the Appendix D for details).

Equation (IV.2) shows that the unexpected excess return $er_t - \mathrm{E}_{t-1}er_t$ can be decomposed into two components: (i) the change in the discounted sum of future expected returns on equity in excess of the risk-free rate and (ii) the change in the discounted sum of future expected excess returns. The two return components are defined as cash flow news Ncf and return news Nr:

$$\begin{aligned} Ncf_t &= \Delta \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j \left(roe_{t+j} - f_{t+j}\right) && \text{(IV.3)} \\ &= \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j \left(roe_{t+j} - f_{t+j}\right) - \mathrm{E}_{t-1} \sum_{j=0}^{\infty} \rho^j \left(roe_{t+j} - f_{t+j}\right) \end{aligned}$$

$$\begin{aligned} Nr_t &= \Delta \mathrm{E}_t \sum_{j=1}^{\infty} \rho^j \left(er_{t+j}\right) \\ &= \mathrm{E}_t \sum_{j=1}^{\infty} \rho^j \left(er_{t+j}\right) - \mathrm{E}_{t-1} \sum_{j=1}^{\infty} \rho^j \left(er_{t+j}\right) && \text{(IV.4)} \end{aligned}$$

$$er_t - \mathrm{E}_{t-1}er_t = Ncf_t - Nr_t + \kappa_t. \quad \text{(IV.5)}$$

[81]I provide a derivation of the formula in Appendix D at the end of this dissertation.

It is obvious from (IV.2) and (IV.3) that cash flow news Ncf positively impact returns. If investors, for example, revise their future earnings expectations from period $t-1$ to t, e.g. due to new information received in t, the revision induces a change in returns. The change is positive (negative) if future earnings expectations increase (decrease) relative to the previous period. The opposite holds for return news Nr. Here, an increase (decrease) in future expected returns relative to the previous period causes a negative (positive) return impact. To understand this relation, observe that the future expected return is the discount factor in the standard valuation model. An increase in the expected return induces higher discounting and (ceteris paribus) results in a lower price and hence a negative return. Accordingly, in IV.5 return news are deducted from cash flow news to obtain the unexpected excess return.

Estimation of the return decomposition. Campbell (1991) proposes the use of a vector autoregressive (VAR) model to implement the decomposition of returns. A VAR model defines a system of equations that links a vector of state variables $z_{i,t}$ to lags of these variables. As my first approach to decompose stock returns, I use the standard VAR specification applied in the literature (see Vuolteenaho, 2002; Campbell, Polk, and Vuolteenaho, 2010; Callen, Segal, and Hope, 2010). The model includes the log excess stock return (er_t), the log return on equity (roe_t), and the log book-to-market ratio (θ_t) as state variables.

$$\underbrace{\begin{bmatrix} er_{i,t} \\ roe_{i,t} \\ \theta_{i,t} \end{bmatrix}}_{z_{i,t}} = \underbrace{\begin{bmatrix} \alpha_{er,i} & \alpha_{roe,i} & \alpha_{\theta,i} \\ \beta_{er,i} & \beta_{roe,i} & \beta_{\theta,i} \\ \gamma_{er,i} & \gamma_{roe,i} & \gamma_{\theta,i} \end{bmatrix}}_{\Psi} \underbrace{\begin{bmatrix} er_{i,t-1} \\ roe_{i,t-1} \\ \theta_{i,t-1} \end{bmatrix}}_{z_{i,t-1}} + u_{i,t}. \tag{IV.6}$$

All state variables are mean-adjusted by subtracting the cross-sectional mean each year so that the intercept in (IV.6) drops. The error term $u_{i,t}$ is assumed to be independent of everything known at $t-1$. The VAR model defines a mean-reverting process for each state variable, where based on an initial shock the state variables are expected to converge to their cross-sectional mean. The coefficient matrix $\mathbf{\Psi}$ specifies the persistence of the shock. Rational expectations are assumed for the processes defined by the VAR. Following this assumption, in each period t the current observations of the state variables are multiplied with $\mathbf{\Psi}$ to obtain the expected values of the state variables in $t+1$. The procedure is applied iteratively to generate the expected values for future periods. Generally, the expected value of the state variables in period $t+\tau$ equals:

$$\mathrm{E}_t z_{t+\tau} = \mathbf{\Psi}^{\tau} z_{i,t} \tag{IV.7}$$

Vuolteenaho (2002) and Campbell, Polk, and Vuolteenaho (2010) run one pooled regression to estimate the coefficient matrix $\mathbf{\Psi}$. This procedure assumes that the estimated relationship between the state variables and their lags captured by $\mathbf{\Psi}$ is constant both across firms and over time. In contrast, Callen, Segal, and Hope (2010) run the VAR model from (IV.6) at the industry-level. This approach explicitly accounts for the possibility that $\mathbf{\Psi}$ varies across industries. However, within industries and over time the coefficient matrix is assumed to be constant. Their model generates one coefficient matrix $\mathbf{\Psi}_i$ for each industry i. For my analysis I follow the estimation approach of Callen, Segal, and Hope (2010) and estimate the VAR model separately for each Fama-French 48 industry. Each regression covers the full time series between 1970 and 2009. The VAR model is estimated using equation-by-equation OLS for each state variable.[82]

Rather than explicitly computing expectations for the state variables to compute cash flow and return news from (IV.3) and (IV.4), Campbell (1991) proposes a simple approach that allows to directly infer cash flow and return news from the estimated VAR.[83] Let $e1' = [1\ 0 \ldots 0]$ be a vector with a length equal to the number of state variables. Defining

[82]In general, the system of equations (IV.6) would be estimated using seemingly unrelated regressions (SUR). Given that the right-hand side of (IV.6) contains the same explanatory variables for each equation, SUR is, however, equivalent to equation-by-equation OLS (see Hayashi, 2000, p. 282).

[83]Note that in the following I drop the index i for convenience. The estimation of the news components for firms in industry i, however, relies on the respective coefficient matrix $\mathbf{\Psi}_i$.

$$\lambda_1' = e1'\rho\mathbf{\Psi}(\mathbf{I} - \rho\mathbf{\Psi})^{-1}, \tag{IV.8}$$

one can directly estimate the return news as

$$\begin{aligned} Nr_t &= \Delta \mathrm{E}_t \sum_{j=1}^{\infty} \rho^j er_{t+j} \\ &= \lambda_1' u_{i,t}. \end{aligned} \tag{IV.9}$$

Following equation (IV.2), Vuolteenaho (2002) indirectly computes cash flow news as residuals from unexpected returns plus return news. Accordingly, cash flow news equal $Ncf_t = (e1' + \lambda_1')u_{i,t}$. The approach, therefore, assigns the approximation error κ to the cash flow news component.

Chen and Zhao (2009), however, argue that the estimation of return news suffers from a small predictive power that introduces a considerable measurement error of the return news component. If cash flow news are backed out as residual, this error can result in a mismeasurement of cash flow news, which absorb the misspecification of the return news estimates. To circumvent this mechanical relation between return and cash flow news induced by the residual approach, I follow Callen, Segal, and Hope (2010) and directly estimate cash flow news from the return on equity used in the VAR model. In the same fashion as the estimation of return news, I calculate cash flow news by defining

$$\lambda_2' = e2'\rho\mathbf{\Psi}(\mathbf{I} - \rho\mathbf{\Psi})^{-1}, \tag{IV.10}$$

where $e2' = [0\ 1\ 0 \ldots 0]$. Correspondingly, cash flow news equal:

$$\begin{aligned} Ncf_t &= \Delta \mathrm{E}_t \sum_{j=0}^{\infty} \rho^j \left(roe_{t+j} - f_{t+j}\right) \\ &= \lambda_2' u_{i,t}. \end{aligned} \tag{IV.11}$$

The equations for λ_1 and λ_2 indicate that the estimation of the cash flow and return news require an estimate for the parameter ρ. I follow the estimation approach of Vuolteenaho (2002) and regress the log return on equity, roe_t, less the log excess stock return, er_t, plus the lagged log book-to-market ratio, θ_{t-1}, on the log book-to-market ratio θ_t.[84] The regression coefficient of θ_t provides an estimate for the parameter ρ. For my sample, I obtain $\rho = 0.957$. The standard error of 0.0007 and the regression R-squared of 96.8% indicate that ρ is estimated accurately. I therefore use this constant ρ-value for my analysis.[85]

2.2 ICC-based return decomposition

There is one particular concern associated with the existing approach to decompose realized returns presented in the previous section. Equations (IV.3) and (IV.4) indicate that the empirical estimation of cash flow and return news require market expectations regarding future excess stock returns and returns on equity. The existing return decomposition model exclusively determines return and cash flow news by the estimated relationship among the state variables and their lags. The procedure, therefore, implicitly assumes that the expected values of the state variables derived from the VAR model capture market expectations.

To address the concerns associated with the use of realized returns as proxy for expected returns, I propose a new approach to decompose stock returns using the implied cost of equity capital. Pastor, Sinha, and Swaminathan (2008) find that implied cost of capital is helpful in detecting time-variation in expected returns. This feature is of special interest for the dynamic nature of return decompositions. Compared to realized returns, the ICC is a forward-looking measure for expected returns that relies on a fundamental valuation relationship.

[84] I provide the formal derivation of the relationship in equation (D.7) in the Appendix.

[85] Vuolteenaho (2002) obtains an almost similar result of $\rho = 0.967$. Overall, the return decomposition is not sensitive to this particular choice of ρ.

Estimation of return components. Implied cost of capital estimation assumes that in each year the cost of equity capital are expected to be constant over the whole lifetime of a company.[86] Nevertheless, ICC estimates can and do change on a yearly basis due to the arrival of new information over time. Formally, the assumption implies that $\mathrm{E}_t r_{t+\tau} = r_t^{ICC}$ for all τ, where r_t^{ICC} is the ICC estimate for period t.[87] I transfer the ICC into a measure for expected excess returns by subtracting the risk-free rate. In this context I make the additional assumption of a flat term structure for the risk-free rate so that in each period t the risk-free rate is expected to be constant and equal to its current realization: $\mathrm{E}_t f_{t+\tau} = f_t$ for all τ. Following these assumptions, I obtain the expected excess return in $t+\tau$ as

$$\mathrm{E}_t r_{t+\tau} = r_t^{ICC} - f_t \equiv er_t^{ICC} \qquad \text{for all } \tau. \tag{IV.12}$$

Using the definition (IV.12) together with (IV.4) the return news simplify to

$$\begin{aligned} Nr_t^{ICC} &= \Delta \mathrm{E}_t \sum_{j=1}^{\infty} \rho^j \left(er_{t+j}\right) = \Delta er_t^{ICC} \sum_{j=1}^{\infty} \rho^j \\ &= \frac{\rho}{1-\rho}\left(er_t^{ICC} - er_{t-1}^{ICC}\right). \end{aligned} \tag{IV.13}$$

The ICC-based return news in (IV.13), therefore, equal the change in the estimated expected excess return measured from ICC scaled by a factor $\frac{\rho}{1-\rho}$.

I now turn to my alternative estimation of the cash flow news component. The ICC method applied in this chapter relies on a residual income model and requires expected return on equity values (or forecasts; I use the term interchangeably) to estimate the ICC. I use a VAR model similar to the portfolio-level VAR model proposed in Chapter III, which is designed to generate return on equity forecasts.[88] In each period t the forecasting model generates expected return on equity values $\mathrm{E}_t roe_{t+\tau}$

[86] Alternatively, one could regard the implied cost of capital as an adequately estimated average of a firm's expected return over the whole lifetime.

[87] To account for the fact that the expected return from (IV.2) is in logs, I also log-transform the estimated implied cost of capital for the ICC-based return decomposition.

[88] I provide details on the forecasting methodology below.

for each future period τ. Given that the VAR model defines a mean-reverting process for all state variables, the return on equity forecasts converge to an average value in the long-term such that for large τ, $\mathrm{E}_t roe_{t+\tau} = \mathrm{E}_t r\bar{o}e$. I rewrite the cash flow news equation from (IV.3) in the following way:

$$Ncf_t^{ICC} = \Delta\mathrm{E}_t \sum_{j=0}^{T} \rho^j roe_{t+j} + \Delta\mathrm{E}_t \sum_{j=T+1}^{\infty} \rho^j roe_{t+j} - \Delta\mathrm{E}_t \sum_{j=0}^{\infty} \rho^j f_{t+j}. \quad \text{(IV.14)}$$

Applying the previous assumption that in each period t the risk-free rate is expected to be constant and equal to its current realization, the equation simplifies to

$$Ncf_t^{ICC} = \Delta\mathrm{E}_t \sum_{j=0}^{T} \rho^j roe_{t+j} + \Delta\mathrm{E}_t \sum_{j=T+1}^{\infty} \rho^j roe_{t+j} - \frac{1}{1-\rho}\Delta f_t. \quad \text{(IV.15)}$$

Provided that T is large enough, the convergence of the return on equity implies that $\Delta\mathrm{E}_t roe_{t+\tau} = \Delta\mathrm{E}_t r\bar{o}e = \mathrm{E}_t r\bar{o}e - \mathrm{E}_{t-1} r\bar{o}e$ for $\tau > T$. Equation (IV.15) then becomes:

$$\begin{aligned} Ncf_t^{ICC} &= \Delta\mathrm{E}_t \sum_{j=0}^{T} \rho^j roe_{t+j} + \Delta\mathrm{E}_t r\bar{o}e \sum_{j=T+1}^{\infty} \rho^j - \frac{1}{1-\rho}\Delta f_t \\ &= \Delta\mathrm{E}_t \sum_{j=0}^{T} \rho^j roe_{t+j} + \frac{\rho^{T+1}}{1-\rho}\Delta\mathrm{E}_t r\bar{o}e - \frac{1}{1-\rho}\Delta f_t. \quad \text{(IV.16)} \end{aligned}$$

I therefore compute my ICC-based cash flow news in (IV.16) from the change of the discounted sum of expected return on equity up to period T plus the change in expected long-term return on equity scaled by $\frac{\rho^{T+1}}{1-\rho}$ minus the change in the risk-free rate scaled by $\frac{1}{1-\rho}$.

Generating VAR-based return on equity forecasts. To generate expected values for return on equity required to estimate the ICC and my alternative cash-flow news measure, I use the reduced form VAR model from Chapter III, which is designed to generate long-term return on equity forecasts. The model closely matches the VAR(1) model applied by Vuolteenaho (2002) and Callen, Segal, and Hope (2010), but includes the total dividends scaled by book equity (henceforth: dividend yield), dy, as an additional state variable.

$$\begin{bmatrix} er_{i,t} \\ roe_{i,t} \\ \theta_{i,t} \\ dy_{i,t} \end{bmatrix} = \phi + \Gamma \begin{bmatrix} er_{i,t-1} \\ roe_{i,t-1} \\ \theta_{i,t-1} \\ dy_{i,t-1} \end{bmatrix} + u_{i,t}. \tag{IV.17}$$

Note that in (IV.17) I do not mean-adjust the state variables but estimate the regression including the intercept vector ϕ.

Distinct from the estimation methodology of the Vuolteenaho VAR approach, I run the VAR model each year over rolling-windows that include data for the preceding ten years (minimum 8 years). I estimate the model at the portfolio-level (portfolio-level VAR). Following this procedure, I obtain an annual estimate of the intercept vector ϕ_i and the coefficient matrix Γ_i for each portfolio i. Hence, in contrast to the existing VAR approach, coefficient estimates vary both across portfolios of firms and over time. Given that the persistence and long-term values of the state variable processes are specified by the VAR coefficient matrix $\mathbf{\Gamma}$ and the intercept vector ϕ, the procedure accounts for portfolio-specific growth dynamics (persistence) and long-term rates depending on the estimates Γ_i and ϕ_i. Moreover, the approach generates out-of-sample predictions as coefficient estimates for year t are computed based on data observable at time t. In contrast, predictions obtained from the Vuolteenaho VAR approach are in-sample as the full sample is used to estimate the VAR model.

Unlike Callen, Segal, and Hope (2010), my portfolio definition is based on firm characteristics rather than industry classification. The reason is that portfolios for return on equity forecasting should group firms with comparable growth dynamics. In industries that contain both growth and value firms growth dynamics can differ considerably across firms. To the extent that growth firms are characterized by small size, low book-to-market, and high beta, firm characteristics like size, the book-to-market ratio, and beta might better capture differences in growth dynamics across firm portfolios. Following this reasoning, the identification of portfolios based on firm characteristics yields more homogeneous portfolios, which promotes the portfolio-level VAR estimation. For portfolio formation, I assign firms into annual portfolios based on size, book-to-market, and beta. I use the terciles for each variable as portfolio breakpoints (low / medium / high). The procedure results in 27 annual portfolios between 1970 and 2009 or 1,080 portfolio-year observations.

Starting in 1970, I run the rolling-window portfolio-level VAR model each year for each of the 27 portfolios using equation-by-equation OLS (see footnote 82). I then generate forecasts for each firm and year from my VAR estimates by first multiplying the current values of the state variables with the coefficient matrix $\mathbf{\Gamma}$ (I drop the portfolio index i for convenience). Adding the intercept ϕ yields expected values for all state variables in period $t = 1$. I use these forecasts iteratively to obtain forecasts for period $t = 2$ and so forth. Generally, the derivation of forecasts for the state variables in period $t + \tau$ follows:[89]

$$\mathrm{E}_t \begin{bmatrix} er_{i,t+\tau} \\ roe_{i,t+\tau} \\ \theta_{i,t+\tau} \\ dy_{i,t+\tau} \end{bmatrix} = \phi \left(\mathbf{\Gamma}^{\tau} - \mathbf{I}\right) \left(\mathbf{\Gamma} - \mathbf{I}\right)^{-1} + \mathbf{\Gamma}^{-1} \begin{bmatrix} er_{i,t} \\ roe_{i,t} \\ \theta_{i,t} \\ dy_{i,t} \end{bmatrix}. \tag{IV.18}$$

I use equation (IV.18) to estimate return on equity forecasts over a period of $T = 50$ years. First, this choice of T allows me to apply an ICC method with a long detailed planning period that reduces the terminal value sensitivity of implied cost of capital estimates. Second, $T = 50$ is large enough to guarantee that the return on equity forecasts have converged such that the requirement $\mathrm{E}_t roe_{t+\tau} = \mathrm{E}_t \bar{roe}$ for $\tau > T$ is fulfilled.

