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Essays on the implied cost of capital with applications to asset pricing and corporate finance

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In memory of the bravest person I know, my late mother.

ABSTRACT

Estimating expected stock returns is at the center of many problems in asset pricing and corporate finance. Given the wide range of studies that use these estimates, it is intuitive that the estimation tools also vary. This thesis will demonstrate three novel applications of a forward-looking expected return estimate, namely the implied cost of capital (ICC).

Chapters 4 and 5 examine two methods from the portfolio choice literature. I find that the ICC performs better than estimates based on time-series models and naive benchmarks, such as the value-weighted and equally-weighted portfolios.

In Chapter 6, the application of the ICC to empirical corporate finance investigates the impact of corporate diversification on a firm's cost of equity. I disentangle two conflicting views in the corporate diversification literature: the coinsurance effect and the diversification discount. I show that the coinsurance effect lowers the cost of equity for diversified firms. However, I also obeserve an increase in the cost of equity related to the inefficiency of a conglomerate's internal capital market.

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ACRONYMS

AEG abnormal earnings growth model

AMEX American Stock Exchange

BL Black and Litterman (1992)

BPS book-value per share

CAPM capital asset pricing model

CDS Credit Default Swap

CFO Chief Financial Officers

CRSP Center for Research in Security Prices

CT ICC method based on Claus and Thomas (2001)

CUSIP Committee on Uniform Securities Identification Procedures

DDM dividend discount model

EGARCH exponential generalized autoregressive conditional heteroskedasticity

EP earnings persistence model

EPS earnings per share

FISD Mergent Fixed Income Securities Database

FYE fiscal year-end

GDP gross domestic product

GLS ICC method based on Gebhardt et al. (2001)

IBES Instiutional Brokers' Estimate System

ICC implied cost of capital

ICE implied cost of equity

MSCI	Morgan Stanley Capital International
MPEG	modified price-earnings-growth
NASDAQ	National Assocation of Securities Dealers Automated Quotations
NBER	National Bureau of Economic Research
NYSE	New York Stock Exchange
OJ	ICC method based on Ohlson and Juettner-Nauroth (2005)
PSS	ICC method based on Pástor et al. (2008)
RI	residual income
RIM	residual income model
ROE	return on equity
SDC	Thomson Reuters SDC Platinum
SIC	Standard Industrial Classification
SP	Standard and Poor's
TR	Thomson Reuters
U.S.	United States of America
USD	United States dollar
WRDS	Wharton Research Data Services

NOMENCLATURE

BAB	Betting against beta factor based on Frazzini and Pedersen (2014)
BPS_0	Reported book value of common equity per share for the last available fiscal year-end
BPS_t	Forecasted book value of common equity per share for period t
CEQ	Certainty equivalent return according to DeMiguel et al. (2009b)
CMA	Conservative investment minus aggressive investment, investment factor based on Fama and French (2014)
E_0	Realized earnings for the last available fiscal year-end
E_t	Forecasted earnings for period t
EPS_0	Realized earnings for the last available fiscal year-end
EPS_t	Forecasted earnings per share for period t
EPS_{LTG}	Forecasted long-term growth rate in earnings
EW	Investment strategy that weights each stock equally
g	Terminal value growth rate
g_s	Short-term growth rate in the OJ method
HIST	Portfolio optimization strategy in which a stock's five-year average historic return is used as the expected return
HML	High book-to-market value minus low book-to-market value, value factor based on Fama and French (1993)

ICC_{CT}	ICC estimate according to Claus and Thomas (2001)
ICC_{GLS}	ICC estimate according to Gebhardt et al. (2001)
ICC_{MPEG}	ICC estimate according to Easton (2004)
ICC_{OJ}	ICC estimate according to Ohlson and Juettner-Nauroth (2005)
ICC_{PSS}	ICC estimate according to Pástor et al. (2008)
ICC_MOM	Portfolio optimization strategy in which a stock's ICC corrected for analysts' sluggishness is used as the expected return
LTG	Analysts' forecast for the long-term growth rate in earnings
MDD	Maximum one-year drawdown according to Grossman and Zhou (1993)
MV	Market value
MVP	Minimum variance portfolio
pr	Payout ratio
Omega	Omega portfolio performance measure according to Kaplan and Knowles (2004)
RMW	Robust profitability minus weak profitability, quality factor based on Fama and French (2014)
SMB	Small minus big, size factor based on Banz (1981) and Fama and French (1993)
TO	One-way portfolio turnover according to DeMiguel et al. (2009b)
Tobin's Q	A firm's market value of equity divided by its book value of equity
VaR	Value-at-risk

VW	Investment strategy that weights each stock proportional to its market value
WML	Recent winners minus recent loosers, momentum factor based on Carhart (1997)

1

INTRODUCTION

1.1 MOTIVATION AND OUTLINE

Expected return estimates[1] are used in many asset pricing and corporate finance studies. These applications cover diverse areas, from portfolio allocation problems (Markowitz 1952) through factor timing (Li et al. 2014) to studying variables that influence the expected return (for example, Botosan 1997) or variables that are influenced by the expected return (for example, Frank and Shen 2016).

Since the expected return is such a central topic in finance, there is a large variety of theories and models that attempt to explain it (see Cochrane 2011 for a summary). These include macroeconomic theories (modelling parts of the economy, such as consumption and aggregate risk, and general equilibrium models), behavioral finance models, and factor models. There is also an extensive literature on expected return models based on frictions, such as segmented markets, intermediated markets, and liquidity (Cochrane 2011).

Despite this wide range of models, the methodology used in most applied finance research settings, as well as in practice, is based on historic stock returns. Indeed, for many years the recommended practice was to use the historic mean return as a proxy for the expected return (Harris and

1 I use "expected return", "cost of (equity) capital", and "discount rate" as synonyms throughout this thesis.

Marston 1992). While this proxy is an unbiased estimate of the true expected return, it contains a large amount of noise (Elton 1999), which can make it unsuitable for specific applications. Also, a long estimation period is necessary to obtain a reliable estimate (Elton 1999). For example, event studies that compare the cost of equity before and after an event cannot use a long estimation period for the post-event estimate. In portfolio allocation problems, employing the historic mean return often leads to extreme allocation decisions due to their high volatility and measurement error (Best and Grauer 1991).

In comparison to using the historic average return, a factor model helps to reduce measurement error. It also reduces complexity by linking the expected return to the exposure to a limited number of factors, which represent systematic risks. The capital asset pricing model (CAPM) was the first factor model to be developed and it is based on work by Sharpe (1964), Lintner (1965), and Mossin (1966). It assumes that the only priced risk factor in the stock market is the market return above the risk-free rate. The expected return of each stock can thus be determined by estimating the sensitivity of the respective stock's return toward the market return using a regression (this sensitivity is named beta). Therefore, this approach also relies on historic data and the estimation of beta is sensitive toward the empirical implementation. Nevertheless, the CAPM is still the method taught in standard textbooks (for example, Berk and DeMarzo 2013) and is (perhaps not surprisingly) a popular choice in practice (Graham and Harvey 2001).

The focus on two select methods to estimate the expected return may reflect the fact that for a long time, cash-flow estimates were deemed to be the more important driver in stock returns. This view has only shifted recently to the discount rate for firm's cash flows (Cochrane 2011). A major break-through was the study by Shiller (1981), which finds that stock prices fluctuate too much to be explained by changes in dividends. Thus, the discount rate for these cash flows has to vary over time and should not be assumed to be constant. This invigorated the return predictability literature, which explores if future returns can be accurately predicted.

Return predictability centers on market returns (see Koijen and Van Nieuwerburgh (2011) or Cochrane (2011) for an overview of the literature) or, more recently, on portfolios (Kelly and Pruitt 2015). As such, they cannot be directly used to estimate the expected return of a single stock. The work in this area has substantially increased our understanding of the time-variance of expected returns as well as its economic drivers. Researchers have proposed various variables to predict stock market returns: financial ratios (for example, price-to-dividend and price-to-earnings), term and credit spread in bond yields, the consumption-wealth ratio, and macroeconomic variables (Koijen and Van Nieuwerburgh 2011). Also, return predictability is no longer seen as conflicting with the efficient market hypothesis (Fama 1965, Fama 1970), as asset pricing equilibrium models have emerged that account for the time-variance in expected returns (Koijen and Van Nieuwerburgh 2011). For example, Campbell and Cochrane (1999) develop a model with fluctuating risk aversion, Bansal and Yaron (2004) and Bansal et al. (2009) focus on fluctuating consumption risk, and Lustig and Van Nieuwerburgh (2005) build a model on heterogeneous agents with time-varying risk-sharing opportunities.

The disadvantages of methodologies implementing past returns to estimate expected returns has spawned a new string of literature which explores methods using a combination of current stock prices, accounting data, and earnings forecasts to compute expected returns (Gebhardt et al. 2001, Claus and Thomas 2001, Easton 2004, Ohlson and Juettner-Nauroth 2005). This novel approach does not rely on a time-series of stock returns but instead uses a valuation equation (such as a residual income model) with the current stock price on the left-hand side and the discounted expected earnings on the right-hand side. Then the equation is solved for the implied discount rate, which is termed the implied cost of capital (ICC).

This thesis explores different applications of the ICC. Especially in portfolio allocation problems, investors can benefit from the predictive power of the ICC, as it employs forward-looking earnings estimates. In Chapter 4, I put the findings from Li et al. (2013) into practice by implementing the market ICC in a Black and Litterman (1992) portfolio optimization for a sample of large, industrialized countries. I find that portfolios based on the ICC outperform those based on the historic mean return, as well as those based on more elaborate time-series models.

The ICC approach also works well on a stock level. Chapter 5 provides evidence that the performance of a maximum Sharpe Ratio optimized portfolio can be improved using the ICC instead of the historic mean return. I show that the strategy based on the ICC is not only superior to an optimization based on historic mean returns but it also outperforms other approaches popular in the literature. These include the minimum-variance portfolio, which completely ignores expected return estimates and only uses the covariance matrix of stock returns. Jagannathan and Ma (2003) argue that because of the large estimation error in historic return estimates, the minimum-variance strategy performs well in portfolio optimization settings. I also include the equally-weighted portfolio in my tests as this strategy outperforms many active investment approaches (DeMiguel et al. 2009b).

In Chapter 6, I apply the ICC approach in a corporate finance setting. I take advantage of the fact that the ICC can be estimated with the current stock price and accounting data, so that I do not need a long history of past data. This makes it an ideal method to employ in event studies. I utilize the ICC to investigate the influence of corporate diversification on the cost of equity. I use the setting of mergers and acquisitions and compare the ICC estimate before and after the takeover. In this study design, it is critical to measure the cost of equity soon after the merger. An estimate based on historic data would need a longer history of stock returns, which then could be polluted by other events.

I do not argue that the ICC is a panacea, which can replace methods based on historic data in all circumstances. Factor models, such as the CAPM, will continue to be the standard approach when evaluating investment strategies. The historic mean return has higher predictive power than many variables suggested in the literature (Welch and Goyal 2008). Also, the CAPM is built on a convincing theoretical foundation, which makes it popular when evaluating the required return for corporate projects. I am merely arguing for an openness toward alternative proxies in certain applications.

All statistical analyses in this thesis were performed using R (R Core Team 2014) version 3.0.3.

1.2 CONTRIBUTION

The portfolio optimization studies in Chapters 4 and 5 extend the literature by providing guidance on how to implement the ICC as a proxy for expected returns. This is a novel approach and, therefore, I pay close attention to the construction of the ICC and how to mitigate documented problems of analyst data (Guay et al. 2011). Existing studies in the portfolio optimization field focus on circumventing the use of return forecasts altogether by employing a minimum variance approach (for example, Clarke et al. 2011 and Chow et al. 2016). This approach implicitly assumes that all expected returns are equal (Chow et al. 2011), which is unlikely to hold in reality. I show that using forward-looking return estimates are superior to a minimum variance approach in my sample.

Furthermore, I offer a novel application of the Black and Litterman (1992) (BL) portfolio optimization method. While most studies use historic data to estimate expected returns (Beach and Orlov 2007, Jones et al. 2007, Bessler et al. 2014), I use forward-looking return estimates. The study by Becker and Gürtler (2010) also employ the ICC in combination with a BL portfolio optimization strategy. However, they perform the optimization on a stock level and do not make corrections for known problems with analyst data. In comparison, I use market level ICC estimates to mitigate measurement errors on the stock level and correct for known problems of analysts' forecasts.

Finally, in Chapter 6, I use the ICC in an event study setting around corporate mergers and acquisitions to shed light into the influence of corporate diversification on the cost of equity. The view in the literature is not consistent on this topic. Some researchers highlight the risk-reduction effect of corporate diversification (Hann et al. 2013), while others point toward the diversification discount (Lang and Stulz 1994, Berger and Ofek 1995). I find that the quality of the internal capital market determines which of the two effects dominate. Moreover, I demonstrate that these effects are statistically as well as economically significant and that they are robust to endogeneity issues, variable measurement, and empirical specifications. This increases our understanding of how corporate diversification influences firm characteristics. The findings also help corporate managers to evaluate potential acquisitions.

2

LITERATURE OVERVIEW

2.1 EXPECTED RETURNS USING HISTORICAL DATA

Expected returns are a fundamental concept in finance (Elton 1999) and a lot of effort is devoted to their estimation as they cannot be observed. The most intuitive method is to use the mean of a sample of historic returns. Indeed, this was previously the recommendation found in textbooks for practitioners (Harris and Marston 1992). Even though the historic mean return is an unbiased estimate of the expected return, it suffers greatly from estimation error and statistical noise (Elton 1999). Even as early as the 1950s, Markowitz (1952) recommends the use of a combination of the historic mean return and judgement. Frankfurter et al. (1971) and Barry (1974) caution against treating the mean historic return as the expected return.

The large estimation error of individual historical stock returns is somewhat mitigated by the use of a factor model. A factor model assumes that every asset can be priced by its exposure to a limited set of factors. These factors represent systematic risks in the market. The first factor model to emerge was the CAPM (Sharpe 1964, Lintner 1965, Mossin 1966), which posits that there is only one relevant factor (the market risk premium) that explains stock returns. Over time, more factors emerged in the literature. Banz (1981) proposes a size factor (based on the firm's market capitalization). Fama and French (1992) develop a three-factor model that includes the two aforementioned factors plus the book-to-market value factor. Jegadeesh and Titman (1993) discover the momentum factor. Further additions are the investment factor (Titman et al. 2004) and the profitability factor (Novy-Marx 2013). These factor models are well-suited in many applications in asset pricing and corporate finance. However, even Fama and French (1997) acknowledge that expected returns based on factor models still contain a large amount of statistical noise.

There are many alternatives to using the historic mean return or a factor model when estimating the expected return. The following will provide an overview of the most prominent methods.[2] During the 1960s, many studies examine the ability of technical indicators, such as stock return filter rules, to forecast stock returns (Alexander 1961, Alexander 1964). The conclusion was that on a stock level and, especially, after taking transaction costs into account, investment strategies based on technical indicators cannot outperform a simple buy-and-hold strategy (Fama and Blume 1966, Jensen and Benington 1970).

Following this, an extensive amount of literature suggests that accounting and economic variables are able to predict stock returns. These include the dividend-to-price ratio (Rozeff 1984, Campbell and Shiller 1988b, Fama and French 1988), earnings-to-price ratio (Campbell and Shiller 1988a), book-to-market ratio (Kothari and Shanken 1997, Pontiff and Schall 1998), payout yield (Boudoukh et al. 2008), nominal interest rates (Fama and Schwert 1977, Breen et al. 1989), interest rate spread (Campbell 1987, Fama and French 1989), default spread (Keim and Stambaugh 1986, Fama and French 1989), and stock market volatility (Guo 2006).

2 See Rapach and Zhou (2013) for a complete survey of this literature.

Given the plethora of prediction variables, researchers started to combine these variables with the aim of arriving at better return forecasts. Bates and Granger (1969) and Timmermann (2006) highlight the potential benefits of combining different predictor variables. Rapach et al. (2010) apply the combination approach to forecasting stock market returns. They use the historic forecasting performance to weight each of the predictor variables. The latest studies employ a diffusion index approach to improve forecasting (Ludvigson and Ng 2007, Kelly and Pruitt 2013, Kelly and Pruitt 2015). They assume that the predictor variables can be modeled as a latent factor structure. This model can be estimated through a principal component regression and the coefficients are then used as predictors. The aim is to filter out the noise contained in each single predictor variable.

A different way to address the problem of statistical noise in variables used for forecasting is to employ a Bayesian approach. Jorion (1986) adopts this technique to forecast expected returns on a stock level. Cremers (2002) employs a Bayesian model averaging approach to forecast the stock market return.

2.2 IMPLIED COST OF CAPITAL METHODS

The term ICC was coined by Gebhardt et al. (2001). I use it to encompass all accounting-based valuation methods that use current stock prices and earnings forecasts in a valuation equation to solve for the discount rate. Strictly speaking, the ICC is the implied cost of *equity* capital but I will follow the literature and use the two terms synonymously. The idea to reverse engineer a valuation model to obtain the discount rate goes back much farther than the study by Gebhardt et al. (2001).

Malkiel (1979) uses a dividend discount model (DDM) in which the current price is equal to the current dividend times one plus the long-term growth rate divided by the ICC minus the long-term growth rate. As this method is very sensitive to the long-term growth rate, Malkiel (1979) also implements a different approach in which the long-term growth rate exponentially declines to the gross domestic product (GDP) growth rate over a course of five years. He obtains the long-term growth rate in dividend growth from Value Line's financial database.

In contrast, Harris (1986), who employs a DDM where the ICC equals the dividend yield plus the long-term growth forecast, obtains forecasts from the Instiutional Brokers' Estimate System (IBES). Gordon and Gordon (1997) also follow the DDM approach but assume a finite growth horizon. Botosan and Plumlee (2002) build on the DDM by using dividend forecasts for the following four years and the respective stock's target price from Value Line.

The approach by Pástor et al. (2008) is a more recent refinement of the DDM. The authors use explicit earnings forecasts from IBES for the first three years. They compute the growth rate in earnings and mean-revert this growth rate to the sum of long-run real GDP growth rate and the long-run average rate of inflation, the latter of which is set to the implicit GDP deflator (estimated using historic data). Earnings for years four to 15 are forecasted using this growth rate. The terminal value in year 15 equals the forecasted earnings from year 16 divided by the ICC. Thereby, they assume that after year 15, any new investments earn zero economic profits. To calculate dividends, the authors forecast the payout ratio as the most recent payout ratio for the first three years and then they interpolate the payout ratio to the steady-state payout ratio in year 15. The steady-state payout ratio is one minus the long-term growth rate over the ICC.

Forecasting dividends can be challenging, especially when a firm has a history of not paying dividends (Kothari et al. 2016). To alleviate this issue, researchers developed valuation models that rely on "clean surplus accounting" (Ohlson 1995). With clean surplus accounting, the DDM can be restated in terms of earnings and changes in book values. One of these methods is the residual income model (RIM). This model equates the current stock price with book-value per share (BPS) and the sum of discounted residual income (Kothari et al. 2016). Residual income is defined as earnings per share (EPS) minus the ICC times BPS from the previous period.

Gebhardt et al. (2001) use a RIM in which they employ explicit earnings forecasts to compute return on equity (ROE) for the subsequent three years. From year four to 12, they linearly interpolate ROE to the median industry ROE. In comparison, Claus and Thomas (2001) compute the ICC on a market level (instead of on a firm level). They use up to five years of analysts' earnings forecasts and assume that the long-term growth rate in residual income equals the expected nominal inflation rate. The authors set the nominal expected inflation rate equal to the nominal risk-free rate minus three percent (i.e. the nominal inflation rate is equal to the nominal risk-free rate minus the real risk-free rate).

The RIM uses book value of equity as a valuation hook and then adjusts this value according to future expected residual income (Easton 2007). Next, I present two versions of the abnormal earnings growth model (AEG), which anchors the firm's value on capitalized earnings and then adjusts this value according to expected abnormal growth in earnings. Easton (2004) develops a modified price-earnings-growth formula in which the growth in abnormal earnings is set to zero. Ohlson and Juettner-Nauroth (2005) transform the AEG model so that a short-term and a long-term growth rate in abnormal earnings can be set.

The methods presented so far require the researcher to make an assumption about the long-term growth rate. This is a difficult choice which can have a large impact on the ICC (Easton 2007). To circumvent this problem, Easton et al. (2002) propose to estimate the ICC and the long-term growth rate simultaneously for a portfolio of firms. To this end, the authors restate the RIM as a regression equation and then obtain values for the ICC and the long-term growth rate from the estimated regression coefficients. This procedure requires an iterative approach, as the ICC is needed for the computation of the left-hand side of the regression equation. Easton et al. (2002) set the ICC starting value to 12 percent (the historical market return in their sample) and then compare that value to the estimated value. If it differs, they use the new value to re-compute the left-hand side variable of the regression equation and re-run the regression. The procedure is repeated until there are no more significant changes in the ICC estimate.

Ashton and Wang (2013) also follow a regression approach but their underlying model is based on linear information dynamics (Ohlson 1990, Ohlson 1995, Feltham and Ohlson 1995, Feltham and Ohlson 1996). They regress expected earnings on current earnings, current book value of equity, and last period's book value of equity (all variables are deflated by share price). This cross-sectional regression is performed for each year of the sample. From the estimated regression coefficients, the authors derive the ICC and the implied long-term growth rate. Their results are in line with the findings of other studies that estimate the ICC, albeit being at the lower end of the range.

Nekrasov and Ogneva (2011) extend the study of Easton et al. (2002) so that the ICC can be estimated on a firm level instead of only on a portfolio or market level. They employ a three-step procedure. First, they run a cross-sectional weighted-least squares regression with the sum of expected four-year earnings (including compounded dividends) over book value on the left-hand side and market-to-book value, risk variables (CAPM beta, size, market-to-book value, and momentum), and growth variables (expected long-term growth rate from IBES, difference between industry ROE and company's forecasted ROE, and research and development expenses over sales) on the right-hand side (note that market-to-book value appears twice in the regression equation). This regression is run iteratively since an estimate of the ICC (which is one of the variables to be estimated through this regression) is required in the calculation of the left-hand side variable. Second, they use the estimated coefficients from the cross-sectional regression previously described to calculate the ICC and the implied growth rate on a market level. Finally, they compute the firm level ICC and growth rate using the residuals and the weights from the weighted-least squares regression above, the company's market-to-book value, the company's risk and growth characteristics, and the average ICC and growth rate estimates.

The literature has also produced a number of refinements to existing methods. The studies mentioned so far estimate the ICC on a yearly basis, sometimes only for companies with a fiscal-year ending on December 31 (e.g. Easton et al. 2002). Daske et al. (2006) demonstrate how existing methods can be modified to allow for a daily ICC estimation. More specifically, they compute a virtual book value of equity at time t (the point in time of the ICC estimation) using the firm's forecasted ROE. Then they adjust the company's forecasted earnings for the next fiscal year-end to reflect only the earnings from t to the financial year-end (instead of the earnings from the last fiscal year-end to the upcoming fiscal year-end). In this way, the authors exclusively use current available information and the estimation is independent of the current date and the fiscal year-end of the company.

Easton and Sommers (2007) find that analysts' earnings forecasts tend to be too optimistic in the U.S., which leads to an upward bias in ICC estimates. They estimate this bias by comparing ICC estimates based on analysts' earnings forecasts to ICC estimates based on subsequently realized earnings. They find that this upward bias is 2.84% in their sample (1993–2004). The authors propose to value-weight ICC estimates when aggregating them to a portfolio or market level instead of equal-weighting the estimates since the optimism bias is smaller for larger firms.

Guay et al. (2011) also investigate the quality of analysts' earnings forecasts and discover that analysts tend to incorporate stock price performance too slowly. This results in a predictable measurement error of the ICC. To correct for this error, the authors propose to sort companies into 12 portfolios based on their past 12-month stock return. Then, for every company, the historical forecast error (up to the respective date) scaled by total assets is computed. Finally, the median historical forecast error of each portfolio is calculated and subsequently used to adjust the earnings forecasts for each firm.

The studies by Larocque (2013) and Mohanram and Gode (2013) look at a range of variables that could be correlated with analysts' forecast errors. Larocque (2013) builds on the framework of Ali et al. (1992), who also investigated whether analysts' forecast errors can be predicted with information available at a respective point in time. She augments the Ali et al. (1992) model by two variables so that in her cross-sectional regression, the forecast error (scaled by the lagged share price) is regressed on the previous period's scaled forecast error, the stock return over the preceding 12 months, the natural logarithm of the market value of equity, and the abnormal stock return between the last earnings announcement date and the forecast date. Then, the average coefficients from the cross-sectional regression over the preceding three years together with each firm's current variables are used to estimate the forecast error for the next two earnings forecasts. Last, forecasted earnings are adjusted by subtracting the estimated forecast error. Larocque (2013) finds that this correction technique substantially lowers resulting ICC estimates but does not improve their correlation with realized returns.

Mohanram and Gode (2013) develop a larger model to predict forecast errors. They run a cross-sectional regression with the earnings forecast error scaled by share price as regressand and the following variables as regressors: firm's accruals divided by lagged total assets, sales growth over the last fiscal year, analysts' long-term growth forecast, property, plant & equipment growth over the last fiscal year, growth in other long-term assets over the last fiscal year, stock return over the preceding 12 months, and the difference between the current earnings forecast and the forecast at the beginning of the respective year. In contrast to Larocque (2013), the authors find that adjusting earnings forecasts for predictable errors significantly improves the association between realized returns and the resulting ICC.

A different approach to dealing with analysts' earnings forecast errors is to replace analyst data altogether. Hou et al. (2012) implement earnings forecasts derived from a pooled cross-sectional regression model using data covering the preceding 10 years. Specifically, they regress dollar earnings for year $t + \tau$ on total assets, dividends, an indicator variable that equals one if the company paid a dividend and zero otherwise, earnings, an indicator variable that equals one if the company had negative earnings and zero otherwise, and accruals. All explanatory variables are taken from year t. The authors find that their model estimates earnings with less bias and for a wider range of companies than estimates from analysts.

Conversely, Allee (2011) uses a time-series regression model, which makes use of the past five years of earnings, to forecast earnings. Gerakos and Gramacy (2013) evaluate numerous models to forecast earnings and find that, at a one-year horizon, a naive random walk model performs as well as cross-sectional models. Motivated by the fact that a random walk model is unsuitable for all ICC methods that rely on short-term earnings growth, Li and Mohanram (2014) propose the earnings persistence model (EP) and the residual income (RI) model (Feltham and Ohlson 1996) to forecast earnings. The EP model estimates a pooled cross-sectional regression with forecasted earnings on the left-hand side and an indicator variable that equals one if earnings are negative and zero otherwise, current earnings, and an interaction term between the indicator variable for negative earnings and current earnings on the right-hand side. The interaction term allows for asymmetric persistence of loss and profit (Li 2011). Their RI model runs the following regression. The dependent variable is again forecasted earnings but the independent variables are the following: an indicator variable that equals one if earnings are negative and zero otherwise, current earnings, an interaction term between the negative earnings indicator variable and current earnings, current book value, and total accruals (from Richardson et al. 2005). All figures are on a per-share level and both regressions use 10 years of data. The authors show that these models outperform the cross-sectional model from Hou et al. (2012) and the random walk model with respect to accuracy, forecast bias, and association with future realized returns.

As an alternative to using standard valuation models like the DDM or RIM, the literature has also produced methods to extract the expected stock return from bond yields and Credit Default Swap (CDS) spreads (Campello et al. 2008, Berg and Kaserer 2013, Friewald et al. 2014).

Table 1 shows a summary of the methods that use accounting valuation models.

Reference	Valuation model	Period	Earnings forecasts data	Long-term growth assumption
Malkiel (1979)	DDM	1966–1977	Value Line	Value Line / GDP growth rate
Harris (1986)	DDM	1982–1984	IBES	Long-term growth forecast from IBES
Gordon and Gordon (1997)	DDM	1985-1991	IBES	Long-term growth forecast from IBES
Botosan and Plumlee (2002)	DDM	1986–2000	Value Line	Use of target price from Value Line
Pástor et al. (2008)	DDM	1981–2002	IBES	Growth after year 15 is value irrelevant
Claus and Thomas (2001)	RIM	1985–1998	IBES	Risk-free rate minus three percent
Gebhardt et al. (2001)	RIM	1979–1995	IBES	Median industry ROE
Easton (2004)	AEG	1981–1999	IBES	No growth in abnormal earnings

Continued on next page

Reference	Valuation model	Period	Earnings forecasts data	Long-term growth assumption
Ohlson and Juettner-Nauroth (2005); implementation according to Gode and Mohanram (2003)	AEG	1984–1998	IBES	Risk-free rate minus three percent
Easton et al. (2002)	RIM	1981–1998	IBES	Estimated simultaneously with the ICC
Ashton and Wang (2013)	RIM	1975–2006	IBES	Estimated simultaneously with the ICC
Nekrasov and Ogneva (2011)	RIM	1980–2007	IBES	Estimated simultaneously with the ICC
Allee (2011)	AEG	1981–2010	Time-series model	No growth in abnormal earnings

Continued on next page

Reference	Valuation model	Period	Earnings forecasts data	Long-term growth assumption
Hou et al. (2012)	DDM, RIM, AEG	1968–2008	Cross-sectional model	According to the respective valuation model
Li and Mohanram (2014)	RIM, AEG	1969–2012	EP and RI model	According to the respective valuation model

Table 1: **Overview of ICC methods.**
This table provides a summary of ICC methods that use accounting valuation models.

2.3 STUDIES USING THE IMPLIED COST OF CAPITAL

Cost of capital estimates based on historical data contain a large amount of statistical noise (Fama and French 1997, Elton 1999), which makes it difficult to uncover relationships in a regression setting. In contrast, ICC estimates are about an order of magnitude less volatile (Lee et al. 2009). Thus, many researchers have used the ICC to study influences on the cost of capital. The following provides an overview of many influential studies in this field.

One stream of literature investigates the impact of corporate governance and disclosure policies on the cost of capital. Botosan (1997) finds that an increase in voluntary disclosure levels lowers the cost of capital for manufacturing firms with little analyst following in the U.S. In a follow-up study, Botosan and Plumlee (2002) examine annual report disclosure levels and report a decrease in the cost of capital for higher disclosure levels. Francis et al. (2005) extends the previous work by looking at disclosure levels and cost of capital around the world. They find that a greater disclosure level leads to a lower cost of capital. Ashbaugh-Skaife et al. (2009) link a firm's internal control deficiencies to higher costs of capital. On a country-level, Hail and Leuz (2006) look at disclosure requirements as well as securities regulation and enforcement thereof and find that firms in countries with stricter requirements and regulation benefit from a lower cost of capital. Furthermore, the same authors show that international firms that cross-list on the U.S. stock market experience a decrease in their cost of capital (Hail and Leuz 2009).

The ICC has also been employed in various other accounting and corporate finance settings. Dhaliwal et al. (2005) find that the ICC increases in the dividend tax. Francis et al. (2004) investigate several attributes of earnings, such as accrual quality, persistence, and smoothness, and link them to the cost of capital. They find that, overall, more favorable values in these attributes correspond to a lower cost of capital. Hribar and Jenkins (2004) link accounting restatements to higher costs of capital. More recent studies show how corporate diversification can lower the cost of capital (Hann et al. 2013) and how having more illiquid real assets increases the cost of capital (Ortiz-Molina and Phillips 2014). Frank and Shen (2016) revisit the relationship between the cost of capital and investment using the ICC instead of the CAPM as a proxy for the cost of capital and find that firms with high cost of capital invest less.

Another stream of literature focuses on the trade-off between expected returns and risk. Pástor et al. (2008) show that the ICC is positively related to risk under reasonable assumptions. Chava and Purnanandam (2010) find that, when using the ICC instead of an expected return proxy based on historical data, default risk is positively related to the expected return. The study by Botosan et al. (2011) investigates the relation between different ICC estimates and various risk proxies, namely unlevered beta, leverage (measured as long-term debt over market value of equity), natural logarithm of the market value of equity, natural logarithm of the book-to-price ratio, and expected earnings growth. They document that only some ICC measures show the expected association with all of these risk proxies.

