Employing the Residual Income Model in Portfolio Optimization

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Abstract

In an empirical study for the German stock market we use consensus analysts' forecasts to derive estimates of implied expected returns using the Residual Income Model. In an out-of-sample study we analyze if the optimal combination of these estimates with time series estimates from realized returns results in an improved performance when implementing portfolio optimization compared to traditional approaches. The results show that an estimator that combines information of analysts' forecasts and time series data is superior to all other strategies. In most of the cases this superiority is even statistically significant. The results differ slightly with respect to different sub-periods and different market-segments. Our results demonstrate that the information contained in analysts' forecasts helps to reduce the severe negative consequences of estimation risk in portfolio optimization.

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1 Introduction

Harry Markowitz (1952) analyzed in his seminal paper on portfolio selection the trade-off between risk and expected return of an investment portfolio. He showed how an investor should optimally choose her investment portfolio with respect to her individual preferences on risk and expected return. This choice depends on the expected returns, variances and covariances of the assets available to the investor. When implementing Markowitz-optimization the problem arises that these true return parameters are not known to the investor. She has to make her portfolio choice based on estimates about the true return parameters. As the average performance of the investment portfolio is the higher the more precise the estimates about the return parameters are the investor wants to employ estimates that are as precise as possible.

The return parameters can be estimated in several different ways. The traditional approach is to use the maximum-likelihood estimator based on time series data of past realized returns.[1] This estimator is unbiased, but shows up to have low precision. As shown by Merton (1980), while the precision of the maximum-likelihood estimator of the variance-covariance-matrix can be improved by an increase in data frequency this is not possible for the estimator of the expected return.[2] As a low precision of the estimators of expected asset returns has negative consequences for the performance in portfolio optimization[3] it is worthwhile to find alternative estimators of expected returns that have a higher precision.

Several approaches have been proposed in the literature how to reduce estimation risk and its severe negative consequences. Grauer/Shen(2002) e.g. impose restrictions on the portfolio weights to avoid extreme positions. Other approaches combine estimators following the principle of rational information processing according to Bayes.[4] Such a combination of estimators was used for the first time in portfolio optimization by Frost and Savarino (1986). They shrink the time series estimator towards an informative prior which is the average return

[1] The maximum-likelihood estimator is equal to the arithmetic mean for most distributions as it is for the normal distribution which is usually assumed in the literature for the distribution of returns. For early implementations of Markowitz optimization based on time series estimators see, for example, Cohen/Pogue (1967), Grubel (1968) or Levy/Sarnat (1970).

[2] Empirical evidence of the high precision of the estimator for the variance-covariance matrix and the comparatively low precision of the estimator for expected returns can be found for example in Jorion (1991).

[3] See Chopra/Ziemba (1993).

[4] See Bayes (1763, 1764).

over all assets. Other approaches impose the structure of an asset pricing model on the prior, as e.g. the CAPM[5]. Black und Litterman (2000) combine an estimator obtained from the CAPM with another un-defined estimator ("subjective estimator"). Pastor (2000) uses the Bayesian procedure to combine an estimator obtained from the Arbitrage Pricing Theory with the time series estimator.

In our paper we take a different approach. As an alternative to the traditional time series estimator expected returns can be estimated from analysts' forecasts about future earnings or dividends etc. Other than time series data about past realized returns that is backward-looking by nature analysts' forecasts about future developments are forward-looking information.[6] Several models exist that use this information to derive implied estimates about expected returns.[7] These models can be grouped into models that are based on forecasts about future cash flows (e.g. Free-Cash-Flow Model) and models based on forecasts of accounting data like the Residual Income Model. Since Ohlson (1995) introduced the model it became increasingly popular in recent years. Using this model expected returns are estimated based on information about today's book value of equity and expected earnings and book values of equity in the future. The first papers that used this model for an estimation of implied expected returns are Botosan (1997), Claus and Thomas (1998) and Gebhardt, Lee, Swaminathan (2000). Botosan analyzes the relationship between corporate information policy and implied expected returns. Claus and Thomas estimate the implied market risk premium using the Residual Income Model. Gebhardt, Lee and Swaminathan estimate the implied cost of equity capital of firms in a first step and reveal the characteristics of the firms that systematically influence the cost of equity capital in a second step. We build on this strand of literature by using the information contained in implied expected returns derived from the Residual Income Model to find an estimator that is more precise than the time series estimator and analyze if its use results in a higher performance when implementing Markowitz-optimization.