Finally, I do not use the estimated intercept coefficients ϕ_i from the portfolio-level VAR to generate forecasts based on (IV.18). Instead, I set these coefficients so that

[89] See Petersen and Pedersen (2008), p. 58.

the long-term values for the state variables converge to the median value over all firms in the same portfolio over the preceding ten years. The reason for this adjustment is that for the estimated intercepts ϕ_i the processes converge to their averages over the estimation period. Given that the mean is more sensitive to potential outliers, I prefer a convergence against the portfolio-specific median.[90] To obtain a convergence of the state variables against the portfolio-specific median I need to adjust the intercept vector that sets the long-term average values. I compute an adjusted intercept vector ϕ_i^* by substituting $u_{i,t} = 0$, and the portfolio-specific medians for er, roe, θ, and dy over the respective estimation period into the VAR model (IV.17) and then solving for the intercept values.

Estimating implied cost of equity capital. I use the long-horizon ICC method from previous Chapter III that utilizes the following finite-horizon residual income model to estimate the ICC:

$$P_0 = bv_0 + \sum_{t=1}^{T} \mathrm{E}_0 \left[\frac{(roe_t - r_E)\, bv_{t-1}}{(1 + r_E)^t} \right] + \mathrm{E}_0 \left[\frac{(roe_T - r_E)\, bv_{T-1}(1 + g_{ae})}{(r_E - g_{ae})(1 + r_E)^T} \right]. \quad \text{(IV.19)}$$

I use the return on equity forecasts from the (rolling-window) portfolio-level VAR model to implement a long-horizon ICC method with a detailed planning period of $T = 50$ years. I assume that there is no growth in residual income beyond the respective period T and set $g_{ae} = 0\%$. In Chapter III I show that due to the large discounting effect the impact of changes in g_{ae} on the terminal value and hence on the ICC estimates are small. Accordingly, an alternative choice of $g_{ae} = 3\%$, does not alter my results.

I obtain the book equity forecasts using a payout ratio that equals the average historical five-year realized payout ratio. I define the realized payout ratio in each year as total dividends divided by net income if net income is positive; otherwise the payout ratio equals current dividends divided by 6% of total assets. Also, if the

[90]Note that all results presented below are robust to this specific modeling assumption.

estimated payout ratio is larger than 1 or smaller than 0, the ratio is set equal the respective boundary value.

In robustness checks I assess to what extent my results depend on the choice of the particular ICC method. I therefore repeat the ICC estimation and return decomposition using two alternative ICC methods. I include the firm-level method of Gebhardt, Lee, and Swaminathan (2001) (GLS), and a combined method that equally weights firm-level ICC estimates from GLS and portfolio-level estimates from Easton, Taylor, Shroff, and Sougiannis (2002) (ETSS).[91] The choice of the methods rests on the evidence from Chapter II, where I show in a simulation setting that, among six firm-level ICC methods, GLS provides the most reliable performance, while the combined method provides a robust measure for firms' cost of capital under various specifications of the simulation environment.

I implement the method of GLS with $T = 12$ and $g_{ae} = 0$. For the first three periods I use the explicit forecasts from my VAR forecasting model. From $t = 3$ to $t = 12$ I use a linear interpolation between roe_3 and the median roe over all firms in the same portfolio during the last ten years.

I implement the method of ETSS using a two-stage formulation of the residual income model (IV.19) with $T = 4$ and aggregate earnings and dividends for the first four years. Rearranging the obtained valuation equation yields,

$$\frac{X_c}{bv_0} = (R - 1) + (R - G)\,\frac{P_0}{bv_0}, \tag{IV.20}$$

where $G = (1 + g_{ae})^4$ is one plus the expected growth in four-year residual income, $R = (1 + r_E)^4$ is one plus the four-year expected equity return, and X_c is the measure of four-period cum-dividend earnings. I run a linear regression of X_c, scaled by the book value of equity on the price-to-book ratio P_0/bv_0 for all firms in the same port-

[91] Portfolio-level methods infer the cost of capital and the growth rate *simultaneously* by rewriting the perpetual version of a valuation model so that it resembles a linear regression equation. Portfolio-level ICC methods only provide one ICC estimate for a portfolio of firms and do not allow for a return decomposition of realized returns on the firm-level.

folio. I begin by assuming a starting value of 12% for r_E and then recover one cost of capital estimate and one implied growth rate for each portfolio from the regression coefficients in (IV.20). I recalculate the dependent variable $\frac{X_c}{bv_0}$ with the values obtained and then iterate regression (IV.20) until the estimates of the cost of equity capital and of the implied growth rate converge.[92] Finally, the combined method estimates are computed as equally weighted average of the ICC estimates from GLS and ETSS.

3 Data and variable description

The empirical basis for this study is the CRSP-CompuStat intersection from 1962 to 2009. I only include non-financial firms that are listed on NYSE, AMEX, and NASDAQ.

Sample selection. My data set starts in 1962 as book equity data is generally not available before that date. To be included in the sample, I require a firm-year to have data on the return on equity, market and book equity, returns, and dividends. Furthermore, I require a firm-year to have a valid beta estimate that I compute from CRSP monthly return data. Applying these restrictions results in a data set with 89,536 firm-year observations that I use for the calibration of the portfolio-level VAR model to forecast return on equity as described in Section 2.2. Panel A of Table IV.1 summarizes the sample selection criteria.

[Insert Table IV.1 here.]

Starting in 1970, I run rolling-window vector-autoregressions for each of the 27 portfolios using data over the preceding 10 years (8 years minimum). I obtain a VAR coefficient matrix for 85,824 firm-year observations. The data set forms the basis to estimate the ICC methods described in Section 2.2. I apply my long-horizon ICC method with a 50-year detailed planning period and obtain 80,922 firm-year

[92]Convergence is achieved if both the change in the growth rate and the change in the cost of capital between two iterations is smaller than 10^{-10}.

estimates of the implied cost of equity capital.[93] The estimation of the Vuolteenaho (2002) VAR model and the ICC-based return components require the availability of lagged observations for returns, return on equity, book-to-market, and implied cost of capital. This criterion is fulfilled by 70,551 observations and I use these observations to compute return decompositions. I obtain 62,621 valid non-missing return decompositions for both decomposition approaches. I follow Callen, Segal, and Hope (2010) and truncate the data at the 1%-level to reduce the impact of extreme outliers.[94] This procedure reduces my final return decomposition sample to 58,171 firm-year observations for 5,454 firms between 1972 and 2009.

The main governance score used in this chapter is the G-index of Gompers, Ishii, and Metrick (2003). The index is based on a score that counts the corporate governance provisions, in particular the number of anti-takeover provisions, enacted by a company. The score covers 24 provisions in total. Data on takeover provisions is provided by the Investor Responsibility Research Center (IRRC).[95] I obtain data on the governance score between 1990 and 2008.[96] Merging my decomposition sample with the governance sample, I obtain 15,441 valid matches. I drop all dual-class shares from the analysis. The final governance return decomposition data set covers 13,962 firm-year observations from 1990-2008.

Panel B of Table IV.1 shows summary statistics for selected financial variables of the final return decomposition data set. The average stock return in my data set is 7.2%, while the corresponding (book) return on equity is 2% higher. The median firm-year has a book-to-market ratio of 0.7, which implies a market value that is

[93] I restrict the algorithm to search for the implied cost of capital in the unit interval, but in some cases it can only find solutions that are either negative or higher than 100%. In these cases the algorithm returns a missing value.

[94] I truncate rather than winsorize the data since for winsorized return components the relation that return and cash flow news add up to the unexpected return component is not fulfilled for every firm-year.

[95] By now, the database is contained in RiskMetrics provided by ISS Governance Services, who acquired IRRC in 2005.

[96] The IRRC data on takeover provisions starts in 1990. The last publication available for my data set refers to the year 2006. Given that after 2000 the data is published every two years, I assume that the governance score remains constant until 2008.

1.4 times above its book value for the median firm-year. Firm size shows the usual skewness with an average market capitalization of about 1.8 bn US-$ compared to a median of 186 mil. US-$. The distribution of firm-years shows that the average (median) firm survives 10.7 (8) years in my sample.

Summary statistics for the governance return decomposition data set are reported in Panel C of Table IV.1. The average governance score is 9.4 (median: 9). Stock returns and returns on equity are on average comparable to the numbers obtained for the full decomposition data set. With an average market capitalization of 5.4 bn US-$ (median: 1.5 bn) firms in the governance sample are, however, considerable larger. This finding is also reflected by the lower average and median book-to-market ratio of 0.58 and 0.49, respectively.

Variable definition. I measure all CRSP variables, i.e. prices, dividends, number of shares outstanding, and returns as of the end of June in year t. The variables are matched with the CompuStat data from the most recent fiscal year $t-1$. This procedure guarantees that all information from the annual financial statement is available at the time of the forecasts and impounded into prices and returns. Annual returns and dividends are compounded from monthly returns and dividends, recorded from the 1st of July to the 30th of June. The market capitalization equals the number of shares outstanding times the share price at the end of June. The proxy for firm size is defined as the log of market capitalization. In each June I compute historic betas based on a regression of monthly stock returns on the CRSP value-weighted market index. I use regressions over the preceding 60 months and require a minimum of 24 months with valid data for the estimation. I use annually compounded T-Bill returns from Ibbotson Associates as the risk-free rate.

For book equity, I use CompuStat common equity and, if common equity is unavailable, the liquidation value of common equity. If available, I add income taxes payable and deferred taxes and investment tax credit to common equity. I treat common equity as missing if it is negative. Data on net income is obtained from CompuStat earnings before extraordinary items. I compute return on equity as net income from the most recent fiscal year divided by book equity from the previous fiscal year. The book-to-market ratio equals book equity from fiscal year $t-1$ divided by the market capitalization as of the end of June in year t. Following Vuolteenaho (2002) I use the natural log of returns, the return on equity, and the book-to-market ratio as state variables when estimating the Vuolteenaho VAR model according to equation (IV.6). The (book) dividend yield equals total dividends in year t scaled by book equity from fiscal year $t-1$. I define leverage as debt divided by debt plus market capitalization, where debt equals long-term debt plus debt in current liabilities plus preferred stock from CompuStat. I winsorize each variable at the 1% level to reduce the impact of extreme outliers.

Data on takeover provisions was first collected in September 1990 and subsequently in December 1995, 1998, 2000, 2002, 2004, and 2006. I assume that the governance score remains constant for the years between two publications. I merge annual returns computed from monthly returns between July 1st of year t and June 30th of year $t+1$ with governance data for year t.[97] Rather than using the raw governance score I compute the G-index that assigns firms into ten portfolios based on their score. The democracy (dictatorship) portfolio includes firms with a governance score smaller or equal to 5 (larger or equal to 14). Between these extremes the G-index increases by one with each additional governance provision.

4 Analysis

I start my analysis by estimating return and cash flow news based on the return decompositions discussed in Section 2. I present the results of the VAR models in Section 4.1 and defer the analysis of the return decomposition approaches to Section 4.2.

[97]The first annual return refers to the period July 1st, 1990, to June 30th, 1991, and is matched with the governance score for 1990. The last return period covers July 1st, 2007, until June 30th, 2008, and is matched with the most recent governance score published in 2006.

4.1 Calibration of VAR models

I begin with the analysis of the VAR models that I utilize to derive return decompositions. Table IV.2 shows coefficient estimates for the VAR models discussed in Section 2.

[Insert Table IV.2 here.]

Panel A of Table IV.2 shows regression coefficients for the standard Vuolteenaho (2002) VAR model estimated using the industry-level regressions of Callen, Segal, and Hope (2010).[98] The number of observations documents that the average Fama-French 48 industry contains 1,305 firm-year observations between 1970 and 2009. The autocorrelation coefficient of excess stock returns is significant and positive. With a value of 0.044 the average coefficient lies between the coefficient reported by Vuolteenaho (0.118) and the insignificant estimate obtained by Callen, Segal, and Hope (2010). Overall, the evidence indicates that the autocorrelation in realized excess returns is low.

I also estimate positive and significant autocorrelation coefficients for return on equity and the book-to-market ratio. The autocorrelation coefficients for the two state variables are considerably larger (0.362 and 0.763) compared to the excess return autocorrelation, but smaller compared to the estimates reported in Vuolteenaho (2002) and Callen, Segal, and Hope (2010).[99] Consistent with the earlier evidence in these two studies, the cross-correlations indicate a significant impact of lagged state variables on the current values of other state variables. In line with previous evidence, all cross-correlations show a positive sign, except the negative and significant effect of lagged book-to-market on return on equity.

The average R-squareds in Panel A highlight an interesting pattern. While the simple industry-level VAR model explains a considerable part of the varia-

[98] The coefficients and (adjusted) R-squareds equal the average estimates from industry-level regressions. I calculate t-statistics from cross-sectional standard errors.

[99] The papers report an autocorrelation coefficient for return on equity (book-to-market) of about 0.49 (0.85) for the sample periods 1954-1996 and 1962-2006, respectively.

tion in return on equity and book-to-market (31.8% and 61.6%), the explained variation of realized excess returns equals 1.8% only. The evidence implies that the expected return model used to calculate return news relies on a realized return calibration that leaves approximately 98% of the variation in excess returns unexplained.

Following the argument of Lundblad (2007), it might be problematic to identify the relation between the state variables and expected returns comprised in realized returns due to the low explanatory power of these variables for realized returns. Using a simulation approach, Lundblad finds that a sample covering more than 100 years is required to identify the relation between volatility (risk) and returns. In line with this reasoning, a sample size of about 40 years used to estimate the Vuolteenaho VAR model is likely not sufficient to detect the underlying relation between the state variables and expected returns.

Panel B and C of Table IV.2 document results for the alternative VAR model from Chapter III with four state variables. In Panel B, I estimate a rolling-window VAR model from the pooled cross-section of firms using data for the preceding ten years (eight years minimum).[100] Using the full cross-section to estimate the rolling-window VAR results in a higher average number of observations (18,858 vs. 1,305 for the industry-level Vuolteenaho VAR model). The number of observations used to calculate the rolling-window VAR varies considerably over time with 4,664 observations in 1970 and 29,258 observations in 2009.

The autocorrelation coefficients are broadly in line the the numbers from Panel A. The return on equity autocorrelation increases to 0.492, which is close to the estimates reported in Vuolteenaho (2002) and Callen, Segal, and Hope (2010). The average excess return autocorrelation is, however, no longer significant for annual regressions. The cross-correlations are consistent with the findings from industry-level regressions. Only the effect of lagged return on equity on the book-to-market ratio

[100]The coefficients and (adjusted) R-squareds equal the average estimates from annual regressions. I calculate t-statistics from time-series standard errors.

becomes insignificant. The coefficient estimates for the lagged dividend yield indicate a significant impact of the additional state variable that is positive for the excess return and the return on equity and negative for the book-to-market ratio.

More importantly, Panel B shows a considerable increase of the R-squared values for the return on equity and excess return equations. While the R-squared for return on equity increases by approximately 10 percentage points, the R-squared for excess returns more than doubles to 4.9%. In contrast, the R-squared for the book-to-market ratio drops by about 5 percentage points to 56.9%. Hence, there seems to be an industry factor related to the book-to-market ratio that is not accounted for by the pooled annual regression leading to the lower R-squared.

Overall, the structure and results for the pooled rolling-window VAR, indicate that the model is not too distinct from the standard VAR approach of Vuolteenaho (2002) in Panel A. In this context, the choice of the forecasting model likely plays a minor role. The crucial question is how the forecasts generated by the VAR models are utilized to estimate the return components. While the existing return decomposition approach utilizes the expected excess returns generated by the VAR to compute return news, ICC-based return decomposition relies on the expected return on equity for computing both cash flow and return news. Besides the direct inclusion of expected return on equity in the cash flow news formula (IV.16), the forecasts also enter the ICC estimation as part of the residual income in the numerator and hence also build the foundation for the return news according to (IV.13). The ICC-based return decomposition should, therefore, benefit from relying on expected values for a variable that is likely to inherit better forecastability.

As described in Section 2.2, I do not apply the pooled rolling-window VAR approach from Panel B to generate expected return on equity values but estimate a rolling-window portfolio-level VAR model that includes annual portfolios of firms rather than the pooled cross-section. The approach computes a coefficient matrix $\mathbf{\Gamma}_i$ for each portfolio-year accounting for the possibility that the relationship among the state variables and their lags varies both across portfolios and over time. Since the VAR coefficient matrix defines the dynamics of the state variable processes, the portfolio-level approach accounts for portfolio-specific growth dynamics. In Chapter III I find that the rolling-window portfolio-level VAR model outperforms the pooled rolling-window VAR approach with respect to tracking future realized earnings. Since the quality of my return decomposition approach crucially depends on the quality of the return on equity forecasts, I stick to the rolling-window portfolio-level VAR estimation.

Panel C of Table IV.2 shows univariate statistics for the 1,080 portfolio-year estimates of the coefficient matrix $\mathbf{\Gamma}_i$. The mean estimates (column (1)) of the four state variable equations are in line with the pooled estimates from Panel B. More interestingly, the standard deviation of the coefficients (column (2)) and the quartile range (columns (3) and (4)) indicate a considerable variation of estimates across portfolio-years. In addition, I report univariate statistics for the portfolio-level long-term rates of the four state variables at the bottom of Panel C. The long-term rate for the return on equity, for example, indicates that it converges to a rate of 10.14% for the median portfolio-year. More importantly, with a standard deviation of 6.35% long-term return on equity shows a considerable variation across portfolios. The fact that the persistence and long-term rates of the processes vary across portfolios, emphasizes the use of the rolling-window portfolio-level VAR model to capture the differences in portfolio-specific long-term growth dynamics.

4.2 Implied cost of capital, return news, and cash flow news

In the following, I analyze the return news and cash flow news computed using the Vuolteenaho and ICC-based return decomposition. Table IV.3 reports univariate statistics for realized returns, expected returns, and return components. I report expected return estimates from the long-horizon ICC method (ICC-based expected returns) and expected returns implied by the fitted values of the Vuolteenaho VAR model (VAR-based expected returns).[101] The sample period covers the years 1972 to 2009.

[Insert Table IV.3 here.]