Contrary to the large body of literature in accounting and corporate finance, the ICC approach has been less frequently used in asset pricing. Notable exceptions are Lee et al. (2009), Li et al. (2013), Li et al. (2014), Tang et al. (2014), and Cooper and Sarkar (2016). Lee et al. (2009) find that the ICC is positively related to world market beta, idiosyncratic risk, financial leverage, and book-to-market ratios, and negatively related to currency beta and firm size. They use a sample of G-7 countries.

Li et al. (2013) show that in the U.S., the market ICC is a strong predictor of future excess market returns. They run a predictive regression model with the excess market return as dependent variable and different forecasting variables (including the ICC) as the independent variables. For the out-of-sample tests, the researchers divide the sample into an estimation period and a forecasting period. First, they run the predictive regression using only the estimation period. They save the resulting coefficients and use them together with the current value of the respective predictor variable to calculate a forecast for the first month of the forecasting period. Then they roll the estimation period one month forward and forecast the market return for the second month of the forecasting period. This is repeated until the last month of the forecasting period. The evaluation of the different predictive variables is performed with the out-of-sample R^2 statistic. The authors find that the ICC outperforms the other tested variables which include dividend yield, earnings yield, book-to-market value, term spread, default spread, Treasury bill rate, and 30-year treasury yield. Cooper and Sarkar (2016) test the ICC's predictive power in eleven developed countries (Australia, Belgium, Canada, Denmark, France, Germany, Japan, the Netherlands, Switzerland, U.K., and U.S.) and find that it outperforms the dividend yield.

Li et al. (2014) compute the ICC for a portfolio of value and growth stocks and term the spread between the ICC estimate of those two portfolios the implied value premium. They continue to show that in the U.S., the implied value premium is a strong predictor for the realized value premium for forecast periods between one and 36 months.

The study by Tang et al. (2014) tests whether asset pricing anomalies are also present when using the ICC instead of mean historic returns. The researchers aggregate the stock level ICC estimate to a portfolio level for long-short dollar-neutral investments. For many anomalies, the results are different when compared to the ones based on realized returns. Accruals and investment anomalies (for example, Sloan 1996 and Titman et al. 2004) turn insignificant ex-ante suggesting that these anomalies are driven by unexpected returns. For the momentum factor (Jegadeesh and Titman 1993), the long-short portfolio's expected return is even significantly negative (instead of significantly positive). The authors confirm the findings from realized returns for the size (Banz 1981) and value factor (Fama and French 1992).

The more practitioner-oriented work by Esterer and Schröder (2014) studies investment strategies using the ICC. Specifically, the authors sort companies into quintiles according to their ICC estimate and analyze the subsequent portfolio returns. Before transaction costs, the highest ICC quintile portfolio outperforms the lowest quintile portfolio based on double portfolio sorts (size, book-to-market, and momentum). This finding is confirmed in time-series regressions with factor mimicking portfolios built on market, size, value, and momentum factors. However, the outperformance turns insignificant when taking transaction costs into account.

3

DATA AND ICC METHODOLOGY

3.1 DATA

In this section, I provide an overview of the databases that are used to calculate the ICC. For the U.S., I obtain all data from Wharton Research Data Services (WRDS).[3] In the first step, I prepare the different files from IBES. I join the summary statistics file, which contains the aggregated analysts' forecasts per company and month, with the summary actual file, which contains the actual or reported values for the forecasted variables as well as some other useful information, such as the shares outstanding. In the next step, I merge the IBES data with the Center for Research in Security Prices (CRSP) stocknames file on the historical Committee on Uniform Securities Identification Procedures (CUSIP). I exclude American depository receipts, real-estate investment trusts, and closed-end funds (Pástor et al. 2008), i.e. I only keep observations with a CRSP share code that starts with one.

I then join the CRSP/Compustat linking table with the IBES table, which allows me to add balance sheet data from Compustat in a next step. As recommended by WRDS, I filter for primary link types between CRSP and Compustat databases. I require non-missing values in date (statpers), share price from IBES (price), shares outstanding from IBES (shout), EPS_1, and

3 I had access to this database while I was visiting INSEAD.

Country	Lists
Canada	WSCN1 to WSCN6
France	WSFR1, WSFR2
Germany	WSBD1, WSBD2
Japan	WSJP1 to WSJP6
United Kingdom	WSUK1 to WSUK6

Table 2: **Worldscope lists**
Worldscope lists for each country. Note that for the U.S., accounting data is obtained from Compustat.

EPS_2. I follow many other studies and use median consensus forecasts (e.g. Claus and Thomas 2001). I check the final dataset for duplicates and decimal errors in prices and shares outstanding (i.e. an increase or decrease by a factor (or multiple) of 10 that is reversed the next month). Moreover, I compare company names across the different data sources with a string distance function to check for potential erroneous matches.

For non U.S. data, I download all the information from Thomson Reuters (TR). TR combines different databases in its Datastream for Office product, among them, IBES and Worldscope. TR also separates its database into static and time series data. Static data includes items such as the company identifier, company name, and Standard Industrial Classification (SIC) code. For this data, no historic values are available, which is intuitive for the identifier but not for the SIC code. As a consequence, only the latest value is stored. The first step is to obtain all the relevant company identifiers, which are stored in lists. I use the Worldscope country lists, which also include dead companies so that no survivorship bias is introduced into the sample. Table 2 provides an overview of the Worldscope lists employed in this dissertation.

Using these lists, I download static information to apply the screens suggested by Ince and Porter (2006) and Schmidt et al. (2014). Specifically, I filter for major listings (MAJOR = "Y") of type equity (TYPE = "EQ") listed on the domestic stock market (for example, GEOLC = GEOGC = "UK" if the country was set to U.K.). Furthermore, I search for suspicious words in the extended company name which indicate that the share is not common stock, e.g. PREF, CONV, WARRANT, etc (Campbell et al. 2010).

After deriving a clean set of company identifiers, I download time-series data from IBES. IBES provides stock prices, shares outstanding, realized earnings, and earnings forecasts on a monthly basis. I remove observations with missing values in date (DATE), stock price (IBP), shares outstanding (IBNOSH), EPS_1 (EPS1MD), EPS_2 (EPS2MD), and fiscal year-end (FYE) (EPS0YR).[4] I also drop rows where the shares outstanding are zero. Finally, I join the accounting data from Worldscope with the time-series data from IBES using the company identifier and the FYE. I include the following variables: total assets (WC02999), book value of common equity (WC03501), reported earnings (WC01751), and dividends (WC05376). Similar to what was done to the WRDS data, I check the final sample for duplicates and decimal errors in prices and shares outstanding.

For some ICC methods, additional data is required. First, I need the yield on the risk-free instrument. I use TR to download the yield on ten-year government bonds for each country. Specifically, I use the following series: CNBCH10 (Canada), FRBRYLD (France), BDBRYLD (Germany), JPBRYLD (Japan), UKGN10Y (U.K.), and FRTCM10 (U.S.). Next, I download data from TR on GDP growth rates and GDP deflator. For

4 A note on how IBES handles corporate actions: IBES adjusts historic stock prices, shares outstanding, and earnings forecasts for corporate actions. This means that market value calculations based on stock price and shares outstanding are valid. Also, the share price is directly comparable to earnings per share.

GDP growth rates I use the following time-series: CNWD3QBGR (Canada), FRWD3QBGR (France), BDWD3QBGR (Germany), JPWD3QBGR (Japan), UKWD3QBGR (U.K.), and USNNKZ35 (U.S.). For GDP deflator I use: CNWDBJ0PR (Canada), FRWDBJ0PR (France), BDWDBJ0PR (Germany), JPWDBJ0PR (Japan), UKWDBJ0PR (U.K.), and USN90ZTS (U.S.).

3.2 ICC METHODOLOGY

In this section, I present details on the implementation of the different ICC calculation methods. I use five methods that are common in the literature: two methods based on the RIM (Claus and Thomas 2001, Gebhardt et al. 2001), two methods based on the AEG (Easton 2004, Ohlson and Juettner-Nauroth 2005), and one method based on the DDM (Pástor et al. 2008).

For all methods, a polynomial equation has to be solved. I use the base R (R Core Team 2014) function `uniroot`, which employs a numerical solver. It is necessary to set the lower bound to zero as any negative solutions are economically meaningless. Furthermore, in case a terminal value term is present, the long-term growth rate is specified as the lower bound. This ensures that the terminal value term is non-negative.

3.2.1 *Data preparation*

The data needs to be carefully processed before the ICC can be computed. First, I check the availability of the long-term earnings growth forecast ($\mathsf{EPS}_{\mathsf{LTG}}$). If it is missing, I compute it as the implied growth rate from EPS_2 to EPS_3. If EPS_3 is missing, I use the implied growth rate from EPS_1 to

EPS_2. I winsorize EPS_{LTG} at two and 50% (Nekrasov and Ogneva 2011). For some ICC methods, earnings forecasts for years three to five are required. Therefore, I calculate missing earnings forecasts with the last available earnings forecast and EPS_{LTG}. For example, if EPS_4 is missing, I compute it as $EPS_4 = EPS_3 * (1 + EPS_{LTG})$.

The next step concerns book value of common equity. First, I compute reported book value per share using book value from Compustat (U.S.) or Worldscope (non U.S. countries) and divide it by shares outstanding from IBES in order to ensure that it can be compared with other per share data from IBES.[5] Second, I assume that it takes four months before the annual report becomes publicly available (Claus and Thomas 2001). Earnings, on the other hand, are announced earlier and IBES moves the earnings forecasts forward as soon as the realized earnings are announced. For example, a company with FYE on December 31 year $t = 0$ announces its earnings in February year $t = 1$. The annual report is released in April year $t = 1$. In February, IBES would move the earnings forecasts one year forward, i.e. EPS_1 would refer to FYE year $t = 1$ and not FYE year $t = 0$. In such cases, I follow Gebhardt et al. (2001) and calculate a synthetic book value assuming clean-surplus accounting ($BPS_t = BPS_{t-1} + EPS_t(1 - pr)$). Book values and the payout ratio (pr) are taken from the last available annual report from Compustat (U.S.) or Worldscope (non U.S. countries) with the following adjustments (according to Gebhardt et al. 2001): if earnings are positive, the payout ratio is calculated as dividends divided by earnings. If earnings are negative, I divide dividends by $0.06 \times$ total assets to estimate the payout ratio. Payout ratios below zero and above one are set to zero and one, respectively. I use reported earnings from IBES as EPS_t.

5 As aforementioned, IBES adjusts its figures for corporate actions.

Along the same argument, it is possible that neither the annual report nor earnings have been released yet but EPS_1 refers to a period in the past. In the example above, this would be the case in January year $t = 1$. To ensure that the earnings' forecasts always pertain to periods in the future (otherwise it would not be possible to discount them in the ICC models), I compute the synthetic book value with the EPS_1 "forecast" using clean-surplus accounting. I then realign the earnings forecasts, i.e. EPS_2 becomes EPS_1, EPS_3 becomes EPS_2, etc. I recompute EPS_5 with the help of EPS_{LTG}.

The residual income models need future book values as an input. If the annual report has been released yet, I forecast future book values using current book value and making use of clean-surplus accounting: $BPS_t = BPS_{t-1} + EPS_t(1 - pr)$. The payout ratio (pr) is taken from the last annual report from Compustat (U.S.) or Worldscope (non U.S. countries) with the adjustment described above. In the case that the annual report has not been released yet, I use the synthetic book value (see above) and the payout ratio from the last available annual report (again adjusted as described above).

3.2.2 *CT method*

The ICC method based on Claus and Thomas (2001) (CT) makes use of a RIM and solves the following equation for the ICC:

$$P_0 = BPS_0 + \sum_{t=1}^{5} \frac{EPS_t - ICC_{CT} \times BPS_{t-1}}{(1 + ICC_{CT})^t} + \frac{(EPS_5 - ICC_{CT} \times BPS_4) \times (1 + g)}{(ICC_{CT} - g) \times (1 + ICC_{CT})^5} \tag{1}$$

where ICC_{CT} is the implied cost of capital according to the CT method, P_0 is the share price at $t = 0$, BPS_0 is the book value per share at $t = 0$, EPS_t

is the forecasted earnings per share for year t, and g is the terminal value growth rate in abnormal earnings, which is set to the maximum of zero and the risk-free yield minus three percent.[6]

3.2.3 *GLS method*

The ICC method based on Gebhardt et al. (2001) (GLS) also uses a RIM. The authors propose the following equation:

$$P_0 = BPS_0 + \sum_{t=1}^{11} \frac{(ROE_t - ICC_{GLS}) \times BPS_{t-1}}{(1 + ICC_{GLS})^t} + \frac{(ROE_{12} - ICC_{GLS}) \times BPS_{11}}{ICC_{GLS} \times (1 + ICC_{GLS})^{11}} \tag{2}$$

where $ROE_t = EPS_{t+1}/BPS_t$ and ICC_{GLS} is the ICC according to GLS. For the first three periods, ROE is calculated using EPS from analysts' forecasts. After period three, ROE is linearly interpolated to the industry median ROE. The industry ROE is a moving median of all profitable companies in that industry over at least the previous five years (and up to the previous ten years). Industries are classified according to Fama and French (1997). Book values for future periods are calculated using clean-surplus accounting. The growth rate beyond period 12 is set to zero.

6 The authors use the risk-free yield minus three percent as the expected inflation rate. The underlying assumption is that the real risk-free rate is approximately three percent.

3.2.4 *MPEG method*

The modified price-earnings-growth (MPEG) method based on Easton (2004) uses the following abnormal earnings growth model:

$$P_0 = \frac{EPS_2 + ICC_{MPEG} \times DPS_1 - EPS_1}{ICC^2_{MPEG}} \tag{3}$$

where ICC_{MPEG} is the ICC according to the MPEG method, EPS_t is forecasted earnings per share for year t, and DPS_t is forecasted dividends per share computed as $EPS_t \times pr$ with pr standing for the last available payout ratio.

3.2.5 *OJ method*

The ICC method based on Ohlson and Juettner-Nauroth (2005) (OJ) also employs an abnormal earnings growth model. I follow the implementation of Gode and Mohanram (2003). The equation is:

$$P_0 = \frac{EPS_1}{ICC_{OJ}} + \frac{g_s \times EPS_1 - ICC_{OJ} \times (EPS_1 - DPS_1)}{ICC_{OJ} \times (ICC_{OJ} - g)} \tag{4}$$

where EPS_t is forecasted earnings per share for year t, DPS_t is forecasted dividends per share computed as $EPS_t \times pr$ with pr standing for the last available payout ratio, ICC_{OJ} is the ICC following the OJ method, and g_s and g_l are the short-term and long-term growth rates, respectively. g_s is set to the average of the growth rate between EPS_1 and EPS_2 and the long-term earnings growth rate (EPS_{LTG}), i.e. $g_s = \left(\frac{EPS_2 - EPS_1}{EPS_1} + EPS_{LTG}\right)\frac{1}{2}$. g_l is equal to the maximum of zero and the risk-free rate minus three percent.

3.2.6 *PSS method*

The ICC method based on Pástor et al. (2008) (PSS) uses a dividend discount model with the following equation:

$$P_0 = \sum_{t=1}^{15} \frac{EPS_t \times pr_{PSS,t}}{(1 + ICC_{PSS})^t} + \frac{EPS_{16}}{ICC_{PSS}(1 + ICC_{PSS})^{15}} \tag{5}$$

where EPS_t is forecasted earnings per share for year t, ICC_{PSS} is the ICC according to the PSS method, and $pr_{PSS,t}$ is the payout ratio according to the PSS methodology. This payout ratio is computed as dividends plus stock repurchases minus new stock issues over net income from the latest annual report. If any of the items in the numerator are missing, the earnings forecast as of December of year $t-1$ for FYE t from IBES is used. If this forecast is also missing, pr_{PSS} is computed as the median pr_{PSS} over all firms in the respective industry-size portfolio. To form the industry-size portfolio in each year, the firms are first sorted into 48 industries based on Fama and French (1997). They then are assigned to three groups based on their market value. The groups each contain an equal amount of firms within each industry. Median payout-ratios of the industry-size portfolios below -0.5 are set to -0.5. Payout ratios on the firm-level below -0.5 and above one are set to the median payout-ratio of the industry-size portfolio.

The payout ratio for the first three years of the forecasting period is obtained according to the procedure above. After year three, the payout ratio reverts linearly to a steady-state value, which is reached at $T = 15$. The steady-state payout ratio is computed as $1 - g/ICC_{PSS}$, i.e. the assumption is that in the steady-state, the return on investment equals the cost of equity.

3.2.7 *Descriptive statistics*

Now I show some summary statistics of the ICC estimates for each country. First, Figure 1 presents the monthly time-series of different ICC methods for the U.S. It is noticeable that all methods follow a similar trend. Indeed, as I will show later in this section, the methods are highly correlated with one another. Moreover, from the beginning of the sample period in 1984 to around the height of the dotcom bubble in 2000, there is a clear downward trend. After the stock market crash in 2000/2001, the ICC increased again until around 2009, only to subsequently trend downwards again.

Figure 2 displays the same time-series plot of ICC estimates for the other countries in the sample. Note that the sample starts in 1990 (instead of 1985 as for the U.S.). Canada (CA) and the U.K. (GB) show a similar pattern as the U.S. Germany (DE) and France (FR) are somewhat close to the U.S., although the downtrend at the beginning of the sample period is not as strong. Japan (JP) shows a clear upward trend over the time frame. This is intuitive when considering the sample period. The Japanese stock market crashed in 1990, but even after the crash, prices were still high compared to earnings. It took a long time before expected earnings rose sufficiently in relation to prices to push the ICC to higher levels.

Next, I present the sample mean and standard deviation of the different ICC methods for each country (Table 3). The estimates for the U.S. are in line with the results from other studies (for example, Claus and Thomas 2001 and Easton 2004). The RIM estimates (CT and GLS) are noticeably smaller, on average, than the estimates based on the AEG and DDM. Also, Japan has the lowest estimates on average. In Panel B, the standard deviation of the ICC estimates can be seen. These figures are quite low, especially when compared to the standard deviation of realized returns. This finding was also reported in other studies (for example, Lee et al. 2009).

Finally, Table 4 provides an overview of how the different ICC methods are correlated with one another. For all countries, the correlations are quite high (not below 0.65). In the U.S., the lowest value is 0.83. Among the methods, MPEG and OJ have a consistently high correlation that is always greater than 0.89.

Panel A: mean ICC estimates					
Country	CT	GLS	MPEG	OJ	PSS
CA	10.6	8.7	12.5	12.6	11.9
DE	9.1	7.6	11.3	11.1	10.2
FR	9.6	8.1	11.5	11.4	10.9
GB	10.6	8.2	11.4	11.8	10.9
JP	6.4	6.9	8.7	8.6	7.9
US	9.8	9.2	11.4	11.5	11.1
Panel B: standard deviation of ICC estimates					
Country	CT	GLS	MPEG	OJ	PSS
CA	1.7	1.2	1.7	1.9	2.8
DE	1.4	1.7	2.3	1.6	2.2
FR	1.6	1.5	1.6	1.3	1.7
GB	1.8	1.5	1.2	1.5	1.5
JP	2.0	1.8	2.7	2.3	2.2
US	1.9	1.4	1.6	1.7	1.7

Table 3: **Summary statistics of ICC estimates.**
This table presents the mean (Panel A) and standard deviation (Panel B) of monthly ICC estimates calculated using the methods described in Section 3.2 for six large, industrialized countries (Canada (CA), Germany (DE), France (FR), U.K. (GB), Japan (JP), U.S. (US)). The firm-level estimates are aggregated using their market value. All estimates are in local currency. The time period starts on December 31, 1989 and ends on December 31, 2014.

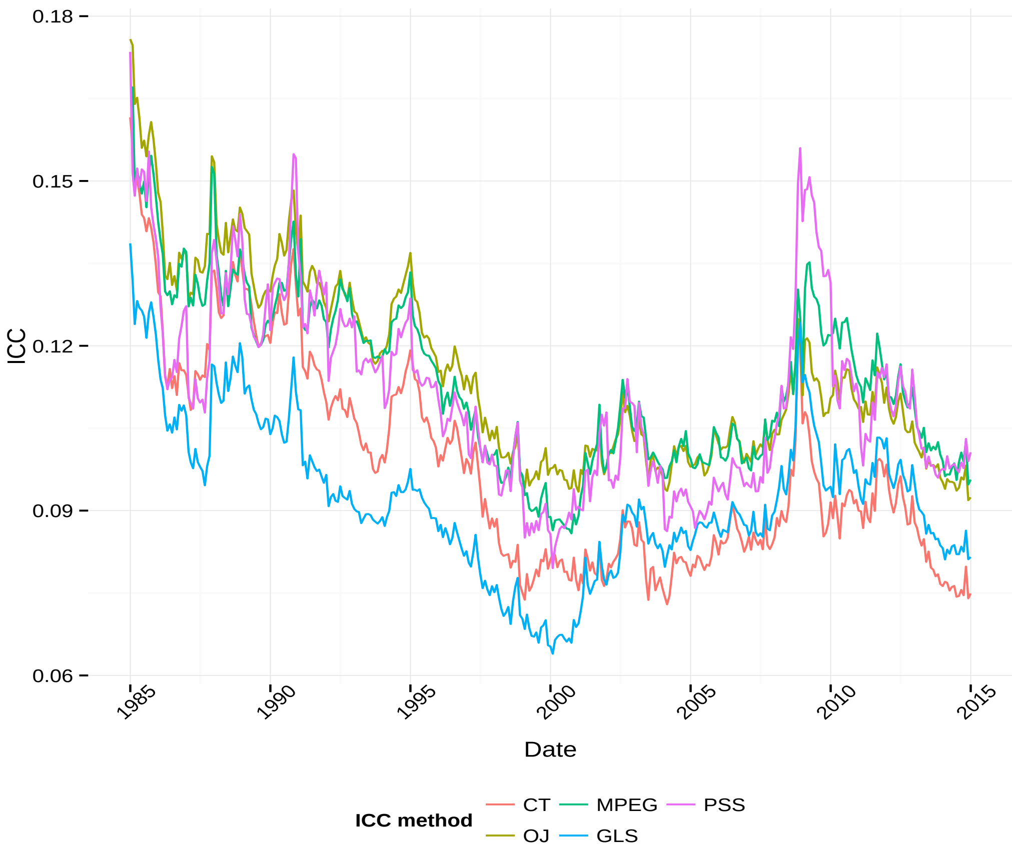

Figure 1: **ICC estimates from different methods over time (U.S.).**
This figure displays the monthly time-series of the different ICC methods presented in Section 3.2 for the U.S. The firm-level estimates are aggregated using their market value. The time period starts on December 31, 1984 and ends on December 31, 2014.

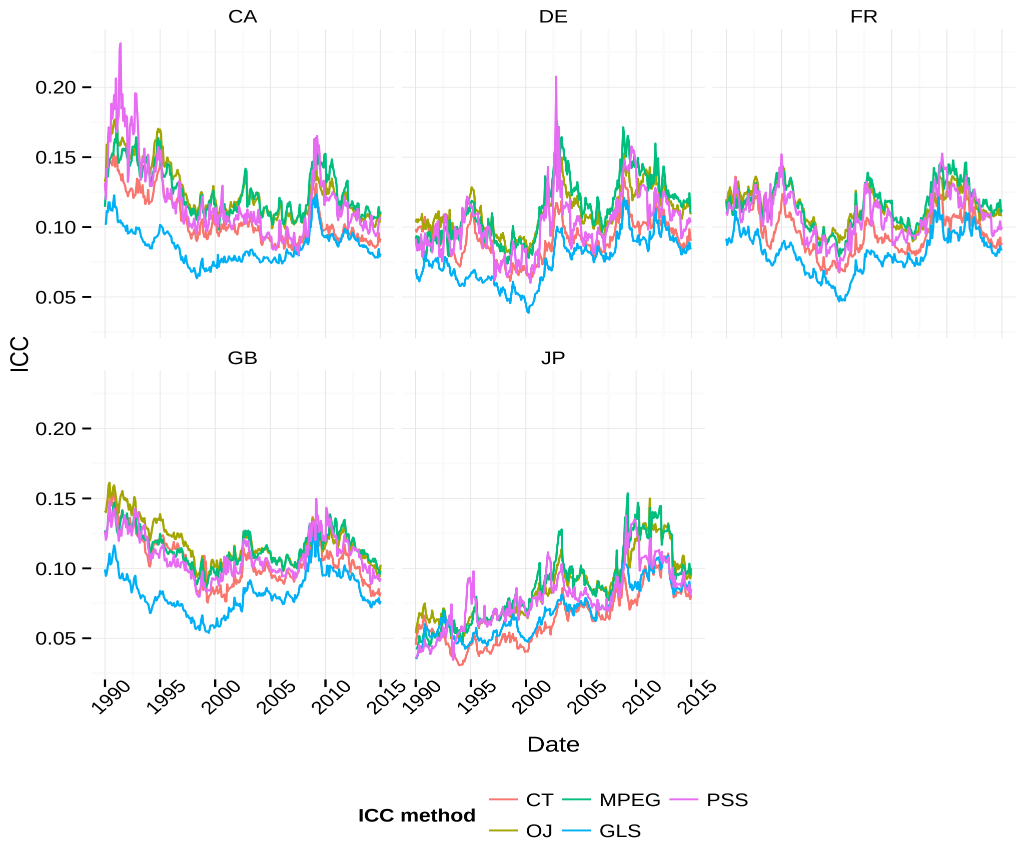

Figure 2: **ICC estimates from different methods over time (international sample).** This figure displays the monthly time-series of the different ICC methods presented in Section 3.2 for five large, industrialized countries (Canada (CA), Germany (DE), France (FR), U.K. (GB), Japan (JP)). The firm-level estimates are aggregated using their market value. All estimates are in local currency. The time period starts on December 31, 1989 and ends on December 31, 2014.

CA	CT	GLS	MPEG	OJ	PSS
CT	1.00	0.72	0.84	0.96	0.87
GLS	0.72	1.00	0.76	0.70	0.73
MPEG	0.84	0.76	1.00	0.92	0.85
OJ	0.96	0.70	0.92	1.00	0.88
PSS	0.87	0.73	0.85	0.88	1.00

DE	CT	GLS	MPEG	OJ	PSS
CT	1.00	0.86	0.74	0.86	0.78
GLS	0.86	1.00	0.84	0.82	0.76
MPEG	0.74	0.84	1.00	0.93	0.86
OJ	0.86	0.82	0.93	1.00	0.85
PSS	0.78	0.76	0.86	0.85	1.00

FR	CT	GLS	MPEG	OJ	PSS
CT	1.00	0.90	0.80	0.86	0.83
GLS	0.90	1.00	0.79	0.72	0.80
MPEG	0.80	0.79	1.00	0.92	0.90
OJ	0.86	0.72	0.92	1.00	0.88
PSS	0.83	0.80	0.90	0.88	1.00

GB	CT	GLS	MPEG	OJ	PSS
CT	1.00	0.68	0.83	0.94	0.83
GLS	0.68	1.00	0.82	0.61	0.82
MPEG	0.83	0.82	1.00	0.89	0.92
OJ	0.94	0.61	0.89	1.00	0.85
PSS	0.83	0.82	0.92	0.85	1.00

JP	CT	GLS	MPEG	OJ	PSS
CT	1.00	0.94	0.84	0.95	0.71
GLS	0.94	1.00	0.90	0.94	0.80
MPEG	0.84	0.90	1.00	0.96	0.90
OJ	0.95	0.94	0.96	1.00	0.84
PSS	0.71	0.80	0.90	0.84	1.00

US	CT	GLS	MPEG	OJ	PSS
CT	1.00	0.85	0.92	0.98	0.86
GLS	0.85	1.00	0.90	0.83	0.88
MPEG	0.92	0.90	1.00	0.95	0.92
OJ	0.98	0.83	0.95	1.00	0.85
PSS	0.86	0.88	0.92	0.85	1.00

Table 4: **Correlation matrix of ICC estimates.**
This table shows correlation matrices of different ICC methods for six large, industrialized countries (Canada (CA), Germany (DE), France (FR), U.K. (GB), Japan (JP), U.S. (US)). The country is given in the top left corner on each table. Correlations are based on monthly ICC estimates calculated using the methods described in Section 3.2. The firm-level estimates are aggregated using their market value. All estimates are in local currency. The time period starts on December 31, 1989 and ends on December 31, 2014.

4

INTERNATIONAL ASSET ALLOCATION USING THE MARKET IMPLIED COST OF CAPITAL

The BL approach to portfolio optimization requires investors' views on expected asset returns as an input. I demonstrate that the market ICC is ideal to quantify those views. I benchmark this approach against a BL optimization using time-series models as investors' views, the eqully-weighted portfolio, as well as allocation methods based on stock market capitalization and GDP. I find that the ICC portfolio offers an increase in average return of 2.1% (yearly) as compared to the value-weighted portfolio, while having a similar standard deviation. The resulting difference in Sharpe Ratios is statistically significant and robust toward the inclusion of transaction costs, varying BL parameters, and a less strictly defined investment universe.[7]

4.1 INTRODUCTION

Benefits of international diversification are well known in the literature (Solnik 1974, Odier and Solnik 1993, Ang and Bekaert 2002, Asness et al. 2011, Basu et al. 2010). However, the optimal diversification strategy has so far received less attention. Some authors use a market capitalization weighting (Odier and Solnik 1993, Asness et al. 2011) while others prefer an optimiza-

7 This chapter is based on Bielstein (2016).

tion framework in which the expected investor utility is maximized (Ang and Bekaert 2002, Das and Uppal 2004). I show that in an international asset allocation setting, the BL approach to portfolio optimization works well in combination with forward-looking return estimates. Specifically, I make use of the predictive power of a relatively new method in finance: the ICC (for example, Claus and Thomas 2001, Gebhardt et al. 2001).

The BL method is an established procedure in the applied portfolio choice literature (Satchell and Scowcroft 2000, Beach and Orlov 2007, Jones et al. 2007, Martellini and Ziemann 2007, Bessler et al. 2014). It has also been used in combination with ICC estimates on a stock level (Becker and Gürtler 2010). The BL approach intends to overcome problems associated with Markowitz (1952) mean-variance optimization by basing the allocation on an equilibrium model. If all investors had identical estimates of expected returns and covariances then the observed market weights of assets are efficient. Now, assuming that these weights are the result of a portfolio optimization process, the expected returns can be derived from the optimization equation. Next, the BL method requires investors' views on the assets' expected returns. The ICC estimates are ideal to quantify these views. They use forward-looking data and are based on information that is available to asset managers at the respective point in time (Claus and Thomas 2001). The expected returns, which are backed out from the optimization equation, are combined with the ICC estimates to form one expected return vector. The last step is to run the optimization in the "usual" way to obtain new optimal portfolio weights. The result is a diversified and balanced allocation that performs well out of sample.

The ICC is the discount rate that equates the present value of a firm's expected cash flows with its share price. Usually, (short-term) cash flow forecasts are obtained from IBES. Depending on the calculation method, an assumption regarding long-term growth is made. Most studies calculate the ICC on a firm level (Gebhardt et al. 2001, Easton 2004, Ohlson and Juettner-Nauroth 2005, Pástor et al. 2008). While it is possible to aggregate firm-level ICC estimates to a market level, I prefer to use the method by Claus and Thomas (2001) which directly calculates a market ICC. The reason for this preference is that firm-level methods typically exclude firms with negative book values or with negative earnings forecasts. Thus, the sample would have a slight bias toward healthier firms instead of reflecting a true market investment. The Claus and Thomas (2001) procedure first aggregates the inputs and then estimates the market ICC. Therefore, all firms with sufficient data are included. Cooper and Sarkar (2016) corroborate this choice as they find that first aggregating the inputs and then calculating the ICC more robustly predicts realized market returns than aggregated company-level ICC estimates. The ICC has been employed in many corporate finance settings (for example, Hail and Leuz 2006, Hann et al. 2013, Frank and Shen 2016) but is less commonly used in asset pricing (some exceptions are Lee et al. 2009, Li et al. 2013, Tang et al. 2014).