[5] See Sharpe (1964), Lintner (1965), Mossin (1966).

[6] These forecasts too do depend on information of the past, i.e. information that is available at the time the forecast is made. Which kind of information and which method was used to generate the forecast is not discussed in this paper.

[7] These models include e.g. the Dividend Discount Model, the Free-Cash-Flow Model or the Residual Income Model. Estimators of expected returns that are derived from this kind of models are referred to as implied expected returns or implied cost of equity capital because they are derived implicitly if the valuation equation of the model used is assumed to hold.

The contribution of our paper is the empirical investigation of the question if the use of implied expected returns based on analysts' forecasts results in an improved investment performance. We employ the implied expected returns separately as well as in combination with the classical time series estimator. When combining the estimators our aim is to diversify estimation errors to obtain an estimator of increased precision. To our knowledge the usage of an estimator of expected returns derived from the Residual Income Model in portfolio optimization has not been considered in the literature so far.

In an out-of-sample for the German stock market we analyze how the estimator derived from the Residual Income Model performs when compared to other traditional investment strategies. These other strategies are on the one hand strategies that are based on other well-known estimation procedures like the time series estimator and the CAPM. On the other hand we use strategies that do not use estimates of expected returns like a naïvely diversified portfolio and the global minimum variance portfolio. As our analysis for the biggest German companies will show the separate use of the implied expected return estimates does not lead to a significantly better performance when compared to other strategies. However, in optimal combination with the time series estimator it results in a performance that is superior to the performance of all other strategies. Slightly different results are obtained with respect to different market-segments and sub-periods dependent on the different quality of the return estimates using analysts' forecasts.

Our paper is organized as follows: In chapter 2 we briefly describe the Residual Income Model that we use to estimate the implied expected returns. Furthermore, we describe how to optimally combine estimators and we present the alternative investment strategies used for comparison. The data used in our analysis is described in chapter 3. In chapter 4 we present our results. Chapter 5 concludes.

2 Methodology

2.1 Estimating the expected rate of return employing the Residual Income Model

The Residual Income Model (alternatively Edwards/Bell/Ohlson Model) is derived from the Dividend Discount Model (DDM).[8] The Dividend Discount Model determines the market value of a company as the present value of all expected future dividends, i.e. the sum of all

[8] See Williams (1938).

expected dividends discounted by the risk-adjusted cost of equity capital μ [9]. If the Clean-Surplus-Relation holds the Dividend Discount Model can be transformed into the Residual Income Model that we will use to infer the implied cost of equity capital.

$$V_t = B_t + \sum_{\tau=1}^{4} \frac{\hat{NI}_{t+\tau} - \hat{\mu}_t^{RIM} \cdot \hat{B}_{t+\tau-1}}{(1+\hat{\mu}_t^{RIM})^{\tau}} + \frac{\hat{NI}_{t+4} - \hat{\mu}_t^{RIM} \cdot \hat{B}_{t+3}}{(\mu_t^{RIM} - g_t)(1+\hat{\mu}_t^{RIM})^4} . \quad (1)$$

V_t denotes the market value and B_t the book value of the firm at time t. $\hat{NI}_{t+\tau}$ and $\hat{B}_{t+\tau}$ are forecasts about future earnings and future book values of the firm at time $t+\tau$. These forecasts are typically generated by financial analysts. The difference between the expected earnings of a period and the book value of the preceding period multiplied by the cost of equity capital is the expected residual income of the period. If the expected residual income of a period is positive the company is expected to generate earnings that are higher than it would be "appropriate" with respect to the capital base of the firm in this period (in terms of book value) and its risk. The sum of the discounted expected residual incomes equals the difference between market and book value of the firm at time t.[10]

The estimation approach requires forecasts about future earnings and book values for an infinite number of periods. But in reality analysts' forecasts are available only for a maximum of four periods. Therefore we have to make simplifying assumptions about the development of earnings and book values in future periods. Several different approaches have been proposed in the literature.[11] In our study we use the simplifying assumption that the residual income grows at a constant rate g in perpetuity from year 5 on.