Panel A of Table IV.3 documents equally- and value-weighted average realized excess returns (columns (1) and (2)) of 1.59% and 6.92%, respectively. The numbers indicate that larger firms on average gained higher realized returns over the sample period than smaller firms. The ICC results imply a market-risk premium based on the implied cost of capital of 4.19% (equally-weighted) or 5.22% (value-weighted). The expected return measure obtained from the Vuolteenaho VAR model, however, produces a considerably lower market risk premium of 0.65% only (2.06% equally-weighted).

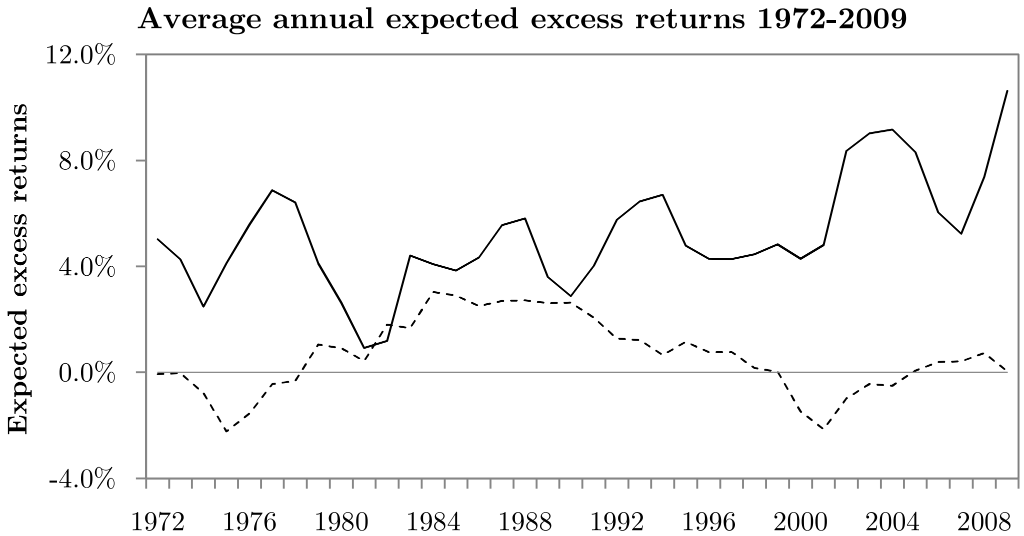
The average returns highlight an interesting aspect and shed doubts on the claim that 40 years of data are sufficient in order to justify the underlying assumption that realized returns equal expected returns in the long-run. Looking at the average value-weighted returns, I observe a difference of more than 6% between realized excess returns and expected excess returns obtained from the Vuolteenaho VAR model. Based on this deviation, it is questionable to what extent the standard Vuolteenaho approach is able to provide an adequate decomposition of stock returns.

To further assess properties of expected excess returns obtained from the two approaches, I analyze the evolution of average expected market excess returns (market risk premia) over time. Figure IV.1 plots annual value-weighted expected market excess returns for the two expected return measures. While ICC-based expected excess returns (solid line) are positive over the whole sample period, expected market excess returns from the VAR model (dashed line) are negative in 12 out of 38 years. Moreover, looking at the recent years of the financial crisis the market risk premium

[101] Since the Vuolteenaho VAR model generates forecasts for the market-adjusted excess return, I add back the cross-sectional average excess return each year to obtain the expected excess return. I compute the expected return by adding the risk-free rate.

Figure IV.1: Average annual expected market excess returns

This figure shows the time-series variation of annual value-weighted market excess returns (market risk premia) between 1972 and 2009. Annual expected excess returns are calculated from the long-horizon ICC method (solid line) and from the fitted values of the Vuolteenaho VAR model (dashed line) minus the annualized return on monthly T-Bills from Ibbotson.

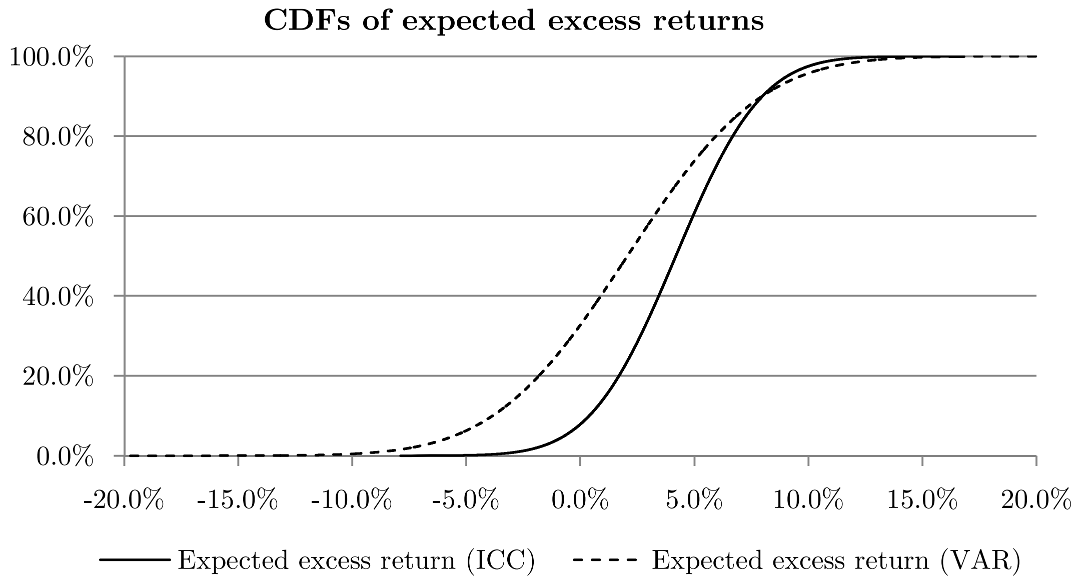


implied by the VAR model is only about 0.5% (2007-2008) and almost zero in 2009. Expected market excess returns obtained from ICC estimates, in contrast, increase steadily from 5.2% in 2007 to 10.6% in 2009 (2008: 7.4%).

I further assess this point by including annual data for the investor sentiment index of Baker and Wurgler (2006) and link it to the market risk premia obtained from the two approaches.[102] A high (low) index value indicates an overall positive (negative) sentiment of market participants. Economic intuition implies that in times of high or positive sentiment market risk premia should be lower compared to times of low or negative sentiment. I compute simple correlations between the measures for expected market excess returns and the sentiment index (results not tabulated). The results show a negative relation between the ICC-based market risk premium and the sentiment index of -0.349, significant at the 5%-level. For the VAR-based market risk premium I obtain a positive relation to the sentiment index (0.303), significant at the

[102]The sentiment index is obtained from Jeff Wurgler's homepage. The index is based on the first principal component of six (standardized) sentiment proxies, where each of the proxies has first been orthogonalized with respect to a set of macroeconomic conditions.

Figure IV.2: Cumulative distribution function of expected excess returns
This figure shows the cumulative distribution functions of the expected excess return measures obtained from the long-horizon ICC method (solid line) and from the fitted values of the Vuolteenaho VAR model (dashed line). Expected excess returns equal the expected return estimates from the two approaches minus the annualized return on monthly T-Bills from Ibbotson.



10%-level. The positive relation contradicts the economic intuition and is additional evidence for the problems associated with the VAR-based expected return measure.

The evidence of negative market-level expected excess returns for a considerable fraction of the sample also holds at the firm-level. Columns (4) to (6) of Panel A document the quartile distribution of the estimates. The numbers in column (4) highlight that the 25% quartile for the VAR-based expected excess return measure (firm-level risk premium) is negative. This finding implies that the Vuolteenaho VAR model computes expected excess returns below the risk-free rate for more than 25% of the sample. To get a more detailed picture, I plot the cumulative distribution functions for the ICC-based (solid line) and VAR-based (dashed line) expected excess return measures in Figure IV.2. The figure shows that the Vuolteenaho VAR model computes negative expected excess returns for almost 40% of the sample. In contrast, expected excess returns obtained from the long-horizon ICC method are positive for more than 90% of the sample and generate a much more convincing expected return pattern.

Overall, the firm- and market-level evidence implies that ICC estimates much better reflect specific properties one would attribute to a consistent expected return measure. Compared to expected return estimates that rely on realized returns, implied cost of equity capital seem to provide a superior measure for firm- and market-level expected returns. Part of the improved consistency may stem from the fact that ICC methods generate an expected return measure derived from a fundamental valuation relationship. Assuming that observed prices reflect fundamental values, implied cost of capital, provide a theoretically consistent measure for expected returns compared to a measure obtained from an ad hoc realized return model. Ultimately, applying a more consistent expected return measure also promotes the estimation of return news obtained from the ICC-based return decomposition.

Panel B of Table IV.3 shows univariate statistics for the return components obtained from the two decomposition approaches. For the ICC-based return decomposition I observe an average value-weighted unexpected return of 1.79% that stems from on average positive cash flow news and positive but smaller return news. The unexpected return component from the Vuolteenaho (2002) decomposition is on average larger (6.91%). The higher number results from a higher cash flow news component in combination with lower return news. I also compute indirect cash flow news (residual) as the sum of unexpected returns and return news. The average values, however, indicate that the differences between directly and indirectly estimated cash flow news are small on average. Furthermore, the equally- and value-weighted returns highlight that all return components contain a size effect leading to larger value-weighted averages for all return components.

The variance estimates (column (3)) support previous findings that cash flow news variation is the main driver of stock return volatility (see Vuolteenaho, 2002; Callen, Segal, and Hope, 2010). For both return decomposition approaches cash flow news variance exceeds return news variation. As expected, indirect cash flow news show a higher variance compared to the direct cash flow news component as it contains the approximation error from the decomposition according to (IV.2). The difference for the ICC-based decomposition is, however, small and exceeds the direct cash flow news variance by only 12.5% (0.3322 vs. 0.3736). For the Vuolteenaho return decomposition the difference between direct and indirect cash flow news amounts to 54.1% (0.0498 vs. 0.0768). More importantly, comparing return and cash flow news variation for the two decomposition approaches, I observe a considerably higher variance for ICC-based return components. The return news (cash flow news) variance for the ICC-based decomposition equals 0.2145 (0.3322) compared to 0.0079 (0.0498) for the standard decomposition approach. Part of this difference arises from the use of market-adjusted excess returns for the Vuolteenaho return decomposition. Cash flow and return news are, therefore, calculated net of market-wide return variation, which explains the higher variation of ICC-based return components.

To shed more light on the interaction between unexpected returns, cash flow news, and returns news, Table IV.4 reports variance-covariance matrices and correlations for the estimated return components. I show standard errors obtained from bootstrapping with 100 replications in parentheses.[103]

[Insert Table IV.4 here.]

Panel A of Table IV.4 presents the covariance and correlations for the ICC-based return components. The numbers on the main diagonal of the variance-covariance matrix equal the variance estimates from the previous table. The covariance estimates show a positive relation between cash flow news on the one hand and return news and unexpected returns on the other hand. The positive covariance between cash flow news and unexpected returns is based on the formal relationship between the two components. Following equation (IV.2) an increase in cash flow news ceteris paribus leads to higher unexpected returns. In line with this reasoning, I observe a significant and positive correlation between the two variables of about 0.5. The positive covariance

[103] Recalculating the standard errors for several seeds does not lead to significant differences and indicates that the number of replications suffices.

between cash flow news and return news implies an even higher correlation of more than 0.8. The number indicates that positive cash flow news, i.e. increased future earnings expectations are accompanied by an increase in future return expectations.

The high correlation of return and cash flow news might arise from a mechanical relation between the two components that is due to the underlying estimation methodology. More specifically, return news might capture part of the estimation error contained in the cash flow news component. Suppose the earnings forecasting model in one period predicts an increase in future earnings. Assume further that the revised expectations are not shared by market participants. In this case, the decomposition approach measures positive cash flow news even though the market does not expect a change in future earnings. Given that earnings forecasts also enter the implied cost of capital estimation, the spurious increase in expected future earnings is compensated by an increase in the expected return so that the stock price is unchanged. Following this example, cash flow and return news show a positive relation, if the market's future earnings expectations are not fully captured by the underlying earnings forecasting model.

With a positive and significant correlation of 0.0885, the relationship between return news and unexpected returns shows an unintuitive pattern. Following equation (IV.2) an increase in return news should ceteris paribus lead to lower unexpected returns. One reason for the observed positive correlation can be the strong and positive correlation between cash flow and return news. Since positive return news come along with positive cash flow news, the overall effect on the unexpected return could be positive implying a spurious positive relation between return news and unexpected returns. To further investigate this point, I run the following pooled multivariate regression of unexpected returns on cash flow and return news:[104]

$$\begin{array}{ccccccccc} er_t - er_{t-1}^{ICC} & = & 0.9104 & \times & Ncf_t^{ICC} & - & 0.8846 & \times & Nr_t^{ICC} + \varepsilon_t \\ & & (0.0077) & & & & (0.0086) & & \end{array}$$

[104] Note that this regression only works for the directly estimated cash flow news. Robust standard errors clustered at the firm-level are shown in parentheses. The R-squared equals 62.9%.

As expected, the coefficient for return news is negative and significant with a point estimate of -0.8846. For the cash flow news coefficient I obtain a significant estimate of 0.9104. Hence, after controlling for cash flow news, return news show the expected positive association with unexpected returns from (IV.2).

Panel B of Table IV.4 repeats the covariance and correlation estimates for the Vuolteenaho (2002) return decomposition. As expected and in line with previous findings of Vuolteenaho (2002) and Callen, Segal, and Hope (2010), the covariance between cash flow news and unexpected return is positive, while return news covary negatively with unexpected returns. The covariances imply correlations of 0.7109 and -0.6041 for cash flow and return news respectively.

The main difference between the two decomposition approaches, however, arises from the correlation between cash flow news and return news. In contrast to the significantly positive and economically large positive correlation obtained for the ICC-based return decomposition, the correlation coefficient for the Vuolteenaho return decomposition equals -0.2332. The relationship between the two return components indicates that the return decomposition approaches produce distinct measures for cash flow and return news. This point is supported by the correlations between the cash flow and return news from the ICC-based and Vuolteenaho return decomposition. (I provide the complete correlation matrix in Appendix E.) The two cash flow news measures show a positive and significant correlation of 0.4581. The number documents a consistent relationship that is, however, far from being perfect (equal to one). More importantly, the correlation between the ICC-based and Vuolteenaho return news is close to zero with a point estimate of 0.0120. The finding supports the hypothesis that differences in the expected return measure presented above transfer into the return news component and lead to considerable differences between the two return news measures.

Finally, Panel C of Table IV.4 shows correlations for the indirect return news measures and the error components of the two decomposition approaches. For the ICC-based return decomposition indirect cash flow news are highly correlated with the direct measure (correlation coefficient of 0.9319). The high correlation indicates that the ICC-based decomposition is robust to the choice of the cash flow news estimation, i.e. direct vs. indirect. As a consequence, the correlations between indirect cash flow news on the one hand and return news and unexpected returns on the other hand closely match those obtained for the direct cash flow news measure. The error component κ is significantly correlated with return and cash flow news. The correlation is, however, economically small and close to zero. For the Vuolteenaho return decomposition correlations are also in line with those obtained for the direct cash flow news measure. The correlation of indirect and direct cash flow news is significant and positive but smaller (0.7502). Interestingly, the error component shows a negative correlation with return news, indicating that small return news are accompanied by a large error component. Hence, the decomposition assigns a larger residual to the indirect cash flow news if return news are low.

Overall, the evidence on the ICC-based and Vuolteenaho return decomposition highlights that the alternative estimation procedures result in distinct measures for cash flow and return news. The two cash flow news measures seem to be more closely related but still show considerable differences, as implied by the correlation of the measures. Furthermore, the measurement of expected returns leads to considerable differences documented by the low correlation between the two return news measures. Due to the missing benchmark problem, expected returns implied by ICC and VAR cannot be directly benchmarked. Nevertheless, my analysis of ICC- and VAR-based expected returns in combination with the evidence of Pastor, Sinha, and Swaminathan (2008) indicate that implied cost of capital provide more reliable estimates of expected returns. The evidence presented above highlights that ICC estimates show specific characteristics that are much more in line with properties attributed to expected returns, both on the firm- and market-level. Hence, given that the implied cost of capital better capture expected returns, the ICC-based return decomposition will also provide more consistent estimates of return components.

5 Application: Corporate governance and returns

In this section I use previous return decompositions to assess the evidence of superior return performance of well-governed firms presented by Gompers, Ishii, and Metrick (2003).

5.1 Returns, return components, and corporate governance

Evidence from the ICC-based return decomposition. I start my analysis with regressions of different return measures on the G-index and various control variables to reassess the relation between corporate governance and returns. The common approach to test the return performance of democracy firms (G-index = 1) and dictatorship firms (G-index = 10) is a hedge-portfolio approach, where monthly portfolio returns are regressed on return factors (size, book-to-market, beta, momentum). The estimated alphas of the regressions capture the abnormal returns and are compared for democracy and dictatorship portfolios. However, since my return decomposition data is only available on an annual basis a hedge-portfolio approach with monthly returns is not feasible for my setting.[105]

Instead, in Table IV.5 I run panel regressions including firm fixed-effects and additional controls for various factors that could influence the relation between returns and the G-index.[106] In particular, I control for size (market capitalization), capital structure (book-to-market and market leverage), profitability (return on equity and sales growth), momentum (lagged return), price, and the CRSP value-weighted market return. For my analysis I split the sample into an early period

[105] Using annual returns does not solve the problem, as hedge-portfolio regressions are time-series regressions and the annual time-series between 1990 and 2008 is too short to deliver meaningful results.

[106] A Hausman test supports the use of a fixed-effects compared to a random-effects model.

1990 to 2002 (Panel A) and a recent period 2003 to 2008 (Panel B). The early subsample covers the time period prior to the publication of the study by Gompers, Ishii, and Metrick (2003). I choose this subsample to assess the claim of Schwert (2003), who argues that many so called return anomalies seem to have weakened or disappeared after the papers that highlighted them were published. Following Schwert, the identification of anomalies leads investors to trade on the anomalous return behavior, which causes anomalies to disappear following their detection.

[Insert Table IV.5 here.]