This study is motivated by Li et al. (2013) who find that in the U.S., the ICC predicts future realized returns on a market level. Cooper and Sarkar (2016) extends the analysis of Li et al. (2013) to an international sample. They find that the ICC also performs well for other developed countries. Here, I calculate the market ICC each year for six large, industrialized countries (Canada, France, Germany, Japan, U.K., and U.S.) and use this estimate as an input to a Black and Litterman (1992) optimization. The choice of countries is determined by data availability for the ICC calculation. For these six countries, there are sufficient earnings forecasts in IBES available to represent the stock market of each country.[8]

The ICC offers many advantages in this setting. First, it only makes use of information available to investors at each point in time (Claus and Thomas 2001) as it is likely that asset managers have access to analysts' forecasts. Second, the ICC is positively related to risk under plausible assumptions (Pástor et al. 2008). Third, ICC estimates are fairly stable over time and don't exhibit the large volatility that is common in estimates that are based on historic stock market data (Lee et al. 2009). Fourth, the ICC is highly correlated with the value factor (Li et al. 2014). One problem with capitalization weighted portfolios is their tilt against the value factor, which means that any positive return to value results in a lower return to the capitalization weighted portfolio (Arnott et al. 2005, Asness et al. 2011).

Researchers have thoroughly investigated potential problems with the ICC. I acknowledge that the data requirements for the ICC will bias the sample toward larger firms (Hou et al. 2012). However, as asset managers usually have an investment universe based on a market index, such as the S&P 500 in the U.S., this restriction will be stricter than the data availability for the ICC. Also, I have set the sample period so that a sufficient amount of companies are included to represent the entire stock market (Claus and Thomas 2001). Easton and Sommers (2007) point out that analysts' cash flow forecasts from IBES in the U.S. are too optimistic, which will result in upwardly biased ICCs. It is not clear whether this bias also holds for the other countries in my sample. Nevertheless, if analysts' forecasts are also too optimistic in other countries then this bias will not significantly change the country allocation, as all countries are equally affected. If an-

8 Claus and Thomas (2001) include the same six countries in their analysis.

alysts' forecasts in other countries show different biases then this would work against my results and the improvement in performance that I find can be regarded as a lower bound. Last, Guay et al. (2011) report that analysts' forecasts do not fully take recent stock price movements into account, thereby weakening the association with realized stock returns. The authors propose to adjust analysts' forecasts based on the firm's recent stock price performance and I follow this procedure. The study from Guay et al. (2011) only looks at U.S. data. I extend these findings to the other countries in my sample and make adjustments to the analysts' forecasts accordingly. As this results in increased portfolio performance, I believe that analysts from other countries are also slow to incorporate recent stock price performance into their forecasts.

This analysis extends the literature in two directions. First, it offers a novel application of the BL method by quantifying investor's views using forward-looking data. Second, it contributes a new use of the ICC procedure in an asset pricing setting.

4.2 EMPIRICAL SET-UP

4.2.1 *Data*

For the U.S., I use the intersection of IBES, CRSP, and Compustat databases. I only include stocks with a CRSP share code starting with 1 (Pástor et al. 2008), i.e. American Depository Receipts, closed-end funds, and Real Estate Investment Trusts are excluded. For Canada, France, Germany, Japan, and the U.K., I use the intersection of IBES, Datastream, and Worldscope databases, accessed through TR. In order to improve the quality of TR data, I follow the screens proposed by Ince and Porter (2006) and Schmidt et al. (2014). Specifically, I delete firms that are not indicated as major listings and those that are not located on the domestic stock market or for which the security type is not marked as equity. Furthermore, I filter stock names for parts that indicate that the issue is not an ordinary share, e.g. "warrant" (Campbell et al. 2010). I require non-missing values in currency, share price, common shares outstanding, earnings[9], and earnings forecasts for the next two fiscal years from IBES. From Compustat and Worldscope, I need non-missing values in total assets, common equity, earnings, and dividends. Moreover, the 12-month lagged return computed from CRSP (U.S.) or Datastream (non U.S. countries) has to be available too as I use it for the adjustment of earnings forecasts, according to Guay et al. (2011). I employ the following screens on returns from Datastream: I set returns above 990% to missing. I also delete returns above 300% that are reversed the next month. Finally, I delete penny stocks, which are defined as stocks for which the unadjusted price in the previous month is less than the five percent quantile of the domestic price distribution over the whole sample period. The sample period is determined by data availability for international earnings forecasts. In order to ensure that the sample is representative of the whole stock market, I start the analysis in 1990 (Lee et al. 2009). The last portfolio is formed in 2014 so that the evaluation period extends to 2015.

9 I need IBES reported earnings to compute the forecast error, which is an input in the earnings forecast adjustment (Guay et al. 2011). For that purpose, I cannot use earnings from Compustat or Worldscope as the calculation method differs in several aspects (Livnat and Mendenhall 2006).

4.2.2 *Calculating market ICC*

I calculate the market ICC for each country according to the Claus and Thomas (2001) method. They solve the following equation for the ICC:

$$MV_0 = BV_0 + \sum_{t=1}^{5} \frac{E_t - ICC \times BV_{t-1}}{(1+ICC)^t} + \frac{(E_5 - ICC \times BV_4) \times (1+g)}{(ICC - g) \times (1+ICC)^5} \quad (6)$$

where MV_0 is the aggregated market value, BV_0 is the aggregated book value, E_t are the aggregated earnings forecasts for years $t = 1, ..., 5$, and g is the long-term growth rate in abnormal earnings. Values are aggregated over all companies for each country at each estimation date. Book values in future periods are calculated using clean-surplus accounting ($BV_{t+1} = BV_t + E_t \times (1 - \text{average payout ratio})$). I use the average payout ratio over the preceding three years. When calculating the payout ratio in any given year, I follow Gebhardt et al. (2001). Specifically, if earnings are positive, the payout ratio is computed as dividends over earnings. If earnings are negative, I divide dividends by $0.06 \times$ total assets to estimate the payout ratio. Payout ratios below zero and above one are set to zero and one, respectively. Then I compute the market value weighted average payout ratio over all companies in the domestic stock market. The long-term growth rate is set to the maximum of the domestic risk-free rate minus three percent and zero. I download yields on ten-year government bonds for each country from TR.

I use data from IBES to compute market values (share price times shares outstanding) and book values (book value per share times shares outstanding). I only require non-missing earnings forecasts for the following two years. Missing forecasts are extrapolated using the long-term growth forecast from IBES, e.g. if E_4 is missing then it is computed as $E_3 \times (1 + \text{LTG})$, where LTG is the long-term growth forecast. If LTG is missing, I substitute it with the implied growth rate from E_2 to E_3. If E_3 is missing, I use the implied growth rate from E_1 to E_2. Long-term growth forecasts are winsorized at 2 and 50% (Nekrasov and Ogneva 2011). I estimate the market ICC on June 30 of each year so that the annual report was already released for the majority of companies (those with December 31 as fiscal year-end). However, since I do not want to drop companies with other fiscal year-ends, I follow Gebhardt et al. (2001) to adjust book values that were not yet published but where IBES has, for that company, updated their earnings forecasts. I assume that the annual report is published at the latest four months after the fiscal year-end. If earnings have already been released but the annual report has not yet been published, I calculate a synthetic book value using clean-surplus accounting ($B_t = B_{t-1} + E_t(1 - \text{payout ratio})$). Book values and the payout ratio are taken from the last available annual report from Compustat (U.S.) or Worldscope (non U.S.). I use the reported earnings from IBES as E_t.

Next, I adjust analysts' earnings forecasts according to Guay et al. (2011). First, I divide companies into portfolios based on their 12-month past return. As in Guay et al. (2011), I use 12 buckets for the U.S. market. For the other countries, there are not enough companies in the cross-section to form 12 buckets that contain a sufficient amount of firms in each bucket to average out idiosyncratic noise (Statman 1987). Therefore, I first combine France and Germany into one region (euro region). Then, I use ten buckets for the euro region, Japan, and the U.K., and eight buckets for Canada. Next, for each country I compute forecast errors as $\frac{\text{EPS}_{forecast} - \text{EPS}_{actual}}{\text{APS}}$, where APS are assets per share obtained from Compustat (U.S.) or Worldscope (non U.S.). Next, I compute the running time-series median forecast error per region/country and portfolio. Finally, the adjusted earnings forecast is calculated as $\mathsf{EPS}_{forecast,adj} = \mathsf{EPS}_{forecast} - (\text{median forecast error} \times \mathsf{APS})$.

In order to compare ICC estimates from different countries a base currency has to be selected. I assume the perspective of an U.S. investor. Therefore, I convert all international figures into USD using spot exchange rates from Morgan Stanley Capital International (MSCI) downloaded via TR. I choose spot exchange rates to convert not only contemporaneous variables but also earnings forecasts. I do not use exchange rate forecasts to convert earnings forecasts for two reasons. First, the data availability of forward exchange rates is very limited in TR, which would substantially reduce the sample. Second, exchange rates are notoriously difficult to forecast (Rossi 2013) and a simple random-walk model often performs better out-of-sample than more complex methods (Meese and Rogoff 1983).

Finally, the data is aggregated per country and the ICC is computed according to Equation 6.

4.2.3 *Alternative expected return proxies*

Devising new return prediction models is a popular undertaking in the literature (see Welch and Goyal 2008 or Rapach and Zhou 2013 for an overview). I employ two common methods. First, I follow Welch and Goyal (2008), who find that no sophisticated return prediction model can consistently outperform the historic average return. I compute the historic average return as the rolling annualized arithmetic average return over the preceding ten years. Second, I estimate an exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model (Nelson 1991), which has been used extensively in the literature (e.g. Glosten et al. 1993, Huang et al. 2010, Cenesizoglu and Timmermann 2012). The following model has a constant mean and time-dependent volatility:

$$ret_t = \mu + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_t^2) \tag{7}$$

$$\log_e(\sigma_t^2) = \omega + \alpha_1 z_{t-1} + \gamma_1(|z_{t-1}| - E|z_{t-1}|) + \beta_1 \log_e(\sigma_{t-1}^2) \tag{8}$$

$$\text{with} \quad z_{t-1} = \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{9}$$

The model allows for an asymmetric relation between returns and volatility, i.e. the volatility in t depends on the sign and magnitude of the innovation in $t-1$ (Nelson 1991). I estimate this model each year at the portfolio rebalancing date (June 30) using data over the preceding ten years. I employ maximum likelihood estimation implemented in R's `rugarch` package (Ghalanos 2014). I then use the estimated coefficients to estimate the expected return for the next year. For both methods, I use returns in USD for all countries.

4.2.4 *Currency risk*

As aforementioned, I convert international ICC and return data into USD. The portfolio analysis also uses unhedged USD returns. The alternative is to hedge all or a fraction of the currency exposure. For example, Black and Litterman (1992) use a hedge ratio of 80%, which they base on the equilibrium U.S. risk premium. My reasons not to hedge foreign exchange risk are the following. First, evidence from Black and Litterman (1992) suggests that the gains from currency hedging are small (0.08%) for equity-only portfolios. It seems unlikely that this gain is sufficiently large to offset the extra transaction costs required for currency hedging (Beach and Orlov 2007). Second, the optimal hedging amount also depends on the investor's risk aversion. Instead of imposing one value for all investors, I opt to not hedge this risk. Further, some investors believe that currency fluctuations are random and, therefore, not worth hedging if the investment horizon is long (Beach and Orlov 2007).

4.2.5 *Summary statistics*

First, I present an overview of the number of companies included in my sample for every country per year (Table 5). For all countries, this number fluctuates over time. Except for the U.K. and the U.S., one can observe an increase in the number of companies over time, which is probably due to an expansion in the IBES coverage. Nevertheless, I follow similar studies that start their sample in 1990 (Pástor et al. 2008, Lee et al. 2009).

Next, I show summary statistics of realized returns (in USD) for each country (Table 6). The average return is highest in North America, followed by the European countries, and is lowest in Japan. This is due to the sample period, as the Japanese stock market crash in 1990 was followed by a decade-long stagnation in stock prices. Table 7 shows the Pearson correlation coefficients (ρ) of monthly realized returns (in United States dollar (USD)) for each sample country. The U.S. capital market seems to be well integrated with the capital markets in Canada ($\rho = 0.79$), U.K. ($\rho = 0.74$), Germany ($\rho = 0.75$), and France ($\rho = 0.76$), but less so with the capital market in Japan ($\rho = 0.44$). This indicates that an U.S. investor may benefit from international diversification through a reduction in portfolio volatility.

Table 8 displays descriptive statistics of the ICC estimates based on unadjusted and adjusted earnings forecasts. The earnings forecasts adjustment is described in Section 4.2.2. The adjusted ICC figures are noticeably smaller than the unadjusted ones (around one to two percentage points). I interpret this finding in the following way: on a country level, analysts' forecast errors related to past stock price performance should average out if the error was similar for positive and negative stock returns. Given that the unadjusted ICC estimates are consistently smaller than the adjusted ones suggests that analysts' forecast errors are larger for past negative stock returns. For example, the stock price declines because of new (negative) information. Analysts are slow to incorporate this new information into their earnings forecasts and do not update their next forecasts. The resulting ICC will be too high, since the (same) earnings have to be discounted with a higher discount rate in order to balance the equation with the current (lower) share price.

Finally, Table 9 presents the summary statistics of the expected return forecasts based on time-series models. The top panel shows data on the moving average mean return and the bottom panel displays statistics on the expected return estimated with the EGARCH model described in Section 4.2.3. Note that the mean for both methods is considerably higher than the estimates from Table 8. This result is in line with other studies that document a lower expected return estimate based on the ICC method than on realized returns (Claus and Thomas 2001). Also noteworthy is the high standard deviation of expected return estimates based on historic return data as compared to those estimates derived from the ICC methodology, which confirms findings in previous studies (Lee et al. 2009).

4.2.6 *Portfolio weights*

4.2.6.1 *Black-Litterman*

The Black and Litterman (1992) method was developed to address some of the problems of mean-variance portfolio optimization, such as extreme portfolio weights (Haugen 1997), high sensitivity to inputs (Best and Grauer 1991), and maximization of estimation error (Michaud 1989). The method starts with the weights from an equilibrium model, then uses a Bayesian framework to update these weights according to the beliefs of the investor (Satchell and Scowcroft 2000). The resulting portfolio is well-balanced, founded on an equilibrium model, and reflects the investor's views in a consistent manner. The BL method has been employed in several portfolio choice studies (Satchell and Scowcroft 2000, Beach and Orlov 2007, Jones et al. 2007, Martellini and Ziemann 2007, Becker and Gürtler 2010, Bessler et al. 2014).

In this study, I will follow the implementation of Meucci (2010) and Bessler et al. (2014). I assume that the prevailing market weighting is the outcome of a utility maximization according to:

$$\max_{\boldsymbol{w}} \quad U = \boldsymbol{w}^{\mathsf{T}}\boldsymbol{\pi} - \frac{\lambda}{2}\boldsymbol{w}^{\mathsf{T}}\boldsymbol{\Sigma}\boldsymbol{w} \tag{10}$$

where $\boldsymbol{w}$ is a vector of asset weights, U is the investor's utility, $\boldsymbol{\pi}$ is a vector of expected excess asset returns (in excess of the risk-free yield), λ is the investor's risk-aversion coefficient, and $\boldsymbol{\Sigma}$ is the asset return covariance matrix. I follow Bessler et al. (2014) by setting $\lambda = 2$ and I estimate $\boldsymbol{\Sigma}$ with the sample covariance matrix using 60 monthly returns. I will refer to $\boldsymbol{\pi}$ as the equilibrium expected excess return vector as it was derived from an equilibrium model assuming that all investors hold identical views (Black and Litterman 1992). Now, I calculate $\boldsymbol{\pi}$ by rearranging the first derivative of Equation 10:

$$\boldsymbol{\pi} = \lambda \boldsymbol{\Sigma} \boldsymbol{w}_m \tag{11}$$

where $\boldsymbol{w}_m$ is the vector of market value weights of each asset which can be easily computed at each point in time.

In the next step, these equilibrium expected excess returns will be combined with my expected excess returns (referred to as "views" hereafter). My views are stored in the vector $\boldsymbol{v}$ and are represented by the ICC estimates for each country (minus the yield on the one-year risk-free investment). The uncertainty of the views is captured by the matrix $\boldsymbol{\Omega}$:

$$\boldsymbol{\Omega} = \frac{1}{c} \boldsymbol{\Sigma} \tag{12}$$

where $c \in (0, \infty)$ reflects the overall confidence in views (Meucci 2005). I set $c = 5$ as this seems a reasonable choice given the low volatility of ICC estimates (Bessler et al. 2014, Meucci 2005).[10]

10 In the robustness section, I run the optimization for different values of c to confirm that the results are not driven by the choice of $c = 5$.

I now have two expected excess return vectors: $\boldsymbol{\pi}$ with the covariance matrix $\tau\boldsymbol{\Sigma}$, and $\boldsymbol{v}$ with the covariance matrix $\boldsymbol{\Omega}$. τ indicates how uncertain the equilibrium returns are. As in Bessler et al. (2014), I set $\tau = 0.1$. I have summarized the parameter settings in Table 10. A result from the BL literature is that the mean of a combination of $\boldsymbol{\pi}$ and $\boldsymbol{v}$ can be written as (see Satchell and Scowcroft (2000) for the derivation):

$$\boldsymbol{\mu}_{\mathrm{BL}} = [(\tau\boldsymbol{\Sigma})^{-1} + \boldsymbol{\Omega}^{-1}]^{-1}[(\tau\boldsymbol{\Sigma})^{-1}\boldsymbol{\pi} + \boldsymbol{\Omega}^{-1}\boldsymbol{v}] \tag{13}$$

Often in the literature, a "pick" matrix $\boldsymbol{P}$ is defined, which allows views on certain assets to be omitted or views for one asset to be stated relative to another (e.g. asset one will outperform asset three by two percent). I implicitly set $\boldsymbol{P}$ to a 6×6 identity matrix as I have views (i.e. ICC or time-series estimates) for each of the six countries in the investment universe and these views are given in absolute values (and not relative to each other).

You can also see that $\boldsymbol{\mu}_{\mathrm{BL}}$ is a weighted average of the equilibrium expected returns and the views (Lee 2000). The first term in brackets is a multiplier, so one can focus on the second term. The second term shows a weighted average of $\boldsymbol{\pi}$ and $\boldsymbol{v}$ with weights equal to $(\tau\boldsymbol{\Sigma})^{-1}$ and $\boldsymbol{\Omega}^{-1}$, respectively. This means that higher values in the matrices reflecting uncertainty lead to a lower weight of the respective expected excess return vector.

The covariance matrix corresponding to the distribution with mean $\boldsymbol{\mu}_{\mathrm{BL}}$ is given by (Meucci 2010):

$$\boldsymbol{\Sigma}_{\mathrm{BL}} = \boldsymbol{\Sigma} + [(\tau\boldsymbol{\Sigma})^{-1} + \boldsymbol{\Omega}^{-1}]^{-1} \tag{14}$$

Finally, I run the optimization according to Equation 10 using $\boldsymbol{\mu}_{\mathrm{BL}}$ as the expected excess return vector and $\boldsymbol{\Sigma}_{\mathrm{BL}}$ as the respective covariance matrix to obtain the portfolio weights at each rebalancing date. I set the following constraints: portfolio weights have to sum to one ($\sum w_i = 1$) and no short selling ($w_i \geqslant 0$ for all N countries). I use the `Rsolnp` package for the optimization (Ghalanos and Theussl 2015).

4.2.6.2 *Benchmark weights*

I use several benchmark strategies. The first two are also based on the BL method described in Section 4.2.6.1. Instead of using the ICC as the expected stock return, I use two alternative methods, namely the historic moving average return and a return forecast based on the EGARCH model from Section 4.2.3. The strategy of combining the BL model with an EGARCH return forecast is similar to Beach and Orlov (2007).

Next, I employ a fundamental-weighting based on the GDP (Arnott et al. 2005, Asness et al. 2011). Specifically, I download the reported GDP figures for each country at each portfolio rebalancing date from TR. The weight for each country is calculated as:

$$w_i = \frac{\mathrm{GDP}_i}{\sum_i^N \mathrm{GDP}_i} \tag{15}$$

where $i \in \{\text{Canada, France, Germany, Japan, U.K., U.S.}\}$ is the set of countries in the investment universe.

Finally, I include two naive strategies: weighting each country according to its aggregated market capitalization in USD (Odier and Solnik 1993, Asness et al. 2011) and equally-weighting each country (DeMiguel et al. 2009b).

Year	CA	DE	FR	GB	JP	US	Total
1990	170	102	149	578	417	2,000	3,416
1991	161	121	162	602	467	2,014	3,527
1992	177	216	218	639	460	2,128	3,838
1993	186	171	212	646	482	2,509	4,206
1994	207	225	226	675	444	3,250	5,027
1995	215	210	249	731	665	3,543	5,613
1996	242	230	291	727	725	3,727	5,942
1997	259	224	313	898	1,140	4,090	6,924
1998	277	311	342	920	1,073	4,148	7,071
1999	332	315	372	840	1,157	4,106	7,122
2000	350	290	372	743	1,039	3,638	6,432
2001	330	368	344	644	1,000	3,345	6,031
2002	328	343	323	652	1,100	3,246	5,992
2003	367	275	304	591	1,050	3,163	5,750
2004	468	256	295	629	1,147	3,293	6,088
2005	540	275	297	736	1,099	3,409	6,356
2006	618	290	321	745	1,226	3,513	6,713
2007	684	325	364	802	1,205	3,532	6,912
2008	655	375	361	818	1,179	3,444	6,832
2009	548	395	342	787	1,095	3,397	6,564
2010	589	410	352	760	1,158	3,315	6,584
2011	650	361	348	752	960	3,159	6,230
2012	671	362	334	734	924	3,132	6,157
2013	631	349	313	693	991	3,083	6,060
2014	601	338	283	671	1,088	3,119	6,100

Table 5: **Number of companies per country**
This table shows the number of companies included in the ICC computation per year and country (Canada (CA), Germany (DE), France (FR), United Kingdom (GB), Japan (JP), and United States (US)).

Country	Count	Mean	SD	Min	Max	P25	P50	P75
CA	300	0.97	5.5	-27.1	20.9	-2.1	1.4	4.4
DE	300	0.75	6.3	-26.9	22.8	-2.5	1.3	4.4
FR	300	0.80	5.8	-21.9	15.0	-2.6	1.0	4.2
GB	300	0.73	4.7	-22.8	15.1	-1.8	0.7	3.7
JP	300	0.28	5.8	-16.3	25.2	-3.3	0.3	3.8
US	300	0.89	4.3	-18.4	11.5	-1.6	1.4	3.6

Table 6: **Summary statistics of realized returns per country**
This table shows summary statistics of realized returns per country (Canada (CA), Germany (DE), France (FR), United Kingdom (GB), Japan (JP), and United States (US)). Local currency returns are converted to USD returns. The columns display the number of observations (Count), sample mean (Mean), standard deviation (SD), minimum (Min), maximum (Max), first quartile (P25), median (P50), and third quartile (P75). All figures except count are in percent. The sample spans the period from June 30, 1990, to June 30, 2015 (monthly frequency).

	CA	DE	FR	GB	JP	US
CA	1.00	0.68	0.69	0.64	0.44	0.79
DE	0.68	1.00	0.89	0.77	0.43	0.75
FR	0.69	0.89	1.00	0.82	0.48	0.76
GB	0.64	0.77	0.82	1.00	0.48	0.74
JP	0.44	0.43	0.48	0.48	1.00	0.44
US	0.79	0.75	0.76	0.74	0.44	1.00

Table 7: **Correlation matrix: ICC and realized returns**
This table displays the Pearson correlation matrix between monthly realized returns (in USD) for each country (Canada (CA), Germany (DE), France (FR), United Kingdom (GB), Japan (JP), and United States (US)). The sample spans the period from June 30, 1990, to June 30, 2015.

Panel A: ICC estimates based on unadjusted earnings forecasts								
Country	Count	Mean	SD	Min	Max	P25	P50	P75
CA	25	10.2	1.5	7.8	13.5	9.2	9.5	11.3
DE	25	9.0	1.4	6.1	11.4	8.5	9.2	10.1
FR	25	9.9	1.7	7.0	13.5	8.6	9.8	11.2
GB	25	10.3	1.5	7.8	13.6	9.4	10.1	11.3
JP	25	6.5	1.9	3.6	11.2	5.0	6.1	7.4
US	25	9.2	1.4	7.3	12.4	8.0	9.1	10.1
Panel B: ICC estimates based on adjusted earnings forecasts								
Country	Count	Mean	SD	Min	Max	P25	P50	P75
CA	25	8.4	1.8	6.0	13.4	7.4	7.8	8.7
DE	25	7.3	1.5	5.1	10.6	6.1	7.2	8.0
FR	25	8.5	2.2	3.5	13.5	7.3	8.1	9.8
GB	25	8.4	2.3	4.7	13.9	6.7	8.1	9.3
JP	25	5.4	1.5	3.2	8.9	4.0	5.6	6.2
US	25	7.9	1.2	6.2	11.2	7.1	7.8	8.6
Panel C: delta between the two ICC methods								
Country	Count	Mean	SD	Min	Max	P25	P50	P75
CA	25	-1.8	1.0	-3.8	0.1	-2.4	-1.5	-1.3
DE	25	-1.7	1.5	-4.4	0.7	-3.3	-1.4	-0.7
FR	25	-1.4	2.0	-8.5	1.8	-1.6	-1.0	-0.5
GB	25	-1.9	1.5	-6.4	0.3	-2.3	-1.6	-1.1
JP	25	-1.0	0.9	-2.3	0.7	-1.5	-1.1	-0.7
US	25	-1.3	0.6	-2.6	-0.3	-1.7	-1.2	-0.8

Table 8: **Summary statistics: ICC estimates**
This table shows summary statistics of the ICC estimates based on unadjusted earnings forecasts (Panel A) and adjusted earnings forecasts (Panel B) for each country (Canada (CA), Germany (DE), France (FR), United Kingdom (GB), Japan (JP), and United States (US)). The columns display the number of observations (Count), sample mean (Mean), standard deviation (SD), minimum (Min), maximum (Max), first quartile (P25), median (P50), and third quartile (P75). The earnings forecasts adjustment is described in Section 4.2.2. The sample spans the period from June 30, 1990, to June 30, 2015 (yearly frequency).

Panel A: Expected return based on the moving average return								
Country	Count	Mean	SD	Min	Max	P25	P50	P75
CA	25	14.0	3.2	9.3	20.3	11.2	13.5	16.4
DE	25	13.5	4.5	4.2	21.7	11.2	12.6	17.2
FR	25	15.5	6.5	3.2	28.1	10.2	15.1	19.5
GB	25	12.0	6.1	0.3	22.9	7.9	10.8	16.2
JP	25	7.6	8.7	-2.0	25.6	2.0	4.3	10.8
US	25	12.2	5.2	0.6	18.9	9.4	13.7	15.6
Panel B: Expected return based on the EGARCH model								
Country	Count	Mean	SD	Min	Max	P25	P50	P75
CA	25	16.9	5.6	3.8	26.2	13.2	18.5	21.6
DE	25	18.1	6.3	5.2	31.4	14.5	17.1	21.4
FR	25	17.1	7.1	7.1	30.6	11.4	16.8	21.9
GB	25	15.0	8.1	0.7	30.3	8.6	13.5	23.0
JP	25	6.0	13.0	-16.7	29.3	-1.9	3.5	8.0
US	25	13.1	6.7	-5.9	26.5	9.1	14.0	16.5

Table 9: **Summary statistics: historic return estimates**
This table shows summary statistics of the moving annualized arithmetic average return over the preceding ten years (Panel A) and expected return estimated by the EGARCH model from Section 4.2.3 (Panel B) for each country (Canada (CA), Germany (DE), France (FR), United Kingdom (GB), Japan (JP), and United States (US)). The columns display the number of observations (Count), sample mean (Mean), standard deviation (SD), minimum (Min), maximum (Max), first quartile (P25), median (P50), and third quartile (P75). The sample spans the period from June 30, 1990, to June 30, 2015 (yearly frequency).

Parameter	Description	Estimate / value
λ	Risk-aversion coefficient	Set to 2
$\boldsymbol{\Sigma}$	$N \times N$ covariance matrix of realized excess returns	Estimated using 60 monthly excess returns
$\boldsymbol{w}_m$	$N \times 1$ vector of market value weights for each country	$\frac{MV_{i,USD}}{\sum_i^N MV_{i,USD}}$
$\boldsymbol{\pi}$	$N \times 1$ vector of equilibrium expected excess returns for each country	$\boldsymbol{\pi} = \lambda \boldsymbol{\Sigma} \boldsymbol{w}_m$
c	Constant that reflects the confidence in the investor's views	Set to 5
$\boldsymbol{\Omega}$	$N \times N$ covariance matrix of uncertainty of views	$\boldsymbol{\Omega} = \frac{1}{c}\boldsymbol{\Sigma}$
τ	Constant indicating the uncertainty of equilibrium returns	Set to 0.1
$\boldsymbol{P}$	$N \times N$ pick matrix	Implicitly set to $N \times N$ identity matrix

Table 10: **BL parameters**
This table shows the parameters used in the BL procedure described in Section 4.2.6.1. The table is based on Beach and Orlov (2007). $N = 6$ is the number of countries in the investment universe.

4.3 PORTFOLIO EVALUATION

The investment strategies discussed so far are evaluated in the following way. The first portfolio formation date is June 30, 1990. The portfolio weights are calculated according to Section 4.2.6. The portfolios are held for one year until the next rebalancing date. The final portfolio formation date is June 30, 2014. The evaluation period extends until June 30, 2015. Figures 3 and 4 show the portfolio weights over time for the different strategies. Clearly, the weights of the strategies based on the BL optimization (EGARCH, ICC_RAW, ICC_ADJ, and MA) display a far higher fluctuation than the weights of the non BL methods (EW, GDP, VW). The BL strategies are not always invested in all of the countries. In contrast, the EW strategy has very stable weights (they only fluctuate between rebalancing dates according to the relative returns of each country). The GDP and, especially, the VW strategies are dominated by the U.S. Also striking is the steady decline of the weight in the Japanese market. As noted in Section 4.1, Japan experienced a decade-long decline in asset prices after the stock market crash in 1990.

I evaluate portfolio performance along several dimensions. I start with a graph showing the cumulative return of each strategy (Figure 5). The collapse of the Internet bubble in 2000–2001 and the financial crisis in 2007–2008 are clearly visible in all strategies. Based on returns alone, both the ICC_RAW and the ICC_ADJ strategies perform very well. The MA strategy comes in third while the other strategies lag behind.

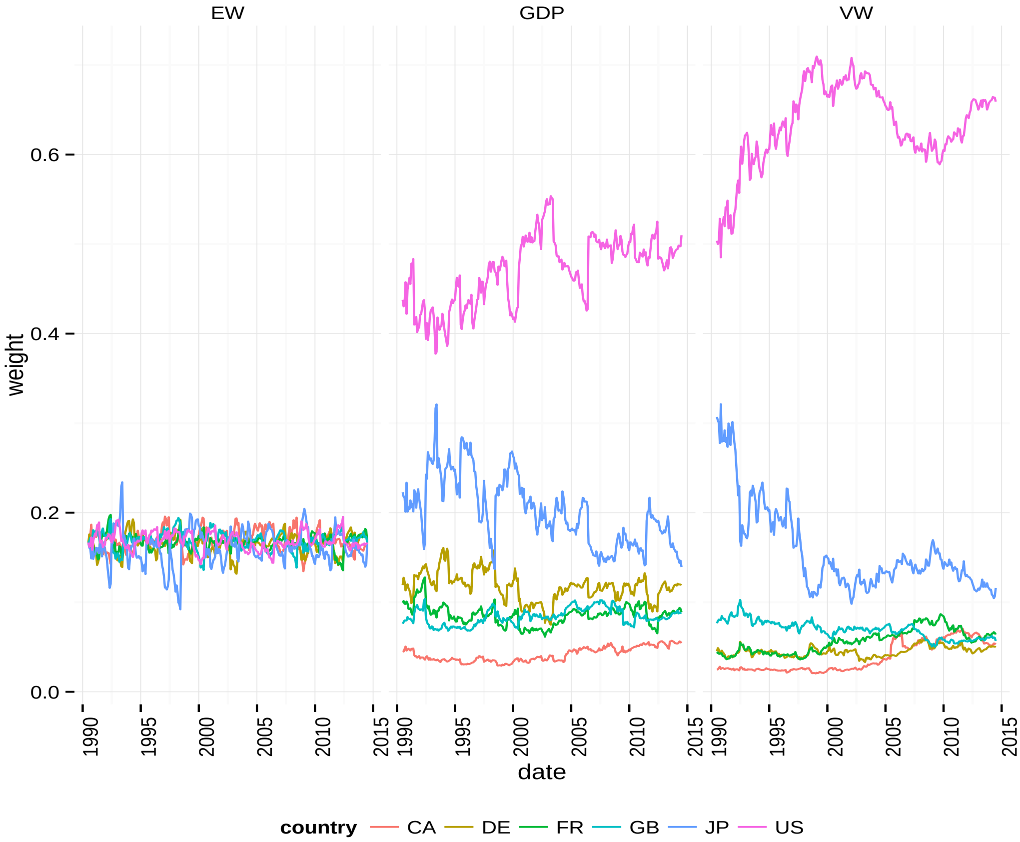

Figure 3: **Portfolio weights over time, part I**
This figure displays the portfolio weights for three investment strategies over time. Each weight corresponds to an investment in the respective country's stock market (Canada (CA), Germany (DE), France (FR), United Kingdom (GB), Japan (JP), and United States (US)). EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP (in USD), and VW is the market value weighted strategy. The evaluation period starts on June 30, 1990, and ends on June 30, 2015.