2.2 Combination of estimates of expected returns

We want to use the estimator of the expected rate of return on equity capital derived from the Residual Income Model in combination with the time series estimator. The motivation of this combination is to gather the information that is contained in each of the separate estimators in

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[9] The expected return μ is equal to the internal rate of return, i.e. the expected return is assumed to be constant for all maturities. Claus/Thomas (2001) estimate the empirical market risk premium and use an approach where the size of the discount factor varies with maturity but the market risk premium remains constant.

[10] If we use an approach like (1) to estimate the implied cost of equity capital of a firm we do assume that the market value of the firm on the left-hand side of (1) is equal to the sum of the current book value and the present value of the expected future residual incomes of the firm on the right-hand side. This implies that the current value of the firm is assumed to be fair and that expected future prices will develop as the RIM implies.

[11] See e.g. Gebhardt/Lee/Swaminathan (1999) and Claus/Thomas (2001).

a single estimator. If the estimation errors of the estimators are not perfectly correlated a diversification of these errors can be reached by this combination.

In order to optimally combine the estimators we follow the Bayesian approach.[12] We assume a return generating process as shown in (2).

$$\tilde{r}_t = \tilde{\mu} + \tilde{\eta}_t \,. \tag{2}$$

$\tilde{r}_t$ is an $N \times 1$-vector of the returns of N assets at time t. $\tilde{\mu}$ und $\tilde{\eta}_t$ are the $N \times 1$-vectors of expected returns and innovations, respectively, of the N assets at time t. For the distribution of asset returns we assume a normal distribution as is usually done in the literature.

$$\tilde{r} \,|\, \tilde{\mu} \sim N(\tilde{\mu}, \Sigma_\eta) \,. \tag{3}$$

Σ_η denotes the variance-covariance-matrix of innovations. The true mean $\tilde{\mu}$ of this distribution is unknown to the investor and as we are in the Bayesian framework this mean is not fixed but a random variable. The idea that the investor has got about the distribution of $\tilde{\mu}$ is the prior distribution $k_{\text{Prior}}(\tilde{\mu})$. For $\tilde{\mu}$ we assume that

$$\tilde{\mu} = \overline{\mu}^{\text{Prior}} + \tilde{\varepsilon} \,. \tag{4}$$

The prior distribution of $\tilde{\mu}$ is given by

$$\tilde{\mu} \sim N(\overline{\mu}^{\text{Prior}}, \Sigma_\varepsilon) \,.^{13} \tag{5}$$

Using (2) and (4) we can rewrite the return generating process as

$$\tilde{r}_t = \overline{\mu}^{\text{Prior}} + \tilde{\varepsilon} + \tilde{\eta}_t \,. \tag{6}$$

If the investor has got any additional information about $\tilde{\mu}$ she has to adjust the assumed distribution of $\tilde{\mu}$ to rationally use all given information. With the additional information the

[12] See Bayes (1763, 1764).

[13] The mean $\overline{\mu}^{\text{Prior}}$ of this distribution is the most probable value for the true mean as long as no other information is available.

"new" most probable value of the unknown mean $\tilde{\mu}$ is the mean of the posterior distribution $k_{Posterior}(\tilde{\mu} | additional\ information)$. This posterior mean can be shown to be a weighted average of the prior mean $\overline{\mu}^{\text{Prior}}$ and the mean given by the additional information $\mu^{add.info.}$.[14]

$$\mu^{Bayes} = \mu^{\text{Prior}} + \Sigma_{\mu^{\text{Prior}}} \cdot (\Sigma_{\mu^{\text{Prior}}} + \Sigma_{\mu^{add.info.}})^{-1} \cdot (\mu^{add.info.} - \mu^{\text{Prior}}). \tag{7}$$

$\Sigma_{\mu^{\text{Prior}}}$ and $\Sigma_{\mu^{add.info.}}$ are $N \times N$-matrices of the variances and covariances of the error terms of the prior estimates and the estimates based on the additional information, respectively. The combined estimator according to (7) is not unbiased but an $\mu - \sigma$-optimizing investor can realize a higher utility on average when using this estimator instead of the maximum-likelihood estimator.[15] The average utility is the higher the more precise the estimator for the true mean.