Panel A of Table IV.5 shows regression results for two different return measures (columns (1)-(2)) for the period 1990 to 2002. The coefficients for the G-index are significant and negative for both return measures.[107] For the unexpected return (column (1)), i.e. the return above the expected return obtained from ICC, the coefficient for the G-index equals -0.016. To account for the evidence of Johnson, Moorman, and Sorescu (2009) that return differences are due to missing industry controls, I repeat the regression for industry-adjusted (excess) returns. I compute industry-adjusted returns as the difference between excess returns and value-weighted industry returns for Fama-French 48 industries. Accounting for industry returns, indeed, slightly reduces the coefficient estimate for the G-index. With an estimate of -0.013 the effect is, however, still negative and highly significant. The economic effect implied by the coefficient estimates is considerable. The effects for unexpected and industry-adjusted excess return indicate that a one standard deviation increase in the G-index (increase by approx. 3) results in an average excess return between -3.9% and -4.8% per year. The difference between a democracy and dictatorship firm is even larger.

Before I draw the attention to the effects of the G-index on return and cash flow news, I analyze whether the return differences observed for the early subsample are also obtained for the post-2002 period. In Panel B of Table IV.5 I repeat the

[107] I obtain similar results for raw returns, excess returns, and unexpected returns according to the Vuolteenaho return decomposition.

return regressions for the recent subsample from 2003 to 2008 (columns (1)-(2)). The coefficient estimates show that there is no significant effect of the G-index on both return measures when considering the time period after 2002.[108] This finding is in line with the evidence of Giroud and Mueller (2010), who find a significant relation between the G-index and returns for the period 1990 to 1999 but not for the full sample period until 2006.[109] Overall, the return evidence supports the finding of Gompers, Ishii, and Metrick (2003) and Giroud and Mueller (2010) that over the 1990s and early 2000s low G-index firms ("good governance") have a superior return performance compared to high G-index firms ("bad governance"). In line with the argument of Schwert (2003), the superior return performance, however, vanishes after the publication of the return anomaly in 2002. The disappearance of the effect might highlight a mere coincidence. Alternatively, it might arise from trading of investors based on the previously detected anomaly, which implies that research findings cause the market to become more efficient.

The ability of the G-index to predict unexpected excess returns raises the question whether the effect arises from differences in cash flow news or return news. I address this question by running panel regressions including firm-fixed effects of cash flow news and return news on the G-index and above control variables. Columns (3) to (6) show results for cash flow and return news obtained from the ICC-based return decomposition.[110] For the early subsample from 1990 to 2002 (Panel A of Table IV.5), I observe a significant and negative effect of the G-index on the cash flow news component (columns (3) and (5)). The effect applies to both measures for cash flow news (direct and indirect). The numbers indicate that a significant part of the inferior return performance over this period is due to lower cash flow news of high G-index firms.

[108]For raw returns and excess returns the effect is also insignificant.

[109]I also checked the return performance for the full sample (1990 to 2008) but do not obtain a significant relation between the G-index and returns.

[110]I provide robustness checks using alternative ICC estimates to compute return decompositions in Section 6.

At the same time, however, the effect on return news is also negative and significant (column (4)). Given that high return news ceteris paribus decrease realized returns, the negative return news effect partly offsets the lower cash flow news of high G-index firms. To assess the net effect I run a t-test to check whether the G-index coefficient for cash flow news (-0.050) significantly exceeds the return news coefficient (-0.025) in absolute terms. The test statistic (t-value of -3.173) shows that the difference (-0.025) is significant at the 1%-level. The effect documents the stronger impact of the G-index on cash flow news that leads to the overall negative effect for excess returns.

Given the high positive correlation between return and cash flow news documented in the previous section, it is possible that the negative effect of the G-index on return news partly reflects a cash flow news effect included in the return news component. The estimation approach of return and cash flow news implies that a measurement error of cash flow news (mismeasurement of expected future earnings) induces a measurement error of the ICC that flows into the return news component, but not vice versa. To get rid of cash flow news included in the return news component I orthogonalize the return news component by running a regression of return news on cash flow news. The residuals of this regression are free of cash flow news and I use them as orthogonalized return news measure for my further analysis.

In contrast to the findings for the original return news component, the effect of the G-index on the orthogonalized return news component (column (6)) documents a positive and significant effect. The effect implies that investors over this period successively increased their future return expectations (cost of capital) for firms with poor governance leading to lower realized returns for these firms. The higher return news for high G-index firms promote the negative effect obtained for cash flow news, since high return news are associated with lower realized returns.

In Panel B of Table IV.5 I repeat the analysis for the recent subsample from 2003 to 2008. For this sample the coefficient estimates for cash flow news (column (3)) are no longer significant, while the indirect cash flow news estimate (column (5)) is only marginally significant. As before return news (column (4)) show a negative and significant relation the the G-index.[111] For the orthogonalized return news measure, however, I do not obtain a significant effect. The finding highlights that – after controlling for cash flow news effects impounded into return news – cash flow and return news of high and low G-index firms do not differ over the post-2002 period. The result explains the indistinguishable return performance of firms with good and poor corporate governance during recent years.

Overall, the evidence in Table IV.5 implies that the superior return performance of firms with good corporate governance between 1990 and 2002 mainly arises from higher cash flow news and lower return news for these firms. One explanation for the findings is that investors during this time had “too” high cash flow expectations for firms with weak governance. Core, Guay, and Rusticus (2006), for example, present evidence that high G-index firms have weaker operating performance compared to low G-index firms. Their analysis, however, does not find evidence that investors are surprised by the weak operating performance. My results indicate that over this time investors were surprised by the weaker operating performance of high G-index firms leading to stronger downward revisions of future expected earnings (negative cash flow news). At the same time, investors increased the expected returns (or cost of capital) for high G-index firms leading to lower realized returns and to the observed positive relation between the G-index and orthogonalized return news. The evidence for the post-2002 period then highlights that differences in returns, cash flow news, and return news for firms with good and weak governance no longer persist, which supports the argument of Schwert (2003) that return anomalies often vanish after their publication.

[111] A t-test shows that the difference between the G-index coefficient for return and cash flow news is not significant (t-value of -0.105).

Evidence from Vuolteenaho return decomposition. Table 6 repeats the return component evidence for return and cash flow news obtained from the Vuolteenaho (2002) VAR model.

[Insert Table IV.6 here.]

The evidence supports my previous findings that the two decomposition approaches deliver distinct measures for cash flow and return news. The results show no significant relation between cash flow news and the G-index for both sample periods (columns (1) and (4)). In line with with the evidence for the ICC-based decomposition, residual cash flow news document a small and marginally significant negative effect (-0.007) for the early subsample (column (3)). Over the same time the coefficient in column (2) , implies a significant and slightly positive effect (0.002) of the G-index on return news. Concerning the post-2002 period none of the return components shows a significant relation to the G-index (columns (4)-(6)).

The evidence presented indicates that the effects for the Vuolteenaho return decomposition are considerably smaller. A likely cause for this finding is the overall lower variance of the return components making it hard to detect return and cash flow news differences across G-index groups. Consistent with previous evidence, I find that the inferior return performance of firms with weak governance over the period 1990 to 2002 is partly due to higher return news of these firms. In line with the ICC-based return decomposition, I do not obtain a significant effect of the G-index on the return components from the Vuolteenaho decomposition over recent years.

The results for the two decomposition approaches indicate that more research is required that analyzes the quality of return decomposition approaches. However, given the deficits of the standard decomposition approach and the firm- and market-level evidence presented above, I have concerns that the return and cash flow news measure adequately capture changes in expectations regarding future earnings (or cash flows) and returns. The different results for the indirect and direct cash flow news measure obtained for the Vuolteenaho return decomposition also point into this direction and raise doubts concerning the robustness of the decomposition approach.

5.2 The impact of product market competition

Giroud and Mueller (2010) provide evidence that return differences between high and low G-index firms mainly occur in industries with low product market competition and persist until recent years for these industries.[112] Their analysis implies that product market competition serves as an additional governance provision that prevents firms or managers in high-competition industries to act against the interest of shareholders. I also check to what extent product market competition is relevant for my sample and repeat the analysis from Table IV.5 for subsamples of firms (terciles) in industries with high, medium, and low product market competition.[113]

[Insert Table IV.7 here.]

For the early subsample Panel A of Table IV.7 shows that my results based on annual return data, do not support the evidence that product market competition is an additional governance provision. I find that return differences (columns (1)-(3)) mainly arise for the mid product market tercile, while for industries with high and low product market competition I cannot observe significant return differences. With respect to cash flow news (columns (4)-(6)) I find a significant and negative effect of the G-index across all product market terciles. For (orthogonalized) return news (columns (7)-(9)) the effect is positive across all terciles but only significant for firms in mid product market competition industries. The results support previous findings of negative cash flow and positive return news effects over the period 1990 to 2002 presented in Section 5.1. The effect, however, does not seem to be related to product market competition.

[112]They define product market competition at the industry-level (Fama-French 48 industries) as a Herfindahl index that equals the sum of squared market shares (based on sales) within an industry.
[113]For convenience I do not report coefficients and standard errors of control variables.

Panel B of Table IV.7 shows results for the recent subsample 2003 to 2008. The effects of the G-index on unexpected returns highlight that returns for firms with good and poor corporate governance are indistinguishable across all product market competition terciles. For high and low product market competition industries the insignificant effect stems from insignificant return and cash flow news effects. Only for the mid product market competition tercile the effect of the G-index on both cash flow and return news is significant and negative. The offsetting effects explain why unexpected returns do not differ for high- and low G-index firms in these industries.

Overall, my results in this section provide supporting evidence for the finding that return differences between high and low G-index firms are present over the 1990s and early 2000s but vanish afterwards. Splitting the subsamples according to product market competitions industries, however, weakens the economic and statistical significance of the results. At the same time, the procedure does not provide additional evidence that product market competition is a substitute for corporate governance as measured by the G-index. It is possible that based on my sample with annual data the variation in returns, return components, and the G-index within the product market competition subsamples is too small to detect consistent and significant effects. Using return decomposition data with higher frequency – quarterly or monthly – may help to improve the evidence on this question, but is beyond the scope of this study.

6 Robustness checks

In this section I check to what extent the results I report in sections 4 and 5 are robust to alternative specifications of the return decomposition and the governance measure applied.

Alternative ICC methods. To the extent that implied cost of equity capital vary depending on the ICC method applied, my evidence for the ICC-based return decomposition might be sensitive to the selection of a specific ICC method. Table IV.8 provides results for return decompositions based on ICC estimates from GLS and the combined ICC method (COMB).

[Insert Table IV.8 here.]

Panel A of Table IV.8 shows the covariance and correlation estimates for the two alternative ICC-based decompositions. I find that for both ICC methods variance and covariance estimates are close to the values obtained for the decomposition based on the long-horizon ICC method. The correlation between cash flow and return news decreases to about 0.65 (before: 0.84) but is still significant and positive and contrasts the small and negative correlation derived from the Vuolteenaho return decomposition. Again the correlation likely stems from the use of earnings forecasts to compute the ICC so that measurement errors of future expected earnings (cash flow news) also influence return news via implied cost of capital estimates.

Like in the case of the decomposition from the long-horizon ICC method, the high correlation between cash flow and return news seems to impact the univariate correlation between unexpected returns and return news. The estimate is negative but small (-0.1566) for the GLS method and positive for the combined method (0.1589). I again run pooled multivariate regressions of unexpected returns on cash flow and return news to orthogonalize the effects of the components on unexpected returns:[114]

$$er_t - er_{t-1}^{GLS} = \underset{(0.0042)}{0.6716} \times Ncf_t^{GLS} - \underset{(0.0051)}{0.7153} \times Nr_t^{GLS} + \varepsilon_t$$

$$er_t - er_{t-1}^{COMB} = \underset{(0.0043)}{0.4075} \times Ncf_t^{COMB} - \underset{(0.0048)}{0.1978} \times Nr_t^{COMB} + \varepsilon_t$$

The results show a significant and negative (positive) effect of return news (cash flow news) on unexpected returns for both ICC methods. This finding documents

[114]Robust standard errors clustered at the firm-level are shown in parentheses. Regression R-squareds equal 68.4% (GLS) and 29.3% (COMB), respectively.

that the expected negative relationship between return news and unexpected returns according to equation IV.2 also holds for the alternative ICC-based decompositions.

In Panel B of Table IV.8 I repeat the panel regressions of unexpected returns and return components on the G-index and control variables. For convenience I do not display the coefficients for control variables. Overall the governance-related findings are in line with the evidence presented above. The effect of the G-index on unexpected returns (columns (1) and (4)) is again negative and significant for the early sample period 1990 to 2002 and vanishes thereafter. Cash flow news (columns (2) and (5)) are significant and negative for the early subsample but also for the post-2002 period. For the decomposition based on GLS there is no effect of the G-index on orthogonalized return news for both subsamples. The combined ICC estimates, however, indicate a significant negative effect of the G-index for return news over the early sample. Since the negative cash flow effect is larger in absolute terms the net effect for unexpected returns is still negative and significant. Altogether the evidence suggests that the ICC-based return decomposition is robust to changes in the underlying ICC method used to estimate expected returns.

Entrenchment index. I now diagnose the robustness of my findings to the use of an alternative governance index. I repeat the panel regressions of unexpected returns and return components but replace the G-index with the entrenchment index (E-index) proposed by Bebchuk, Cohen, and Ferrell (2009). Like the G-index the E-index is computed as a composite score that adds the number of (anti-)governance provisions. The E-index only includes 6 of the 24 provisions covered by the G-index. Bebchuk, Cohen, and Ferrell (2009) argue that these provisions are the most important ones and the main drivers for the results reported by Gompers, Ishii, and Metrick (2003). I provide the results for the alternative governance measure in Table IV.9.

[Insert Table IV.9 here.]

The E-index evidence in Table IV.9 supports the previous findings for the G-index. The effect of the E-index on unexpected returns is negative for the early subperiod (column (1)) with an approximately similar coefficient estimate (-0.015 compared to -0.016). Statistically the effect is, however, indistinguishable from zero. In line with above evidence, the effect of the G-index on cash flow news (orthogonalized return news) is negative (positive) over this period (columns (2)-(3)). For the recent period 2003 to 2008 (columns (4)-(6)) I do not observe significant differences in unexpected returns, cash flow, or return news related to governance. As before, weak governance seems to be associated with lower cash flow news and higher return news over the pre-2002 period. In recent years the effects, however, seem to vanish and the superior return performance of well-governed firms disappears.

7 Conclusions

In this chapter I present a new approach to decompose realized stock returns using estimates derived from implied cost of equity capital estimation. In contrast to the existing decomposition approach of Vuolteenaho (2002), the ICC-based return decomposition does not rely on an ad hoc realized return model. Instead, my approach utilizes implied cost of equity capital from a long-horizon ICC method as measure for expected returns when calculating the return news component of realized returns. Compared to expected returns obtained from the Vuolteenaho VAR model, I find that ICC estimates much better reflect specific properties one would attribute to a consistent expected return measure, both on the firm- and market level. The evidence indicates that implied cost of capital provide more reliable estimates of expected returns, which further promotes the estimation of return components using the ICC-based return decomposition.

A comparison of the return components from the Vuolteenaho and ICC-based return decomposition shows remarkable differences. In particular, the correlation between return and cash flow news from the two decomposition approaches document a different relationship. This diverse relationship mainly stems from differences in the return news component obtained from the two approaches. While the relationship between the two cash flow news components indicates a significant and positive correlation, the return news components, in contrast, are more or less unrelated. The finding highlights that the alternative modeling approach based on implied cost of capital leads to considerable differences in the obtained return decomposition and the relationship among the return components.

I subsequently propose a setting to assess return anomalies using the ICC-based return decomposition. My analysis focuses on the governance return anomaly and promotes previous evidence that over the 1990s and early 2000s returns for firms with weak corporate governance are significantly lower compared to firms with good governance. The decomposition of returns implies that the effect arises from higher cash flow and lower return news for firms with good corporate governance However, consistent with the argument of Schwert (2003), investors learned about the weaker operating performance of these firms over time, so that the return and cash flow news effects vanish accordingly and the governance return puzzle disappears during recent years.

Ultimately, my conclusions about the properties of return components and their relation to the G-index depend upon the ability of the ICC-based decomposition to capture cash flow news and return news. Regarding the return news the crucial issue is the quality of the implied cost of equity capital as measure for expected returns. Unfortunately, I cannot present direct evidence for my conclusion that long-horizon ICC estimates provide a better measure for expected returns than estimates derived from an arbitrary VAR model calibrated for realized returns. While expected returns are not observable, realized returns are not eligible as benchmark. Developing tests to assess the quality of expected returns and return news measures that do not rely on realized returns, therefore, is an important issue for future research.

Like for return news, the quality of the cash flow news component crucially depends upon the question to what extent earnings forecasts generated by the portfolio-level VAR model proxy for the market's earnings expectations. The concerns particularly address medium- and long-term forecasts. In line with existing empirical evidence on time-series properties of earnings (return on equity), earnings forecasts in the long-run are assumed to be mean-reverting. Whether the speed of mean-reversion and the long-term earnings levels implied by the portfolio-level VAR model capture the market's expectations concerning the earnings process is, however, an open issue. Following this reasoning, more research is required that quantifies the ability of earnings forecasting models to generate the market's earnings expectations over the medium- and long-run.

Finally, the application of return decompositions to assess well-known return anomalies, like the long-run price drifts following IPOs, SEOs, buybacks, dividend announcements and omissions, earnings announcements, or stock splits/reversals, might be a promising field for future research. The knowledge whether return differences are due to revised cash flow or return expectations is important to build hypothesis about the sources that underlie these differences. In this study, my aim is to provide an alternative decomposition approach that has the potential to overcome some of the obvious problems of the standard decomposition and to introduce the concept of return decomposition to the assessment of these return puzzles. I leave a more exhaustive analysis concerning the robustness, quality, and application of return and cash flow news for future research.

Tables

Table IV.1: Sample selection and summary statistics

This table shows the sample selection criteria and sample characteristics for the data set used in this chapter. Panel A lists the sample selection criteria applied to compute implied cost of equity capital (ICC) and the return decompositions. Panel B contains univariate statistics for selected financial variables that characterize the final return decomposition data set (1972-2009). Panel C repeats the univariate statistics from Panel B for the data set that combines the return decomposition data with governance data (G-index) from Gompers, Ishii, and Metrick (2003).