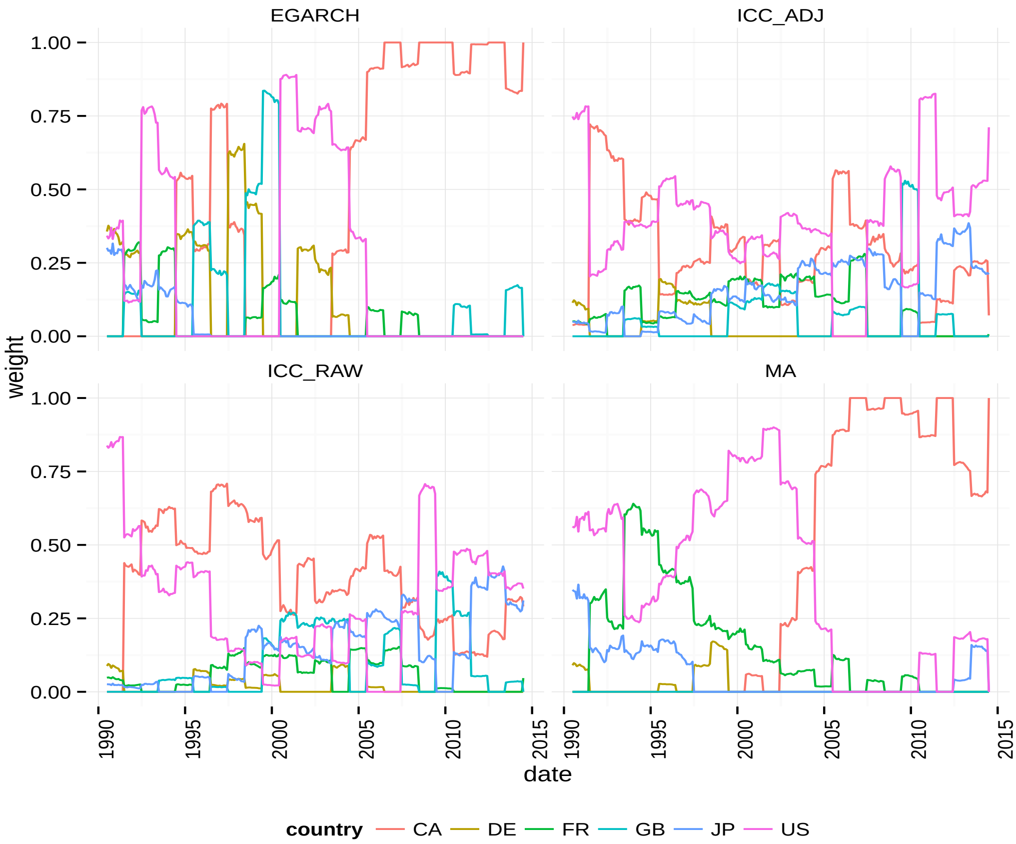

Figure 4: **Portfolio weights over time, part II**
This figure displays the portfolio weights for four investment strategies over time. Each weight corresponds to an investment in the respective country's stock market (Canada (CA), Germany (DE), France (FR), United Kingdom (GB), Japan (JP), and United States (US)). EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), ICC_ADJ uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), and MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3). The evaluation period starts on June 30, 1990, and ends on June 30, 2015.

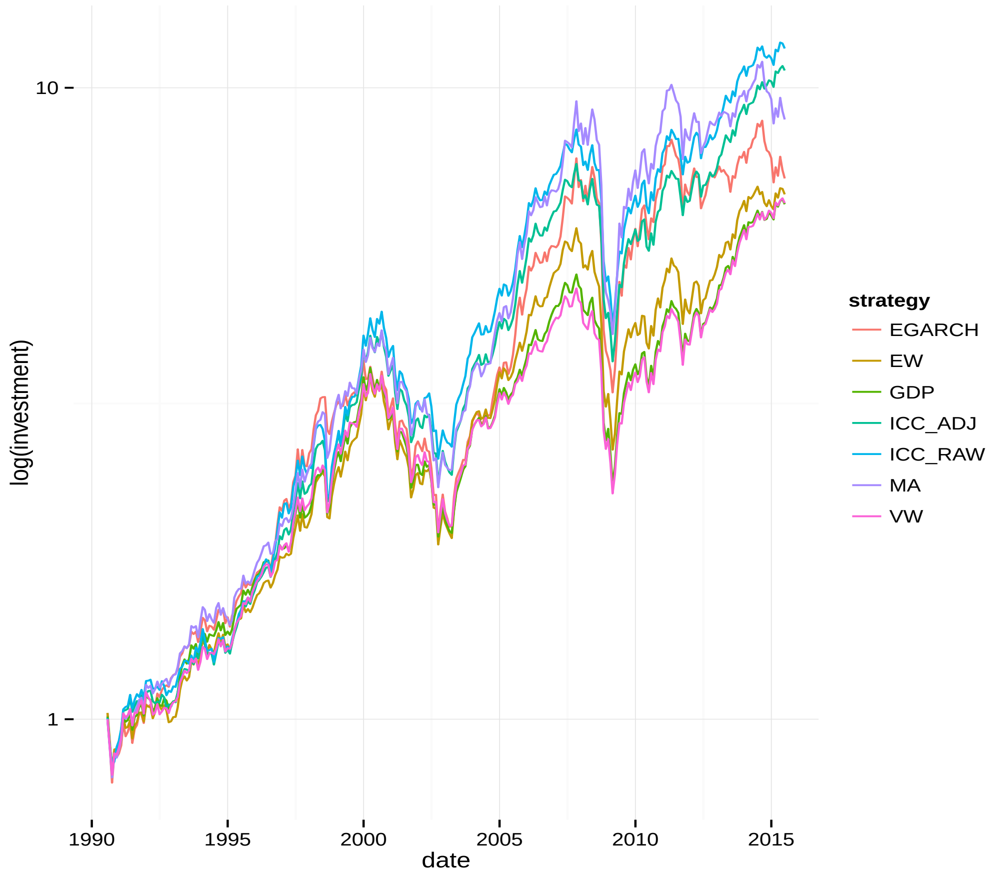

Figure 5: **Cumulative return, cross-country allocation**
This figure displays the hypothetical development of a 1 USD investment for each investment strategy. EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, ICC_ADJ uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3), and finally VW is the market value weighted strategy. The evaluation period starts on June 30, 1990, and ends on June 30, 2015.

Next, I compute performance and risk metrics for each strategy (Table 25). These include the Sharpe Ratio (Sharpe 1966):

$$SR_i = \frac{\bar{r}_{i,ec}}{\sigma_{i,ec}} \tag{16}$$

where $\bar{r}_{i,ec}$ is the mean excess return of portfolio i over the risk-free return and $\sigma_{i,ec}$ is the standard deviation of excess returns of portfolio i.

When comparing Sharpe Ratios of different strategies one has to take the time-series nature and distributional properties (heavy tails and negative skewness) of stock return data into account (Jobson and Korkie 1981a). Ledoit and Wolf (2008) developed a procedure that constructs a studentized time-series bootstrap interval.[11] I use this method to statistically compare Sharpe Ratios in my analyses.

Furthermore, I compute the maximum one-year drawdown (Grossman and Zhou 1993) as the worst twelve month return in the sample for each portfolio:

$$MDD_i = -\min(r_{i,12m}) \tag{17}$$

where $r_{i,12m}$ is the the return over the preceding 12 months of portfolio i.

Some authors have criticized the use of the Sharpe Ratio when returns are not approximately normally distributed (see Farinelli et al. (2008) for an overview). One risk-adjusted measure that captures higher moments in the return distribution is the Omega metric (Shadwick and Keating 2002). It relates the likelihood of returns above a specified target return to the likelihood of returns below the specified target return. Consequently, a higher ratio is preferred to a lower one. I use the risk-free return as the

11 I thank Michael Wolf for making the R code freely available on his website.

target return. My implementation is based on Kaplan and Knowles (2004):

$$\text{Omega} = \frac{\bar{r}_{i,ec}}{\frac{1}{T}\sum_{t=1}^{T}\max(0 - r_{i,ec}, 0)} + 1 \tag{18}$$

where $\bar{r}_{i,ec}$ is the mean excess return of portfolio i over the risk-free return and $t = 1, ..., T$ are the months in the portfolio evaluation period.

I also compute the certainty-equivalent (CEQ) return which represents the risk-free return that an investor would accept instead of a risky portfolio strategy (DeMiguel et al. 2009b). It is calculated as:

$$\text{CEQ} = \bar{r}_{i,ec} - \frac{\lambda}{2}\sigma^2_{i,ec} \tag{19}$$

where $\bar{r}_{i,ec}$ is the mean excess return of portfolio i over the risk-free return, λ is the risk-aversion coefficient which I set to two (see Section 4.2.6.1), and $\sigma^2_{i,ec}$ is the variance of the excess return of portfolio i.

In order to give an impression of how expensive a strategy would be to implement, I calculate the average one-way portfolio turnover (DeMiguel et al. 2009b):

$$\text{TO} = \frac{1}{2}\frac{1}{T}\sum_{t=1}^{T}\sum_{n=1}^{N}(|w_{i,n,t+1} - w_{i,n,t}|) \tag{20}$$

where $w_{i,n,t}$ is the weight of country n at time t of strategy i. A small turnover also arises for the naive strategies EW and VW, as countries perform differently between rebalancing dates and some stocks within each country leave the stock market or are added.

The two strategies based on the ICC have the highest average return and the lowest risk of all portfolios. Consequently, they display the highest

Sharpe Ratio which is also significantly different from the value-weighted portfolio at the five percent level. Regarding the maximum drawdown return, the ICC portfolios, the GDP, and the VW strategies perform similarly well. The ranking based on the Sharpe Ratio is confirmed by the Omega measure, indicating that higher order moments are not distorting the Sharpe Ratio in this study.[12] The CEQ measure paints a similar picture, in that the two ICC strategies are delivering the best results. Finally, the strategies based on the BL method (EGARCH, ICC_RAW, ICC_ADJ, and MA) all have relatively high turnover compared to the EW, GDP, and VW portfolios.

Table 12 shows how often the different investment strategies outperform the value-weighted portfolio. I calculate the return for each strategy for each year (June 30 $t-1$ to June 30 t). Then I record if the respective investment strategy outperformed the VW portfolio. According to this measure, the best performing strategy is the BL method using adjusted ICC estimates. It outperforms the value-weighted portfolio in 60% of the years in the sample period.

Next, I compute additional risk measures in order to provide a better understanding of the return distributions for the different investment strategies. More precisely, I use the portfolio returns to calculate skewness, kurtosis, and value-at-risk measures:

$$\text{skewness} = \mathbf{E}\left[\left(\frac{r_{i,t} - \bar{r}_i}{\sigma_i}\right)^3\right] \tag{21}$$

12 Eling (2008) studies numerous performance metrics applied to mutual fund returns and arrives at a similar conclusion.

$$\text{kurtosis} = \mathbf{E}\left[\left(\frac{r_{i,t} - \bar{r}_i}{\sigma_i}\right)^4\right] \tag{22}$$

$$\text{VaR}_\alpha = q_\alpha \tag{23}$$

where $r_{i,t}$ is the return for strategy i in month t, $\bar{r}_i$ is the mean monthly return for strategy i, σ_i is the standard deviation of the monthly returns for strategy i, and q_α is the α quantile of the return distribution for strategy i. The results are presented in Table 13. All return distributions display negative skewness, with the EGARCH and MA strategies showing the least skewed distributions (around -0.6). The other strategies display skewness in the range of -0.8 to -0.9. Likewise, all return distributions have excess kurtosis (i.e. kurtosis exceeding three) indicating that there is more probability mass in the tails as compared to the normal distribution. The strategies VW and GDP have the least heavy-tailed return distributions while EGARCH and MA have the heaviest tails. These findings are mirrored in the empirical value-at-risk estimates. For example, the 1% value-at-risk is almost -14% for the EGARCH and MA strategies followed by -12% for the EW strategy. For the other strategies, the 1% value-at-risk lies between -10% and -11%.

Finally, in Figure 6, I plot the return distribution for each investment strategy. For all strategies, heavy tails and negative skewness are visible.

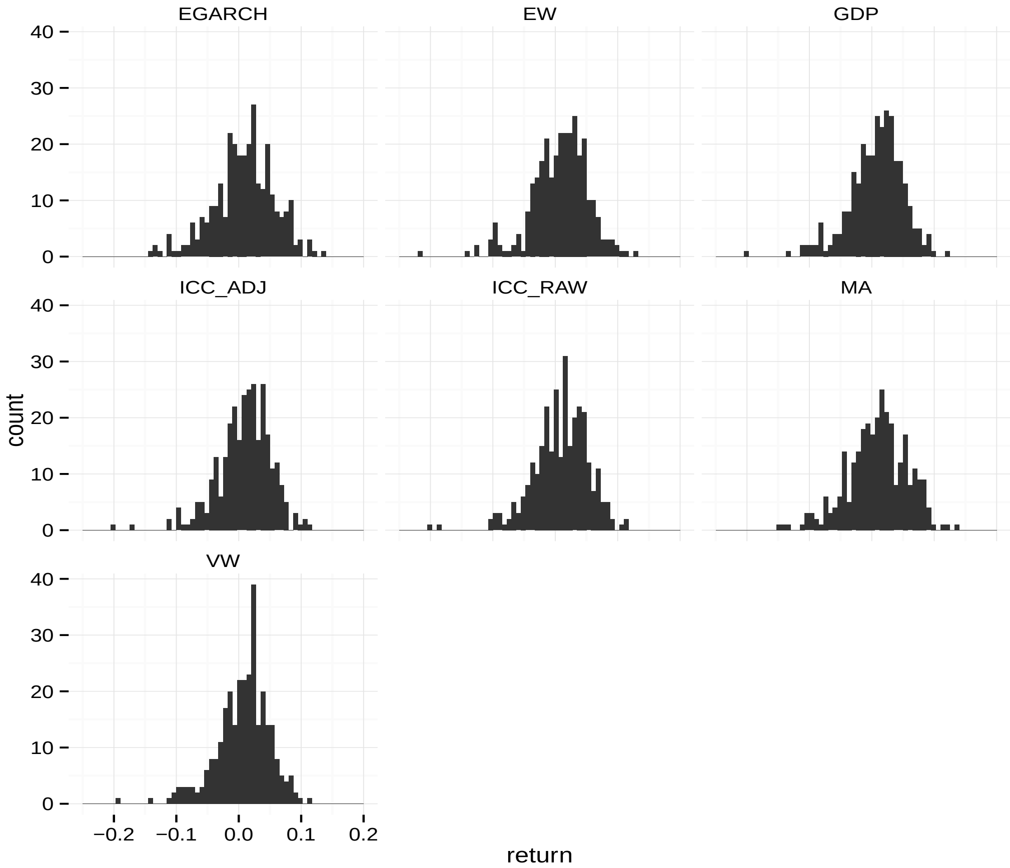

Figure 6: **Histograms of return distributions**
This figure shows histograms of the return distribution for the different investment strategies. EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, ICC_ADJ also uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3), and finally VW is the market value weighted strategy. The evaluation period starts on June 30, 1990, and ends on June 30, 2015.

	SR	P	Return %	SD %	MDD %	Omega	CEQ %	TO %
EGARCH	0.107	0.811	8.21	18.16	52.96	1.331	3.48	30
EW	0.112	0.910	7.96	15.66	48.98	1.339	3.66	4
GDP	0.112	0.909	7.80	14.80	46.64	1.341	3.64	4
ICC_ADJ	0.150	0.026	9.92	14.90	45.45	1.476	5.67	26
ICC_RAW	0.154	0.046	10.28	15.21	45.14	1.488	5.97	22
MA	0.122	0.730	9.14	17.79	52.86	1.383	4.44	15
VW	0.113	1.000	7.82	14.67	45.65	1.344	3.68	2

Table 11: **Performance and risk metrics, cross-country allocation**
This table presents performance and risk metrics for the different investment strategies. SR indicates the (monthly) Sharpe Ratio (Sharpe 1966). P is the p-value of the method by Ledoit and Wolf (2008), which tests whether the respective Sharpe Ratio is different from the VW Sharpe Ratio. Return % is the geometric average return (annualized) over the sample period in percent. SD % is the (annualized) standard deviation in percent. MDD % represents the maximum one-year drawdown in percent (Grossman and Zhou 1993). Omega is a risk-adjusted performance measure that takes higher moments into account (Shadwick and Keating 2002). CEQ % stands for certainty equivalent return and is equal to the average return minus the portfolio variance multiplied by the risk-aversion coefficient divided by two (DeMiguel et al. 2009b). TO % is the average one-way portfolio turnover over all portfolio formation dates in percent (DeMiguel et al. 2009b). EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, ICC_ADJ uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3), and finally VW is the market value weighted strategy. The evaluation period starts on June 30, 1990, and ends on June 30, 2015.

	Count Outperf.	Outperf. %
VW	0	0
EGARCH	13	52
EW	12	48
GDP	11	44
ICC_ADJ	15	60
ICC_RAW	15	60
MA	14	56

Table 12: **Count of outperformance per year, cross-country allocation**
This table shows how often the different investment strategies outperform the value-weighted (VW) strategy. I evaluate the performance of each strategy per year (from June 30 in $t-1$ to June 30 in t) and record if the return was higher than the VW portfolio. EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), GDP weighs each country proportional to its GDP, ICC_ADJ also uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3), and finally VW is the market value weighted strategy.The evaluation period starts on June 30, 1990 and ends on June 30, 2015.

	Skewness	Kurtosis	VaR 5%	VaR 2.5%	VaR 1%
EGARCH	-0.600	5.908	-7.73	-10.90	-13.67
EW	-0.816	5.197	-8.40	-9.71	-12.28
GDP	-0.824	4.918	-7.78	-9.29	-10.97
ICC_ADJ	-0.880	5.367	-6.46	-9.17	-10.80
ICC_RAW	-0.811	5.175	-6.55	-8.71	-10.02
MA	-0.644	6.191	-7.42	-10.02	-13.68
VW	-0.800	4.823	-7.61	-9.03	-10.62

Table 13: **Additional risk metrics, cross-country allocation**
This table presents additional risk metrics for the different investment strategies. Skewness indicates the skewness of the respective return distribution. Kurtosis displays the kurtosis of the respective return distribution. VaR stands for value-at-risk and the percentage indicates the threshold loss. It is calculated using the historical return distribution and presented in percentage notation. EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, ICC_ADJ also uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3), and finally VW is the market value weighted strategy. The evaluation period starts on June 30, 1990, and ends on June 30, 2015.

4.4 ROBUSTNESS CHECKS

4.4.1 *Transaction costs*

All investment strategies incur transaction costs. The total amount depends on the costs of trading and the portfolio turnover. Table 25 gives an indication of how expensive the different portfolios would be to implement by showing the portfolio turnover. The costs per trade include broker commissions, bid-ask spread, and the price impact per trade. Domowitz et al. (2001) estimate these costs on a cross-country level. The strategies in this study buy and sell the market portfolio in different countries. A retail investor could easily invest in these market portfolios through exchange-trade funds. Therefore, it is reasonable to assume that transaction costs occur on a country level. Table 14 shows the transaction costs per country. These figures are a conservative estimate since transaction costs have decreased substantially over the sample period.

Table 15 displays performance and risk metrics for the different investment strategies, taking trading costs into account. For portfolios with low turnover (EW, GDP, and VW), the performance is virtually unaffected by the inclusion of transaction costs. However, the other strategies do display a drop in their performance measures. Nonetheless, the ranking is not significantly affected as the two ICC strategies perform best. When comparing the Sharpe Ratio from the ICC_ADJ strategy with the Sharpe Ratio of the value-weighted portfolio, the significance level is still below the five percent significance threshold.

Country	Transaction costs (bp)
Canada	52.4
Germany	37.7
France	29.5
Japan	41.3
United Kingdom	54.5
United States	38.1

Table 14: **Transaction costs per country**
This table shows total transaction costs (explicit and implicit, in basis points (bp)) per country according to Domowitz et al. (2001).

4.4.2 *Subperiods*

In this section, I confirm that the findings are not driven by the sample period selection. To this end, I first divide the sample period into subperiods of five years each (June 1990 – June 1995, June 1995 – June 2000, etc.). Then I compute the geometric average return (Table 16) and the Sharpe Ratio (Table 17) for every investment strategy. The earlier findings are corroborated by this analysis, the ICC_ADJ strategy performs among the top three (based on the Sharpe Ratio) in three out of five subperiods.

Subperiods can also be defined using economic characteristics. I divide the sample period into economic expansion and contraction periods and compute performance metrics for the different strategies (Table 18). In order to classify each month as either an expansion or a contraction month, I use data from the National Bureau of Economic Research (NBER)[13]. The two strategies based on the ICC have the highest returns in both market regimes. Moreover, the standard deviation is among the lowest from the

13 NBER make their business cycle data available on their website: http://www.nber.org/cycles/cyclesmain.html. Contractions are defined as the months between the peak of the business cycle and the trough. Expansions are the months between the trough of the business cycle and the peak.

tested strategies. I conclude that the ICC portfolios perform well compared to the alternatives in both economic expansion and contraction periods.

4.4.3 *Sensitivity analysis of BL parameters*

For the BL approach, some assumptions are necessary when setting the various parameters. I followed the literature when doing so, nonetheless, I want to ensure that the results are robust toward these assumptions. Table 19 displays the results when repeating the BL procedure described in Section 4.2.6.1, but after varying input parameters. For the reader's convenience, I have reprinted the results for the investment strategies that do not use the BL approach (Panel A).

Panel B shows the Sharpe Ratios when varying the risk-aversion coefficient λ. The two ICC strategies show a slight decrease in their Sharpe Ratios as λ increases. In comparison, the EGARCH and MA portfolios experience a monotonic increase in their Sharpe Ratios for increasing values of λ. As the risk-aversion coefficient increases, the estimate for the portfolio risk (based on the covariance matrix) becomes more important. This thus implies that the estimate for the expected return is imprecise when using the EGARCH and MA method. Placing less weight on these expected return estimates (and more weight on the estimate of the covariance matrix) results in an increased Sharpe Ratio.

In Panel C, the confidence level c is analyzed. c reflects the confidence in the investor's views. A higher value of c puts more weight on the investor's views in relation to the equilibrium expected returns. The two ICC based strategies have their optimum between five and ten. This suggests that a balance between views and equilibrium data is best. For the EGARCH and MA strategies, the picture is again different. They have their highest Sharpe Ratios when $c = 0.1$, the lowest value in the analysis. Therefore, placing as little weight as possible on the views based on the EGARCH or MA models produces the highest Sharpe Ratios.

Finally, Panel D presents varying values of the parameter τ. τ indicates the uncertainty in the equilibrium returns, with higher values meaning more uncertainty and, consequently, less weight on the equilibrium expected returns. The results mirror the findings from panels B and C. The portfolios based on the ICC have their highest Sharpe Ratio when τ is set to between 0.1 and 0.15. For the EGARCH and MA strategies, it is optimal to place as much weight on the equilibrium expected returns as possible, i.e. their optimum is at the lowest value of τ.

4.4.4 *Unrestricted investment universe*

I limit the investment universe to firms with analysts' earnings forecasts in order to be able to compute the market ICC. Clearly, this requirement shapes the selection of companies. To rule out the possibility that this selection effect drives the relatively poor performance of the investment strategies that do not use ICC estimates, I drop this data requirement for all strategies that do not use ICC estimates and re-compute the portfolio metrics. Table 20 presents the results. The strategies EW, GDP, VW, and MA all experience a slight drop in their Sharpe Ratios.[14] On the contrary, the EGARCH portfolio now has a somewhat higher Sharpe Ratio (0.109 vs. 0.107 before). This improved Sharpe Ratio is still substantially smaller than the Sharpe Ratios of the ICC based investment strategies. These results

14 EW: 0.107 vs. 0.112 before, GDP: 0.106 vs. 0.112, VW: 0.102 vs. 0.113, MA: 0.113 vs. 0.122.

establish that the selection effect does not significantly affect the ordering of the investment strategies.

	SR	P	Return %	SD %	MDD %	Omega	CEQ %
EGARCH	0.103	0.703	7.92	18.15	52.99	1.316	3.21
EW	0.111	0.895	7.92	15.66	49.00	1.337	3.63
GDP	0.112	0.875	7.77	14.80	46.66	1.339	3.60
ICC_ADJ	0.146	0.046	9.68	14.88	45.52	1.460	5.44
ICC_RAW	0.150	0.066	10.06	15.21	45.32	1.473	5.76
MA	0.120	0.780	9.01	17.78	52.87	1.375	4.32
VW	0.113	1.000	7.80	14.67	45.66	1.343	3.66

Table 15: **Performance and risk metrics, cross-country allocation – after transaction costs**
This table presents performance and risk metrics for the different investment strategies taking transaction costs (based on Domowitz et al. 2001) into account. SR indicates the (monthly) Sharpe Ratio (Sharpe 1966). P is the p-value of the method by Ledoit and Wolf (2008), which tests whether the respective Sharpe Ratio is different from the VW Sharpe Ratio. Return % is the geometric average return (annualized) over the sample period in percent. SD % is the (annualized) standard deviation in percent. MDD % represents the maximum one-year drawdown in percent (Grossman and Zhou 1993). Omega is a risk-adjusted performance measure that takes higher moments into account (Shadwick and Keating (2002)). CEQ % stands for certainty equivalent return and is equal to the average return minus the portfolio variance multiplied by the risk-aversion coefficient divided by two (DeMiguel et al. 2009b). EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, ICC_ADJ uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3), and finally VW is the market value weighted strategy. The evaluation period starts on June 30, 1990, and ends on June 30, 2015.

	90-95	95-00	00-05	05-10	10-15
EGARCH	9.6	16.4	2.2	8.8	4.5
EW	7.6	18.6	1.0	1.7	11.9
GDP	8.7	17.8	-0.9	0.4	14.2
ICC_ADJ	8.0	22.4	1.3	5.1	14.1
ICC_RAW	8.3	23.6	2.7	5.2	12.8
MA	10.0	19.6	3.3	8.7	4.8
VW	7.8	18.4	-0.8	0.2	14.8

Table 16: **Subperiod analysis, cross-country allocation – returns**
This table shows the average geometric returns (annualized) for five year windows (June 1990 – June 1995, June 1995 – June 2000, etc). EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, ICC_ADJ uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3), and finally VW is the market value weighted strategy.

	90-95	95-00	00-05	05-10	10-15
EGARCH	0.119	0.230	0.023	0.104	0.101
EW	0.083	0.282	-0.002	0.018	0.243
GDP	0.107	0.266	-0.038	-0.006	0.312
ICC_ADJ	0.100	0.316	0.003	0.064	0.346
ICC_RAW	0.106	0.306	0.027	0.066	0.309
MA	0.128	0.291	0.040	0.103	0.106
VW	0.089	0.274	-0.036	-0.011	0.333

Table 17: **Subperiod analysis, cross-country allocation – Sharpe Ratios**
This table presents the (monthly) Sharpe Ratios (Sharpe 1966) for five year windows (June 1990 – June 1995, June 1995 – June 2000, etc). EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, ICC_ADJ uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the moving average historical returns (Section 4.2.3), and finally VW is the market value weighted strategy.

	Expansion			Contraction		
	SR	Return %	SD %	SR	Return %	SD %
EGARCH	0.180	10.48	15.40	-0.143	-2.05	32.18
EW	0.201	10.54	13.51	-0.222	-2.33	26.28
GDP	0.199	10.09	12.76	-0.211	-2.08	24.95
ICC_ADJ	0.232	11.71	13.14	-0.170	-1.60	24.05
ICC_RAW	0.232	12.04	13.61	-0.171	-1.57	23.73
MA	0.193	11.02	15.15	-0.120	-1.69	31.37
VW	0.194	9.83	12.68	-0.188	-1.83	24.73

Table 18: **Business cycle analysis, cross-country allocation**
This table presents selected performance measures for expansion and contraction periods (obtained from NBER). SR indicates the (monthly) Sharpe Ratio (Sharpe 1966), Return % is the geometric average return (annualized) for the respective time period in percent. SD % is the (annualized) standard deviation in percent. EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, ICC_ADJ also uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the moving average historical returns (Section 4.2.3), finally VW is the market value weighted strategy.

Panel A: benchmark portfolios							
	SR						
EW	0.112						
GDP	0.112						
VW	0.113						
Panel B: varying risk-aversion coefficient λ							
	1	2	3	4	5	6	
ICC_ADJ	0.148	0.150	0.147	0.145	0.143	0.141	
ICC_RAW	0.164	0.154	0.149	0.146	0.144	0.143	
EGARCH	0.102	0.107	0.110	0.115	0.118	0.120	
MA	0.116	0.122	0.124	0.130	0.134	0.135	
Panel C: varying confidence parameter c							
	0.1	2	5	10	20	30	100
ICC_ADJ	0.137	0.147	0.150	0.146	0.137	0.137	0.137
ICC_RAW	0.137	0.148	0.154	0.157	0.152	0.149	0.144
EGARCH	0.134	0.118	0.107	0.102	0.099	0.099	0.098
MA	0.136	0.127	0.122	0.116	0.110	0.108	0.104
Panel D: varying parameter τ							
	0.025	0.05	0.1	0.15	0.3	0.5	1
ICC_ADJ	0.145	0.148	0.150	0.150	0.139	0.137	0.135
ICC_RAW	0.146	0.150	0.154	0.156	0.153	0.147	0.142
EGARCH	0.123	0.115	0.107	0.105	0.098	0.098	0.098
MA	0.130	0.124	0.122	0.120	0.113	0.110	0.107

Table 19: **Sensitivity analysis: varying BL parameters**
This table displays the (monthly) Sharpe Ratio (Sharpe 1966) for different investment strategies and varying BL parameters. For convenience, the portfolios that do not use the BL approach are reprinted in Panel A. SR is the Sharpe Ratio. Panels B to D show how the Sharpe Ratio is affected when varying the risk-aversion coefficient λ (Panel B), the confidence parameter c (Panel C), and the parameter τ (Panel D), respectively. See Section 4.2.6.1 for a description of the BL implementation. EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, ICC_ADJ uses the BL method with expected returns proxied by the ICC estimates adjusted for analysts' sluggishness (Section 4.2.2), ICC_RAW uses the BL method with expected returns estimated by the ICC (Section 4.2.2), MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3), and finally VW is the market value weighted strategy. The evaluation period starts on June 30, 1990, and ends on June 30, 2015.