(7) can be easily interpreted if we consider the one-asset-case or assume alternatively uncorrelated errors for the prior estimates as well as for the estimates based on the additional information in the multi-asset-case. Then we obtain a simplified estimator for the posterior mean in (7):

$$\mu_i^{Bayes} = \left(\frac{\rho_i^{\text{Prior}}}{\rho_i^{add.info.} + \rho_i^{\text{Prior}}} \right) \cdot \mu_i^{\text{Prior}} + \left(\frac{\rho_i^{add.info.}}{\rho_i^{add.info.} + \rho_i^{\text{Prior}}} \right) \cdot \mu_i^{add.info.}. \tag{8}$$

The weights $\left(\frac{\rho_i^{\text{Prior}}}{\rho_i^{add.info.} + \rho_i^{\text{Prior}}} \right)$ and $\left(\frac{\rho_i^{add.info.}}{\rho_i^{add.info.} + \rho_i^{\text{Prior}}} \right)$ in (8) are relative precisions, i.e. the precisions of the prior estimator ρ_i^{Prior} and the estimator based on the additional information $\rho_i^{add.info.}$ for asset i in relation to the sum both of these precisions.

In our empirical study we combine the RIM-estimator and the time series estimator ("TSE").[16] We use the RIM-estimator as prior estimate and adjust this prior estimate according to the additional information in form of m realized returns for each of the N

[14] See, for example, Greene (2000), p. 87.
[15] See, for example, Memmel (2004).
[16] In the remainder of the paper we will use the expression $\hat{\mu}_{i,r,t}^{Bayes}$ for the Bayesian estimator of the *excess* return above the risk-free rate of return. Estimators for expected *excess* returns are assigned with the subindex r.

assets. Hence the posterior distribution is $k_{Posterior}(\tilde{\mu}|r_m)$. At each point of time t we estimate the prior as well as the time series estimator based on the latest information. Accordingly the conditional mean at time t takes the form[17]

$$\hat{\mu}_{i,r,t}^{Bayes} = \hat{\mu}_{i,r,t}^{RIM} + \hat{\Sigma}_{\mu_t^{RIM}} \cdot (\hat{\Sigma}_{\mu_t^{RIM}} + \hat{\Sigma}_{\mu_t^{TSE}})^{-1} \cdot (\hat{\mu}_{i,r,t}^{TSE} - \hat{\mu}_{i,r,t}^{RIM}) . \tag{9}$$

As our sample contains 206 companies the empirical implementation of the Bayesian approach would require to estimate more than 20,000 potential correlations between our estimators to proceed as shown in (9).[18] However, this would lead us to estimate too many parameters out of our limited data to get the variance-covariance-matrices $\hat{\Sigma}_{\mu_t^{RIM}}$ and $\hat{\Sigma}_{\mu_t^{TSE}}$. To avoid this we use the simplifying approach as presented in (8) that assumes that the errors of the estimators are pairwise uncorrelated so that $\hat{\Sigma}_{\mu_t^{RIM}}$ and $\hat{\Sigma}_{\mu_t^{TSE}}$ become diagonal matrices and the combined estimator for asset i becomes

$$\hat{\mu}_{i,r,t}^{Bayes} = \left(\frac{\hat{\rho}_{i,t}^{RIM}}{\hat{\rho}_{i,t}^{TSE} + \hat{\rho}_{i,t}^{RIM}} \right) \cdot \hat{\mu}_{i,r,t}^{RIM} + \left(\frac{\hat{\rho}_{i,t}^{TSE}}{\hat{\rho}_{i,t}^{TSE} + \hat{\rho}_{i,t}^{RIM}} \right) \cdot \hat{\mu}_{i,r,t}^{TSE} . \tag{10}$$