Panel A: Sample selection

Step	**Adjustment**	**Firm-year obs.**
(1)	CRSP-CompuStat Merged universe (1962 - 2009)	133,884
(2)	Drop financial institutions (SIC 6000–6999)	110,338
(3)	Variable availability for rolling-window portfolio VAR model (1962-2009)	89,536
	Compute forecasting parameters for 27 annual portfolios from 1970-2009	
(4)	Delete observation pre-1970 observations	85,824
	Compute ICC using long-horizon RI model with 50 periods & g=0%	
(5)	Drop firms with no valid ICC estimate	80,922
(6)	Availability of lagged variables for return decomposition	70,551
	Compute Vuolteenaho and ICC-based return decomposition	
(7)	Drop observations with missing return decomposition	62,621
(8)	Truncate decomposition data	58,171
	Final return decomposition data set: period 1972-2009	**58,171**
(9)	Merge with governance (G-index) data	15,441
(10)	Drop dual-class shares	13,962
	Final governance return decomposition data set: 1990-2008	**13,962**

Panel B: Sample characteristics - Return decomposition data (1972-2009)

		Quartiles				
	Mean	**25%**	**50%**	**75%**	**SD**	**N**
Return	7.19%	-13.99%	8.34%	29.50%	36.13%	58,171
Return on equity	9.17%	4.99%	10.45%	15.72%	13.53%	58,171
Book-to-Market	0.87	0.42	0.71	1.13	0.65	58,171
Market capitalization	1,769.86	39.96	186.31	915.21	6,170.01	58,171
Leverage	25.54%	6.32%	20.93%	40.56%	21.88%	58,059
Sales growth	12.47%	1.11%	9.40%	19.40%	25.94%	58,171
Beta	1.06	0.65	1.02	1.40	0.59	58,171
Payout ratio	24.12%	0.00%	19.29%	42.00%	24.88%	58,171
Firm-years	10.67	3.00	8.00	15.00	9.35	5,454

Panel C: Sample characteristics - Governance return decomposition data (1990-2008)

Governance score	9.39	7.00	9.00	11.00	2.70	13,962
Return	7.87%	-9.44%	9.48%	26.81%	31.36%	13,962
Return on equity	10.33%	5.71%	10.66%	16.58%	13.26%	13,962
Book-to-Market	0.58	0.30	0.49	0.75	0.41	13,962
Market capitalization	5,376.27	575.35	1,517.85	4,411.65	11,038.24	13,962
Leverage	21.04%	5.38%	16.66%	33.39%	18.50%	13,923
Sales growth	10.52%	0.89%	7.59%	16.59%	22.18%	13,962
Beta	1.03	0.57	0.94	1.36	0.66	13,962
Payout ratio	28.93%	0.00%	24.35%	50.12%	27.65%	13,962
Firm-years	7.80	3.00	6.00	12.00	5.49	1,791

Table IV.2: Calibration of VAR models

In this table I show results for the vector autoregressive (VAR) models applied to forecast return on equity and to decompose stock returns. Panel A shows regression results for the VAR model of Vuolteenaho (2002), where current stock returns, the return on equity, and the book-to-market ratio are regressed on lags of each variable. Following Callen, Segal, and Hope (2010) I apply the model at industry-level (Fama-French 48 industries) implying one regression per industry. Panel B documents the results for an alternative VAR model that adds the dividend yield to the set of state variables. The model is estimated each year between 1970 and 2009 over rolling-windows including data over the preceding ten years (minimum eight years). Panel C applies the VAR approach from Panel B for portfolios of firms (rolling-window portfolio-level VAR). Firms are annually assigned into 27 portfolios based on firms beta, size and book-to-market ratio (tercile breakpoints). Panel C shows univariate statistics for the 1,080 portfolio-year coefficient estimates and the rates against which for the state variables are expected to converge in the long-run. t-values are displayed in brackets.

Panel A: Vuolteenaho (2002) / Callen et al. (2009) - Industry-level VAR approach

Independent variables	***ret(t-1)***	***roe(t-1)***	***btm(t-1)***	**Avg. N**	**R^2**
Stock return (t)	0.044	0.092	0.058	1,305	1.8%
	[13.05]	[7.39]	[72.52]		
Return on equity (t)	0.088	0.362	-0.044	1,305	31.8%
	[121.88]	[56.83]	[-132.73]		
Book-to-market (t)	0.072	0.088	0.763	1,305	61.6%
	[18.12]	[5.04]	[637.55]		

Panel B: Pooled rolling-window VAR approach

	Int.	***ret(t-1)***	***roe(t-1)***	***btm(t-1)***	***dy(t-1)***	**Avg. N**	**R^2**
Stock return (t)	-0.091	0.004	0.202	0.123	0.756	18,858	4.9%
	[-9.45]	[0.40]	[5.76]	[17.67]	[7.49]		
Return on equity (t)	0.050	0.075	0.492	-0.025	0.424	18,858	41.7%
	[22.17]	[29.59]	[72.54]	[-12.70]	[15.50]		
Book-to-market (t)	0.268	0.018	-0.022	0.755	-0.898	18,858	56.9%
	[25.83]	[1.91]	[-0.58]	[107.68]	[-8.13]		
Dividend yield (t)	0.008	0.002	0.012	-0.002	0.729	18,858	56.9%
	[15.29]	[3.48]	[6.84]	[-5.06]	[132.80]		

Panel C: Rolling-window portfolio-level VAR approach

	Mean	SD	Quartiles			N
			25%	50%	75%	
	(1)	(2)	(3)	(4)	(5)	(6)
Return equation						
ret (t-1)	0.016	0.059	-0.022	0.016	0.054	1080
roe (t-1)	0.089	0.145	-0.001	0.078	0.166	1080
btm (t-1)	0.152	0.058	0.112	0.142	0.186	1080
dy (t-1)	0.185	0.658	-0.081	0.201	0.516	1080
Return on equity equation						
ret (t-1)	0.083	0.029	0.063	0.082	0.101	1080
roe (t-1)	0.440	0.098	0.373	0.438	0.504	1080
btm (t-1)	-0.042	0.040	-0.057	-0.037	-0.023	1080
dy (t-1)	0.364	0.350	0.186	0.325	0.500	1080
Book-to-market equation						
ret (t-1)	0.014	0.070	-0.028	0.011	0.055	1080
roe (t-1)	0.060	0.135	-0.020	0.060	0.129	1080
btm (t-1)	0.703	0.086	0.660	0.716	0.762	1080
dy (t-1)	-0.424	0.713	-0.682	-0.387	-0.179	1080
Dividend yield equation						
ret (t-1)	0.000	0.003	-0.002	0.000	0.002	1080
roe (t-1)	0.017	0.018	0.005	0.011	0.023	1080
btm (t-1)	-0.004	0.004	-0.006	-0.003	-0.001	1080
dy (t-1)	0.549	0.167	0.437	0.554	0.673	1080
Long-term (convergence) rates						
ret	7.11%	9.02%	1.59%	8.36%	12.72%	1080
roe	10.14%	6.35%	8.30%	10.71%	13.20%	1080
btm	0.733	0.366	0.441	0.668	0.961	1080
dy	1.90%	2.05%	0.00%	1.43%	3.41%	1080

Table IV.3: Evidence on expected returns and return decomposition

This table shows univariate statistics for returns and return components. Panel A documents evidence for realized and expected (excess) returns. Expected (excess) returns are derived from implied cost of equity capital estimates (ICC) and the Vuolteenaho VAR model. Statistics include the averages of annual equally- and value-weighted returns (columns (1) and (2)), the standard deviation (Panel A – column (3)) and variance (Panel B – column (3)), the quartiles (columns (4)-(6)), and the number of observations (column (7)). Panel A documents the return results and Panel B shows statistics for cash flow news and return news.

Panel A: Realized and expected returns

	Average return			Quartiles			
	Equally-weighted	Value-weighted	SD / VAR	25%	50%	75%	N
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Expected return (ICC)	9.78%	10.82%	2.80%	7.95%	9.86%	11.79%	58,171
Expected return (VAR)	7.66%	6.25%	5.36%	4.38%	7.71%	11.08%	58,171
Realized return	7.19%	12.51%	36.13%	-13.99%	8.34%	29.50%	58,171
Expected excess return (ICC)	4.19%	5.22%	2.96%	2.30%	4.14%	6.05%	58,171
Expected excess return (VAR)	2.06%	0.65%	4.61%	-0.46%	2.22%	4.80%	58,171
Realized excess return	1.59%	6.92%	36.03%	-19.61%	2.68%	23.99%	58,171

Panel B: Return decomposition

ICC-based return decomposition:							
Unexpected return (ICC)	-2.56%	1.79%	0.1296	-23.87%	-1.78%	19.60%	58,171
Return news	0.74%	1.97%	0.2145	-30.07%	0.24%	29.98%	58,171
Cash flow news	-1.74%	3.39%	0.3322	-38.92%	-2.98%	32.81%	58,171
Cash flow news (residual)	-1.82%	3.75%	0.3736	-40.73%	-2.88%	34.08%	58,171
Vuolteenaho return decomposition:							
Unexpected return (VAR)	0.17%	6.91%	0.1034	-19.27%	0.31%	19.96%	58,171
Return news	0.85%	-0.77%	0.0079	-3.98%	0.97%	5.82%	58,171
Cash flow news	1.04%	6.68%	0.0498	-9.82%	1.97%	13.52%	58,171
Cash flow news (residual)	1.01%	6.14%	0.0768	-15.14%	1.46%	17.76%	58,171

Table IV.4: Correlation of returns and return components

This table shows covariance and correlation estimates for returns and return components. Panel A documents the variance-covariance matrix and simple correlations between cash flow news, return news, and unexpected returns for the ICC-based return decomposition. Panel B includes the corresponding numbers for the return decomposition of Vuolteenaho (2002). The unexpected return in Panel A (Panel B) equals the realized return minus the expected return obtained from ICC (average annual cross-sectional return). Panel C summarizes the correlation of cash flow news, return news, and unexpected returns with indirectly estimated cash flow news (Residual Ncf) and the estimation error. I report standard errors obtained using the bootstrap methodology in parentheses.

Panel A: ICC-based return decomposition

	Variance-covariance matrix				Correlation	
	Ncf	***Nr***	***u_ret***		**Pearson**	**Spearman**
Cash flow news: Ncf	0.3322	0.2246	0.1037	Ncf and Nr:	0.8414	0.8292
	(0.0022)	(0.0015)	(0.0010)		(0.0015)	(0.0016)
Return news: Nr	0.2246	0.2145	0.0148	Ncf and u_ret:	0.4999	0.4861
	(0.0015)	(0.0014)	(0.0007)		(0.0032)	(0.0034)
Unexpected return	0.1037	0.0148	0.1296	Nr and u_ret:	0.0885	0.0768
(over ICC): u_ret	(0.0010)	(0.0007)	(0.0008)		(0.0043)	(0.0043)

Panel B: Vuolteenaho (2002) return decomposition

Cash flow news	0.0498	-0.0046	0.0510	Ncf and Nr:	-0.2332	-0.3638
	(0.0004)	(0.0001)	(0.0004)		(0.0058)	(0.0041)
Return news	-0.0046	0.0079	-0.0173	Ncf and u_ret:	0.7109	0.7650
	(0.0001)	(0.0001)	(0.0002)		(0.0036)	(0.0026)
Unexpected return	0.0510	-0.0173	0.1034	Nr and u_ret:	-0.6041	-0.6412
(VAR model)	(0.0004)	(0.0002)	(0.0007)		(0.0036)	(0.0029)

Panel C: Correlation with indirect cash flow news and error estimates

	Pearson correlation			Spearman correlation		
	Ncf	***Nr***	***u_ret***	***Ncf***	***Nr***	***u_ret***
ICC-based return decomposition:						
Residual Ncf	0.9319	0.8099	0.6560	0.9326	0.7917	0.6237
	(0.0008)	(0.0015)	(0.0022)	(0.0008)	(0.0018)	(0.0027)
Error component	-0.0304	0.0454	0.5089	0.0250	0.0453	0.5085
	(0.0055)	(0.0046)	(0.0048)	(0.0043)	(0.0042)	(0.0037)
Vuolteenaho (2002) return decomposition:						
Residual Ncf	0.7502	-0.3804	0.9668	0.7922	-0.4611	0.9673
	(0.0036)	(0.0050)	(0.0003)	(0.0027)	(0.0038)	(0.0005)
Error component	-0.0832	-0.2902	0.5942	0.1692	-0.3990	0.6565
	(0.0075)	(0.0064)	(0.0038)	(0.0050)	(0.0041)	(0.0035)

Table IV.5: Returns, return components, and the G-index

This table shows results from panel regressions of stock returns and return components on the G-index and various control variables. The return regressions (column (1)-(2)) include unexpected (excess) returns obtained from ICC, and industry-adjusted returns (return minus value-weighted industry return for Fama-French 48 industries). Columns (3)-(6) show results for the ICC-based return components. The sample is split in two subperiods: 1990 to 2002 (Panel A) and 2003 to 2008 (Panel B). The G-index is based on the governance score from Gompers, Ishii, and Metrick (2003). The index ranks firms into ten governance portfolios and varies between 1 ("good governance") and 10 ("bad governance"). I control for size (market capitalization), capital structure (book-to-market and market leverage), profitability (return on equity and sales growth), momentum (lagged return), price, and the CRSP value-weighted market return. All regressions include firm-fixed effects. All variables are measured annually. Standard errors (clustered at the firm-level) are shown in parentheses. Stars indicate significance at the 10%, 5%, and 1%-level.

Panel A: Early period 1990 – 2002

	Return measures		**ICC-based return decomposition**			
	Unexpec. return (ICC)	**Industry-adjusted return**	**Cash flow news (Ncf)**	**Return news (Nr)**	**Cash flow news (residual)**	**Return news (orthogonal)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
G-index	-0.016 ***	-0.013 ***	-0.050 ***	-0.025 ***	-0.041 ***	0.010 **
	(0.0055)	(0.0049)	(0.0089)	(0.0067)	(0.0093)	(0.0045)
Market return	-0.085 **	-0.409 ***	-1.032 ***	-0.885 ***	-0.971 ***	-0.160 ***
	(0.0369)	(0.0358)	(0.0447)	(0.0353)	(0.0486)	(0.0283)
Log of MCAP	-0.070 ***	-0.036 **	-0.076 ***	0.027 **	-0.044 *	0.080 ***
	(0.0186)	(0.0151)	(0.0202)	(0.0133)	(0.0245)	(0.0107)
Book-to-market	-0.546 ***	-0.450 ***	-0.532 ***	-0.019	-0.565 ***	0.355 ***
	(0.0407)	(0.0328)	(0.0507)	(0.0309)	(0.0536)	(0.0301)
Market leverage	-0.323 ***	-0.256 ***	-0.191 *	0.062	-0.261 **	0.196 ***
	(0.0749)	(0.0659)	(0.111)	(0.077)	(0.1148)	(0.0559)
Price	0.007 ***	0.005 ***	0.006 ***	0.001 **	0.008 ***	-0.003 ***
	(0.0017)	(0.0013)	(0.0013)	(0.0005)	(0.002)	(0.0008)
Return on equity	-0.074	0.003	0.395 ***	0.062	-0.012	-0.216 ***
	(0.0501)	(0.048)	(0.1075)	(0.0795)	(0.1003)	(0.0595)
Sales growth	0.008	-0.022	-0.312 ***	-0.246 ***	-0.239 ***	-0.027
	(0.0161)	(0.0157)	(0.0429)	(0.035)	(0.0395)	(0.0182)
Lagged return	-0.285 ***	-0.230 ***	-0.235 ***	0.033	-0.251 ***	0.199 ***
	(0.0131)	(0.0134)	(0.0289)	(0.0261)	(0.0312)	(0.0126)
Intercept	0.804 ***	0.531 ***	1.176 ***	0.069	0.873 ***	-0.758 ***
	(0.1062)	(0.0948)	(0.1393)	(0.1031)	(0.1607)	(0.0733)
N	7,023	7,023	7,023	7,023	7,023	7,023
R-squared	35.8%	27.0%	13.8%	9.1%	16.0%	20.7%

Panel B: Recent period 2003 − 2008

	Return measures		ICC-based return decomposition			
	Unexpec. return (ICC)	**Industry-adjusted return**	**Cash flow news (Ncf)**	**Return news (Nr)**	**Cash flow news (residual)**	**Return news (orthogonal)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
G-index	-0.005	0.002	-0.033	-0.031 *	-0.036 *	-0.008
	(0.0091)	(0.0089)	(0.0204)	(0.0175)	(0.0216)	(0.0076)
Market return	0.651 ***	-0.122 ***	-1.472 ***	-1.851 ***	-1.200 ***	-0.815 ***
	(0.03)	(0.0338)	(0.1022)	(0.0877)	(0.0994)	(0.0327)
Log of MCAP	0.106 ***	0.061 ***	-0.064	-0.059	0.047	-0.014
	(0.0212)	(0.0209)	(0.0474)	(0.0393)	(0.0502)	(0.0169)
Book-to-market	-0.614 ***	-0.560 ***	-0.610 ***	-0.009	-0.624 ***	0.420 ***
	(0.0366)	(0.0379)	(0.0827)	(0.0625)	(0.0826)	(0.0303)
Market leverage	-0.150 *	-0.064	0.112	0.122	-0.028	0.043
	(0.0818)	(0.0793)	(0.1866)	(0.1516)	(0.1931)	(0.0627)
Price	0.004 ***	0.003 ***	0.007 ***	0.005 ***	0.009 ***	0.000
	(0.0005)	(0.0005)	(0.0012)	(0.001)	(0.0012)	(0.0004)
Return on equity	-0.214 ***	-0.197 ***	0.775 ***	0.210 *	-0.004	-0.335 ***
	(0.07)	(0.0678)	(0.152)	(0.1247)	(0.1518)	(0.0718)
Sales growth	0.036	0.034	-0.187 ***	-0.122 **	-0.086	0.009
	(0.0234)	(0.0237)	(0.0634)	(0.0524)	(0.0633)	(0.0226)
Lagged return	-0.364 ***	-0.268 ***	-0.512 ***	-0.190 ***	-0.554 ***	0.170 ***
	(0.0116)	(0.0136)	(0.0373)	(0.0333)	(0.0372)	(0.0124)
Intercept	-0.629 ***	-0.283 *	0.797 **	0.568 *	-0.061	0.007
	(0.171)	(0.1655)	(0.3885)	(0.3227)	(0.4085)	(0.1408)
N	4,493	4,493	4,493	4,493	4,493	4,493
R-squared	60.6%	37.1%	13.5%	16.8%	14.9%	42.1%

Table IV.6: Vuolteenaho return decomposition and the G-index

This table repeats the analysis from previous Table IV.5 for the Vuolteenaho (2002) return decomposition. The results for the early sample (1990-2002) are reported in columns (1)-(3) and for the recent subsample (2003-2008) in columns (4)-(6). The return components include cash flow news, return news, and indirectly estimated cash flow news computed as residual from unexpected returns and return news. The G-index is based on the governance score from Gompers, Ishii, and Metrick (2003). The index ranks firms into ten governance portfolios and varies between 1 ("good governance") and 10 ("bad governance"). I control for size (market capitalization), capital structure (book-to-market and market leverage), profitability (return on equity and sales growth), momentum (lagged return), price, and the CRSP value-weighted market return. All regressions include firm-fixed effects. All variables are measured annually. Standard errors (clustered at the firm-level) are shown in parentheses. Stars indicate significance at the 10%, 5%, and 1%-level.