	SR	P	Return %	SD %	MDD %	Omega	CEQ %	TO %
EGARCH	0.109	0.800	8.29	17.87	53.65	1.341	3.51	43
EW	0.107	0.758	7.68	15.47	48.07	1.321	3.36	4
GDP	0.106	0.614	7.45	14.72	45.85	1.319	3.28	4
MA	0.113	0.659	8.51	17.72	53.36	1.350	3.83	16
VW	0.102	1.000	7.27	14.86	45.31	1.305	3.18	3

Table 20: **Performance and risk metrics, cross-country allocation – full investment universe**
This table presents performance and risk metrics for the investment strategies that do not use the ICC based on the full investment universe. SR indicates the (monthly) Sharpe Ratio (Sharpe 1966). P is the p-value of the test whether the respective Sharpe Ratio is different from the VW Sharpe Ratio using the method by Ledoit and Wolf (2008). Return % is the geometric average return (annualized, in percent) over the sample period. SD % is the (annualized) standard deviation in percent. MDD % represents the maximum one-year drawdown in percent (Grossman and Zhou 1993). Omega is a risk-adjusted performance measure that takes higher moments into account (Shadwick and Keating (2002)). CEQ % stands for certainty equivalent return and is equal to the average return minus the portfolio variance multiplied by the risk-aversion coefficient divided by two (DeMiguel et al. 2009b). TO is the average one-way portfolio turnover over all portfolio formation dates in percent. EGARCH is based on the BL method with expected returns estimated through an EGARCH model (Section 4.2.3), EW is the equally-weighted portfolio, GDP weighs each country proportional to its GDP, MA is another strategy based on the BL approach with expected returns estimated by the historical moving average return (Section 4.2.3), finally VW is the market value weighted strategy. The evaluation period starts on June 30, 1990 and ends on June 30, 2015.

4.5 CONCLUSION

I demonstrate how to improve naive international diversification strategies by using a Black and Litterman (1992) optimization setting. I find that a forward-looking expected return proxy, the ICC, outperforms sophisticated time-series models as well as a simple moving average. In this analysis, I took the point of view of an U.S. investor. However, given that benefits to diversification are usually higher for non-U.S. investors (Driessen and Laeven 2007), my results are likely generalizable to other countries.

One drawback of the BL approach is the difficulty of obtaining investor's views on the expected return of different asset classes. The ICC offers a way to solve this problem. It provides expected return estimates that are based on forward-looking data. It is also reasonable to assume that asset managers have access to analysts' earnings estimates, as this data is available in many commercial financial databases (for example, TR). Using the market ICC, asset managers can identify markets that are relatively cheap compared to their forecasted aggregated earnings and growth rates. This leads to superior performance in the resulting portfolio, which continues to hold when controlling for risk, as measured by the standard deviation of portfolio returns.

There are limitations to this study. First, the ICC's predictive power increases with the investment horizon (Li et al. 2013). It works well for a one year horizon. The ICC is not suitable for a short investment horizon of one month or less. Second, the ICC computation has high data requirements and the implementation is not trivial. Some asset managers might be reluctant to invest in such a set-up. Third, the BL approach assumes an equilibrium for the entire world market. For practical reasons, I only use the stock markets of six large industrialized countries. Finally, the country weights of the ICC portfolios fluctuate significantly over time. Asset managers may find it challenging to shift the allocation so radically.

The information content of country ICC estimates varies across countries. An interesting future research topic would be to investigate the drivers of these differences. For example, how much does the number of analysts covering a market influence the quality of the market ICC? How important is the predictive ability of each analyst for the market ICC? A different avenue for further research would be to combine the ICC or analysts' forecasts with new trends in data science, such as machine learning. Kelly and Pruitt (2015), for example, use price-dividend ratios and machine learning algorithms to forecast stock market returns.

Overall, my findings contribute to the international diversification and BL literature. The results are also relevant to asset managers who have to allocate money across countries.

5

MEAN-VARIANCE OPTIMIZATION USING FORWARD-LOOKING RETURN ESTIMATES

Despite its theoretical appeal, Markowitz (Markowitz 1952) mean-variance portfolio optimization is plagued by practical issues. It is especially difficult to obtain reliable estimates for a stock's expected return. Recent research has therefore focused on minimum volatility portfolio optimization, which implicitly assumes the same expected return for all assets. I provide guidance on how to use expected return forecasts in a maximum Sharpe Ratio portfolio optimization setting. Furthermore, I demonstrate that following these recommendations leads to portfolios that outperform on a risk-adjusted basis the minimum volatility portfolio as well as naive benchmarks such as the value-weighted and equally-weighted market portfolio.[15]

5.1 INTRODUCTION

Mean-variance portfolio optimization based on Markowitz (1952) continues to be a frequently discussed topic in academic research and among practitioners. While the theory is intuitive and appealing, the practical issues associated with the implementation of this framework are numerous. For example, several authors point toward the high sensitivity of optimal

15 This chapter is based on Bielstein and Hanauer (2016).

portfolio weights to expected asset returns (Best and Grauer 1991, Chopra and Ziemba 1993). In order to mitigate the effect of large estimation errors when forecasting returns from historic data (Elton 1999), one approach is to impose constraints on the portfolio weights (for example, Frost and Savarino 1988 and Haugen 1997). In contrast, Jagannathan and Ma (2003) propose to ignore the expected return altogether and rather to focus on the minimum variance portfolio (MVP).[16]

The MVP is the left-most tip of the Markowitz efficient frontier. For its computation, only the asset covariance matrix is needed (i.e. there is no need for stock return forecasts). Recent studies analyze different approaches to minimum volatility optimization. Clarke et al. (2006) find that the minimum volatility portfolio outperforms the market value-weighted portfolio in the U.S. equity market. Clarke et al. (2011) investigate the drivers of minimum volatility portfolio weights. Other authors examine low volatility construction methods (Chow et al. 2014) and the impact of constraints on the minimum volatility portfolio (Chow et al. 2016). These studies show that the MVP consistently outperforms a value-weighted benchmark on a risk-adjusted basis. This finding indicates that current methods to estimate the asset covariance matrix work well. However, the minimum variance portfolio is only mean-variance efficient if you assume that all assets have the same expected return (Chow et al. 2011). Clearly, this assumption is unlikely to hold in reality.

To address this shortcoming, I show that the implied cost of capital (see, for example, Gebhardt et al. 2001) can be used as a reasonable alternative. The implied cost of capital is defined as the discount rate that matches analyst earnings forecasts with the current stock price and therefore, can be

16 I use minimum variance portfolio and minimum volatility portfolio interchangeably throughout this chapter.

interpreted as the expected return of a stock. I provide evidence that these forward-looking estimates deliver better results than naive estimates based on historic returns. Moreover, I demonstrate how to correct for a known bias (see Guay et al. 2011) in these estimates. The resulting expected return forecasts lead to optimized portfolios that robustly outperform the minimum volatility portfolio as well as value-weighted and equally-weighted market benchmarks.

5.2 EXPECTED STOCK RETURNS

Although expected stock returns are the most important input for many portfolio optimization applications, they are extremely difficult to estimate. Already early studies have criticized the practice of treating the mean time-series stock return as the "true" value (Frankfurter et al. 1971, Barry 1974). As a response to this criticism, authors proposed to use a Bayesian technique to estimate the expected return which explicitly takes the uncertainty of the time-series mean into account (Jorion 1986, Frost and Savarino 1986). A different approach is to use a factor model, such as the CAPM. Jorion (1991) compares the historic average stock return with estimates derived from a Bayesian approach and from the CAPM. Fama and French (1992) build upon the CAPM by including two more factors. However, the authors acknowledge that expected returns based on these models contain a large amount of statistical noise (Fama and French 1997). As mean-variance optimized portfolios are very sensitive to estimates of the expected return (Best and Grauer 1991), the usefulness of those models may be limited. Furthermore, historic estimates of the expected return require a very long history in order to be a reliable estimate for the true expected return (Elton 1999).

The drawbacks of the use of historic data to estimate the expected stock return has prompted a new strand of literature, which led to the development of an estimation method using earnings forecasts (Gebhardt et al. 2001, Claus and Thomas 2001, Easton 2004, Ohlson and Juettner-Nauroth 2005, Pástor et al. 2008). This approach does not rely on historic stock return data but instead, backs out the discount rate that equates the current stock price with discounted future cash flows. This discount rate is an internal rate of return implied by the current stock price, hence its name, ICC. The ICC offers numerous advantages in a portfolio optimization setting. First, the estimates are about one-tenth as volatile as those based on historic returns (Lee et al. 2009). Second, they are based on information that was available to investors at the respective point in time (Claus and Thomas 2001). Third, the ICC is positively correlated with risk under reasonable assumptions (Pástor et al. 2008).

This relatively new approach is not a panacea, of course, but also faces some criticism. I argue that these criticisms are either mitigated in this study setting or explicitly incorporated in the expected return estimate. Hou et al. (2012) argue that the availability of ICCs is biased toward larger firms because those firms are more likely to be covered by analysts. As is common in portfolio selection studies,[17] I limit the investment universe to the 1000 largest companies based on the previous month's market capitalization. Even for early years, this constraint is more limiting than the availability of ICC estimates. Researchers have also investigated how ICC estimates are affected by measurement errors (Mohanram and Gode 2013, Wang 2015). While those studies find that these measurement errors can be associated with firm characteristics, which could lead to spurious results in

17 Amenc et al. 2012, Chow et al. 2016, Chow et al. 2014, DeMiguel et al. 2009a.

a regression setting, I only employ the ICC as a proxy for the expected stock return. I do not use the ICC as a variable in a regression. Finally, Guay et al. (2011) report that analysts' earnings forecasts are sluggish with respect to information contained in historic stock returns. This is a problem in the current study as it weakens the association between the ICC and future realized stock returns. As a remedy, I include a momentum variable (stock return of the past twelve months lagged by one month, see Jegadeesh and Titman 1993 and Carhart 1997) in my return forecasts.

As mentioned above, the literature offers different methods to calculate the ICC. I choose the methodology of Gebhardt et al. (2001) to calculate the ICC because previous studies have found a robust and strong association with future realized returns (Nekrasov and Ogneva 2011, Mohanram and Gode 2013), which is also confirmed in my sample.

5.3 METHODOLOGY

5.3.1 *Data*

The investment universe is based on the intersection of CRSP and Compustat databases. I follow the procedures outlined in Fama and French (1993) and Chow et al. (2011). More precisely, I include only stocks with share codes 10 or 11 that are traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or National Assocation of Securities Dealers Automated Quotations (NASDAQ) (exchange code 1, 2, or 3). Also, according to Fama and French (1993), I require that the book value of common equity is positive and non-missing. Next, I remove observations with missing returns in the previous 60 months, so that I have a full set of returns to estimate the covariance matrix. Furthermore, I need an ICC estimate[18] and the momentum variable[19]. The latter requirement is non-binding as I only consider stocks with a 60 month return time-series. I drop observations with missing market value (calculated as the product of share price and common shares outstanding). Finally, I select the 1000 largest stocks by last month's market capitalization. Table 21 provides an overview of my screens. The variables ICC and momentum are winsorized at the first and last percentile at each portfolio formation date. The sample period begins in 1985 because coverage of companies in the IBES database (required for the ICC computation) starts off low and increases substantially over time with 1985 being the first year where the coverage approximates the whole stock market (Claus and Thomas 2001). The sample ends in 2014 with the portfolio evaluation ending one year later in 2015. The portfolio formation date is June 30. I choose this date because most companies have their financial year-end on December 31 so that their annual report will be public by June 30 of the following year.

Table 22 provides summary statistics of my sample. The average market capitalization is 8.1 billion USD. Note that the ICC estimate is, almost by an order of magnitude, less volatile than the return estimate based on the five-year time-series average return. Previous studies have also documented this finding (Lee et al. 2009).

Examining the correlations between the variables in my sample also gives interesting insights (Table 23). The ICC estimate is negatively correlated (-0.21) with the momentum variable indicating that analysts might be slow

18 Data requirements and methodology are described in Chapter 3.
19 Stock return of the past twelve months lagged by one month, see Jegadeesh and Titman (1993) and Carhart (1997).

Number	Screen
1	Merge CRSP with Compustat
2	Share codes 10 or 11
3	Traded on the NYSE, AMEX, or NASDAQ (exchange code 1, 2, or 3)
4	Book value is larger than 0 and non-missing
5	No missing returns in the previous 60 months
6	Non-missing values in the following variables: momentum ICC, and market value
7	Select largest 1000 stocks by last month's market cap

Table 21: **Sample screens of investment universe**
This table shows the screens I apply to build the investment universe. I use the following databases: CRSP, Compustat, and IBES.

to incorporate recent changes in stock prices into their earnings forecasts.[20] Furthermore, the ICC measure is positively correlated (0.58) with the book-to-market value. This is expected as the ICC can be viewed as a value measure (Li et al. 2014). In line with this finding, the ICC is negatively correlated (−0.23) with the annualized five-year average time-series return. Stocks that performed well in the recent past tend to be expensive and would therefore have a low book-to-market value.

5.3.2 *Inputs*

The optimization technique I employ maximizes the expected portfolio Sharpe Ratio. Therefore, I have to compute the covariance matrix of the investment universe as well as the expected return for each security. I estimate the covariance matrix using 60 monthly returns. As I have more stocks than time periods, I have to shrink the covariance matrix in order to

20 If earnings forecasts are not adjusted, an increase in the share price will lead to a lower discount rate so that the discounted future cash flows equal the share price again.

	Mean	SD	P25	P50	P75
MV (bn $)	8.100	24.039	1.011	2.172	5.551
MOM	0.203	0.458	-0.041	0.150	0.365
RET_HIST	0.149	0.172	0.045	0.133	0.237
ICC	0.096	0.026	0.079	0.095	0.112

Table 22: **Summary statistics of investment universe**
This table shows summary statistics of the investment universe. The columns display the sample mean (Mean), standard deviation (SD), first quartile (P25), median (P50), and third quartile (P75). The market capitalization (MV), momentum return (MOM), annualized five-year historic average return (RET_HIST), and the ICC are displayed. The sample spans the period from June 30, 1985, to June 30, 2014 (yearly frequency).

	MV	MOM	RET_HIST	ICC	BM	Beta
MV	1.00	0.00	0.01	-0.12	-0.11	-0.06
MOM	0.00	1.00	0.38	-0.21	-0.26	0.07
RET_HIST	0.01	0.38	1.00	-0.23	-0.39	-0.00
ICC	-0.12	-0.21	-0.23	1.00	0.58	0.09
BM	-0.11	-0.26	-0.39	0.58	1.00	-0.06
Beta	-0.06	0.07	-0.00	0.09	-0.06	1.00

Table 23: **Correlation matrix**
This table displays a correlation matrix including the main variables in the data set: market capitalization (MV), momentum return (MOM), annualized five-year historic average return (RET_HIST), implied cost of capital (ICC), book-to-market value (BM), and the beta according to the CAPM (Beta) estimated over the preceding 60 months.

be able to invert it (which is required for the mean-variance optimization, Clarke et al. 2006). Furthermore, shrinking the covariance matrix helps to reduce estimation errors (Chow et al. 2014). I use the method developed by Ledoit and Wolf (2004), which has been employed in many other studies (for example, Clarke et al. 2006 and Chow et al. 2014).

I use the firm-level ICC (calculated according to Gebhardt et al. 2001) as the basis for the expected stock return measure. In order to correct for analysts' sluggishness with respect to information in past stock returns (Guay et al. 2011), I perform the following adjustments. First, I standardize (i.e.

subtracting the mean and dividing by the standard deviation) the momentum variable for each company at each portfolio formation date. Second, I compute a rescaled momentum variable by multiplying the standardized variable with the ICC standard deviation. I then calculate the expected excess return of each stock with the following formula:

$$\mathtt{expected\_return}_{i,t} = \mathtt{ICC}_{i,t} + \mathtt{MOM}_{i,t,rescaled} - \mathtt{risk\_free\_yield}_t \quad (24)$$

where $\mathtt{expected\_return}_{i,t}$ is the expected return of stock i at time t, $\mathtt{ICC}_{i,t}$ is the ICC estimate calculated according to Gebhardt et al. (2001) for stock i at time t, $\mathtt{MOM}_{i,t,rescaled}$ is the rescaled momentum variable described above for firm i at time t, and $\mathtt{risk\_free\_yield}_t$ is the one-year maturity U.S. treasury rate at time t (downloaded from TR Datastream).

5.3.3 *Optimization*

The portfolio formation date is June 30 of each year in the sample period (1985–2014). On each rebalancing date, I calculate the portfolio weights that maximize the expected portfolio Sharpe Ratio:

$$\max_{\boldsymbol{w}} \frac{\boldsymbol{expected\_return}^{\top}\boldsymbol{w}}{\sqrt{\boldsymbol{w}^{\top}\boldsymbol{\Sigma}\boldsymbol{w}}} \quad (25)$$

where $\boldsymbol{w}$ is a vector containing the optimal weights, $\boldsymbol{expected\_return}$ is a vector of my expected return measure, and $\boldsymbol{\Sigma}$ is the (shrunken) covariance matrix of all stocks in the investment universe. The optimization constraints are the following: full investment ($\sum w_i = 1$), no short selling ($w_i \geqslant 0$ for all N stocks), and a maximum weight of 5% ($w_i \leqslant 0.05$ for all

N stocks). Furthermore, I round weights smaller than 0.01% to 0. In the absence of measurement errors, the optimization would work best without constraints. In practice though, measurement errors are prevalent and several authors have shown that imposing constraints improve portfolio metrics (Jagannathan and Ma 2003, Chow et al. 2016). Moreover, these constraints are common in portfolio choice studies (Chow et al. 2011, Clarke et al. 2011, Kritzman et al. 2010). In order to obtain the optimal portfolio weights, I use the Rsolnp package (Ghalanos and Theussl 2015), which employs a general non-linear augmented Lagrange multiplier method solver (Ye 1987).

5.4 PORTFOLIO EVALUATION

5.4.1 *Benchmarks*

I benchmark the optimized portfolio against several strategies common in the literature. First, a naive diversification strategy which just holds every stock in the investment universe weighted by its market value. Second, also a simple diversification strategy that equally weights each stock in the investment universe (DeMiguel et al. 2009b). Third, the MVP, which has been used extensively in recent research (Clarke et al. 2006, Clarke et al. 2011, Soe 2012, Chow et al. 2016). For the latter approach, I compute the optimized portfolio weights at each rebalancing date that minimize the expected portfolio standard deviation:

$$\min_{\boldsymbol{w}_{MVP}} \sqrt{\boldsymbol{w}_{MVP}^{\top} \boldsymbol{\Sigma} \boldsymbol{w}_{MVP}} \tag{26}$$

where $\boldsymbol{w}_{MVP}$ is a vector containing the optimal weights, and $\boldsymbol{\Sigma}$ is the (shrunken) covariance matrix of all stocks in the investment universe. The optimization constraints are the same as for the maximum Sharpe Ratio optimization (Section 5.3.3).

Finally, I also include a maximum Sharpe Ratio optimization, but I use historic data to estimate the expected return. More precisely, I run the optimization from Equation 25 at each portfolio formation date and use the vector of average five-year time-series returns as $\boldsymbol{expected\_return}$.

5.4.2 *Portfolio descriptive statistics*

Figure 7 shows how many stocks the optimizer selects at each portfolio formation date for the three different optimization strategies. You can see that the MVP portfolio tends to select more stocks than the other two methods. Also, for all strategies, the number of stocks fluctuates over time. The number of stocks in the ICC_MOM portfolio ranges from 23 to 57.

Table 24 presents investability indicators for all portfolios in this study. As expected, the market value-weighted portfolio has the lowest turnover since it replicates the investment universe. The equally-weighted portfolio has an average turnover of 40%, which reflects the need to rebalance stocks at each portfolio formation date due to different stock performances over the year. Note that the MVP's turnover is about 20 percentage points lower than the turnover of the two strategies based on the maximum Sharpe Ratio optimization. I include two portfolio concentration measures: the effective number of stocks (effective N)[21] and the sum of the weights of the

21 Calculated as the reciprocal of the Hirshman-Herfindahl index (Hirschman 1945, Herfindahl 1950) of portfolio weights (Chow et al. 2014).

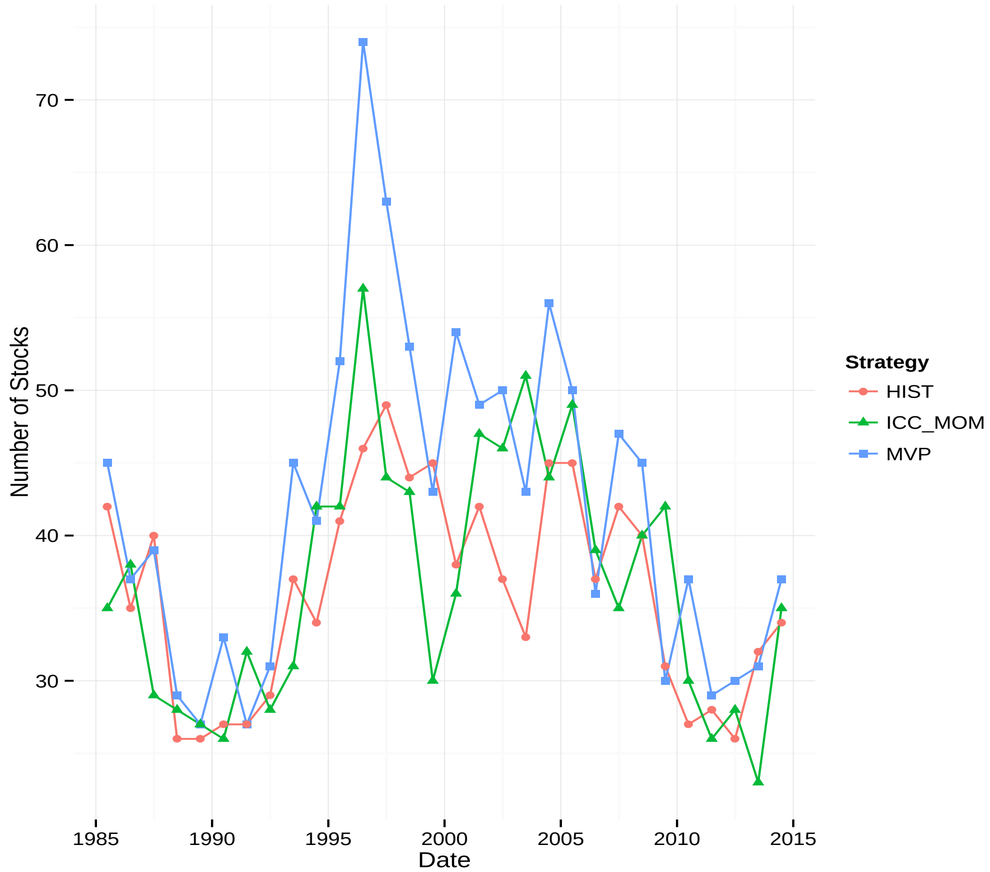

Figure 7: **Number of stocks over time**
This figure shows the number of stocks in the optimized portfolio for each optimization strategy. HIST is the strategy that maximizes the expected portfolio Sharpe Ratio using a time-series average return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2). MVP is the minimum variance portfolio (Section 5.4.1).

ten largest portfolio positions (W top 10). The equally-weighted portfolio has the lowest concentration followed by the value-weighted portfolio as these strategies invest in all stocks in the investment universe. The average effective number of stocks is significantly lower for the three optimization strategies (25 to 28) although the MVP portfolio has a somewhat higher number than the HIST and ICC_MOM portfolios.

	Turnover	# of stocks	Effective N	W top 10
VW	0.04	1000	150	0.19
EW	0.20	1000	1000	0.01
MVP	0.46	42	28	0.48
HIST	0.65	36	25	0.49
ICC_MOM	0.64	37	25	0.49

Table 24: **Investability indicators**
This table shows investability indicators for all portfolios in this study. Turnover is the average one-way portfolio turnover at each portfolio formation date. # of stocks is the average number of stocks in each portfolio at each portfolio formation date. Effective N is the reciprocal of the Hirshman-Herfindahl index of portfolio weights. W top 10 is the sum of the weights of the ten largest portfolio positions. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

5.4.3 *Portfolio performance and risk*

Figure 8 displays the hypothetical development of a 1 USD investment in each of the different portfolio strategies at the beginning of the sample period. The ICC_MOM portfolio clearly outperforms the other strategies with the equally-weighted portfolio coming in second. The MVP displays the lowest cumulated return but this comparison ignores risk.

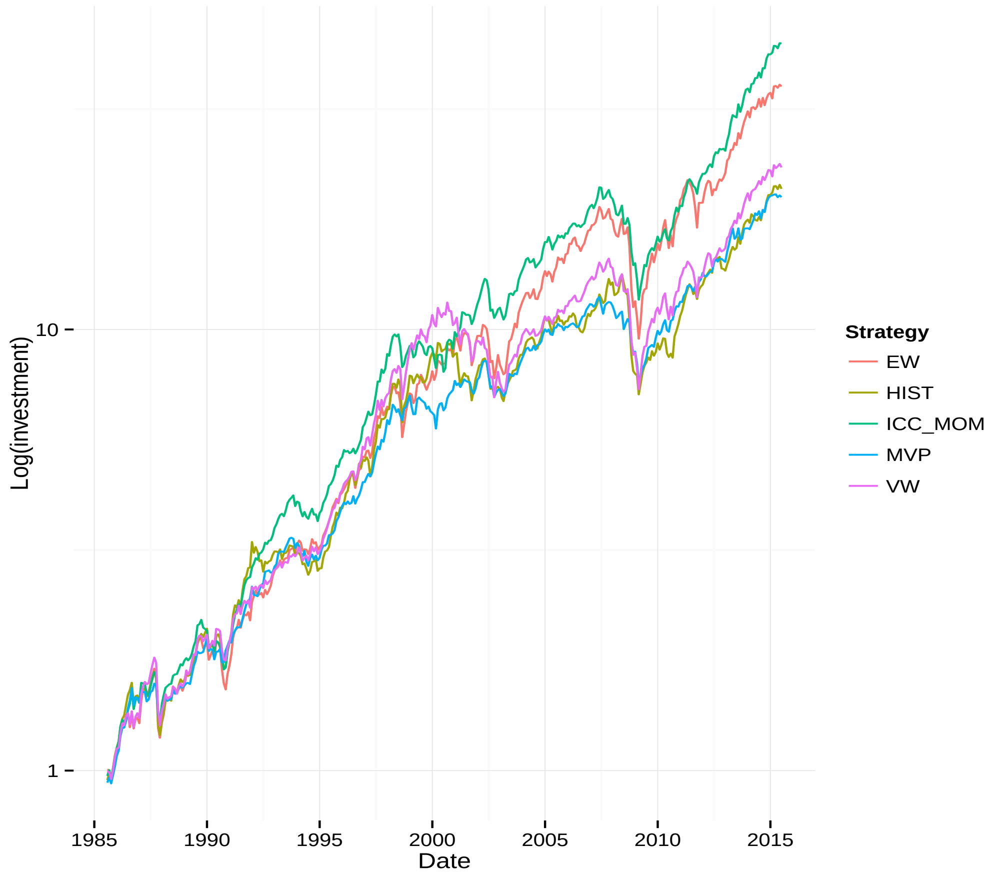

Figure 8: **Cumulative return**
This figure displays the hypothetical development of a 1 USD investment for each of the investment strategies. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

Next, I calculate performance and risk metrics for each strategy (Table 25). To calculate the ex post Sharpe Ratio, I need the return of the risk-free asset, which I obtain from Kenneth French's website[22]. I compute the maximum one-year drawdown (Grossman and Zhou 1993) as the worst twelve month return in the sample for each portfolio:

$$MDD_i = -\min(r_{i,12m}) \tag{27}$$

where $r_{i,12m}$ is the the return over the preceding 12 months of portfolio i.

These figures corroborate the dominance of the ICC_MOM strategy. It has the highest Sharpe Ratio and Information Ratio. The risk (as measured by the portfolio standard deviation) is somewhere between the MVP (lowest) and equally-weighted (highest) portfolios. Note that when measured by the Sharpe Ratio, the MVP portfolio now comes in second, beating the equally-weighted portfolio. This change in ranking is driven by the low standard deviation of the MVP portfolio. Also noteworthy is the poor performance of the HIST portfolio. It shows a relatively low return while displaying a high level of risk. This finding is in line with the literature. Various studies have discussed the problems associated with the use of the historic mean return as a proxy for the expected return in a mean-variance portfolio optimization (Jobson and Korkie 1981b, Michaud 1989, DeMiguel et al. 2009b).

A different way to demonstrate these results is through a risk-return plot (Figure 9). As an investor prefers a high return and a low standard deviation, portfolios to the north-west of the graph dominate those to the south-east. The ICC_MOM portfolio, with its high average return and mod-

22 http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

erate standard deviation, has the most preferable position in the risk-return space. The MVP portfolio displays a low return but also has a very low standard deviation.

An investor might also be interested in how often the optimization strategies outperform the value-weighted portfolio (Table 26). The sample period comprises 30 years. I compare the cumulated return of all the different strategies twelve months after each portfolio formation date. In 19 out of 30 years (63% of the time) the ICC_MOM strategy outperforms the value-weighted portfolio. In comparison, the HIST portfolio only outperforms the value-weighted portfolio 50% of the time.

Next, I compute additional performance and risk measures for the different portfolio strategies. These measures take the non-normality of portfolio returns into account (Farinelli et al. 2008). As an alternative to the Sharpe Ratio, I calculate the Omega metric (Shadwick and Keating 2002), which captures higher moments in the return distribution. The Omega metric considers the distribution of returns above a specified target return in relation to the distribution of returns below the specified target return. A higher value is preferable to a lower one. The risk-free return is my target return. I follow Kaplan and Knowles (2004) for the implementation:

$$\text{Omega} = \frac{\bar{r}_{i,ec}}{\frac{1}{T}\sum_{t=1}^{T}\max(0 - r_{i,ec}, 0)} + 1 \tag{28}$$

where $\bar{r}_{i,ec}$ is the mean excess return of portfolio i over the risk-free return.

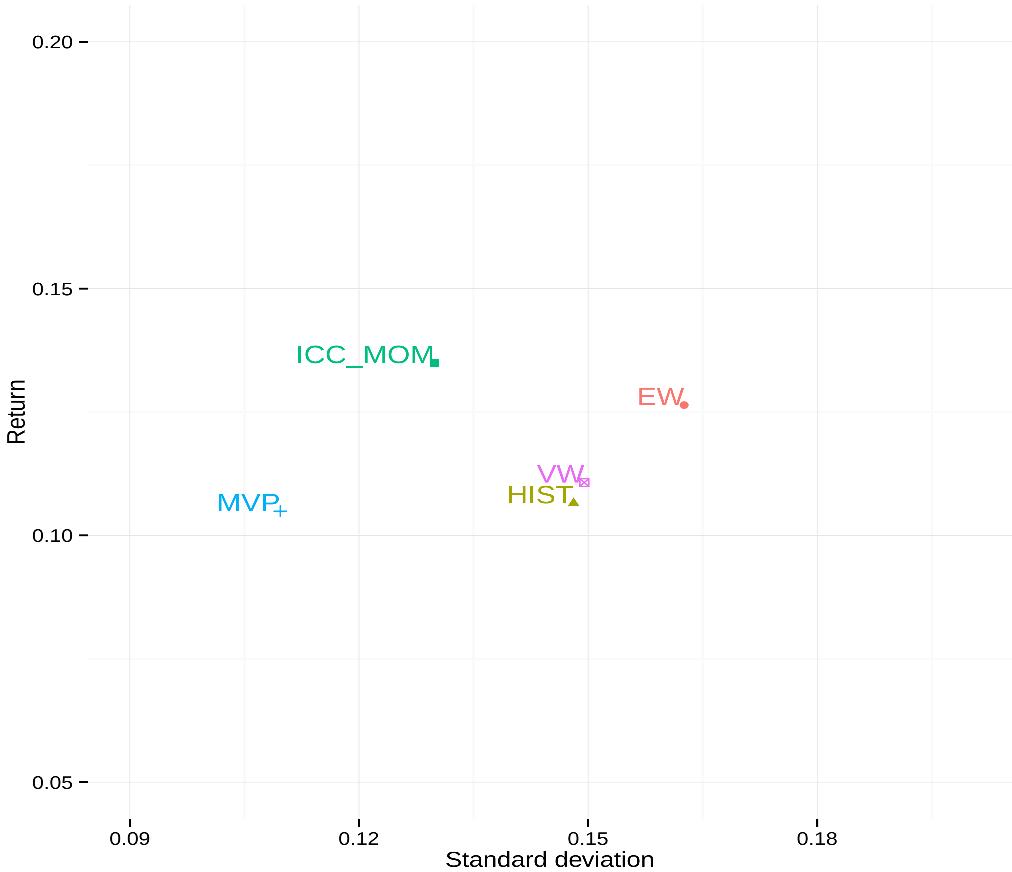

Figure 9: **Risk-return graph**
This figure presents the different portfolio strategies in the risk-return space. The geometric average return (annualized) is plotted against the portfolio standard deviation (annualized). VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

As additional risk measures, I compute skewness, kurtosis, and value-at-risk. These measures also summarize the return distributions of the different portfolio strategies.

$$\text{skewness} = \mathbf{E}\left[\left(\frac{r_{i,t} - \bar{r}_i}{\sigma_i}\right)^3\right] \tag{29}$$

$$\text{kurtosis} = \mathbf{E}\left[\left(\frac{r_{i,t} - \bar{r}_i}{\sigma_i}\right)^4\right] \tag{30}$$

$$\text{VaR}_\alpha = q_\alpha \tag{31}$$

where $r_{i,t}$ is the return for strategy i in month t, $\bar{r}_i$ is the mean monthly return for strategy i, σ_i is the standard deviation of the monthly returns for strategy i, and q_α is the α quantile of the return distribution for strategy i.