To determine the precisions on the diagonal of matrix $\hat{\Sigma}_{\mu_t^{RIM}}$ at time t we use all of the data available at time t. We compute the mean squared error of the RIM-estimator as[19]

$$MSE_t(\hat{\mu}_i^{RIM}) = E(\hat{\mu}_{i,t}^{RIM} - r_{i,t})^2 = \frac{1}{T} \sum_{\tau=1}^{T} (\hat{\mu}_{i,\tau}^{RIM} - r_{i,\tau})^2 . \tag{11}$$

T is the number of past RIM-estimates of asset i available at time t (consequently T is equal to or smaller than the number of periods at time t).[20] As estimator of the precision we

[17] The estimator for the expected excess return using the Residual Income Model is computed as $\hat{\mu}_{i,r,t}^{RIM} = \hat{\mu}_{i,t}^{RIM} - r_{f,t}$. The time series estimator $\hat{\mu}_{i,r,t}^{TSE}$ for the expected excess return of asset i is the arithmetic mean of the realized excess returns of the T periods preceding t. We choose $T = 52$ weeks as estimation period.

[18] When empirical data is used to compute weights instead of employing pre-specified weights this estimation procedure is also referred to as ‚empirical Bayes'. See e.g. Jorion (1991).

[19] The MSE is computed based on weekly data: The RIM-estimates are inferred every week for a horizon of one year. Then this estimate is divided by 52 to attain an estimate that refers to the horizon of one week. From this estimate the realized return of the week following the estimation day is subtracted.

use the reciprocal of the MSE. We use an analogous procedure to estimate the precision of the time series estimator.

2.3 Alternative estimation procedures and investment strategies

Alternative estimators of the expected rate of return

Our aim is to analyze if the use of the implied cost of equity capital obtained from the RIM leads to an empirically higher performance in the Markowitz optimization than other estimators. Therefore we compare its performance with the performance of investments strategies based on "traditional" estimators. These traditional estimators are the maximum-likelihood estimator based on past returns (i.e. the time series estimator "TSE"), the estimator derived from the Capital Asset Pricing Model ("CAPM") and the shrinkage estimator ("SHRK").

For the estimation of the expected excess return using the CAPM we employ the security market line:

$$\hat{\mu}_{i,r,t}^{CAPM} = \hat{\beta}_{i,t} \cdot (\hat{\mu}_{m,r,t}). \qquad (12)$$

$\hat{\beta}_{i,t}$ is estimated from the realized excess returns of asset i and the market index in the preceding 52 weeks. The estimator for the expected excess return of the market portfolio $\hat{\mu}_{m,r,t}$ is the arithmetic mean of the realized excess returns of the market index over the last 52 weeks.

To obtain the shrinkage estimator (sometimes referred to as James/Stein-estimator[21]) for the expected excess return we shrink the time series estimator towards the long-term mean of the excess returns of the biggest German companies.[22] The composition of the shrinkage-estimator is as follows:

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[20] Because a reliable estimation of the precision via the MSE requires a sufficient amount of data we use the MSE as an estimator of the precision only if there are at least 52 weeks of data available at time t to compute the MSE. Otherwise we assume the RIM-estimator and the time series estimator to be equally precise and give each a weight of 50 per cent.

[21] See Stein (1955) and James/Stein (1961).

[22] This approach was invented by Jorion (1985). The implementation in this paper follows Kempf/Kreuzberg/Memmel (2002).

$$\hat{\mu}_{i,r,t}^{SHRK} = \phi \underline{1} + T\hat{\tau}^2 I \cdot \left(\hat{\Sigma}_t^{TSE} + T\hat{\tau}^2 I \right)^{-1} \cdot (\hat{\mu}_{i,r,t}^{TSE} - \phi \underline{1}) . \quad (13)$$

$\hat{\Sigma}_t^{TSE}$ is the time series estimator of the variance-covariance matrix.[23] $\hat{\tau}$ is an estimator for the inhomogenity of the market: the larger $\hat{\tau}$ the higher the differences between the expected returns of the assets. ϕ is an $(N \times 1)$-vector of ones that is multiplied with the mean of the annual excess return of the biggest German companies. This mean is 6.5 per cent p.a. and was calculated for the time 1955 until 1993. For the period from 1955 to 1987 – before the index DAX 30 was calculated – we use the recalculated DAX 30 from Stehle (2004). Afterwards we use the DAX 30. I is an identity matrix of the dimension $N \times N$ and $\underline{1}$ is a vector of N ones.