	Early period: 1990 − 2002			**Recent period: 2003 − 2008**		
	Cash flow news (Ncf)	**Return news (Nr)**	**Cash flow news (residual)**	**Cash flow news (Ncf)**	**Return news (Nr)**	**Cash flow news (residual)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
G-index	0.001	0.002 *	-0.007 *	-0.004	0.002	-0.003
	(0.0035)	(0.0013)	(0.0043)	(0.0056)	(0.0022)	(0.0076)
Market return	-0.257 ***	0.100 ***	-0.263 ***	-0.361 ***	0.202 ***	-0.634 ***
	(0.02)	(0.0079)	(0.0299)	(0.0209)	(0.0117)	(0.0256)
Log of MCAP	-0.052 ***	0.006 *	-0.009	0.027 **	-0.024 ***	0.126 ***
	(0.009)	(0.0036)	(0.0151)	(0.0114)	(0.0061)	(0.0173)
Book-to-market	-0.292 ***	0.181 ***	-0.353 ***	-0.316 ***	0.224 ***	-0.360 ***
	(0.0221)	(0.0132)	(0.0293)	(0.0234)	(0.0146)	(0.0282)
Market leverage	-0.063	0.017	-0.227 ***	0.031	-0.048 *	-0.163 **
	(0.0435)	(0.0171)	(0.058)	(0.0473)	(0.0254)	(0.069)
Price	0.003 ***	-0.001 ***	0.006 ***	0.002 ***	-0.001 ***	0.004 ***
	(0.0007)	(0.0002)	(0.0014)	(0.0003)	(0.0001)	(0.0004)
Return on equity	1.146 ***	0.350 ***	0.323 ***	1.047 ***	0.319 ***	0.175 ***
	(0.0391)	(0.0154)	(0.041)	(0.0471)	(0.02)	(0.059)
Sales growth	-0.031 ***	0.016 **	0.012	-0.008	0.061 ***	0.076 ***
	(0.0111)	(0.0069)	(0.0141)	(0.0168)	(0.0085)	(0.0215)
Lagged return	-0.244 ***	0.017 ***	-0.260 ***	-0.258 ***	0.024 ***	-0.321 ***
	(0.0078)	(0.0036)	(0.0109)	(0.0079)	(0.0036)	(0.01)
Intercept	0.440 ***	-0.175 ***	0.227 ***	-0.116	0.037	-0.813 ***
	(0.0591)	(0.0264)	(0.0843)	(0.0961)	(0.0517)	(0.1395)
N	7,023	7,023	7,023	4,493	4,493	4,493
R-squared	44.5%	40.3%	33.3%	51.2%	45.8%	47.4%

Table IV.7: Return components, G-index, and product-market competition

This table repeats results from previous Table IV.5 for industry subsamples with low, medium, and high product market competition (tercile breakpoints). I compute product market competition as a Herfindahl index based on firms' total sales share in its industry. I derive return components using the ICC-based return decomposition. Panel A shows results for the subperiod 1990-2002 and Panel B for the subperiod 2003-2008. Independent variables are defined as in the previous tables. For convenience I do not display coefficients for control variables. All regressions include firm-fixed effects. All variables are measured annually. Standard errors (clustered at the firm-level) are shown in parentheses. Stars indicate significance at the 10%, 5%, and 1%-level.

Panel A: Early sample (1990 – 2002)

	Unexpected return			**Cash flow news**			**Orthogonalized return news**		
	Product market competition			**Product market competition**			**Product market competition**		
	Low	**Mid**	**High**	**Low**	**Mid**	**High**	**Low**	**Mid**	**High**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
G-index	-0.016	-0.027 ***	-0.008	-0.062 ***	-0.073 ***	-0.043 ***	0.013	0.019 *	0.009
	(0.0123)	(0.0104)	(0.0082)	(0.0198)	(0.0175)	(0.0124)	(0.0107)	(0.0098)	(0.0064)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	2,131	2,639	2,253	2,131	2,639	2,253	2,131	2,639	2,253
R-squared	37.7%	42.3%	43.5%	13.4%	15.8%	15.5%	18.5%	22.7%	29.6%

Panel B: Recent sample (2003 – 2008)

G-index	-0.013	-0.005	-0.002	-0.045	-0.079 **	0.001	0.008	-0.027 **	-0.003
	(0.0154)	(0.0157)	(0.017)	(0.0379)	(0.0383)	(0.0435)	(0.0141)	(0.0123)	(0.0151)
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Fixed-effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	1,458	1,612	1,423	1,458	1,612	1,423	1,458	1,612	1,423
R-squared	64.2%	65.7%	61.5%	13.1%	11.9%	17.7%	42.7%	45.6%	44.2%

Table IV.8: Robustness check - Alternative ICC methods

This table shows the results of two robustness checks, where I assess alternative specifications to see how the evidence regarding the return decomposition and governance effects are affected by the choice of the ICC method. The alternative specifications include ICC estimates based on the methods of GLS and the combination (simple average) of estimates from GLS and ETSS. Panel A shows the covariance and correlation results for cash flow news, return news, and unexpected returns. In Panel B I repeat the regressions of returns and return components on the G-index and control variables from previous Table IV.5. For convenience I only report the G-index coefficients and standard errors. All variables are measured annually. Standard errors (clustered at the firm-level) are shown in parentheses. Stars indicate significance at the 10%, 5%, and 1%-level.

Panel A: ICC-based return decomposition from alternative ICC methods

	Variance-covariance matrix				Correlation	
	Ncf	***Nr***	***u_ret***		**Pearson**	**Spearman**
ICC estimates from GLS:						
Cash flow news: Ncf	0.3339	0.1689	0.1036	Ncf and Nr:	0.6656	0.6588
	(0.0019)	(0.0011)	(0.0011)		(0.0026)	(0.0025)
Return news: Nr	0.1689	0.1928	-0.0246	Ncf and u_ret:	0.5016	0.4911
	(0.0011)	(0.0010)	(0.0008)		(0.0038)	(0.0034)
Unexpected return	0.1036	-0.0246	0.1278	Nr and u_ret:	-0.1566	-0.1464
(over ICC): u_ret	(0.0011)	(0.0008)	(0.0009)		(0.0048)	(0.0044)
Combined ICC estimates (50% GLS - 50% ETSS):						
Cash flow news: Ncf	0.3113	0.1733	0.0926	Ncf and Nr:	0.6494	0.6588
	(0.0022)	(0.0016)	(0.0009)		(0.0029)	(0.0026)
Return news: Nr	0.1733	0.2289	0.0254	Ncf and u_ret:	0.4966	0.4864
	(0.0016)	(0.0014)	(0.0007)		(0.0034)	(0.0036)
Unexpected return	0.0926	0.0254	0.1117	Nr and u_ret:	0.1589	0.1368
(over ICC): u_ret	(0.0009)	(0.0007)	(0.0008)		(0.0043)	(0.0043)

Panel B: Governance-related evidence for alternative ICC methods

	Early period: 1990-2002			Recent period: 2003-2008		
	Unexpec. return (ICC)	**Cash flow news (Ncf)**	**Return news (orth.)**	**Unexpec. return (ICC)**	**Cash flow news (Ncf)**	**Return news (orth.)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Return decomposition with ICC estimates from GLS:						
G-index	-0.014 **	-0.041 ***	0.002	-0.004	-0.034 *	-0.012
	(0.0053)	(0.0088)	(0.0052)	(0.0086)	(0.0201)	(0.0089)
Controls	yes	yes	yes	yes	yes	yes
Firm-fixed effects	yes	yes	yes	yes	yes	yes
N	6,925	6,925	6,925	4,553	4,553	4,553
R-squared	36.3%	13.5%	27.5%	61.1%	13.6%	52.2%
Decomposition with combined ICC estimates (50% GLS - 50% ETSS):						
G-index	-0.015 ***	-0.045 ***	-0.011 **	-0.013	-0.042 **	-0.009
	(0.0054)	(0.0087)	(0.0047)	(0.0092)	(0.0211)	(0.0137)
Controls	yes	yes	yes	yes	yes	yes
Firm-fixed effects	yes	yes	yes	yes	yes	yes
N	6,368	6,368	6,368	3,604	3,604	3,604
R-squared	34.4%	12.6%	3.6%	56.1%	12.6%	4.1%

Table IV.9: Robustness check - Entrenchment index

This table shows a robustness check for the governance evidence based on an alternative governance measure. I use the entrenchment index (E-Index) of Bebchuk, Cohen, and Ferrell (2009) instead of the G-index. Columns (1)-(3) include results for the early sample period 1990 to 2002 and columns (4)-(6) for the recent sample 2003 to 2008. I include all control variables from the previous tables. All regressions include firm-fixed effects. All variables are measured annually. Standard errors (clustered at the firm-level) are shown in parentheses. Stars indicate significance at the 10%, 5%, and 1%-level.

	Early period: 1990-2002			**Recent period: 2003-2008**		
	Unexpected return (ICC)	**Cash flow news (Ncf)**	**Return news (orth.)**	**Unexpected return (ICC)**	**Cash flow news (Ncf)**	**Return news (orth.)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
E-index	-0.015	-0.050 ***	0.015 *	0.000	-0.051	-0.009
	(0.0112)	(0.0161)	(0.0088)	(0.0134)	(0.031)	(0.011)
Market return	-0.080 **	-1.025 ***	-0.162 ***	0.650 ***	-1.460 ***	-0.818 ***
	(0.0375)	(0.0456)	(0.0287)	(0.0302)	(0.1046)	(0.0332)
Log of MCAP	-0.284 ***	-0.229 ***	0.199 ***	-0.364 ***	-0.510 ***	0.170 ***
	(0.0133)	(0.0293)	(0.0127)	(0.0116)	(0.0379)	(0.0125)
Book-to-market	-0.080 ***	-0.096 ***	0.084 ***	0.108 ***	-0.067	-0.024
	(0.0181)	(0.0194)	(0.0105)	(0.0216)	(0.0488)	(0.0169)
Market leverage	-0.564 ***	-0.554 ***	0.363 ***	-0.618 ***	-0.620 ***	0.405 ***
	(0.0417)	(0.0531)	(0.0313)	(0.0374)	(0.085)	(0.0304)
Price	-0.326 ***	-0.218 *	0.205 ***	-0.136	0.141	0.036
	(0.076)	(0.1136)	(0.0568)	(0.0852)	(0.1964)	(0.0634)
Return on equity	0.007 ***	0.006 ***	-0.003 ***	0.004 ***	0.007 ***	0.000
	(0.0017)	(0.0013)	(0.0008)	(0.0005)	(0.0012)	(0.0004)
Sales growth	-0.083 *	0.364 ***	-0.209 ***	-0.222 ***	0.791 ***	-0.328 ***
	(0.0496)	(0.1091)	(0.0604)	(0.0714)	(0.1543)	(0.0728)
Lagged return	0.012	-0.306 ***	-0.028	0.044 *	-0.174 ***	0.016
	(0.0159)	(0.0425)	(0.0183)	(0.0235)	(0.0646)	(0.0226)
Intercept	0.829 ***	1.184 ***	-0.773 ***	-0.669 ***	0.766 *	0.072
	(0.107)	(0.1424)	(0.075)	(0.1721)	(0.3942)	(0.1363)
N	6,914	6,914	6,914	4,396	4,396	4,396
R-squared	35.7%	13.4%	20.7%	60.7%	13.2%	42.1%

Appendix

A Steady-state values for financial ratios

The plowback rate is defined as $pb = (e_t - d_t)/e_t$. With this definition, the clean surplus relation (II.5) becomes $bv_t = bv_{t-1} + e_t pb$. We can therefore write the growth rate of equity $g_{E,t}$ as:

$$g_{E,t} = \frac{bv_t - bv_{t-1}}{bv_{t-1}} = \frac{e_t pb}{bv_{t-1}} = roe_t pb. \tag{A.1}$$

In a steady state, the growth rates for sales and for the book value of equity are the same, which gives (II.7).

Pre-tax income is $S_t(m - d)$, so that net income can be expressed as:

$$e_t = (m - d)(1 - T)S_t. \tag{A.2}$$

The growth rate of equity from (A.1) becomes:

$$g_{E,t} = \frac{pb(m - d)(1 - T)S_t.}{bv_{t-1}}. \tag{A.3}$$

We can rewrite $bv_t = (1 + g_{E,t})bv_{t-1}$ and, in a steady state, $g_{E,t} = g_{S,t}$. Substituting these expressions and rearranging gives (II.8).

B Duration

Let fcf_t be the expected free cash flow of the firm at time t. Let DUR be the equity duration for the data generating process and define it as:

$$DUR = \frac{1}{1 + r_E} \sum_{t=1}^{\infty} t \frac{fcf_t}{P_0^{DGP}(1 + r_E)^t}. \tag{B.1}$$

is defined as a weighted average of the maturities of all future free cash flows (earnings, dividends, etc.), where the weight for each maturity is the proportion of the corresponding cash flow in the value of the firm.[115]

[115] We premultiply by $1/(1 + r)$ for convenience. Our definition of duration in equation (B.1) corresponds to the definition of "modified duration" in the literature because we divide by $1 + r_E$.

The concept of duration can also be applied to valuation models independently of whether they discount cash flows, dividends, or abnormal earnings. This follows from a general property of duration, which allows us to easily obtain the duration for the data generating process and for each of the models. Let P_0 be the current equity value:

$$P_0 = \sum_{t=1}^{t=\infty} fcf_t \left(1 + r_E\right)^{-t}. \tag{B.2}$$

Then the first derivative is:

$$\frac{dP_0}{dr_E} = -\sum_{t=1}^{t=\infty} t \, fcf_t \left(1 + r_E\right)^{-(t+1)}. \tag{B.3}$$

Multiplying both sides of (B.3) by $1/P_0$ yields

$$-\frac{dP_0(r_E)}{dr_E}\frac{1}{P_0} = DUR. \tag{B.4}$$

Hence, the sensitivity of percentage changes in equity values with respect to the CoEC is equal to their duration. From (B.4) we can obtain the duration simply from calculating the first derivative of the respective valuation equation.

We demonstrate this claim for the simple case of dividends and the constant growth model:

$$P_0^{Gordon} = \frac{d_1}{r_E - g}, \tag{B.5}$$

where P_0^{Gordon} is the equity value according to the Gordon growth model for some constant dividend growth rate g and dividend d_1. From (B.4) and (B.5) we have:

$$DUR^{Gordon} = -\frac{dP_0^{Gordon}}{dr_E}\frac{1}{P_0^{Gordon}} = \frac{r_E - g}{d_1}\frac{d_1}{\left(r_E - g\right)^2}5 = \frac{1}{r_E - g}. \tag{B.6}$$

We can proceed similarly with the valuation equations of all residual income and abnormal earnings growth models used by the ICC methods we discuss in Chapter II.

This definition facilitates the exposition because it eliminates the factor $1 + r_E$ from (B.4).

Claim 1: Equity duration measures average maturity. This claim follows directly from the definition and from observing that the weight w_t of maturity t is $fcf_t(1+r_E)^t/P_0$ and that $\sum_t w_t = 1$. Then $DUR = (1+r_E)^{-1}\sum_t t w_t$. For example, the equity duration of a firm that has only one cash flow at time T (all other cash flows are zero) is simply $T(1+r_E)^{-1}$ because then $w_T = 1$. Hence, apart from the normalization factor $1/(1+r_E)$, duration measures the average maturity of the cash flows associated with the firm.

Claim 2: Equity duration is an increasing function of the growth rate. Define the t-period growth rate of cash flows by $1+G_t = fcf_t/fcf_0$. Then from the definition of the weight w_t above, $w_t = (1+G_t)fcf_0(1+r_E)^t/P_0$, which is increasing in the growth rate. Hence, for faster growing firms later maturities receive a higher weight so that the average maturity becomes larger. For the Gordon growth model, DUR^{Gordon} increases with the constant growth rate g.

Claim 3: Derivation of equation (II.21)**.** The claim in the text that the sensitivity of firm value with respect to the CoEC is proportional to the equity duration is expressed in (B.4). Apply the implicit function theorem to (II.19) to obtain:

$$\frac{dP_0^{DGP}(r_E)}{dr_E}dr_E = \frac{dP_0^M(r_E^M)}{dr_E^M}dr_E^M \Rightarrow -DUR^{DGP}P_0 dr_E = -DUR^M P_0 d_E^M. \quad \text{(B.7)}$$

Dividing both sides by $-P_0$ and rearranging yields (II.21).

We note that duration analysis applies strictly only to firm-level methods and not to industry-level methods, because for the latter (II.19) does not hold individually for each firm.[116]

[116] Industry-level methods determine the growth rate endogenously, but the sensitivity of the ICC to the true cost of capital depends on the cash flow patterns for the entire portfolio and not on the patterns of the individual firm. Exploring this more intricate relationship analytically is beyond the scope of this appendix.

C Definition of financial signals

The following list provides the formulas used to compute the financial signals. The definitions are based on Lev and Thiagarajan (1993). Δ refers to the percentage change of a variable relative to the average of the prior two years. As an example, $\Delta\text{Inventory}_t = [\text{Inventory}_t - \text{E}(\text{Inventory})]/\text{E}(\text{Inventory})$, where $\text{E}(\text{Inventory}) = \frac{1}{2}\left(\text{Inventory}_{t-1} + \text{Inventory}_{t-2}\right)$. Data on inventory, sales, accounts receivable, gross margin (sales minus cost of goods sold), capital expenditures, S&A, tax expense, pretax income (plus amortization of intangibles), and number of employees is derived from CompuStat. Prices are obtained from CRSP.