The results are presented in Table 27. First, the ranking according to the Omega metric confirms the ranking according to the Sharpe Ratio from Table 25. The ICC_MOM portfolio has the highest value followed by the MVP strategy. The MVP portfolio performs well on the additional risk measures. It has the lowest skewness, kurtosis, and value-at-risk at the threshold loss of 1%. The ICC_MOM portfolio comes in second for skewness and value-at-risk at the threshold loss of 1%. Its kurtosis is slightly higher than the VW portfolio, but it has the lowest value-at-risk with a threshold loss of 5%. Overall, these additional performance and risk metrics corroborate the findings from Table 25.

	SR	Return %	SD %	MDD %	TE	IR
VW	0.1581	11.07	14.95	41.95	0.0000	
EW	0.1741	12.64	16.26	41.70	0.0152	0.0896
MVP	0.1879	10.49	10.97	28.55	0.0311	-0.0283
HIST	0.1519	10.65	14.81	40.77	0.0242	-0.0136
ICC_MOM	0.2238	13.49	12.99	36.01	0.0264	0.0597

Table 25: **Performance and risk metrics**
This table presents performance and risk metrics for the different investment strategies. SR indicates the (monthly) Sharpe Ratio. Return % is the geometric average return (annualized) over the sample period in percent. SD % is the (annualized) standard deviation in percent. MDD % stands for the maximum one-year drawdown in percent (Grossman and Zhou 1993). TE represents the tracking error versus the value-weighted portfolio. IR is the information ratio against the value-weighted portfolio. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

5.4.4 *Portfolio risk attribution*

In this section, I investigate to what extent the portfolio returns can be explained by known risk factors. To this end, I regress the portfolio excess returns on the returns of different risk factors. First, I run regressions including the market (Market) factor (Sharpe 1964, Lintner 1965, and Mossin 1966), the size (SMB) factor (Banz 1981, Fama and French 1992), the value (HML) factor (Fama and French 1992, Fama and French 1993), and the momentum (WML) factor (Jegadeesh and Titman 1993, Carhart 1997).[23] The results are presented in Table 28. The variation in the market value-weighted portfolio (Regression (1)) is almost entirely accounted for by the variation in the risk-factors (R^2 of 99%). The exposure to larger firms and

23 All factors were downloaded from French (2016): http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

	Count outperf.	Outperf. %
VW	0	0
EW	18	60
MVP	13	43
HIST	15	50
ICC_MOM	19	63

Table 26: **Count of outperformance per year**
This table shows how often the different investment strategies outperform the value-weighted strategy. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

higher book-to-market firms is explained by the construction of the investment universe. It reflects the data requirements for computing the ICC and the selection of the 1000 largest companies by market capitalization.

The equally-weighted portfolio also has a high exposure to the market factor but the SMB coefficient is positive, which means that small stocks are overweighted. Due to the yearly rebalancing, stocks with an above average return that tend to be expensive are (partially) sold. This leads to a positive exposure to the HML factor. For the same reason, the WML factor loads negatively, however, it is not statistically significant.

The MVP portfolio has the smallest exposure to the market factor, which is not surprising as the optimizer selects stocks that have a low correlation with other stocks. Also noteworthy is the high loading on the HML factor. Stocks with a low standard deviation tend to be value stocks and this is reflected in the positive HML coefficient.

The strategy based on the time-series mean return tends to have a stronger exposure to growth stocks (the HML coefficient loads negatively), albeit this effect is not significant. This portfolio loads positively on the WML

	Omega	Skewness	Kurtosis	VaR 5%	VaR 1%
VW	1.509	-0.831	5.72	-6.83	-10.29
EW	1.584	-0.969	6.59	-6.87	-11.06
MVP	1.628	-0.653	4.30	-5.08	-8.63
HIST	1.496	-0.913	6.12	-6.15	-11.07
ICC_MOM	1.803	-0.779	5.80	-4.85	-10.04

Table 27: **Additional performance and risk metrics**
This table presents additional performance and risk metrics for the different investment strategies. Omega is a risk-adjusted performance measure that takes higher moments into account (Shadwick and Keating 2002). Skewness indicates the skewness of the respective return distribution. Kurtosis displays the kurtosis of the respective return distribution. VaR stands for value-at-risk and the percentage indicates the threshold loss. It is calculated using the historical return distribution and presented in percentage notation. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

factor as the average return will be higher for stocks with a strong recent performance.

Finally, the ICC_MOM strategy captures the value and momentum premium. It achieved a positive alpha of 2.6% (annualized), which is significantly different from zero at the 10% level.

The second set of regressions includes the aforementioned factors plus the betting against beta (BAB) factor from Frazzini and Pedersen (2014),[24] which reflects the premium for low-beta stocks. Table 29 presents the results. All portfolios have a positive exposure toward the BAB factor, ranging from very low (0.02, VW), to moderately high (0.21, HIST). The Sharpe Ratio optimized and minimum volatility portfolios display the highest exposure to the BAB factor. This reflects the fact that the optimizer tends

24 The factor returns were downloaded from https://www.aqr.com/library/data-sets/betting-against-beta-equity-factors-monthly.

to select stocks that are less correlated with the market (low-beta). The previously significantly positive alpha of the ICC_MOM strategy is now no longer significant (1.75%, annualized). The WML factor is also now no longer significant in Regressions (4) and (5).

Last, I run regressions including the five Fama-French factors (Fama and French 2014): Market, SMB, HML, a profitability factor (RMW), and an investment factor (CMA), plus the WML factor (Jegadeesh and Titman 1993, Carhart 1997).[25] Table 30 shows that the RMW factor loads significantly positively in all regression settings, which indicates an overweighting of strong profitability firms. The factor pertaining to investment (CMA) produces positive coefficients for the VW, EW, and MVP portfolios, suggesting that these portfolios overweight firms that invest conservatively. This is intuitive for the MVP portfolio as low-risk companies tend to be mature firms with stable investment outlays. The coefficient of the CMA factor is significant and negative for the HIST portfolio, which suggests that this portfolio leans toward firms that have high investments. This finding ties in with the results from Regression (3) in Table 28. The HIST portfolio selects growth firms that tend to have higher investment needs. Finally, the CMA factor is small and not significant for the ICC_MOM strategy.

25 These factor returns were downloaded from French (2016): http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

	Dependent variable:				
	Return				
	VW	EW	MVP	HIST	ICC_MOM
	(1)	(2)	(3)	(4)	(5)
Alpha	0.0003*	0.001	0.001	0.001	0.002*
	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)
Market	0.99***	1.01***	0.57***	0.82***	0.75***
	(0.01)	(0.02)	(0.03)	(0.04)	(0.03)
SMB	−0.13***	0.27***	−0.15***	−0.01	−0.004
	(0.01)	(0.03)	(0.04)	(0.06)	(0.04)
HML	0.08***	0.28***	0.40***	−0.04	0.43***
	(0.01)	(0.03)	(0.04)	(0.06)	(0.05)
WML	−0.01	−0.02	0.07***	0.10***	0.08**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
Observations	360	360	360	360	360
Adjusted R^2	0.99	0.96	0.59	0.73	0.71

Table 28: **Risk attribution regressions – four factors**
This table shows risk attribution regressions. Risk factors are market (Market), size (SMB), value (HML), and momentum (WML). The dependent variable is the excess portfolio return from the respective investment strategy. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2). *, **, and *** indicate a significant difference from zero on a ten-, five-, and one-percent level, respectively.

	Dependent variable:				
	Return				
	VW	EW	MVP	HIST	ICC_MOM
	(1)	(2)	(3)	(4)	(5)
Alpha	0.0002	0.0005	0.001	−0.0005	0.001
	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)
Market	0.99***	1.01***	0.57***	0.82***	0.75***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)
SMB	−0.13***	0.27***	−0.15***	−0.01	−0.01
	(0.01)	(0.03)	(0.04)	(0.06)	(0.04)
HML	0.06***	0.25***	0.32***	−0.18***	0.34***
	(0.01)	(0.04)	(0.04)	(0.05)	(0.05)
WML	−0.01**	−0.03	0.04*	0.05	0.04
	(0.01)	(0.02)	(0.02)	(0.03)	(0.04)
BAB	0.02**	0.05*	0.12***	0.21***	0.14***
	(0.01)	(0.02)	(0.03)	(0.04)	(0.04)
Observations	360	360	360	360	360
Adjusted R^2	0.99	0.96	0.60	0.75	0.72

Table 29: **Risk attribution regressions – four factors and BAB**
This table shows risk attribution regressions. Risk factors are market (Market), size (SMB), value (HML), momentum (WML), and betting against beta (BAB). The dependent variable is the excess portfolio return from the respective investment strategy. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2). *, **, and *** indicate a significant difference from zero on a ten-, five-, and one-percent level, respectively.

	Dependent variable:				
	Return				
	VW	EW	MVP	HIST	ICC_MOM
	(1)	(2)	(3)	(4)	(5)
Alpha	−0.0003*	−0.0005	0.0002	−0.0002	0.001
	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)
Market	1.00***	1.04***	0.60***	0.83***	0.76***
	(0.005)	(0.01)	(0.03)	(0.03)	(0.03)
SMB	−0.10***	0.34***	−0.12***	0.10**	0.05
	(0.01)	(0.02)	(0.04)	(0.05)	(0.05)
HML	0.02***	0.17***	0.29***	−0.01	0.39***
	(0.01)	(0.03)	(0.05)	(0.07)	(0.05)
WML	−0.02***	−0.04**	0.06**	0.10***	0.07**
	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)
RMW	0.12***	0.23***	0.13**	0.32***	0.18***
	(0.01)	(0.03)	(0.05)	(0.07)	(0.06)
CMA	0.06***	0.13***	0.18**	−0.22**	0.01
	(0.01)	(0.04)	(0.08)	(0.09)	(0.08)
Observations	360	360	360	360	360
Adjusted R^2	1.00	0.97	0.59	0.76	0.71

Table 30: **Risk attribution regressions – six factors**
This table shows risk attribution regressions. Risk factors are market (Market), size (SMB), value (HML), momentum (WML), profitability (RMW), and investment (CMA). The dependent variable is the excess portfolio return from the respective investment strategy. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2). *, **, and *** indicate a significant difference from zero on a ten-, five-, and one-percent level, respectively.

5.5 ROBUSTNESS TESTS

5.5.1 *Alternative expected return proxies*

In Section 5.3.2, I described how I constructed the expected return measure. My approach was to add the rescaled momentum variable to the ICC estimate. For this robustness test, I explore different expected return proxies. First, I evaluate a more sophisticated method to combine the ICC estimate with a correction for analysts' sluggishness. This procedure also starts by standardizing (i.e. subtracting the mean and dividing by the standard deviation) the momentum variable for each company in each month. Next, I compute a rescaled momentum variable by multiplying the standardized variable with the ICC standard deviation. Instead of simply adding the rescaled momentum variable as previously done, I here weight it with the factor w_{MOM}/w_{ICC}:

$$expected\_return_{i,t} = ICC_{i,t} + \frac{w_{i,t,MOM}}{w_{i,t,ICC}} \times MOM_{i,t,rescaled} - risk\_free\_yield_t \tag{32}$$

where $expected\_return_{i,t}$ is the expected return of stock i at time t, $ICC_{i,t}$ is the ICC estimate calculated according to Gebhardt et al. (2001) for stock i at time t, $w_{i,t,MOM}$ and $w_{i,t,ICC}$ are the weights calculated by taking the reciprocal of the method's (either MOM or ICC) historic mean squared forecast error (the computation of the mean squared forecast error is based on Stock and Watson 2004, I compute it on a company-level over the preceding three years) for stock i at time t, $MOM_{i,t,rescaled}$ is the rescaled momentum variable described above for firm i at time t, and $risk\_free\_yield_t$ is the one-year maturity U.S. treasury rate at time t (downloaded from TR Datastream). In order to avoid the fraction w_{MOM}/w_{ICC} from becoming very large (for small values of w_{ICC}), I winsorize the weights at 0.25 and 0.75. These expected (excess) returns are used in Equation 25 to calculate optimized portfolios. I abbreviate this strategy with ICC_MOM_W.

My second approach is to discard the correction for analysts' sluggishness altogether and simply use the raw ICC estimates. To show that my correction does indeed add value to the resulting portfolio, I run the optimization from Equation 25 again, but using the ICC variable (minus the risk-free yield) as the expected excess return.

Third, for each stock I calculate the expected return using the CAPM (Sharpe 1964, Lintner 1965, Mossin 1966). More precisely, I use the following equation:

$$\mathsf{expected\_return}_{\mathsf{CAPM},i,t} = \beta_{i,t} \times \mathsf{MRP} \tag{33}$$

where $\mathsf{expected\_return}_{\mathsf{CAPM},i,t}$ is the expected excess return according to the CAPM for stock i at time t, $\beta_{i,t}$ is the coefficient of the independent variable from regressing the excess stock returns on the excess market returns (using the preceding 60 months), and MRP is the market risk premium, which I set to 4%. Note that the risk-free yield cancels out as it would be added to the standard CAPM formula but then subtracted when calculating the expected excess return.

Fourth, instead of using only the GLS method for calculating the ICC, I estimate the ICC according to five established methods from the literature, and take the median value.[26] In addition to Gebhardt et al. (2001), these

26 I only include firms for which all ICC estimates are available.

include Easton (2004), Ohlson and Juettner-Nauroth (2005), and Pástor et al. (2008). The method by Gebhardt et al. (2001) is based on a residual income model. The methodologies by Easton (2004) and Ohlson and Juettner-Nauroth (2005) are derived from an abnormal earnings-growth model. The method by Pástor et al. (2008) uses a dividend-discount model. Details regarding the implementation of these additional methods can be found in Chapter 3.

We replicated the performance and risk metrics of the strategies from Section 5.4 for comparison reasons and show them together with the robustness tests in Table 31. First, you can see that the ICC_MOM_W portfolio exhibits a somewhat higher average return but also a higher standard deviation compared to the ICC_MOM strategy. The Sharpe Ratios of those two strategies are about equal. Thus, I recommend to use the simpler method (ICC_MOM) as the implementation is easier. Second, the strategy based only on the unadjusted ICC estimates (ICC_RAW) performs markedly worse than the corrected one. It also underperforms the MVP portfolio. This supports the case for adjusting the raw ICC estimates for analysts' sluggishness (Guay et al. 2011). The optimization technique using expected returns based on the CAPM yields a similar performance as the unadjusted ICC strategy. It nonetheless lags behind the ICC_MOM portfolio. Last, the median ICC measure performs worse than the GLS one, irrespective of whether I adjust for analysts' sluggishness. However, the adjusted median ICC method still outperforms all non-ICC methods.

5.5.2 *Subperiods*

I want to rule out that the results are driven by the sample period selection. To this end, I perform the following subperiod analyses. First, I divide the sample period into subperiods of five years (1985 to 1990, 1990 to 1995, etc). I then calculate the geometric average return (Table 32) and the Sharpe Ratio (Table 33) for each of the investment strategies. My earlier findings are supported by these results. The ICC_MOM portfolio shows the highest Sharpe Ratio in three out of six subperiods.

5.5.3 *Transaction costs*

So far, I have not taken transaction costs into consideration. Section 5.4.2 provides investability indicators for each investment strategy, which give an idea of how expensive a strategy would be to implement in terms of transaction costs. In this robustness test, I explicitly include transaction costs. More precisely, I assume one-way total trading costs of 50 basis points (bp) (Novy-Marx and Velikov 2016). These total costs include explicit costs, such as broker commissions, and implicit costs, such as the price impact of a trade. I am aware that transaction costs have decreased significantly over the sample period and that the assumption of 50 bp is conservative. Table 34 displays performance and risk metrics for the different investment strategies taking trading costs into account. For all portfolios, the performance metrics are somewhat worse than when trading costs are not considered. The different effect of transaction costs on the performance metrics reflect the different turnover ratios for each strategy. The market value-weighted portfolio is least affected, followed by the equally-weighted strategy. The optimized portfolios (MVP, HIST, ICC_MOM) are more affected as their turnover is higher. However, with respect to the Sharpe Ratio, the original ranking is preserved.

5.5.4 *Different investment universe*

The data requirements for calculating the ICC are substantial (Hou et al. 2012) which clearly shapes the investment universe. I argue that this restriction becomes less and less limiting over the sample period as analyst coverage increases over time (Claus and Thomas 2001). Nevertheless, in this section, I drop the requirement that an ICC estimate has to be available for all strategies that do not use ICC estimates (i.e. VW, EW, MVP, HIST) and re-compute the portfolio weights and returns. Table 35 presents the results. The value-weighted portfolio is not affected by this change, while the equally-weighted portfolio experiences a slight increase in its Sharpe Ratio. I conclude that on an aggregated level, the two investment universes are very similar. However, for the minimum volatility strategy, lifting the restriction leads to an increase in the Sharpe Ratio from 0.1879 to 0.1958. Here the optimizer seems to benefit by being able to select stocks that do not fulfill the data requirements needed to compute the ICC. The HIST portfolio experiences a very slight decrease in its Sharpe Ratio. To facilitate comparisons, I have added the ICC_MOM portfolio to Table 35 and you can see that it still provides the highest Sharpe Ratio out of all investment strategies.

5.5.5 *Stricter optimization constraints*

Recall that I imposed a maximum weight of 5% for each stock in the portfolio optimization (Section 5.3.3). The investor faces a trade-off between a potentially high portfolio concentration and higher tracking error but more freedom for the optimizing algorithm and lower portfolio concentration and lower tracking error but also less freedom for the optimizing algorithm. A maximum weight of 5% already leads to a substantial portfolio concentration (Table 24), which probably is the maximum acceptable level for investment managers. As Table 24 also shows, the average number of stocks in the optimized portfolios is just above 30, which is the lower threshold to average out idiosyncratic risks (Statman 1987). Therefore, I apply a stricter upper bound on portfolio weights to achieve greater diversification and lower tracking error for this robustness test. The new upper bound is defined as the minimum of 1.5% and 20 times the stock's weight in the market value weighted portfolio (Chow et al. 2016).

You can see the results in Table 36. First, considering the portfolio Sharpe Ratios, it is noticeable that the optimization strategies that outperformed the VW portfolio (i.e. MVP and ICC_MOM) now have a lower Sharpe Ratio, whereas the strategy that underperformed the VW portfolio (i.e. HIST) now has a higher Sharpe Ratio, when compared to the one in Table 25. This result is in line with the reasoning above: the optimizer has less freedom and, therefore, the resulting allocation will resemble more strongly the market portfolio. Also note that the original ranking by the Sharpe Ratio from Table 25 is preserved. Second, for all optimization strategies the tracking error is substantially lower now than the tracking error in Table 25.

	SR	Return %	SD %	MDD %	TE	IR
VW	0.1581	11.07	14.95	41.95	0.0000	
EW	0.1741	12.64	16.26	41.70	0.0152	0.0896
MVP	0.1879	10.49	10.97	28.55	0.0311	-0.0283
HIST	0.1519	10.65	14.81	40.77	0.0242	-0.0136
ICC_MOM	0.2238	13.49	12.99	36.01	0.0264	0.0597
ICC_MOM_W	0.2242	14.11	13.86	35.09	0.0240	0.0890
ICC_RAW	0.1778	11.54	13.63	45.53	0.0284	0.0068
CAPM	0.1735	10.90	12.84	36.41	0.0244	-0.0156
ICC_MD	0.1555	10.65	14.26	41.82	0.0291	-0.0139
ICC_MOM_MD	0.1933	12.55	14.02	37.70	0.0263	0.0383

Table 31: **Performance and risk metrics – robustness tests**
This table presents performance and risk metrics for the different investment strategies. SR indicates the (monthly) Sharpe Ratio. Return % is the geometric average return (annualized) over the sample period in percent. SD % is the (annualized) standard deviation in percent. MDD % stands for the maximum one-year drawdown in percent (Grossman and Zhou 1993). TE represents the tracking error versus the value-weighted portfolio. IR is the information ratio against the value-weighted portfolio. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2). ICC_MOM_W is the maximum Sharpe Ratio portfolio using the forecast-error weighted ICC measure adjusted for analysts' sluggishness (Section 5.5.1). ICC_RAW is the maximum Sharpe Ratio portfolio using the raw ICC estimates. CAPM is the maximum Sharpe Ratio portfolio where the expected return is derived from the CAPM (Section 5.5.1). ICC_MD is the maximum Sharpe Ratio portfolio using the median of four different ICC methods. Finally, ICC_MOM_MD is the maximum Sharpe Ratio portfolio using the median of four different ICC methods and adjusting this estimate according to the procedure described in Section 5.3.2.

	85-90	90-95	95-00	00-05	05-10	10-15
VW	15.9	12.6	23.6	-0.4	-0.3	17.2
EW	14.3	14.2	17.1	10.6	2.0	18.4
MVP	13.2	13.0	13.9	9.0	-0.4	15.1
HIST	15.3	10.8	21.5	2.9	-3.5	19.2
ICC_MOM	14.3	18.0	12.4	14.6	0.1	22.9

Table 32: **Subperiod analysis – returns**
This table shows the average geometric returns (annualized) for five year windows in percent. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

	85-90	90-95	95-00	00-05	05-10	10-15
VW	0.157	0.202	0.337	-0.034	-0.025	0.392
EW	0.131	0.213	0.227	0.157	0.018	0.352
MVP	0.137	0.235	0.199	0.190	-0.071	0.456
HIST	0.146	0.122	0.273	0.014	-0.104	0.474
ICC_MOM	0.135	0.336	0.153	0.248	-0.047	0.628

Table 33: **Subperiod analysis – Sharpe Ratios**
This table presents the (monthly) Sharpe Ratio for five year windows. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

	SR	Return %	SD %	MDD %	TE	IR
VW	0.1573	11.02	14.95	41.97	0.0000	
EW	0.1705	12.42	16.27	41.84	0.0153	0.0806
MVP	0.1757	9.99	10.97	28.97	0.0311	-0.0399
HIST	0.1390	9.94	14.84	41.13	0.0243	-0.0348
ICC_MOM	0.2093	12.77	13.01	36.46	0.0265	0.0406

Table 34: **Performance and risk metrics – after transaction costs**
This table presents performance and risk metrics after transaction costs (50 bp one-way, based on Novy-Marx and Velikov 2016) for the different investment strategies. SR indicates the (monthly) Sharpe Ratio. Return % is the geometric average return (annualized) over the sample period in percent. SD % is the (annualized) standard deviation in percent. MDD % stands for the maximum one-year drawdown in percent (Grossman and Zhou 1993). TE represents the tracking error versus the value-weighted portfolio. IR is the information ratio against the value-weighted portfolio. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

	SR	Return %	SD %	MDD %	TE	IR
VW	0.1581	11.07	14.97	42.03	0.0000	
EW	0.1747	12.66	16.24	41.98	0.0151	0.0908
MVP	0.1958	10.46	10.40	28.53	0.0304	-0.0315
HIST	0.1496	10.47	14.70	41.11	0.0238	-0.0203
ICC_MOM	0.2238	13.49	12.99	36.01	0.0264	0.0597

Table 35: **Performance and risk metrics – full investment universe**
This table presents performance and risk metrics for the different investment strategies using an investment universe not restricted by the availability of an ICC estimate. SR indicates the (monthly) Sharpe Ratio. Return % is the geometric average return (annualized) over the sample period in percent. SD % is the (annualized) standard deviation in percent. MDD % stands for the maximum one-year drawdown in percent (Grossman and Zhou 1993). TE represents the tracking error versus the value-weighted portfolio. IR is the information ratio against the value-weighted portfolio. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

	SR	Return %	SD %	MDD %	TE	IR
VW	0.1581	11.07	14.95	41.95	0.0000	
EW	0.1741	12.64	16.26	41.70	0.0152	0.0896
MVP	0.1781	10.36	11.48	31.59	0.0272	-0.0341
HIST	0.1761	11.90	14.56	40.78	0.0177	0.0329
ICC_MOM	0.1817	11.64	13.48	37.87	0.0188	0.0138

Table 36: **Performance and risk metrics – stricter optimization constraints**
This table presents performance and risk metrics for the different investment strategies when imposing stricter optimization constraints. SR indicates the (monthly) Sharpe Ratio. Return % is the geometric average return (annualized) over the sample period in percent. SD % is the (annualized) standard deviation in percent. MDD % stands for the maximum one-year drawdown in percent (Grossman and Zhou 1993). TE represents the tracking error versus the value-weighted portfolio. IR is the information ratio against the value-weighted portfolio. VW is the market value-weighted portfolio. EW is the equally-weighted portfolio. MVP is the minimum variance portfolio (Section 5.4.1). HIST is the maximum Sharpe Ratio portfolio using the five-year average time-series return as the expected return (Section 5.4.1). ICC_MOM is the maximum Sharpe Ratio portfolio using the ICC measure adjusted for analysts' sluggishness (Section 5.3.2).

5.6 CONCLUSION AND OUTLOOK

Recent studies on portfolio optimization have focused on minimum volatility strategies. This was motivated by two findings from the literature: expected returns are notoriously difficult to estimate while having a large impact on the optimized portfolio weights. In this study, I provide guidance on how to include an expected return proxy into the portfolio optimization process. I demonstrate that the ICC, when adjusted appropriately, performs well as a proxy for expected returns in this sample. The resulting portfolio outperforms benchmarks such as the equally-weighted market portfolio and the minimum volatility portfolio. These results are robust toward different time periods, inclusion of transaction costs, an extended set of expected return proxies, and a less strictly defined investment universe.

Naturally, there are also some limitations with this approach. I only explored the U.S. equity market because the coverage of analysts' forecasts is broad and the properties of the ICC estimates have been extensively studied. These characteristics may not hold for other markets where both, coverage and quality of forecasts, could be significantly worse. Moreover, computing the ICC involves numerically solving a polynomial equation for each company at each point in time. This may be difficult to implement on a broad level. Finally, the resulting portfolio may be too concentrated and require too much turnover for some investment managers.

My study could be extended along three dimensions. First, generally improving the ICC estimates and making them more accurate and less noisy could lead to substantial benefits in the portfolio optimization process. Second, the ICC computation method by Gebhardt et al. (2001) requires analysts' forecasts which limits the investment universe. A new strand of literature examines alternatives to these analysts' forecasts (Hou et al. 2012, Li and Mohanram 2014). These techniques could substantially increase the available ICC estimates. Third, since the computation of ICC estimates is not trivial, it would be rewarding to investigate whether alternative, simpler, proxies (based on expected earnings) also capture the same information.

6

THE COST OF EQUITY EFFECT OF M&A TRANSACTIONS: DISENTANGLING COINSURANCE FROM THE DIVERSIFICATION DISCOUNT

Whether corporate diversification has a positive or negative impact on a firm's cost of equity is an ongoing debate. I contribute to this discussion by demonstrating that a bright side (coinsurance effect) and a dark side (diversification discount) coexist. Analyzing mergers and acquisitions in the U.S., I find that the coinsurance effect decreases the cost of equity of the merged firm. However, at the same time, I observe an increase in the cost of equity related to the inefficiency of the firm's internal capital market. Both effects are statistically and economically significant. The results are robust to endogeneity concerns, different empirical specifications, and variable measurement.[27]

27 This chapter is based on the working paper Bielstein et al. (2016). Compared to the working paper, I focus in this chapter on the effect on the cost of equity instead of the cost of capital. An earlier version of the working paper was entitled "Two sides of the same coin: disentangling the coinsurance effect and the diversification discount in M&A transactions". Compared to this earlier version, we substantially increased the data quality by using Compustat database instead of TR Worldscope. We then re-computed all variables and estimates and re-run all regressions and analyses. Furthermore, we added a theoretical model to corroborate the empirical findings, provided a stronger motivation why using the implied cost of capital is beneficial in this setting, and extended the literature review.

6.1 introduction

This study aims to reconcile two conflicting views in the corporate diversification literature: the coinsurance effect and the diversification discount. Hann et al. (2013) show that corporate diversification reduces the deadweight cost of financial distress. As this cost is related to the business cycle, it reduces systematic risk and hence, the firm's cost of equity. I refer to this finding as the coinsurance effect. In contrast, other studies find that diversified companies have a lower valuation than their stand-alone peers (e.g. Lang and Stulz 1994 and Berger and Ofek 1995). This lower valuation could be caused by either lower expected cash flows or a higher discount rate. So far, most of the literature has focused on the first explanation, suggesting that allocational problems on internal capital markets, for example, cross-subsidization, are responsible for negative cash flow effects (e.g. Lamont 1997, Lang and Stulz 1994). As a consequence, there is only limited evidence as to whether and to what extent the diversification discount might be driven by a discount rate effect, i.e. by an increase in systematic risk of diversified firms. For instance, Lamont and Polk (2001) present evidence in favor of this explanation.

By extending the model of Hann et al. (2013), I first show that cross-subsidization might indeed cause an increase in systematic risk. Next, by using the special case of mergers and acquisitions (M&As), I provide novel evidence in favor of the hypothesis that internal capital market inefficiencies may cause an increase in systematic risk of diversified firms and, therefore, cause the diversification discount. At the same time, however, I also find that the coinsurance effect is present in every single diversification decision. Hence, the coinsurance effect and the diversification discount coexist and it is unclear which of the two effects dominate in any given transaction.

My dataset consists of M&As in the U.S. in which the buyer acquires 100 percent of the target firm and for which I am able to measure the cost of capital for the acquirer and the target before the takeover and for the merged firm afterwards. Thereby, I avoid matching diversified firms to stand-alone ones, which mitigates endogeneity concerns.

An essential input in this study is the proxy for the cost of equity. As I compare the acquirer and target firms before the takeover to the merged firm after the takeover, I cannot use a cost of equity estimation method that relies on a long data history. Also, the proxy measure needs to reflect investors' risk perception of the company and it should be forward-looking. The implied cost of equity approach meets these requirements.[28] Moreover, this approach is in line with the study on the coinsurance effect by Hann et al. (2013).

My setting allows me to relate the instantaneous change in corporate diversification of the acquirer to the instantaneous change in its cost of equity. In order to measure the overall impact of the merger on the cost of equity, I calculate a weighted average cost of equity for the post-takeover (merged) firm and compare this figure to the cost of equity that a synthetic firm, consisting of the acquirer and target, would have had immediately before the merger. The resulting difference between those two costs of equity can be interpreted as a consequence of the organizational change that emerged due to the M&A.

28 I use the median of five different methods common in the literature (see Chapter 3 for details on the methodology) in order to minimize possible measurement errors specific to each model.