Like the Bayesian estimator $\hat{\mu}_{i,r,t}^{Bayes}$ in (9) the shrinkage-estimator $\hat{\mu}_{i,r,t}^{SHRK}$ also is a combination of the time series estimator and another estimator. For the estimator $\hat{\mu}_{i,r,t}^{Bayes}$ we use the additional information of analysts' forecasts from which we can derive an *individual* prior estimate for the expected excess return on each asset. For the shrinkage-estimator $\hat{\mu}_{i,r,t}^{SHRK}$ instead we use only time series data from which we derive a *single* prior for all assets.

Alternative investment strategies that are not based on estimation about expected earnings

Even if the use of the implied cost of equity capital that we obtain from the Residual Income Model and its combination with the time series estimator will lead to a more precise estimator and hence to a better performance when implementing Markowitz-optimization it could still be more favourable to follow an investment strategy that does not depend on estimations about expected future returns at all. A strategy like this would totally avoid the negative consequences of estimation errors in expected returns.

We want to enclose the alternative to totally avoid estimation risk in expected returns and therefore include three further strategies in our analysis: investing in the market according to the index weights ("HDAX"), investing in all assets with equal weight (naïve diversification "EQUAL"), and investing in the global minimum variance portfolio ("GMVP").

[23] The variance-covariance matrix is estimated using the approach of the single-index model according to $\widehat{Cov}(\tilde{r}_{i,r,t}, \tilde{r}_{j,r,t}) = \hat{\beta}_{i,t} \cdot \hat{\beta}_{j,t} \cdot \widehat{Var}(\tilde{r}_{m,r,t})$.

2.4 Investment modalities

Investments are made for a holding period of 13 weeks, then the portfolio is restructured. Companies are included in the investment universe at time t for which (i) a time series estimator is available at time t, (ii) a RIM-estimator is available at time t and (iii) it applies that they are still member of the respective index at the end of the investment period, i.e. at time $t+13\,weeks$.

The portfolio that we invest in when implementing Markowitz-optimization is the portfolio of a $\mu-\sigma-$optimizing investor. Her preference function is of the form

$$\phi = \mu_W - \frac{\gamma}{2} \cdot \sigma_W^2 . \tag{14}$$

μ_W and σ_W are the expected return and standard deviation of returns of the portfolio. At the end of each investment period the portfolio is restructured according to adjustments in expected returns, variances and covariances of the assets and according to changes in the investment universe. γ is the parameter of risk aversion. With the magnitude of γ varies the part of the investment that is made in the riskless asset. The higher γ the higher the weight in the riskless investment.[24]

The vector w_t^* of the optimal weights of the investor in the N assets is given by: [25]

$$w_t^* = \frac{1}{\gamma} \cdot \hat{\Sigma}_t^{TSE-1}(\hat{\mu}_{r,t}) . \tag{15}$$

2.5 Performance measure

For the comparison of the performance of the different investment strategies we use the empirical sharpe ratio (SR)

[24] We choose $\gamma = 100$. The specific value of γ does not influence our results as our performance measure presented in chapter 2.5 is independent of the value of γ.