	Signal	**Measured as**
1	Inventory	ΔInventory - ΔSales
2	Accounts receivable	ΔAccounts receivable - ΔSales
3	Gross margin	ΔSales - ΔGross margin
4	Capital expenditure	ΔIndustry capital expenditures - ΔFirm capital expenditures
5	Sales and administrative expenses (S&A)	ΔS&A - ΔSales
6	Effective tax rate	$\left[\left(\frac{1}{3}\sum_{\tau=1}^{3} ETR_{t-\tau}\right) - ETR_t\right] \times \frac{\Delta e_t}{P_{t-1}}$, where $ETR_t = \frac{\text{Tax Expense}_t}{\text{Pretax Income}_t}$
7	Labor force	$\left[\left(\frac{\text{Sales}_{t-1}}{\text{No. of employees}_{t-1}}\right) - \left(\frac{\text{Sales}_t}{\text{No. of employees}_t}\right)\right] / \left(\frac{\text{Sales}_{t-1}}{\text{No. of employees}_{t-1}}\right)$

D Derivation of the return decomposition

The return decomposition starts with the definition of log accounting return on equity $roe_t = \log\left(\frac{BV_t + D_t}{BV_{t-1}}\right)$ and log stock return $r_t = \log\left(\frac{P_t + D_t}{P_{t-1}}\right)$, where BV_t and P_t, respectively, equal the book and market value of equity and D_t represents the total dividends. Expanding the two definitions with D_t and rearranging term yields the following equations:

$$roe_t = \Delta d_t + \gamma_{t-1} + \log\left(1 + \exp(-\gamma_t)\right) \quad (D.1)$$

$$r_t = \Delta d_t + \delta_{t-1} + \log\left(1 + \exp(-\delta_t)\right), \quad (D.2)$$

where $\gamma_t = d_t - b_t$ equals the log dividend to book equity ratio and $\delta_t = d_t - p_t$ the log dividend to market equity ratio. Following (D.1) and (D.2) the difference between the accounting return on equity roe_t and the stock return r_t equals

$$roe_t - r_t = \gamma_{t-1} - \delta_{t-1} + \log\left(1 + \exp(-\gamma_t)\right) - \log\left(1 + \exp(-\delta_t)\right). \quad (D.3)$$

Given the non-linearity of equation (D.3) a linear approximation of the log-functions is required. To achieve this goal apply a Taylor expansion around a single mean as the expansion point for both functions, where this mean is a convex combination of the unconditional means of the variables. Let $\bar{\gamma}$ and $\bar{\delta}$ be the unconditional means of each log function and $\bar{\phi} = \lambda\bar{\gamma} + (1-\lambda)\bar{\delta}$ be the convex combination of the unconditional means, one can write the Taylor expansions of the log functions as:

$$\log\left(1 + \exp(-\gamma_t)\right) \approx \log\left(1 + \exp(-\bar{\phi})\right) - \frac{\exp(-\bar{\phi})}{1 + \exp(-\bar{\phi})}(\gamma_t - \bar{\phi}) \quad (D.4)$$

$$\log\left(1 + \exp(-\delta_t)\right) \approx \log\left(1 + \exp(-\bar{\phi})\right) - \frac{\exp(-\bar{\phi})}{1 + \exp(-\bar{\phi})}(\delta_t - \bar{\phi}) \quad (D.5)$$

Replacing the expressions in equation (D.3) then gives

$$roe_t - r_t = \gamma_{t-1} - \delta_{t-1} - \rho(\gamma_t - \delta_t) + \xi_t, \quad (D.6)$$

where $\rho = \frac{\exp(-\bar{\phi})}{1+\exp(-\bar{\phi})}$ is a number smaller but close to one. Note that (D.6) accounts for the approximation error by introducing the error term ξ_t so that the approximate formula for the excess accounting return becomes an equality. Using the definition for γ_t and δ_t one obtains

$$\begin{aligned} roe_t - r_t &= \rho(b_t - m_t) - (b_{t-1} - m_{t-1}) + \xi_t \\ &= \rho\theta_t - \theta_{t-1} + \xi_t, \quad (D.7) \end{aligned}$$

with θ_t being the log book-to-market equity ratio. Solving for θ_{t-1} and iterating forward directly yields

$$\begin{aligned}\theta_{t-1} &= \sum_{j=0}^{N}\rho^j r_{t+j} - \sum_{j=0}^{N}\rho^j roe_{t+j} + \sum_{j=0}^{N}\rho^j \xi_{t+j} + \rho^{N+1}\theta_{t+N} \\ &= \sum_{i=0}^{N}\rho^j er_{t+j} + \sum_{j=0}^{N}\rho^j f_{t+j} - \sum_{j=0}^{N}\rho^j roe_{t+j} + \sum_{j=0}^{N}\rho^j \xi_{t+j} + \rho^{N+1}\theta_{t+N}, \quad \text{(D.8)}\end{aligned}$$

where I replace the stock return r_t by the sum of the excess stock return er_t and the risk-free rate f_t. For large N, $\rho^{N+1}\theta_{t+N}$ converges to zero as $\rho < 1$. By defining $k_{t-1} \equiv \sum_{j=0}^{N}\rho^j \xi_{t+j}$ and rearranging terms, one obtains

$$\theta_{t-1} = k_{t-1} + \sum_{j=0}^{\infty}\rho^j er_{t+j} - \sum_{i=0}^{\infty}\rho^j (roe_{t+j} - f_{t+j}). \quad \text{(D.9)}$$

In a final step, computing the difference in expectations of (D.9) between t and $t-1$ yields the following expression for the unexpected (excess) return with $\kappa_t = \Delta \mathrm{E}_t k_{t-1}$:

$$er_t - \mathrm{E}_{t-1} er_t = \Delta \mathrm{E}_t \sum_{j=0}^{\infty}\rho^j \left(roe_{t+j} - f_{t+j}\right) - \Delta \mathrm{E}_t \sum_{j=1}^{\infty} er_{t+j} + \kappa_t. \quad \text{(D.10)}$$

E Correlation of return components

The following table shows correlations for the return components obtained from the Vuolteenaho (2002) and ICC-based return decomposition. The lower left (upper right) part of the matrix contains Pearson (Spearman) correlation coefficients. Bootstrapped standard errors are displayed in brackets.

Table E.1: Correlation of return components

	ICC-based return decomposition			Vuolteenaho return decomposition			Indirect return news		Error components	
	Ncf	**Nr**	**u_ret**	**Ncf_v**	**Nr_v**	**u_ret_v**	**Ncf_r**	**Ncf_v_r**	**err**	**err_v**
Cash flow news: Ncf		0.8292	0.4861	0.4583	-0.2463	0.4305	0.9326	0.4274	0.0250	0.1649
		[0.0017]	[0.0036]	[0.0040]	[0.0043]	[0.0038]	[0.0008]	[0.0038]	[0.0040]	[0.0042]
Return news: Nr	0.8414		0.0768	0.1324	0.0038	0.0932	0.7917	0.1144	0.0453	0.0325
	[0.0015]		[0.0041]	[0.0043]	[0.0042]	[0.0041]	[0.0020]	[0.0039]	[0.0043]	[0.0044]
Unexpected return	0.4999	0.0885		0.6219	-0.5334	0.8335	0.6237	0.8092	0.5085	0.5767
(over ICC): u_ret	[0.0034]	[0.0042]		[0.0028]	[0.0033]	[0.0017]	[0.0029]	[0.0018]	[0.0032]	[0.0031]
Cash flow news: Ncf_v	0.4581	0.1246	0.5976		-0.3638	0.7650	0.4721	0.7922	0.1692	0.1692
	[0.0037]	[0.0043]	[0.0034]		[0.0037]	[0.0024]	[0.0040]	[0.0026]	[0.0035]	[0.0045]
Return news: Nr_v	-0.2236	0.0120	-0.5136	-0.2332		-0.6412	-0.3059	-0.4611	-0.2556	-0.3990
	[0.0049]	[0.0048]	[0.0038]	[0.0055]		[0.0031]	[0.0043]	[0.0039]	[0.0048]	[0.0045]
Unexpected return	0.4367	0.1001	0.8575	0.7109	-0.6041		0.5574	0.9673	0.4578	0.6565
(VAR model): u_ret_v	[0.0039]	[0.0045]	[0.0014]	[0.0032]	[0.0037]		[0.0033]	[0.0004]	[0.0032]	[0.0029]
Cash flow news	0.9319	0.8099	0.6560	0.4463	-0.2934	0.5809		0.5620	0.3272	0.3599
(residual): Ncf_r	[0.0009]	[0.0017]	[0.0023]	[0.0040]	[0.0046]	[0.0033]		[0.0032]	[0.0037]	[0.0039]
Cash flow news	0.4351	0.1200	0.8305	0.7502	-0.3804	0.9668	0.5800		0.4746	0.6554
(residual): Ncf_v_r	[0.0041]	[0.0044]	[0.0015]	[0.0034]	[0.0052]	[0.0004]	[0.0032]		[0.0035]	[0.0033]
Error component: err	-0.0304	0.0454	0.5089	0.0395	-0.2276	0.4661	0.3341	0.4679		0.6182
	[0.0057]	[0.0049]	[0.0042]	[0.0069]	[0.0064]	[0.0040]	[0.0045]	[0.0048]		[0.0029]
Error component: err_v	0.0996	0.0297	0.5263	-0.0832	-0.2902	0.5942	0.3324	0.5965	0.6573	
	[0.0051]	[0.0051]	[0.0036]	[0.0070]	[0.0059]	[0.0033]	[0.0039]	[0.0037]	[0.0046]	

Bibliography

Abarbanell, J. S., and B. J. Bushee, 1997, “Fundamental Analysis, Future Earnings, and Stock Prices”, *Journal of Accounting Research*, 35(1), pp. 1–24.

Abarbanell, J. S., and B. J. Bushee, 1998, “Abnormal Returns to a Fundamental Analysis Strategy”, *The Accounting Review*, 73(1), pp. 19–45.

Albrecht, W. S., L. L. Lookabill, and J. C. McKeown, 1977, “The Time-Series Properties of Annual Earnings”, *Journal of Accounting Research*, 15(2), pp. 226–244.

Allee, K. D., 2008, “Examining the Cost of Equity Capital Benefits of Analyst Following Using Time-Series Forecasts Earnings”, *Working Paper*.

Amihud, Y., and H. Mendelson, 1986, “Asset Pricing and the Bid-Ask Spread”, *Journal of Financial Economics*, 17(2), pp. 223–249.

Ang, A., and J. Chen, 2007, “CAPM Over the Long Run: 1926-2001”, *Journal of Empirical Finance*, 14(1), pp. 1–40.

Arellano, M., and O. Bover, 1995, “Another Look at the Instrumental-Variable Estimation of Error-components Models”, *Journal of Econometrics*, 68(1), pp. 29–51.

Baker, M., and J. Wurgler, 2006, “Investor Sentiment and the Cross-Section of Stock Returns”, *Journal of Finance*, 61(4), pp. 1645–1680.

Balachandran, B. V., R. Balakrishnan, and K. Sivaramakrishnan, 1997, “On the

Efficiency of Cost-Based Decision Rules for Capacity Planning”, *Accounting Review*, 72(4), 599–619.

Ball, R., and R. Watts, 1972, “Some Time Series Properties of Accounting Income”, *Journal of Finance*, 27(3), pp. 663–681.

Banz, R. W., 1981, “The Relationship Between Return and Market Value of Common Stocks”, *Journal of Financial Economics*, 9(1), pp. 3–18.

Barth, M. E., and S. Kallapur, 1996, “The Effects of Cross-Sectional Scale Differences on Regression Results in Empirical Accounting Research”, *Contemporary Accounting Research*, 13(2), pp. 527–567.

Beaver, W., P. Kettler, and M. Scholes, 1970, “The Association Between Market Determined and Accounting Determined Risk Measures”, *Accounting Review*, 45(4), pp. 654–682.

Beaver, W. H., and S. G. Ryan, 2000, “Biases and Lags in Book Value and Their Effects on the Ability of the Book-to-Market Ratio to Predict Book Return on Equity”, *Journal of Accounting Research*, 38(1), pp. 127–148.

Bebchuk, L., A. Cohen, and A. Ferrell, 2009, “What Matters in Corporate Governance?”, *Review of Financial Studies*, 22(2), pp. 783–827.

Beneish, M. D., 1999, “The Detection of Earnings Manipulation”, *Financial Analysts Journal*, 55(5), pp. 24–36.

Bernard, V. L., and J. K. Thomas, 1989, “Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?”, *Journal of Accounting Research*, 27(Supplement), pp. 1–36.

Bhattacharya, U., H. Daouk, and M. Welker, 2003, “The World Price of Earnings Opacity”, *The Accounting Review*, 78(3), pp. 641–678.

Bhushan, R., 1989, “Firm Characteristics and Analyst Following”, *Journal of Ac-*

counting and Economics, 11(2-3), pp. 255–274.

Black, F., 1972, "Capital Market Equilibrium with Restricted Borrowing", *Journal of Business*, 45(3), pp. 444–455.

Black, F., M. C. Jensen, and M. Scholes, 1972, "The Capital Asset Pricing Model: Some Empirical Tests", in *Studies in the Theory of Capital Markets*, ed. by M. C. Jensen. Praeger, New York, vol. 81, pp. 79–121.

Botosan, C. A., 1997, "Disclosure Level and the Cost of Equity Capital", *The Accounting Review*, 72(3), pp. 323–329.

Botosan, C. A., and M. A. Plumlee, 2002, "A Re-examination of Disclosure Level and the Expected Cost of Equity Capital", *Journal of Accounting Research*, 40(1), pp. 21–40.

——— , 2005, "Assessing Alternative Proxies for the Expected Risk Premium", *The Accounting Review*, 80(1), pp. 21–53.

Botosan, C. A., M. A. Plumlee, and H. Wen, 2010, "The Relation Between Expected Returns, Realized Returns, and Firm Characteristics", *Working Paper*.

Bradshaw, M. T., 2002, "The Use of Target Prices to Justify Sell-Side Analysts'Stock Recommendations", *Accounting Horizons*, 16(1), pp. 27–41.

——— , 2004, "How Do Analysts Use Their Earnings Forecasts in Generating Stock Recommendations?", *The Accounting Review*, 79(1), pp. 25–50.

Bradshaw, M. T., M. S. Drake, J. N. Myers, and L. A. Myers, 2010, "A Re-Examination of Analysts' Superiority over Time-Series Forecasts of Annual Earnings", *Working Paper*.

Brav, A., R. Lehavy, and R. Michaely, 2005, "Using Expectations to Test Asset Pricing Models", *Financial Management*, 34(3), pp. 31–64.

Brooks, C., 2008, *Introductory Econometrics for Finance*. Cambridge University

Press, 2nd edn.

Brooks, L. D., and D. A. Buckmaster, 1976, "Further Evidence of the Time Series Properties of Accounting Income", *Journal of Finance*, 31(5), pp. 1359–1373.

Brown, L. D., 1993, "Earnings Forecasting Research: Its Implications for Capital Markets Research", *International Journal of Forecasting*, 9(3), pp. 295–320.

Brown, L. D., R. L. Hagerman, P. A. Griffin, and M. E. Zmijewski, 1987, "Security Analyst Superiority Relative to Univariate Time-Series Models in Forecasting Quarterly Earnings", *Journal of Accounting and Economics*, 9(1), pp. 61–87.

Brown, L. D., and M. S. Rozeff, 1978, "The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings", *Journal of Finance*, 33(1), pp. 1–16.

Callen, J., D. Segal, and O.-K. Hope, 2010, "The Pricing of Conservative Accounting and the Measurement of Conservatism at the Firm-Year Level", *Review of Accounting Studies*, 15(1), pp. 145–178.

Callen, J. L., O.-K. Hope, and D. Segal, 2005, "Domestic and Foreign Earnings, Stock Return Variability, and the Impact of Investor Sophistication", *Journal of Accounting Research*, 43(3), pp. 377–412.

Callen, J. L., and D. Segal, 2004, "Do Accruals Drive Firm-Level Stock Returns? A Variance Decomposition Analysis", *Journal of Accounting Research*, 42(3), pp. 527–560.

Campbell, J., and J. Mei, 1993, "Where Do Betas Come From? Asset Price Dynamics and the Sources of Systematic Risk", *Review of Financial Studies*, 6(3), pp. 567–592.

Campbell, J. Y., 1991, "A Variance Decomposition For Stock Returns", *Economic Journal*, 101(405), pp. 157–179.

Campbell, J. Y., and J. Ammer, 1993, "What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns", *Journal of Finance*, 48(1), pp. 3–37.

Campbell, J. Y., C. Polk, and T. Vuolteenaho, 2010, "Growth or Glamour? Fundamentals and Systematic Risk in Stock Returns", *Review of Financial Studies*, 23(1), pp. 305–344.

Campbell, J. Y., and R. J. Shiller, 1988a, "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors", *Review of Financial Studies*, 1(3), pp. 195–228.

——— , 1988b, "Stock Prices, Earnings, and Expected Dividends", *Journal of Finance*, 43(3), pp. 661–676.

Campbell, J. Y., and T. Vuolteenaho, 2004, "Bad Beta, Good Beta", *American Economic Review*, 94(5), pp. 1249–1275.

Carhart, M. M., 1997, "On Persistence in Mutual Fund Performance", *Journal of Finance*, 52(1), pp. 57–82.

Chan, K., and A. Hameed, 2006, "Stock Price Synchronicity and Analyst Coverage in Emerging Markets", *Journal of Financial Economics*, 80(1), pp. 115–147.

Chen, H., M. T. Kacperczyk, and H. Ortiz-Molina, 2011, "Labor Unions, Operating Flexibility, and the Cost of Equity", *Journal of Financial and Quantitative Analysis*, 46(1), pp. 25–58.

Chen, L., and X. Zhao, 2009, "Return Decomposition", *Review of Financial Studies*, 22(12), pp. 5213–5249.

Claus, J., and J. Thomas, 2001, "Equity Premia as Low as Three Percent? Evidence from Analysts' Earnings Forecasts for Domestic and International Stocks", *Journal of Finance*, 56(5), pp. 1629–1666.

Cochrane, J. H., 1999, "New Facts in Finance", *Federal Reserve Bank of Chicago Economic Perspectives*, 23(3), pp. 36–58.