The literature focuses on the existence of internal capital markets as the main difference between diversified and stand-alone firms. Following this strand of literature, I propose two main channels of how diversification can influence the cost of equity. On one side, there might be a coinsurance effect that reduces the deadweight cost of financial distress. On the other side, allocational problems on internal capital markets may cause an additional deadweight loss. The theoretical literature suggests that the degree of diversification can be regarded as the optimal outcome of trading off the net advantages of internal capital markets against those of external resource allocation (Gertner et al. 1994). I exploit the fact that in order to move towards an optimal degree of diversification, a company is likely to become active in the M&A market. Following Lang and Stulz (1994), I create a direct measure of internal capital market efficiency and use this as a mediator in regressing the cost of equity variable on the diversification variable. Based on a simple model showing that cross-subsidization causes the cost of equity of a diversified firm to increase, I present evidence that the impact of diversification on the cost of equity depends on the efficiency of internal capital markets. For example, a firm with an efficient internal capital market can benefit from further diversification through a decrease in its cost of equity as the coinsurance effect reduces the cost associated with financial distress. In contrast, a firm with an inefficient internal capital market is penalized for further diversification through an increase in its cost of equity (diversification discount), as the market weighs the agency problems of internal resource allocation higher than the benefits of smoother cash flows.

Several studies emphasize the importance of taking the endogeneity of a company's decision to diversify into account (for example, Campa and

Kedia 2002 Graham et al. 2002 Chevalier 2004 Villalonga 2004a). Moreover, as my sample only includes M&As, I face a sample selection bias because I am limited to takeovers that actually occurred. My method to address these issues is twofold. First, I avoid matching diversified firms with stand-alone ones by comparing a company to itself, before and after a merger. To achieve this, I calculate the cost of equity of a synthetic firm consisting of the acquirer and target before the takeover, and I limit my sample to M&As in which the acquirer buys 100 percent of the target in one transaction (hence, the target merges into the acquirer). Thereby, I control for many firm idiosyncrasies and avoid all the problems related to the matching of stand-alone firms to conglomerates. Second, I perform a Heckman (1979) two-stage procedure in which I explicitly model the firm's decision to participate in the market for corporate control in a first-stage regression. I then include the inverse Mills ratio in the second-stage regressions. Last, it is worth noting that simple endogeneity concerns are unable to explain the two opposing effects of the cost of equity. For example, if one believes that companies with currently high valuations (which tend to have relatively low implied costs of equity) use their overvalued stocks for takeovers and the capital market revises their valuations after the transactions, I would measure on average an increase in the cost of equity. However, I am able to find effects in both directions – an increase as well as a decrease in the cost of equity – based on the quality of the internal capital market. The outlined example is unable to explain the observed decrease.

Another concern regarding endogeneity is the following. Suppose that concentrated acquirers are trapped in low-growth industries and therefore face pressure to undertake diversifying acquisitions in order to leave that industry. Due to this pressure, concentrated acquirers tend to make bad takeover deals which lead to an increase in their cost of equity. I show that my results also hold when focused acquirers are excluded from my sample. Hence, my results are not solely driven by concentrated acquirers in low-growth industries.

In my analysis, I regress the change in the cost of equity on the change in corporate diversification, the quality of the existing internal capital market, and an interaction term of both variables. I also include various control variables, such as changes in the credit rating and leverage. The rationale behind the implemented interaction term is that it allows the change in corporate diversification to influence the cost of equity in two opposing directions, depending on the quality of the existing internal capital market. I find that these three variables are highly significant and that the direction of their effects are predicted by my simple model. Moreover, they are also economically meaningful.

My findings are robust to different specifications. For example, my results remain unchanged if I approximate the quality of the existing internal capital market indirectly with the acquirer's pre-takeover degree of diversification (this variable reflects the level of experience a company has with handling internal capital markets). Overall, this study provides evidence that the coinsurance effect and the diversification discount coexist, and firm specific characteristics, especially the quality of the internal capital market, determine which effect dominates.

6.2 RELATED LITERATURE

The term coinsurance effect goes back to Lewellen (1971) who provides theoretical arguments how a conglomerate merger can reduce a company's risk. Hann et al. (2013) further develop these arguments and link them to the company's systematic risk through the deadweight costs of financial distress. They also show that diversified firms have, on average, a lower cost of capital than their stand-alone peers thus giving empirical evidence for the coinsurance effect. Kim and McConnell (1977) analyze the coinsurance effect in the context of M&As. They find that although the leverage of the combined firm increases, there are no statistically negative returns for bondholders. This supports the hypothesis that the company's risk related to its assets has decreased.

Regarding the diversification discount, Lang and Stulz (1994) find that Tobin's Q and firm diversification are negatively related. Berger and Ofek (1995) compare imputed stand-alone values for individual business segments with the value of the diversified company. They find a 13 to 15 percent average value loss from diversification. Lamont and Polk (2002) investigate exogenous changes in diversification and show that these are negatively related to firm value.

More recent research highlight some potential problems when investigating corporate diversification, namely endogeneity issues and technical problems of computing value measures. Clearly, the firm's decision to diversify or to focus is not random but endogenous. Researchers have proposed different econometric methods to account for the endogeneity problem. Villalonga (2004a) shows that when conglomerates are compared with stand-alone companies that have the same propensity to diversify, the diversification discount disappears. Campa and Kedia (2002) also consider self-selection of diversifying firms and find that there is a strong negative correlation between firm value and a firm's choice to diversify. Graham et al. (2002) show that after considering the target firm's characteristics, almost all of the valuation discount of the combined entity disappears. Another potential problem is companies' segment data. Villalonga (2004b) points out that the empirical evidence on the diversification discount might be an artifact caused by specific characteristics of segment data. Finally, Glaser and Müller (2010) as well as Custódio (2014) evaluate the impact of accounting. The former explain part of the diversification discount with the fact that diversified firms have larger gaps between book value and market value of debt than focused firms. The latter finds that, due to purchase accounting, post-merger Tobin's Q measures of acquirers tend to be biased downwards.

This chapter is also related to the literature on internal capital markets. On the one hand, a number of studies analyze agency problems caused by poorly governed internal capital markets (for example, Jensen 1986 Scharfstein and Stein 2000 Rajan et al. 2000). On the other hand, Stein (1997) shows how internal capital markets within a conglomerate are able to reduce the harmful impact of credit constraints on long-term investment decisions. In case of tightening external capital markets, several studies stress the importance of functioning internal capital markets (see, for example, Kuppuswamy and Villalonga 2016 Yan et al. 2010 Hovakimian 2011). Last, the recent survey of Gatzer et al. (2014) suggests that Chief Financial Officers (CFO) of diversified firms value the benefits of the coinsurance effect as the main financial advantages of their diversification.

6.3 MODEL

I build upon the model of Hann et al. (2013) which shows how the coinsurance effect reduces a diversified firm's systematic risk. Hann et al. (2013)

posit that financial distress causes a deadweight loss, through, for instance, costs associated with foregone investment opportunities, business interruption, and firm reorganization. Assuming that a firm's cash flows are positively correlated with the economic environment, these costs tend to arise in bad economic times. If a stand-alone company acquires another company, this acquisition will reduce the acquirer's default probability, at least as long as the cash flows of the acquired firm are not perfectly correlated with the cash flows of the acquiring firm. As a consequence, the cost of equity of the combined firm will be lower than the firm value weighted average of the cost of equity of the two stand-alone firms.

Following Hann et al. (2013), this idea can be formalized as follows. I assume two identical firms with uncorrelated cash flows. This assumption is not necessary for the outcome of the model, but merely reduces complexity. The firms' cash flows can be high (H) or low (L). Their probability of realization is correlated with the state of the economy. If the economy is in a good (bad) state, H will be realized with probability p_g (p_b). In the bad state a deadweight cost equal to the company's cash flow L is incurred so that investors' payout is zero. In their Internet appendix, Hann et al. (2013) define systematic risk as $\beta_s = \frac{C_g}{C_b} - 1 = \frac{p_g}{p_b} - 1$ where C is the company's cash flow in the good (g) and bad (b) state, respectively. I assume that the two firms carry positive systematic risk, i.e. $p_g > p_b$.

If the two firms merge, a coinsurance effect arises because financial distress now only occurs if both segments realize a low cash flow. This happens with probability $(1-p_g)^2$ (in the good state of the economy) or probability $(1-p_b)^2$ (in the bad state of the economy). Hence, the cash flows

C_g (C_b) paid out to investors in the good (bad) state of the economy are determined as follows:

$$C_g = 2p_gH + 2p_g(1 - p_g)L$$
$$C_b = 2p_bH + 2p_b(1 - p_b)L$$

Hence, systematic risk of the combined firm is given by:

$$\beta_c = \frac{2p_gH + 2p_g(1 - p_g)L}{2p_bH + 2p_b(1 - p_b)L} - 1$$

As Hann et al. (2013) show in their Internet appendix, when assuming $p_g > p_b$ it follows that $\beta_s > \beta_c$.

Now, I extend the Hann et al. (2013) model by introducing internal capital markets. Assume that company 1 in the high cash flow state (H) can make a follow-up investment with a net present value (NPV) equal to V.[29] For simplification, I assume that this investment is riskless. In the low cash flow state (L), the investment cannot be undertaken, possibly due to capital constraints and insufficient internal cash flows. This setting offers a simple way to ensure that the investment opportunity is neutral with respect to the company's beta. However, these assumptions could be relaxed without loss of generality.

29 Note that Hann et al. (2013) in their Internet appendix introduce an extension of their model where they analyze the impact of integration costs on systematic risk. While technically this is not so different from what I present here, the economic reasoning is. What Hann et al. (2013) have in mind are agency costs associated with organizational problems. By conditioning these agency costs on the state of the economy, they argue that agency costs might reinforce the coinsurance effect as long as the share of cash flows consumed by them is smaller in bad states of the economy as compared to good states. If this is not the case, no general conclusion can be drawn with respect to the impact of these agency costs on the cost of capital. My approach is different, as I explicitly take into account foregone investment opportunities due to inefficient internal capital markets.

In the next step, I assume that for the combined company, the follow-up investment is only possible if both segments (former companies 1 and 2) have high cash flows. This models one of the fundamental problems of diversified firms, namely cross-subsidization of different business segments. If both segments flourish, sufficient cash flows are generated to finance all investments. However, if only one segment generates high cash flows, a portion of these cash flows are used to cover expenses in the other, less profitable segment. (see e.g. Lamont 1997 Gertner et al. 2002 Stein 2003 Ozbas and Scharfstein 2010). Also, external financing of this positive NPV investment could be unavailable or costly due to financial constraints. Furthermore, the combined firm might be affected by adverse selection costs of external financing due to its increased opaqueness. Of course, I could somewhat relax this assumption by assuming that the positive NPV investment can be partly realized in the case that only one segment is successful. This, however, would unnecessarily increase the complexity of the model.

Summarizing this idea of cross-subsidization on internal capital markets, the combined company's cash flows conditional on the state of the economy can be written as follows:

$$\begin{aligned} C_g &= 2p_g H + p_g^2 V + 2p_g(1-p_g)L \\ C_b &= 2p_b H + p_b^2 V + 2p_b(1-p_b)L \end{aligned}$$

It follows that systematic risk of the combined firm – taking internal capital market inefficiencies into account – is given as:

$$\beta_c^{ICM} = \frac{2p_g H + p_g^2 V + 2p_g(1-p_g)L}{2p_b H + p_b^2 V + 2p_b(1-p_b)L} - 1$$

Now, if $p_g > p_b$ then $\beta_c^{ICM} > \beta_c$.[30] Thus, internal capital market inefficiencies increase the cost of equity, as they make a firm more cyclical. I acknowledge that this outcome is expected given how I modeled internal capital market inefficiencies. The odds that a profitable investment opportunity will not be undertaken are higher in a bad economic environment than in a good one. Even though this is an assumption, it captures a widely acknowledged drawback of internal capital markets: cross-subsidization.

If deadweight costs of financial distress and internal capital market inefficiencies exist simultaneously, the net effect on the systematic risk of the combined firm is unclear. This is because the two effects go in opposite directions. The total impact on the systematic risk is $\beta_c^{ICM} - \beta_s$. This total effect can be decomposed into two separate effects. The first is the coinsurance effect, which is equal to $\beta_c - \beta_s$ with $\beta_c < \beta_s$ as long as $p_g > p_b$ holds. The coinsurance effect reduces the cost of equity because deadweight costs of financial distress (which are higher in an economic downturn) decrease. The second effect is the diversification discount, which is equal to $\beta_c^{ICM} - \beta_c$ with $\beta_c^{ICM} > \beta_c$ as long as $p_g > p_b$ holds. Because of internal capital market inefficiencies, which have a stronger negative impact in a bad economic environment, systematic risk increases. Higher systematic risk increases the cost of equity and reduces firm valuation. However, the overall impact for the combined firm is unclear. This model cannot predict which of the two opposing effects dominates.

In the empirical part of the paper, I show that both effects, the coinsurance effect as well as the diversification discount, can be identified independently of each other. Moreover, I show that for firms with larger internal

30 The proof is shown in Appendix A.1.

capital market inefficiencies the diversification discount effect tends to outweigh the coinsurance effect.

6.4 sample and variables

6.4.1 *Sample construction*

The sample is based on takeovers from Thomson Reuters SDC Platinum (SDC). I then add stock market data from CRSP, accounting data from Compustat (annual files), and analysts' forecasts from IBES. Data on corporate credit ratings is obtained from Mergent Fixed Income Securities Database (FISD). I limit the sample to targets and acquirers that are listed U.S. firms as I need financial information on those firms and cross-border or foreign M&As may be influenced by different factors. The sample period starts in 1985 because that is when IBES firm coverage is sufficiently large (Claus and Thomas 2001) and ends in 2014. I require that the acquirer takes over 100 percent of the target company to ensure that the target is fully integrated into the acquirer and thus the acquirer's diversification level is actually impacted by the takeover. I exclude financial (SIC code starting with 6) and utility (SIC code starting with 49) firms as these industries are highly regulated. Furthermore, I exclude very small takeovers as I do not expect those takeovers to significantly influence the acquirer's cost of equity. To this end, I implement two restrictions: the transaction value has to be at least 50 million USD and the relative size of the target's firm value to the acquirer's firm value at announcement date is at least one percent. As I use Compustat segment files, I confirm the data quality by comparing the sum of segment sales to the total sales figure from Compustat fundamentals annual files. I drop observations where segment sales are obviously wrong, i.e., the sum of segment sales exceeds total sales by five percent or more. Table 37 summarizes the screens. In the end, I obtain 623 takeovers for the analyses.

No.	Screen
1	Acquirer and target are both listed companies in the United States
2	Announcement and effective dates are between 1985 and 2014
3	Acquirer takes over 100 percent of the target company
4	Acquirer and target are not identical
5	Excluding financial (SIC code 6xxx) and utility firms (SIC code 49xx)
6	Transaction value is greater than 50 million USD (inflation adjusted, base year 2000)
7	Target's firm value is at least one percent of acquirer's firm value
8	Sum of segment sales from Compustat segment files do not exceed total sales from Compustat fundamentals annual files by more than five percent
9	No missing values in all variables that are included in the main regression analysis

Table 37: **Sample screens of M&A data set.**
The table shows the sample screens applied to the data set. I use the following databases: SDC, CRSP, Compustat, IBES, and FISD.

6.4.2 *Implied cost of equity*

In this setting, it is crucial to measure the cost of equity at a given point in time with little (or no) historic data. I compare the cost of equity of the target and acquirer before the merger with the cost of equity of the merged firm after the takeover. This means that after the merger, I cannot use historic data predating the merger effective date, which limits the use of a historical cost of equity estimation. Furthermore, historical estimates contain a large amount of noise (Fama and French 1997 Elton 1999). This makes inference more difficult in a regression setting.

The implied cost of equity (ICE) method offers numerous advantages in this study set-up. It uses forward-looking data (analysts' earnings forecasts) and is conditional on information available to investors at a given point in time (Claus and Thomas 2001). Pástor et al. (2008) show that the ICE is positively related to risk under reasonable assumptions. Chava and Purnanandam (2010) find that the ICE is positively related to default risk. Other studies have also acknowledged the usefulness of the ICE when analyzing how certain firm characteristics influence a firm's cost of capital (e.g. Hann et al. 2013 Ortiz-Molina and Phillips 2014 Frank and Shen 2016).

The ICE is the discount rate that equates expected future cash flows with the share price at a respective point in time. In the literature, there are several different established estimation methods. In order to ensure that my results are not driven by a particular approach and to minimize potential measurement errors, I use the median implied cost of equity of five different methods: Claus and Thomas (2001), Gebhardt et al. (2001), Easton (2004), Ohlson and Juettner-Nauroth (2005), and Pástor et al. (2008). Method one and two are based on a residual income model, method three and four are derived from an abnormal earnings-growth model, and the last method uses a dividend-discount model. A summary of these different methods can be found in Chapter 3.

Inputs for estimating the implied cost of equity include accounting data. Therefore, when computing the implied cost of equity, it is important to ensure that there is no look-ahead bias. The implied cost of equity measurement before the merger is straightforward. The time of measurement is the month-end before the announcement date of the merger. The accounting data used refers to the preceding fiscal year-end. After the takeover, I use the fiscal year-end following the merger effective date so that the merger is reflected in the accounting data. I assume that it takes four months until the respective company's annual report is released to the public. This means that we use the fiscal year-end (post-merger) plus four months as the implied cost of equity measurement point in time. For an overview of this timeline, see Figure 10. I winsorize cost of equity estimates at the top and bottom one percent.

There is ample evidence that takeovers are clustered in time (e.g. Andrade et al. 2001 Harford 2005 Moeller et al. 2005 Duchin and Schmidt 2013) and that this clustering might be systematically correlated with the interest rate and/or discount rate level in the market. To account for this potential bias, I calculate the median implied cost of equity over the five different methods for each company in the sample period for the U.S. market.[31] For each period, I then calculate the market implied cost of equity as the value-weighted implied cost of equity over all available companies. Finally, I subtract this market implied cost of equity from each sample firm's implied cost of equity. As a result, only the relative cost of equity, and not the absolute value, is considered.

6.4.3 *Hypothetical and realized cost of equity*

As described in the previous section, I estimate the cost of equity (*CE*) of the acquirer and target before the merger. Then, I weight the target's and acquirer's cost of equity before the acquisition with their respective

31 In order to calculate the implied cost of equity for a specific company, the data requirements need to be fulfilled.

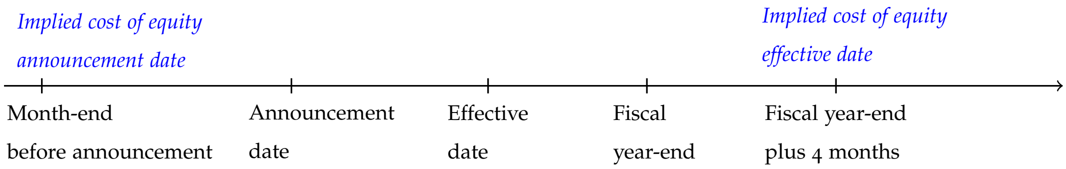

Figure 10: **Timeline of takeover and variable measurement**
This figure shows the timeline of takeover and variable measurements. The implied cost of equity is measured at the month-end before the merger announcement date and four months after the fiscal year-end following the merger effective date. The merger announcement and effective dates are taken from SDC. The fiscal year-end is obtained from Compustat. The implied cost of equity is calculated using the median of five different calculation methods.

market values (taken from IBES) to obtain the hypothetical cost of equity (*HypotheticalCE*$_M$):

$$\mathrm{HypotheticalCE}_M = \frac{MV_T}{MV_T + MV_A} \times CE_T + \frac{MV_A}{MV_T + MV_A} \times CE_A \quad (34)$$

where MV is the market value from IBES. If one ignores the effects of the merger the formula above measures the cost of equity of a hypothetical combination of the target and acquirer. To put it differently, this is a naive benchmark against which the cost of equity of the merged firm after the takeover will be compared to.

Next, I compute the cost of equity of the merged firm (*RealizedCE*$_M$) as the merged firm's implied cost of equity. The time of measurement is four months after the fiscal year-end following the merger effective date. Finally, the dependent variable (*DeltaCE*) for the empirical investigation is equal to the deviation of the realized cost of equity (*RealizedCE*$_M$) from the hypothetical cost of equity (*HypotheticalCE*$_M$):

$$\mathrm{DeltaCE} = \mathrm{RealizedCE}_M - \mathrm{HypotheticalCE}_M \quad (35)$$

6.4.4 *Diversification*

Corporate segment data is obtained from Compustat's segment files. Managers have some discretion over the classification of segments and different segments do not necessarily reflect different industries. That is why I aggregate segment sales by their three-digit SIC code.[32] I measure the acquirer's level of concentration before the takeover ($Concentration_A$) using a Hirshman-Herfindahl index (HHI)[33] based on segment sales:

$$Concentration_A = \sum_{k=1}^{K} \left(\frac{Sales_{segment\_k}}{Sales_{total}} \right)^2 \tag{36}$$

This definition allows me to construct a concentration measure for the acquiring firm before the takeover in the same way that I can construct a diversification measure for the takeover itself. Thus, the diversification measure for the takeover (*Diversification*) is the change in the acquirer's concentration due to the takeover:

$$Diversification = Concentration_A - Concentration_M \tag{37}$$

with the merged firm's concentration defined in a similar way as the acquirer's concentration before the takeover. For negative values of *Diversification*, the acquirer is more focused after the takeover than before. For positive values of *Diversification*, the takeover is diversifying and the merged firm is less focused. Keep in mind that *Diversification* refers to the change

32 Hyland and Diltz (2002) find that up to a quarter of reported changes in the number of segments stem from changes in reporting policy, not changes in the level of diversification. See also Denis et al. (1997) and Hayes and Lundholm (1996).

33 The index is based on Hirschman (1945) and Herfindahl (1950). Comment and Jarrell (1995) use a similar measure.

in diversification through the takeover and $Concentration_A$ indicates the acquirer's pre-merger level of concentration.

6.4.5 *Internal capital market friction*

The internal capital market is the main driver for determining whether diversification is beneficial or detrimental. In order to quantify internal capital market quality, I create the following measure of internal capital market friction ($ICMF_A$) which is loosely based on Shin and Stulz (1998):

$$\mathrm{ICMF}_A = 0.5 - (\mathrm{Correlation}(SIO, SI)/2) \tag{38}$$

where *SIO* are the segment investment opportunities (measured as the lagged segment sales growth rate (from Compustat)) and *SI* are the standardized segment investments (measured as segment capital expenditure divided by segment assets (form Compustat)). Defining $ICMF_A$ in this way, instead of using the correlation directly, has the advantage that the interpretation is similar to $Concentration_A$. An $ICMF_A$ value of one means that the acquirer's internal capital market is inefficient. At the other end, an $ICMF_A$ value close to zero indicates an efficient internal capital market. If the acquirer is fully concentrated before the merger I set this variable to one as it cannot be computed.[34]

34 The main conclusions are unaffected by this assumption as shown in Section 6.5.3.2.

6.4.6 *Control variables*

A few preliminary remarks are necessary before I present the control variables. To incorporate credit ratings in the regressions I convert character ratings into numerical ones, similar to other empirical studies in this field (e.g. Amato and Furfine 2004 Bannier and Hirsch 2010 Bongaerts et al. 2012): AAA is translated to one, AA to two, and so forth until D which is given the number ten. As stated earlier, intermediate ratings are ignored. Figures referring to after the merger are calculated at the time the implied cost of equity is calculated. An overview of all control variables is presented in Table 38.

This study design, which compares the merged firm with a hypothetically combined firm based on the pre-takeover acquirer and target, already controls for all factors that equally influence the cost of equity before and after the takeover. I include the following variables as I believe that they influence the change in the cost of equity before and after the merger. To control for any changes in the cost of equity that relate purely to the difference in ratings, I include the rating change between the merged firm and the acquirer (*RatingChange*). Operational synergies are often cited as a rational for takeovers. They will change future earnings, but not directly the cost of equity. However, as I indirectly make use of future earnings (analysts' earnings forecasts are an input for the cost of equity estimation), I include the variable *Synergies* in the regressions. I need to account for the change in leverage (*LeverageChange*) as this influences the cost of equity directly. The following variables are common controls in the M&A literature (for example, Moeller 2005 Fu et al. 2013): *TransactionValue*, *FriendlyTakeover*, and *MultipleBidders*. As a larger target (relative to the acquirer) will have a higher impact on the acquirer, I include the variable *RelativeSize*. The variables $ReturnOnEquity_A$, $LongTermGrowth_A$, $Leverage_A$, $MarketToBook_A$ are all intended to control for acquirer characteristics that could influence the change in the cost of equity. Finally, I control for selection effects by including the inverse Mills ratio (IMR_A), which I obtain from a first-stage regression that models the decision to undertake an acquisition.[35] To mitigate the effect of extreme values, I winsorize *Synergies*, $ReturnOnEquity_A$, and $MarketToBook_A$ at the top and bottom percentile. Furthermore, the variable $LongTermGrowth_A$ is winsorized at two and 50 percent.

6.4.7 *Selection control*

Clearly, the fact that some companies undertake acquisitions and others do not is not random but rather the outcome of a decision process that each company makes. The researcher has to take this selection bias into account when comparing stand-alone with diversified firms (for example, Campa and Kedia 2002 Villalonga 2004a). My method of addressing this issue is twofold. First, I avoid comparing stand-alone with diversified companies in the cross-section but rather compare merger participants before and after the event. Acquirer idiosyncrasies should cancel out by taking differences of variables before and after the takeover. Second, I control for the self-selection bias of undertaking a merger by performing a Heckman (1979) two-stage procedure. The first-stage regression models the decision to undertake a merger:

$$\boldsymbol{Merger} = \boldsymbol{X\beta} + \boldsymbol{\epsilon} \tag{39}$$

35 See Section 6.4.7 for more details on the first-stage regression.

Variable	Description
Financial Controls	
RatingChange[1]	Numeric merged firm's rating minus numeric acquirer's rating
Synergies[*,2,3]	Estimated takeover synergies (actual earnings for the merged firm minus the sum of target and acquirer's forecasted earnings scaled by merged firm's total assets
LeverageChange[2,3]	Merged firm's leverage ratio (as defined below) minus leverage ratio of a hypothetically combined firm of acquirer and target (weighted by their firm values)
Takeover Controls	
TransactionValue[4,2]	Takeover's transaction value (if missing I use the target's market value), inflation adjusted, base year 2000
FriendlyTakeover[4]	Dummy, one if takeover attitude is friendly
MultipleBidders[4]	Dummy, one if more than one bidder
RelativeSize[2,3]	Target enterprise value divided by acquirer enterprise value
IMR_A	Inverse Mills ratio from a first-stage regression modeling the decision to undertake a takeover (see Section 6.4.7 for details)
Acquirer Controls	
$\text{ReturnOnEquity}_\text{A}$[*,3]	Acquirer's return on equity
$\text{LongTermGrowth}_\text{A}$[2]	Acquirer's consensus long-term earnings growth forecast (winsorized at two and 50 percent)
Leverage_A[2,3]	Acquirer's book value of debt divided by the sum of book value of debt and market value of equity
$\text{MarketToBook}_\text{A}$[*,2,3]	Acquirer's market-to-book ratio

Table 38: **List of control variables**
* indicates a winsorization at the bottom and top percentile. I calculate pre-merger figures at the month-end before the merger announcement date. Post-merger figures are obtained at the point in time when the implied cost of equity was calculated. Numerical superscripts indicate the data source:[1] FISD, [2] IBES, [3] Compustat, [4] SDC.

where $\boldsymbol{Merger}$ is a dummy variable that indicates if a takeover took place (one) or not (zero), $\boldsymbol{X}$ is a regressor matrix with variables that explain the decision to undertake a merger and ϵ is a vector with error terms. I select the following variables:[36] firm's market share (based on sales from Compustat), leverage ratio (debt over assets from Compustat), natural logarithm of assets (from Compustat), dummy variable that equals one if a dividend was paid (based on dividends from Compustat) and zero otherwise, cash flow normalized by assets (earnings plus depreciation over assets from Compustat), market-to-book ratio (market value from CRSP, book value from Compustat), natural logarithm of firm age proxied by years covered in CRSP, dummy variable that equals one if the firm was a constituent of the Standard and Poor's (SP) industrial or transportation index, industry adjusted market-to-book ratio (based on Villalonga 2004a) lagged by one year, a Hirschman-Herfindahl index of industry sales (sales from Compustat, industry defined by the three digit SIC code), United States of America (U.S.) GDP growth rate (from the Bureau of Economic Analysis), number of months the economy was in contraction over the last twelve months (NBER), number of merger announcements over the last twelve months (based on SDC), natural logarithm of dollar volume of merger announcements over the last twelve months (based on SDC), natural logarithm of dollar volume of share issues over the last twelve months (based on SDC).

From this probit regression I compute the inverse Mills ratio and use it as a variable in the main regressions.

36 Many of the following variables are also used by Villalonga (2004a) and Campa and Kedia (2002). I believe that the decision to diversify and the decision to undertake a merger are influenced by similar variables.

6.5 EMPIRICAL RESULTS

6.5.1 *Descriptive statistics*

I first present descriptive statistics on variables related to the takeover and the acquirer (Table 39). On average, a takeover in this sample increases diversification by 2.42 percent. The variable *RatingChange* is positive meaning that, on average, the merged firm's credit rating is worse than the acquirer's credit rating before the takeover. The mean increase in leverage is 7.77 percent, which is intuitive as debt is often used to finance a takeover. Synergies are on average positive (0.36 percent of total assets). Acquirer's pre-takeover concentration is, on average, 80.91 percent and the median value is 100.00 percent, meaning that there is a considerable amount of single-segment firms in the sample.

Cost of equity measurements play an important role in the regressions. Descriptive data on these variables are shown in Table 40. Acquirer's mean cost of equity minus the market cost of equity (0.50 percent) is lower than that of the target (1.02 percent). This could be caused by the larger size of acquiring companies; by their, on average, better rating, which implies lower risk; or by benefits of the coinsurance effect if you assume that larger companies are more likely to be diversified. After the takeover is completed, the merged company has, on average, a cost of equity that is 1.22 percentage points higher than the market level. Interestingly, the cost of equity of a hypothetically combined firm (0.51 percent, measured with reference to the market cost of equity) is lower than the actual realized cost of equity after the merger (1.22 percent). This implies that the difference of those two variables (*DeltaCE* which is the dependent variable for the main

Variable	Obs	Mean	SD	P25	P50	P75
Diversification	623	2.42%	14.13%	0.00%	0.00%	1.44%
$\text{Concentration}_\text{A}$	623	80.91%	26.00%	57.53%	100.00%	100.00%
ICMF_A	552	83.23%	34.08%	100.00%	100.00%	100.00%
Rolling ICMF_A	598	83.92%	27.68%	66.67%	100.00%	100.00%
RatingChange	623	0.17	1.29	0.00	0.00	1.00
Synergies	623	0.36%	2.94%	-0.41%	0.68%	1.80%
LeverageChange	623	7.77%	14.39%	-0.76%	3.89%	13.53%
TransactionValue*	623	1,956	6,076	251	636	1,421
RelativeSize	623	18.54%	15.90%	5.66%	13.77%	27.62%
FriendlyTakeover	623	0.96	0.19	1.00	1.00	1.00
MultipleBidders	623	0.07	0.25	0.00	0.00	0.00
$\text{ReturnOnEquity}_\text{A}$	623	16.70%	24.00%	8.46%	16.71%	24.15%
$\text{LongTermGrowth}_\text{A}$	623	16.58%	8.84%	10.50%	15.00%	20.00%
$\text{MarketToBook}_\text{A}$	623	4.41	4.57	2.01	3.02	4.74

Table 39: **Summary statistics – takeover and acquirer variables**
This table reports summary statistics of the takeover and acquirer variables from the main sample covering takeovers taking place in the U.S. between 1985 and 2014. I show the number of observations (Obs), sample mean (Mean), sample standard deviation (SD), first quartile (P25), median (P50), and third quartile (P75). * indicates values in million USD (inflation adjusted, base year 2000). $\text{ReturnOnEquity}_\text{A}$ and $\text{MarketToBook}_\text{A}$ are winsorized at the top and bottom percentile. $\text{LongTermGrowth}_\text{A}$ is winsorized at two and 50 percent. A detailed description of all variables is given in Section 6.4

regressions) is on average positive. However, it is important to remember that the average leverage ratio is increasing and the average rating is decreasing. Without controlling for all other factors no conclusions can be drawn.