[25] For the computation of the variance-covariance matrix please see footnote 24.

$$\widehat{SR} = \frac{\widehat{\mu - r_f}}{\hat{\sigma}}. \tag{16}$$

The empirical sharpe ratio is the average realized excess return in the investment period divided by the average risk taken to realize this return in form of the standard deviation of returns. We test for statistically significant differences in the empirical sharpe ratios of two strategies i and j with the test of Jobson and Korkie (1981) and employ the correction of the test statistic according to Memmel (2003).

$$z = \frac{\widehat{SR}_i - \widehat{SR}_j}{\sqrt{\hat{V}}} \tag{17}$$

$$\text{with } \hat{V} = \frac{1}{T}\left[2(1-\rho_{i,j}) + \frac{1}{2}(\widehat{SR}_i^2 + \widehat{SR}_j^2 - SR_i SR_j (1+\rho_{i,j}^2)\right]. \tag{18}$$

3 Data

Our empirical study is based on the companies of the German index DAX 100 and its „successor" the HDAX, respectively. The DAX 100 was computed for the first time on April 11, 1994 and contained the 30 biggest German companies of the blue chip index DAX 30 and the 70 next smaller companies of the mid-cap index MDAX. Since March 24, 2003 instead of the DAX 100 the HDAX is computed. The HDAX contains 110 instead of 100 firms: the 30 firms of the DAX 30, the firms of the MDAX which were reduced to 50 on March 24, 2003 and the 30 firms of the technology-oriented index TecDAX which was computed for the first time in March 2003.

Our sample period covers 11 years. The investment period begins in April 1994 when the HDAX was computed for the first time. The last investment ends in July 2004.[26]

Data requirements and data preparation regarding the RIM-estimator

As forecasts for expected earnings and book values we use the consensus forecasts of the I/B/E/S-database which are available through Thomson Financial Datastream. The history of

[26] All companies that were members of the indices HDAX, MDAX, and DAX 30 during our sample period are listed in Table 11 in the appendix.

consensus forecasts has a monthly frequency. We obtain the history of unadjusted stock prices V_t from the Worldscope Database of Thomson Financial Datastream on a weekly frequency. Time series data of realized earnings and book values are obtained from this database, too. According to the yearly frequency of financial statements these data have a yearly frequency.[27]

Table 1 summarizes the data types in our study and the various data sources.

Data Type	**Data Source**	**Data Frequency**	**Used for estimator**
Performance index for all companies of the index and the index itself	Datastream	weekly	ZEIT, SHRK, CAPM
Realized stock prices	Datastream	weekly	RIM
Realized book values and earnings per share	Datastream (WorldScope)	yearly	RIM
Analysts' forecasts of future book values and earnings per share	Datastream (IBES)	monthly	RIM
Risk-free rate of return (3-month-FIBOR)	Datastream	weekly	-

Table 1: *Summary of data used in the empirical study*

Estimation in the case of incomplete data

If there are data missing for realized stock prices or book values at a point of time we cannot estimate the implied cost of equity capital with the Residual Income Model. If forecasts about future earnings or book values are not completely available for the forecast horizon up to 4 years we assume a constant growth rate from the year on for which the forecast with the next shorter horizon is available or – if there are no forecast available at all – from the realized values of earnings and book values at estimation time t on.[28]

[27] For the growth rate of residual income in perpetuity g we assume a value of 0. Alternatively, we repeated the analysis with a growth rate of 0.03 accounting for inflation as in Claus/Thomas (1998) without altering the results substantially.

[28] Claus/Thomas (1998) proceed in a similar manner. However, they discard observations for which there are not at least earnings forecasts for year 1 and 2 and the long-term growth rate available.

Finally we check if the earnings forecasts for the fourth and the book value forecast for the third year following the estimation time t is negative. For all t for which these forecasts are not positive we do not calculate the implied expected returns as the results of these calculations have no economic intuition. A negative earnings or book value forecast in the respective periods would imply for the estimation approach chosen that from year 4 on the firm will never have positive earnings again or that from year 3 on the firm will never have a positive book value.

In the case of no missing observations the total number of RIM estimates for companies when they are included in the HDAX would be 54,070. However, there are 3,905 estimates (about 7 per cent) missing so that only 50,165 estimates are available.

Characteristics of the RIM-estimates

In Figure 1 we give an impression of the size and the distribution of the means of the RIM-estimators. We depict the distribution of the means of the implied expected returns p.a. for the cross section of assets of the HDAX.