Cohen, R. B., C. Polk, and T. Vuolteenaho, 2003, "The Value Spread", *Journal of Finance*, 58(2), 609–642.

——— , 2009, "The Price Is (Almost) Right", *Journal of Finance*, 64(6), pp. 2739–2782.

Core, J. E., W. R. Guay, and T. O. Rusticus, 2006, "Does Weak Governance Cause Weak Stock Returns? An Examination of Firm Operating Performance and Investors' Expectations", *Journal of Finance*, 61(2), pp. 655–687.

Cremers, K. J. M., and A. Ferrell, 2010, "Thirty Years of Shareholder Rights and Firm Valuation", *Working Paper*.

Daske, H., 2006, "Economic Benefits of Adopting IFRS or US-GAAP: Have the Expected Cost of Equity Capital Really Decreased?", *Journal of Business Finance & Accounting*, 33(3-4), pp. 329–373.

Daske, H., L. Hail, C. Leuz, and R. Verdi, 2008, "Mandatory IFRS Reporting around the World: Early Evidence on the Economic Consequences", *Journal of Accounting Research*, 46(5), pp. 1085–1142.

Davis, J. L., E. F. Fama, and K. R. French, 2000, "Characteristics, Covariances, and Average Returns: 1929 to 1997", *Journal of Finance*, 55(1), pp. 389–406.

Dechow, P. M., S. P. Kothari, and R. Watts, 1998, "The Relation Between Earnings, Cash Flows and Accruals", *Journal of Accounting and Economics*, 25(2), pp. 133–168.

Dechow, P. M., R. G. Sloan, and M. T. Soliman, 2004, "Implied Equity Duration: A New Measure of Equity Risk", *Review of Accounting Studies*, 9(2-3), pp. 197–228.

Dechow, P. M., R. G. Sloan, and A. P. Sweeney, 1995, "Detecting Earnings Management", *The Accounting Review*, 70(2), pp. 193–225.

Dhaliwal, D., L. Krull, and O. Z. Li, 2007, "Did the 2003 Tax Act Reduce the Cost of Equity Capital?", *Journal of Accounting and Economics*, 43(1), pp. 121–150.

Diether, K. B., C. J. Malloy, and A. Scherbina, 2002, "Differences of Opinion and the Cross Section of Stock Returns", *Journal of Finance*, 57(5), pp. 2113–2141.

Dorn, D., G. Huberman, and P. Sengmueller, 2008, "Correlated Trading and Returns", *Journal of Finance*, 63(2), pp. 885–920.

Easton, P., 2009, "Estimating the Cost of Capital Implied by Market Prices and Accounting Data", *Foundations and Trends in Accounting*, 2(4).

Easton, P., G. Taylor, P. Shroff, and T. Sougiannis, 2002, "Using Forecasts of Earnings to Simultaneously Estimate Growth and the Rate of Return on Equity Investment", *Journal of Accounting Research*, 40(3), pp. 657–676.

Easton, P. D., 2004, "PE Ratios, PEG Ratios, and Estimating the Implied Expected Rate of Return on Equity Capital", *Accounting Review*, 79(1), pp. 73–95.

Easton, P. D., and S. J. Monahan, 2005, "An Evaluation of Accounting-Based Measures of Expected Returns", *The Accounting Review*, 80(2), pp. 501–538.

Easton, P. D., and G. A. Sommers, 2007, "Effect of Analysts' Optimism on Estimates of the Expected Rate of Return Implied by Earnings Forecasts", *Journal of Accounting Research*, 45(5), pp. 983–1015.

Elton, E. J., 1999, "Expected Return, Realized Return, and Asset Pricing Tests", *Journal of Finance*, 54(4), pp. 1199–1220.

Fama, E. F., and K. R. French, 1992, "The Cross-Section of Expected Stock Returns", *Journal of Finance*, 47(2), pp. 427–465.

——— , 1993, "Common Risk Factors in the Returns on Stocks and Bonds", *Journal of Financial Economics*, 33(1), pp. 3–56.

——— , 1995, “Size and Book-to-Market Factors in Earnings and Returns”, *Journal of Finance*, 50(1), pp. 131–155.

——— , 1997, “Industry Costs of Equity”, *Journal of Financial Economics*, 43(2), pp. 153–193.

——— , 2000, “Forecasting Profitability and Earnings”, *Journal of Business*, 73(2), pp. 161–175.

——— , 2002, “The Equity Premium”, *Journal of Finance*, 57(2), pp. 637–659.

——— , 2006a, “Profitability, Investment and Average Returns”, *Journal of Financial Economics*, 82(3), pp. 491–518.

——— , 2006b, “The Value Premium and the CAPM”, *The Journal of Finance*, 61(5), pp. 2163–2185.

Fama, E. F., and J. D. MacBeth, 1973, “Risk, Return, and Equilibrium: Empirical Tests”, *The Journal of Political Economy*, 81(3), pp. 607–636.

Francis, J., 1990, “Accounting for Futures Contracts and the Effect on Earnings Variability”, *The Accounting Review*, 65(4), pp. 891–910.

Francis, J., P. Olsson, and D. R. Oswald, 2000, “Comparing the Accuracy and Explainability of Dividend, Free Cash Flow and Abnormal Earnings Equity Value Estimates”, *Journal of Accounting Research*, 38, pp. 45–70.

Francis, J., and D. Philbrick, 1993, “Analysts’ Decisions As Products of a Multi-Task Environment”, *Journal of Accounting Research*, 31(2), pp. 216–230.

Frank, M. Z., and V. K. Goyal, 2009, “Capital Structure Decisions: Which Factors are Reliably Important?”, *Financial Management*, 38(1), pp. 1–37.

Freeman, R. N., J. A. Ohlson, and S. H. Penman, 1982, “Book Rate-of-Return and Prediction of Earnings Changes: An Empirical Investigation”, *Journal of Accounting Research*, 20(2), pp. 639–653.

Gebhardt, W. R., C. M. C. Lee, and B. Swaminathan, 2001, “Towards an Implied Cost of Capital”, *Journal of Accounting Reserach*, 39(1), pp. 135–175.

Giroud, X., and H. M. Mueller, 2010, “Does Corporate Governance Matter in Competitive Industries?”, *Journal of Financial Economics*, 95(3), pp. 312–331.

Gode, D., and P. Mohanram, 2003, “Inferring the Cost of Capital Using the Ohlson-Juettner Model”, *Review of Accounting Studies*, 8(4), pp. 399–431.

Gode, D., and P. Mohanram, 2008, “Improving the Relationship Between Implied Cost of Capital and Realized Returns by Removing Predictable Analyst Forecast Errors”, *Working Paper*.

Gompers, P., J. Ishii, and A. Metrick, 2003, “Corporate Governance and Equity Prices”, *Quarterly Journal of Economics*, 118(1), pp. 107–155.

Graham, J. R., and C. R. Harvey, 2001, “The Theory and Practice of Corporate Finance: Evidence from the Field”, *Journal of Financial Economics*, 60(2-3), pp. 187–243.

Greenball, M. N., 1968, “The Accuracy of Different Methods of Accounting for Earnings - A Simluation Approach”, *Journal of Accounting Research*, 6(1), pp. 114–129.

Guay, W., S. Kothari, and S. Shu, 2005, “Properties of Implied Cost of Capital Using Analysts’ Forecasts”, *Working Paper*.

Hail, L., and C. Leuz, 2006, “International Differences in the Cost of Equity Capital: Do Legal Institutions and Securities Regulation Matter?”, *Journal of Accounting Research*, 44(3), pp. 485–531.

——— , 2009, “Cost of Capital Effects and Changes in Growth Expectations around U.S. Cross-Listings”, *Journal of Financial Economics*, 93(3), pp. 428–454.

Hastie, T., R. Tibshirani, and J. Friedman, 2001, *The Elements of Statistical Learning:*

Data Mining, Inference, and Prediction. New York, Springer-Verlag.

Hayashi, F., 2000, *Econometrics*. Princton University Press, 1st edn.

Hayes, R. M., 1998, "The Impact of Trading Commission Incentives on Analysts' Stock Coverage Decisions and Earnings Forecasts", *Journal of Accounting Research*, 36(2), pp. 299–320.

Healy, P. M., S. C. Myers, and C. D. Howe, 2002, "R&D Accounting and the Tradeoff Between Relevance and Objectivity", *Journal of Accounting Research*, 40(3), pp. 677–710.

Hong, H., J. D. Kubik, and A. Solomon, 2000, "Security Analysts' Career Concerns and Herding of Earnings Forecasts", *RAND Journal of Economics*, 31(1), pp. 121–144.

Hou, K., and D. T. Robinson, 2006, "Industry Concentration and Average Stock Returns", *Journal of Finance*, 61(4), pp. 1927–1956.

Hou, K., and M. A. Van Dijk, 2010, "Profitability Shocks and the Size Effect in the Cross-Section of Expected Stock Returns", *Working Paper*.

Hou, K., M. A. Van Dijk, and Y. Zhang, 2010, "The Implied Cost of Capital: A New Approach", *Working Paper*.

Hughes, J., J. Liu, and J. Liu, 2009, "On the Relation between Expected Returns and Implied Cost of Capital", *Review of Accounting Studies*, 14(2-3), pp. 246–259.

Johnson, S. A., T. C. Moorman, and S. Sorescu, 2009, "A Reexamination of Corporate Governance and Equity Prices", *Review of Financial Studies*, 22(11), pp. 4753–4786.

Kadous, K., S. D. Krische, and L. M. Sedor, 2006, "Using Counter-Explanation to Limit Analysts' Forecast Optimism.", *The Accounting Review*, 81(2), pp. 377–397.

Knechel, W. R., 1988, "The Effectiveness of Statistical Analytical Review as a

Substantive Auditing Procedure: A Simulation Analysis", *Accounting Review*, 63(1), pp. 74–95.

Kothari, S., J. S. Sabino, and T. Zach, 2005, "Implications of Survival and Data Trimming for Tests of Market Efficiency", *Journal of Accounting and Economics*, 39(1), pp. 129–161.

Kothari, S. P., 2001, "Capital Markets Research in Accounting", *Journal of Accounting and Economics*, 31(1-3), pp. 105–231.

Labro, E., and M. Vanhoucke, 2007, "A Simulation Analysis of Interactions among Errors in Costing Systems", *Accounting Review*, 82(4), pp. 939–962.

——— , 2008, "Diversity in Resource Consumption Patterns and Robustness of Costing Systems to Errors", *Management Science*, 54(10), pp. 1715–1730.

Lambert, R. A., 2009, "Discussion of 'On the Relation between Expected Returns and Implied Cost of Capital'", *Review of Accounting Studies*, 14(2-3), pp. 260–268.

Lambert, R. A., and D. F. Larcker, 1989, "Estimating the Marginal Cost of Operating a Service Department when Reciprocal Services Exist", *Accounting Review*, 64(3), pp. 449–467.

Lang, M. H., K. V. Lins, and D. P. Miller, 2004, "Concentrated Control, Analyst Following, and Valuation: Do Analysts Matter Most When Investors Are Protected Least?", *Journal of Accounting Research*, 42(3), pp. 589–623.

LaPorta, R., 1996, "Expectations and the Cross-Section of Stock Returns", *Journal of Finance*, 51(5), pp. 1715–1742.

Larocque, S. A., 2010, "Analyst Forecast Errors and Cost of Equity Capital Estimates", *Working Paper*.

Lee, C. M. C., D. Ng, and B. Swaminathan, 2009, "Testing International Asset Pricing Models Using Implied Costs of Capital", *Journal of Financial and Quantitative*

Analysis, 44(2), pp. 307–335.

Lettau, M., and J. A. Wachter, 2007, "Why Is Long-Horizon Equity Less Risky? A Duration-Based Explanation of the Value Premium", *Journal of Finance*, 62(1), pp. 55–92.

Lev, B., and S. R. Thiagarajan, 1993, "Fundamental Information Analysis", *Journal of Accounting Research*, 31(2), pp. 190–215.

Lin, H., and M. F. McNichols, 1998, "Underwriting Relationships, Analysts' Earnings Forecasts and Investment Recommendations", *Journal of Accounting and Economics*, 25(1), pp. 101–127.

Lintner, J., 1965, "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets", *The Review of Economics and Statistics*, 47(1), pp. 13–37.

Lipe, R., and R. Kormendi, 1994, "Mean Reversion in Annual Earnings and Its Implications for Security Valuation", *Review of Quantitative Finance and Accounting*, 4(1), pp. 27–46.

Love, I., and L. Zicchino, 2006, "Financial Development and Dynamic Investment Behavior: Evidence from Panel VAR", *Quarterly Review of Economics and Finance*, 46(2), pp. 190–210.

Lundblad, C., 2007, "The Risk Return Tradeoff in the Long Run: 1836-2003", *Journal of Financial Economics*, 85(1), pp. 123–150.

Lundholm, R. J., and R. G. Sloan, 2006, *Equity Valuation and Analysis With EVal*. McGraw-Hill Irwin, 2nd edn.

Maines, L. A., and J. R. M. Hand, 1996, "Individuals' Perceptions and Misperceptions of Time-Series Properties of Quarterly Earnings", *The Accounting Review*, 71(3), pp. 317–336.

McNichols, M., and P. C. O'Brien, 1997, "Self-Selection and Analyst Coverage", *Journal of Accounting Research*, 35, pp. 167–199.

Modigliani, F., and M. H. Miller, 1958, "The Cost of Capital, Corporation Finance and the Theory of Investment", *American Economic Review*, 48(3), pp. 261–297.

——— , 1961, "Dividend Policy, Growth, and the Valuation of Shares", *Journal of Business*, 34(4), pp. 411–433.

Nekrasov, A., and M. Ogneva, 2010, "Using Earnings Forecasts to Simultaneously Estimate Firm-Specific Cost of Equity and Long-Term Growth", *Working Paper*.

O'Brien, P. C., 1988, "Analysts' Forecasts as Earnings Expectations", *Journal of Accounting and Economics*, 10(1), pp. 53–83.

O'Brien, P. C., M. F. McNichols, and H.-W. Lin, 2005, "Analyst Impartiality and Investment Banking Relationships.", *Journal of Accounting Research*, 43(4), pp. 623–650.

O'Hanlon, J., and A. Steele, 2000, "Estimating the Equity Risk Premium Using Accounting Fundamentals", *Journal of Business Finance & Accounting*, 27(9-10), pp. 1051–1083.

Ohlson, J., and Z. Gao, 2006, "Earnings, Earnings Growth, and Value", *Foundations and Trends in Accounting*, 1(1), pp. 1–70.

Ou, J. A., and S. H. Penman, 1989a, "Accounting Measurement, Price-Earnings Ratio, and the Information Content of Security Prices", *Journal of Accounting Research*, 27(Supplement), pp. 111–144.

——— , 1989b, "Financial Statement Analysis and the Prediction of Stock Returns", *Journal of Accounting and Economics*, 11(4), pp. 295–329.

Pastor, L., M. Sinha, and B. Swaminathan, 2008, "Estimating the Intertemporal Risk-Return Tradeoff Using the Implied Cost of Capital", *Journal of Finance*, 63(6), pp. 2859–2897.

Pastor, L., and R. F. Stambaugh, 1999, “Costs of Equity Capital and Model Mispricing”, *Journal of Finance*, 54(1), pp. 67–121.

——— , 2003, “Liquidity Risk and Expected Stock Returns”, *Journal of Political Economy*, 111(3), pp. 642–685.

Penman, S., 2009, *Financial Statement Analysis and Security Valuation*. McGraw-Hill Irwin, 4th edn.

Penman, S. H., and X.-J. Zhang, 2002, “Accounting Conservatism, the Quality of Earnings, and Stock Returns”, *The Accounting Review*, 77(2), pp. 237–264.

Petersen, K. B., and M. S. Pedersen, 2008, *The Matrix Cookbook*. Technical University of Denmark.

Piotroski, J. D., 2000, “Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers”, *Journal of Accounting Research*, 38(Supplement), pp. 1–41.

Ramnath, S., S. Rock, and P. Shane, 2008, “The Financial Analyst Forecasting Literature: A Taxonomy with Suggestions for Further Research”, *International Journal of Forecasting*, 24(1), pp. 34–75.

Rees, W., and C. Sutcliffe, 1993, “Mathematical Modelling and Stochastic Simulation of Accounting Alternatives”, *Journal of Business Finance & Accounting*, 20(3), pp. 351–358.

Reinganum, M. R., 1981, “Misspecification of Capital Asset Pricing : Empirical Anomalies Based on Earnings’ Yields and Market Values”, *Journal of Financial Economics*, 9(1), pp. 19–46.

Richardson, S., S. H. Teoh, and P. D. Wysocki, 2004, “The Walk-Down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives.”, *Contemporary Accounting Research*, 21(4), pp. 885–924.

Ross, S. A., 1976, "The Arbitrage Theory of Capital Asset Pricing", *Journal of Economic Theory*, 13(3), pp. 341–360.

Schwert, G. W., 2003, "Anomalies and Market Efficiency", in *Handbook of the Economics of Finance*, ed. by G. Constantinides, M. Harris, and R. Stulz. Elsevier, Amsterdam, chap. 17, pp. 937–971.

Sedor, L. M., 2002, "An Explanation for Unintentional Optimism in Analysts' Earnings Forecasts", *The Accounting Review*, 77(4), pp. 731–753.

Sharpe, W. F., 1964, "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk", *Journal of Finance*, 19(3), pp. 425–442.

Sloan, R. G., 1996, "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?", *The Accounting Review*, 71(3), pp. 289–315.

Vassalou, M., and Y. Xing, 2004, "Default Risk in Equity Returns", *Journal of Finance*, 59(2), pp. 831–868.

Vuolteenaho, T., 2002, "What Drives Firm-Level Stock Returns?", *Journal of Finance*, 57(1), pp. 233–264.

Watts, R. L., and R. W. Leftwich, 1977, "The Time Series of Annual Accounting Earnings", *Journal of Accounting Research*, 15(2), pp. 253–271.

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Ich versichere hiermit ehrenwörtlich, dass ich die vorstehende Dissertation selbständig und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Alle Stellen, die wörtlich oder sinngemäß aus veröffentlichten oder unveröffentlichten Schriften entnommen worden sind, sind als solche kenntlich gemacht. Darüber hinaus versichere ich, dass ich nicht die Hilfe einer kommerziellen Promotionsvermittlung/-beratung in Anspruch genommen habe.

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