Variable	Obs	Mean	SD	P25	P50	P75
Absolute CE_A	629	10.35	2.79	8.55	10.02	11.73
Absolute CE_T	629	10.87	3.30	8.87	10.51	12.66
Absolute CE_M	629	10.89	2.87	9.03	10.48	12.24
CE_A	629	0.50	2.64	-1.14	0.14	1.54
CE_T	629	1.02	3.33	-1.03	0.62	2.90
RealizedCE_M	629	1.22	2.88	-0.76	0.73	2.54
HypotheticalCE_M	629	0.51	2.44	-1.05	0.23	1.54
DeltaCE	629	0.71	2.72	-0.73	0.58	2.02

Table 40: **Summary statistics – cost of equity variables**
This table shows summary statistics of the cost of equity variables from the main sample covering takeovers taking place in the U.S. between 1985 and 2014. I show the number of observations (Obs), sample mean (Mean), sample standard deviation (SD), first quartile (P25), median (P50), and third quartile (P75). All figures are in percent. *Absolute CE* is the level cost of equity proxied by the median implied cost of equity of five different methods: Claus and Thomas (2001), Gebhardt et al. (2001), Easton (2004), Ohlson and Juettner-Nauroth (2005), and Pástor et al. (2008). See Section 3.2 for details on the methodology. The subscripts *A*, *T*, and *M* indicate the acquirer and target before the takeover and the merged firm after the takeover, respectively. The implied cost of equity is winsorized at the top and bottom percentile. The time of measurement is the month-end before the merger announcement date (for acquirer and target) and four months after the fiscal year-end following the merger effective date (for the merged firm). *CE* is the relative cost of equity calculated as the absolute cost of equity minus the market cost of equity. The market cost of equity is the market value weighted median implied cost of equity of the five methods mentioned above. $Hypothetical_M$ is the market value weighted average of the acquirer and target cost of equity before the merger. *DeltaCE* is calculated as the difference between $RealizedCE_M$ and $HypotheticalCE_M$.

6.5.2 *Regression results*

As stated before, I believe that the internal capital market is a main driver in determining whether corporate diversification is beneficial or detrimental. This means that the quality of the acquirer's internal capital market before the takeover should influence the relationship between corporate diversification and the cost of equity. To test this hypothesis, I interact *Diversification* with $ICMF_A$. As $ICMF_A$ can vary substantially over time (in particular, if the firm has only a few segments), I also include a rolling average version of the $ICMF_A$ variable. The variable *Rolling* $ICMF_A$ is the rolling average of $ICMF_A$ over the preceding three years. As an alternative proxy for the acquirer's experience with internal capital markets, I use the variable $Concentration_A$ and build a similar interaction term.

Table 41 presents the main regression results. As a proxy for experience with internal capital markets, Regression (2) and Regression (5) use the internal capital market friction variable, whereas Regression (1) and Regression (4) use the acquirer's pre-merger concentration measure. Finally, Regression (3) and Regression (6) implement the rolling average version of $ICMF_A$. The last three regressions include year (from the merger effective date) and acquirer's industry fixed effects (based on the two-digit SIC code).

Before interpreting the coefficients on diversification and internal capital market inefficiency, I would like to point out two other results. First, the selection control variable IMR_A is not significant in any of the regressions indicating that the selection effect is not a problem in this setting. Second, the variable *LeverageChange* is highly significant and positive in each model.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			DeltaCE			
Interaction	0.1072***	0.0794***	0.1183***	0.1061***	0.0713***	0.1208***
	(0.03)	(0.01)	(0.04)	(0.03)	(0.02)	(0.04)
Diversification	-0.0941***	-0.0744***	-0.1091***	-0.0955***	-0.0703***	-0.1152***
	(0.01)	(0.02)	(0.04)	(0.03)	(0.02)	(0.04)
$\text{Concentration}_{\text{A}}$	0.0131***			0.0081		
	(0.00)			(0.01)		
ICMF_{A}		0.0117***			0.0113***	
		(0.00)			(0.00)	
Rolling ICMF_{A}			0.0116***			0.0109**
			(0.00)			(0.00)
IMR_{A}	-0.0038	-0.0042	-0.0037	0.0011	0.0000	-0.0003
	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)
Synergies	0.1274*	0.1396*	0.1232*	0.1019	0.1122	0.1017
	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)
RatingChange	-0.0004	-0.0007	-0.0010	-0.0011	0.0002	-0.0010
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
LeverageChange	0.0539***	0.0566***	0.0448***	0.0494***	0.0411***	0.0472***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
ln(TransactionValue)	-0.0004	-0.0009	0.0007	0.0000	0.00010	0.0004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FriendlyTakeover	0.0049	0.0075	0.0045	0.0066	0.0026	0.0045
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
MultipleBidders	-0.0073	-0.0043	-0.0066	-0.0028	0.0006	-0.0075
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
RelativeSize	0.0137	0.0131	0.0204	0.0169	0.0145	0.0194
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
$\text{ReturnOnEquity}_{\text{A}}$	0.0025	0.0053	0.0022	0.0071	0.0025	0.0029
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\text{LongTermGrowth}_{\text{A}}$	-0.0230	-0.0322	-0.0337	-0.0548**	-0.0402**	-0.0368*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
$\text{Leverage}_{\text{A}}$	-0.0031*	-0.0022	0.0035	0.0082	-0.0045	0.0061
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\text{MarketToBook}_{\text{A}}$	0.0005	0.0006	0.0007	0.0007	0.0006	0.0007
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-0.0068	-0.0036	-0.0378*	-0.0359	-0.0210	-0.0395
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Fixed Effects	No	No	No	Yes	Yes	Yes
Observations	629	558	604	629	558	604
Adjusted R^2	0.132	0.137	0.133	0.139	0.149	0.134

Table 41: **Takeover diversification and the quality of internal capital market**
This table displays the results of regressing the measure of cost of equity (as defined in Section 6.4.3) on takeover diversification (as defined in Section 6.4.4), a proxy for internal capital market friction (see Section 6.4.5 and Section 6.4.4), an interaction term of the latter two variables, and various control variables (see Section 6.4.6). The sample covers takeovers in the U.S. from 1985 to 2014. The interaction term is the product of *Diversification* and *Concentration*$_A$ (Regressions (1) and (4)), *Diversification* and *ICMF*$_A$ (Regressions (2) and (5)), and *Diversification* and *Rolling ICMF*$_A$ (Regressions (3) and (6)). *Rolling ICMF*$_A$ is the three-year rolling average of *ICMF*$_A$. *IMR*$_A$ is the inverse Mills Ratio from a first-stage regression that models a firm's decision to undertake a merger. Fixed effects include effective year fixed effects and acquirer industry fixed effects, based on the two-digit SIC code. Heteroscedasticity-consistent standard errors are shown in parentheses. *, **, and *** indicate a significant difference from zero on a ten-, five-, and one-percent level, respectively.

This is intuitive as a higher leverage increases a stock's risk and therefore also increases the expected return.

Regarding the variables of interest, coefficients for the interaction term and the takeover diversification variable are highly significant across all the different specifications. Note that the interaction term has a positive sign and the takeover diversification term has a negative sign. To interpret these results, consider Regression (2). Given an acquirer with inefficient internal capital markets (i.e. $ICMF_A$ equal to one), a ten percentage point increase in *Diversification* indicates a net increase of five basis points ($-0.00744 + 0.00794$) in the cost of equity. In this example, the diversification discount outweighs the coinsurance effect. Now, consider an acquirer for which the internal capital market works perfectly (i.e. $ICMF_A$ equal to zero). The same ten percentage point increase in *Diversification* leads to a net decrease of 74.4 basis points ($-0.00744 + 0$) in the cost of equity. Even though $Concentration_A$, $ICMF_A$, and *Rolling* $ICMF_A$ are significant in five out of six regressions, I neglect those coefficients here as they are relatively small. These results provide evidence that the diversification discount and the coinsurance effect coexist. While the diversification discount dominates in takeovers when the acquirer has a weak internal capital market, the coinsurance effect is more important in transactions in which the acquirer already has an efficient internal capital market in place.[37]

To illustrate these results, I plot fitted values in Figure 11 and demonstrate a hypothetical cost of equity development in Table 42. Figure 11 shows the predicted cost of equity when the acquirer is concentrated and

37 Note that the diversification discount is reflected in the positive estimates for the interaction term in Table 41 as this implies an increase in the cost of equity. For the coinsurance effect (modeled by the takeover diversification variable), the opposite holds true.

diversified (left side) and when the acquirer has efficient and inefficient internal capital markets before the takeover (right side).

Table 42 shows the hypothetical development of the cost of equity based on the estimates from Regression (2) of Table 41. All variables except *Diversification*, $ICMF_A$, and *Interaction* are set to their in-sample mean values. For different values of *Diversification* and $ICMF_A$, I calculate the impact on the predicted cost of equity. The conclusions are similar to Figure 11. Greater diversification is only beneficial if the acquirer has an efficient internal capital market. For example, an internal capital market inefficient acquirer (mean $ICMF_A$ plus one standard deviation) that diversifies (mean *Diversification* plus one standard deviation) is predicted to have a 1.40 percentage points increase in its cost of equity. For the same transaction, an internal capital market efficient acquirer (mean $ICMF_A$ minus one standard deviation) would benefit from a 0.26 percentage point decrease in its cost of equity.

I use the results of Regression (2) in Table 41 to evaluate the economic impact of my analysis. I investigate the partial impact of *Diversification* on the dependent variable ($Delta_{CE}$) by focusing on two cases: an acquirer with an efficient internal capital market undertaking a diversifying takeover and an acquirer with an inefficient (or lacking) internal capital market also undertaking a diversifying acquisition. In the first case, an average diversifying takeover yields a reduction of 43 basis points in the cost of equity, all else being equal. Taking the mean firm value for merged firms in that subsample, this reduction is equal to savings of around 74 million USD in the expected equity return in the first year. When considering internal capital market inefficient acquirers, an average diversifying takeover increases the cost of equity by 6.8 basis points, all else being equal. In this subsample,

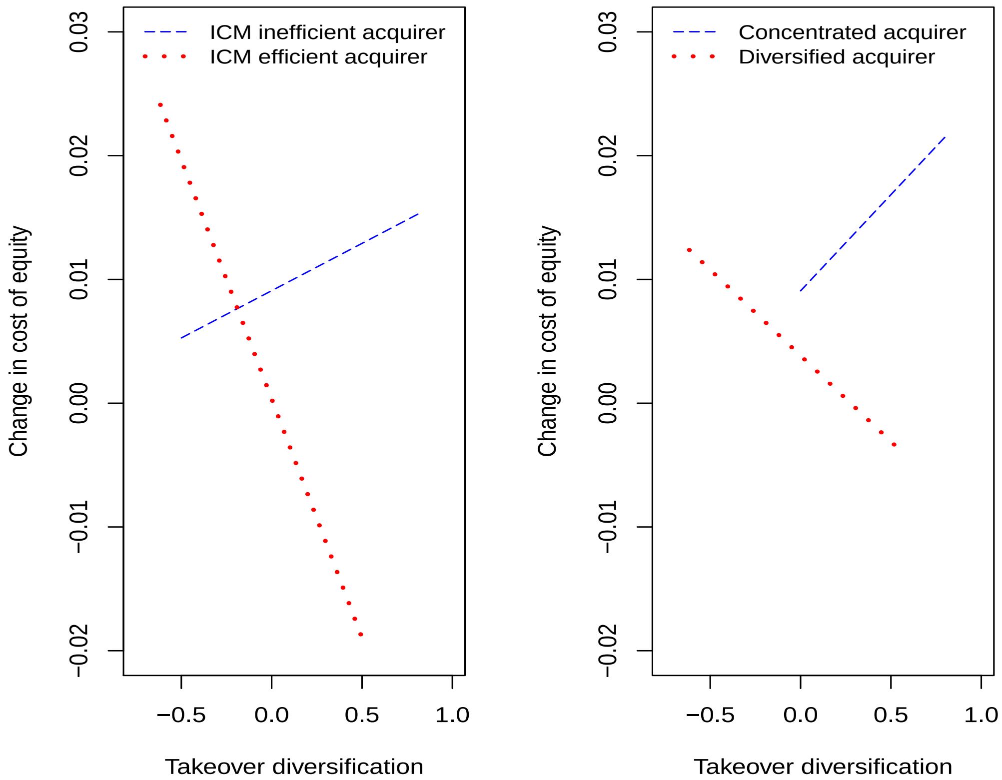

Figure 11: **Cost of equity prediction**
These two plots show a prediction of the cost of equity depending on the level of takeover diversification. They are based on fitted values from a regression of $Delta_{CE}$ (see Section 6.4.3) on $ICMF_A$ (see Section 6.4.5) on the left side and from a regression of $Delta_{CE}$ on $Concentration_A$ (see Section 6.4.3) on the right side. In both regressions the sample median value of $ICMF_A$ or $Concentration_A$ is used to split the main sample.

	Takeover diversification						
$ICMF_A$	$\mu-\sigma$	$\mu-\frac{2}{3}\sigma$	$\mu-\frac{1}{3}\sigma$	μ	$\mu+\frac{1}{3}\sigma$	$\mu+\frac{2}{3}\sigma$	$\mu+\sigma$
$\mu-\sigma$	0.72	0.56	0.39	0.23	0.07	-0.09	-0.26
$\mu-\frac{2}{3}\sigma$	0.75	0.63	0.51	0.38	0.26	0.14	0.02
$\mu-\frac{1}{3}\sigma$	0.78	0.70	0.62	0.54	0.45	0.37	0.29
μ	0.80	0.77	0.73	0.69	0.65	0.61	0.57
$\mu+\frac{1}{3}\sigma$	0.83	0.83	0.84	0.84	0.84	0.84	0.85
$\mu+\frac{2}{3}\sigma$	0.86	0.90	0.95	0.99	1.03	1.08	1.12
$\mu+\sigma$	0.89	0.97	1.06	1.14	1.23	1.31	1.40

Table 42: **Economic effects**
This table estimates the economic effects of diversification. All figures are in percent. I run Regression (2) of Table 41 and store the coefficients. Then I predict the cost of equity variable (*DeltaCE*, see Section 6.4.3) by using the stored regression coefficients, the sample mean values of the control variables, and the value of the measure of internal capital market friction ($ICMF_A$, see Section 6.4.5) and takeover diversification (*Diversification*, see Section 6.4.4) according to the position in the table above. μ indicates the mean value of *Diversification* (along the first row) and $ICMF_A$ (along the first column) in the respective sample and σ denotes the corresponding standard deviation.

the average value of the merged firm is 18.6 billion USD which translates into extra costs of around 13 million USD in the first year. This example underlines the practical relevance of my findings.

6.5.3 *Robustness tests*

6.5.3.1 *Level cost of equity*

One concern might be that the relative measure of the cost of equity (relative to the market) is driving the results. To address this point (and also to provide more interpretable estimates), I re-estimate Regression (2) from Table 41 using level cost of equity when calculating the dependent variable. The results are presented in Regression (1) of Table 43. The results are qualitatively unchanged. The p-values of the coefficients of interest increase somewhat but remain below the one percent level. The magnitude of these coefficients is somewhat smaller compared to the ones from Table 41 but the sign is the same. The decrease in significance and magnitude may be due to not controlling for the general development of the cost of equity within the measurement periods. My proxy for the cost of equity is the implied cost of equity. On a market-wide level, this measure follows trends (for example, Li et al. (2013)). Since I do not account for this variation in the above regression setting, the estimated coefficients are less precise.

6.5.3.2 *Excluding concentrated acquirers*

It is not possible to compute the internal capital market friction variable for fully concentrated acquirers (i.e. acquirers that only have one business segment). In those cases, I assign the value of one to $ICMF_A$. To show that the findings are not driven by this decision, I exclude all takeovers where the acquirer is fully focused and re-run Regression (2) of Table 41. The results are presented in Table 43, Regression (2). The interaction term between *Diversification* and $ICMF_A$ is significant at the ten percent level and the coefficient of *Diversification* remains significant at the one percent level, despite a large drop in the number of observations. Furthermore, the signs and magnitudes of the main coefficients are similar to the ones in Table 41.

This regression also helps to mitigate another concern. One could argue that the characteristics of the target are systematically different for focused and diversified acquirers. Specifically, suppose that focused firms tend to be under pressure to diversify because they are stuck in low growth industries. This pressure could lead them to make financially bad deals in the M&A market. After the merger, the market takes this financially detrimental transaction into account and, consequently, the cost of equity increases, which drives the results. In such a scenario, the characteristics of the target company would vary dependent on the pre-merger concentration level of the acquirer. However, given that the results remain qualitatively unchanged when excluding focused firms, this alternative explanation cannot fully explain the findings.

6.5.3.3 *Overlapping takeovers*

It is possible that one acquirer undertakes a series of takeovers that overlap. This should work against my findings as it introduces additional noise into the regressions. Nevertheless, I perform robustness checks to ensure that the results are not influenced by the existence of overlapping takeovers. More precisely, I drop all takeovers for which the announcement date lies between the announcement and effective date of another merger from the same acquirer. I do the same check with the effective date. I then re-run Regression (2) from Table 41. The coefficient (t-statistic) of *Diversification* is -0.0685 (-3.26) and the coefficient (t-statistic) of *Interaction* is 0.0754 (3.27). Hence, the results are virtually unchanged.

6.5.3.4 *Selection model*

All the regressions include IMR_A to control for a possible endogeneity issue, as suggested by previous studies on takeovers and corporate diversification. It is noteworthy that this selection variable is statistically insignificant in all the regressions, indicating that in this setting, endogeneity may not be a major concern. As Regression (3) of Table 43 shows, the previous results are unchanged if I drop the first-stage decision model.

6.5.3.5 *Alternative set of control variables*

The set of control variables included in the main regression strikes a balance between influence on the change in cost of equity and data availability. In Regression (4) of Table 43, I use a different set of control variables that aim to capture differences between the acquirer and the target before the takeover. Specifically, I compute the following differences between acquirer and target variables: return on equity, long-term earnings growth forecast, and industry adjusted market-to-book ratio. I compute the industry-adjusted market-to-book ratio by subtracting the imputed market-to-book ratio from the company's market-to-book ratio. The imputed market-to-book ratio is the asset weighted average of the firm's segment market-to-book ratios. The segment market-to-book ratios are industry market-to-book ratios based on the three digit SIC code (this procedure follows Villalonga 2004a). Finally, I also include the percentage of cash payment for the takeover. The coverage for the new control variables is not as wide, hence the drop in observations to 435 (down from 558 in Regression (2) of Table 41). The main coefficients have the expected signs and magnitudes. They are also highly statistically significant.

	(1)	(2)	(3)	(4)
Dependent Variable	Absolute DeltaCE	DeltaCE	DeltaCE	DeltaCE
Interaction	0.0572***	0.0416*	0.0797***	0.0676**
	(0.02)	(0.02)	(0.02)	(0.03)
Diversification	-0.0554***	-0.0698***	-0.0747***	-0.0656***
	(0.02)	(0.02)	(0.02)	(0.03)
$ICMF_A$	0.0115***	0.0081**	0.0113***	0.0079*
	(0.00)	(0.00)	(0.00)	(0.00)
IMR_A	-0.0053	-0.0026		-0.0035
	(0.00)	(0.01)		(0.00)
Synergies	0.1224	0.1818	0.1401	0.1254
	(0.08)	(0.20)	(0.07)	(0.09)
RatingChange	-0.0013	0.0007	-0.0007	-0.0009
	(0.00)	(0.00)	(0.00)	(0.00)
LeverageChange	0.0657***	0.0463**	0.0563***	0.0609***
	(0.01)	(0.02)	(0.01)	(0.01)
ln(TransactionValue)	-0.0006	-0.0007	-0.0005	0.0009
	(0.00)	(0.00)	(0.00)	(0.00)
FriendlyTakeover	0.0076	0.0128	0.0077	0.0188***
	(0.01)	(0.01)	(0.01)	(0.01)
MultipleBidders	-0.0052	-0.0007	-0.0043	-0.0005
	(0.01)	(0.01)	(0.01)	(0.01)
RelativeSize	0.0121	0.0166	0.0103	-0.0059
	(0.01)	(0.02)	(0.01)	(0.01)
$ReturnOnEquity_A$	0.0036	0.0045	0.0056	
	(0.01)	(0.01)	(0.01)	
$LongTermGrowth_A$	-0.0348	-0.0789**	-0.0308	
	(0.02)	(0.04)	(0.02)	
$Leverage_A$	-0.0078	-0.0029	-0.0034	
	(0.01)	(0.02)	(0.01)	
$MarketToBook_A$	0.0007	0.0004	0.0006	
	(0.00)	(0.00)	(0.00)	
PercentageOfCash				-0.0074**
				(0.00)
Constant	-0.0053	-0.0041	-0.0107	-0.0160
	(0.01)	(0.02)	(0.01)	(0.01)
Differences Controls	No	No	No	Yes
Sample Restriction	None	Diversified Acquirers	None	None
Observations	558	218	558	429
Adjusted R^2	0.150	0.094	0.137	0.192

Table 43: **Robustness tests**
This table shows variations of Regression (2), Table 41). A detailed explanation of most variables is given in Section 6.4. The interaction term is the product of *Diversification* and $ICMF_A$. IMR_A is the inverse Mills Ratio from a first-stage regression that models a firm's decision to undertake a merger. Regression (1) uses an absolute measure of the cost of equity (instead of one relative to the market level) as the dependent variable. Regression (2) excludes focused acquirers. Regression (3) does not use a Heckman two-stage procedure. Regression (4) has additional controls: *PercentageOfCash* is the percentage of cash payment in the takeover; differences controls include the difference of target and acquirer with regard to *ReturnOnEquity*, *LongTermGrowth*, and *MarketToBook*. Because of outliers, the differences of *MarketToBook* are winsorized at the top and bottom percentile. *t* statistics based on heteroscedasticity-consistent standard errors shown in parentheses. *, **, and *** indicate a significant difference from zero on a ten-, five-, and one-percent level.

6.6 CONCLUSION

In this study, I provide insight regarding two apparently contradictory effects in the corporate diversification literature. On the one hand, it is argued that the coinsurance effect decreases the cost of equity for conglomerates due to a decrease in their systematic risk. On the other hand, there is empirical evidence that diversified firms have lower valuations than similar stand-alone firms, which could be related to a higher cost of equity of these conglomerates.

The main differences between diversified and focused firms lie in the variability of the firm's cash-flows and the existence of an internal capital market. Whereas focused firms have only one cash flow stream and no experience with internal capital markets, diversified firms have imperfectly correlated segment cash flows and experience with internal capital markets. However, the quality of internal capital markets can vary among diversified firms.

I am able to include both variables (quality and experience) in my investigations, thereby providing empirical evidence that the cost of equity of a combined firm is driven by a coinsurance effect as well as a diversification discount. When analyzing M&As, I find, for diversifying transactions, that firms with efficient internal capital markets (or with a high level of experience with internal capital markets) benefit from the coinsurance effect. Their cost of equity, on average, significantly decreases after the merger. However, a diversifying transaction has the opposite effect on companies with inefficient internal capital markets (or that are inexperienced with internal capital markets). In those cases the cost of equity increases. This is in line with the theoretical model from Section 6.3 predicting that cross-subsidization in conglomerates increases their systematic risk.

These effects also have economic significance. For example, a firm with an efficient internal capital market that increases its diversification through a merger by the sample mean amount can expect a cost of equity decrease of 43 basis points relative to the market rate. For the average-sized company in my sample, this translates into cost of equity savings of around 74 million USD for the first year after the merger. In contrast, for an average acquirer with an inefficient capital market the cost of equity increases by 6.8 basis points.

I acknowledge that this study has some limitations. First, the data requirements for the cost of equity measure are high which limits the sample size. I can only include public acquirers taking over listed targets. This also means that I have to exclude firms that do not take part in the takeover market. Furthermore, both firms need to be covered by analysts in order to compute the implied cost of equity. Second, estimating the cost of equity is a notoriously difficult task, which is prone to measurement errors.

To conclude, my findings enhance our understanding of corporate diversification by disentangling two important concepts, the diversification discount and the coinsurance effect and their impact on the firm's cost of equity. They are also relevant for corporate managers who have to evaluate potential acquisitions.

7 CONCLUSION

7.1 SUMMARY

This thesis set out to explore different applications of an expected stock return proxy that uses forward-looking data, namely the ICC. In Chapter 1, I motivate why estimating the expected stock return is such a central topic in finance and outline the role that the ICC plays in this literature.

In Chapter 2, I provide an overview of the various estimation approaches for expected returns, as well as of studies that have employed the ICC. The purpose is to highlight research questions that lend themselves to be answered using the ICC. For example, due to its low volatility, the ICC is an ideal measure for uncovering relationships in a regression setting (Lee et al. 2009).

As I propose novel applications of the ICC, I pay careful attention to its data requirements and computation, which I describe in detail in Chapter 3. I use established financial databases, namely CRSP and Compustat for the U.S. and TR Datastream and Worldscope for international countries. Analysts' earnings forecasts are taken from IBES for all countries. I closely follow the literature when computing ICC estimates and I especially take care to use only information that was available to the investor at the time of computation. The descriptive statistics in Chapter 3 are in line with the results from other studies, thereby validating my methodology.

Chapters 4 to 6 present the empirical applications of the ICC to problems in finance. The first of these applications looks at the BL approach to portfolio optimization in a cross-country setting. I show that the market ICC is ideal for quantifying investors' views on expected country-level returns. The resulting portfolio outperforms, on a risk-adjusted basis, several different investment allocation methods (for example, market capitalization, GDP, and equally-weighted). It is also superior to using a simple moving average return model or a more sophisticated EGARCH time-series model based on historic stock returns to proxy for the expected market return.

Chapter 5 applies the ICC to a Markowitz (1952) mean-variance optimization setting. The optimization is performed on a stock-level. I demonstrate that correcting the ICC estimates for a known bias in analysts' earnings forecasts (Guay et al. 2011) leads to a portfolio that outperforms the minimum-variance portfolio as well as other common benchmarks, such as the value-weighted and equally-weighted portfolio. The results also hold when controlling for portfolio risk.

Finally, Chapter 6 exploits the fact that the ICC can be estimated without historic data to investigate the relationship between corporate diversification and the cost of equity. I reconcile two conflicting views from the corporate diversification literature: on the one hand, conglomerates' imperfectly correlated segment cash flows should reduce the dead-weight cost of financial distress, which is related to the business cycle. Thus, diversified firms should have lower cost of equity compared to similar stand-alone firms (Hann et al. 2013). This finding is known as the coinsurance effect. On the other hand, the documented diversification discount (Lang and Stulz 1994, Berger and Ofek 1995) could be the outcome of higher cost of equity for diversified firms (Lamont and Polk 2001). I find that diversified firms indeed benefit from a coinsurance effect, which lowers their cost of equity. At the same time, I observe that an inefficient internal capital market increases a diversified firm's cost of equity. This is consistent with many studies that document problems associated with internal capital markets (for example, Lamont 1997, Lang and Stulz 1994).

7.2 LIMITATIONS

A major concern for the portfolio optimization studies is that ICCs only have predictive power for longer horizons (Li et al. 2013, Tang et al. 2014). In this thesis, I rebalance portfolios annually and the portfolios based on the ICC perform strongly. This would probably not be the case for shorter rebalancing intervals. Thus, the ICC is not suitable for investment managers who want to rebalance their portfolio frequently.

There are also some practical issues to be considered when integrating the ICC into the investment process. First, the data requirements for estimating the ICC are high and involve merging several different databases. Second, to compute the ICC, one has to numerically solve a polynomial equation. This is computationally intensive, especially on a stock-level. Portfolio managers may find the implementation difficult for a broad investment universe. Furthermore, I have explored ICC estimates for international countries on a market-level. On a stock-level, I provide evidence only for the U.S., as the coverage and quality of the underlying analyst data has been extensively studied. Stock-level ICC estimates in a sample of international countries may have substantially less predictive power.

The main drawback of the study design from Chapter 6 is the small sample size. Only listed companies that are active in the takeover market can be included. Moreover, the firms have to be covered by analysts so that earnings forecasts are available and the ICC can be computed before and after the takeover event. Finally, estimating the cost of equity using any method is notoriously difficult and I cannot completely exclude the possibility that measurement errors may be correlated with the outcome variable.

7.3 OUTLOOK

Research involving the ICC offers many promising avenues for future studies. First, while the properties and biases of analysts' forecasts are well studied in the U.S., there is little evidence for other countries. Unanswered questions remain, such as: are analysts in other countries also slow to react on recent stock price changes (Guay et al. 2011)? Are there other variables that systematically influence analysts' forecast errors? How large are the cross-country differences in analysts' forecast errors? Investigating these questions would help to improve the ICC's predictive power in an international sample.

In the applied portfolio choice literature, it would be interesting to test a wider range of ICC computation methods, such as the ones using mechanical earnings forecasts (Hou et al. 2012, Li and Mohanram 2014) or methods that estimate the ICC and the terminal value growth rate simultaneously (Easton et al. 2002, Nekrasov and Ogneva 2011). With the proliferation of alternative data sets (so-called big data), it would be rewarding to test other sources of firms' earnings forecasts. For instance, the company Estimize aggregates crowd-sourced earnings estimates from its website. Another worthwhile comparison could be to include simpler proxies for the expected return, such as the forward earnings-price ratio.

As seen in Chapter 6, the ICC offers numerous advantages in event studies. Foremost, it does not rely on a long history of data. Consequently, it can be estimated soon after an event takes place. This opens the door to many new applications around mergers and acquisitions, such as investigating the cost of equity effects of mergers that use more or less cash, or which target characteristics influence the cost of equity of the merged firm and by how much.

A

APPENDIX

A.1 BETA OF AN INTERNAL CAPITAL MARKET INEFFICIENT FIRM

In the following, I will show that $\beta_c^{ICM} > \beta_c$ holds, provided $p_g > p_b$:

$$
\begin{aligned}
& \frac{2p_g H + p_g^2 V + 2p_g(1-p_g)L}{2p_b H + p_b^2 V + 2p_b(1-p_b)L} - 1 > \frac{2p_g H + 2p_g(1-p_g)L}{2p_b H + 2p_b(1-p_b)L} - 1 \\
\Longleftrightarrow\ & p_g(2H + p_g V + 2L - 2p_g L) \times p_b(2H + 2L - 2p_b L) > \\
& p_g(2H + 2L - 2p_g L) \times p_b(2H + p_b V + 2L - 2p_b L) \\
\Longleftrightarrow\ & p_g 2VH + p_g 2VL - 4p_b L^2 > p_b 2VH + p_b 2VL - p_g 4L^2 \\
\Longleftrightarrow\ & p_g(2VH + 2VL + 4L^2) > p_b(2VH + 2VL + 4L^2) \\
\Longleftrightarrow\ & p_g > p_b \qquad \text{q.e.d.}
\end{aligned}
\tag{40}
$$

A.2 CONTRIBUTION TO WORKING PAPERS

Working paper 1: International asset allocation using the market implied cost of capital

Authors: Patrick Bielstein

I developed the research design, collected all the data, conducted all anlyses, interpreted the results, and prepared and revised the manuscript.

P. Bielstein
Patrick Bielstein

Working paper 2: Mean-variance optimization using forward-looking return estimates

Authors: Patrick Bielstein, Matthias Hanauer

I developed the research design, collected all the data, conducted most analyses, and prepared and revised the manuscript in accordance with suggestions provided by Matthias Hanauer. Matthias Hanauer contributed to the research methods, data analysis, and the interpretation of the results, as well as provided manuscript edits.

P. Bielstein	Hanauer M.
Patrick Bielstein	Matthias Hanauer

Working paper 3: The cost of capital effect of M&A transactions: disentangling coinsurance from the diversification discount

Authors: Patrick Bielstein, Mario Fischer, Christoph Kaserer

The dataset was prepared by Mario Fischer and myself. The data analysis was an interactive process which occured primarily between Mario Fischer and myself. The interpretation of the results and writing the paper was an iterative, cooperative process involving all authors.

P. Bielstein	M. Fischer	Ch. Kaserer
Patrick Bielstein	Mario Fischer	Christoph Kaserer

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