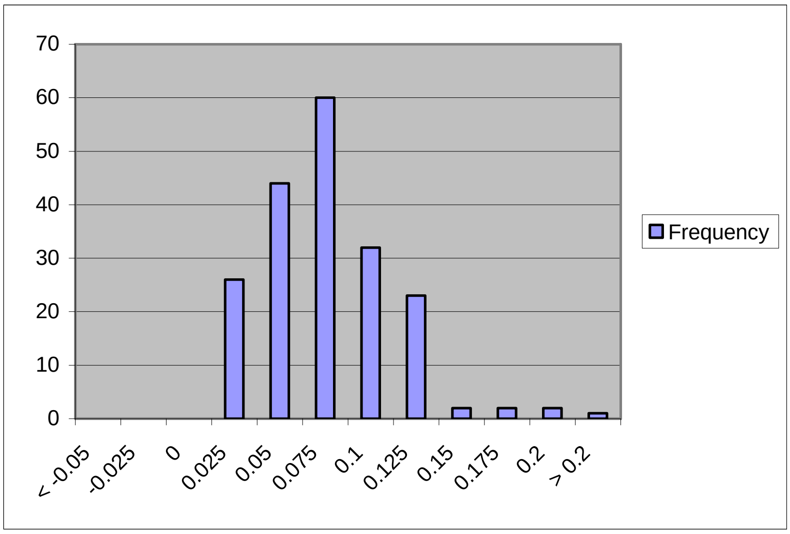

Figure 1: *Distribution of means of the RIM-estimators for the members of the HDAX*

The distribution of the standard deviations of the RIM-estimator for each of the assets in the HDAX are depicted in Figure 2:

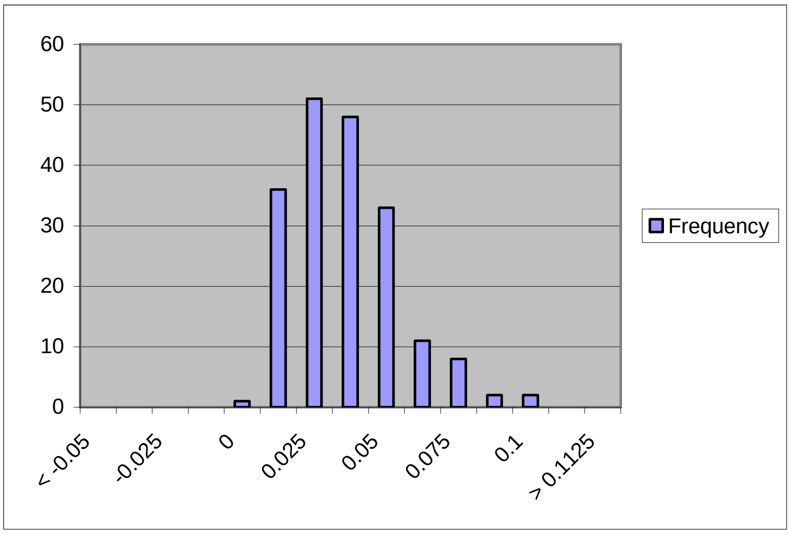

Figure 2: *Distribution of standard deviations of the RIM-estimators for the members of the HDAX*

The particular characteristics of the estimators obtained from the Residual Income Model become particularly apparent when compared to other estimators like the time series estimator. The dispersion of the means is much smaller than it is for the time series estimator as the comparison of Figure 1 and Figure 3 shows.[29] This is partly because estimates obtained from the RIM cannot become negative. But also in the positive range the dispersion of the means is much smaller than it is for the time series estimator. For example, we have only one company for which the mean of its RIM-estimators is above 20 per cent p.a. However, for the time series estimator we have 49 – about a quarter of all companies – that have a mean estimator above 20 per cent p.a.

The difference in dispersion of the expected return estimates can be seen also when we compare the standard deviations of the different estimators for each asset in Figure 2 and Figure 4.[30] For none of the firms is the standard deviation of the RIM-estimator higher than 10 per cent. For the time series estimator, however, 95 per cent of all firms have a standard deviation higher than 10 per cent.

[29] Please notice that class size in Figure 1 is only the fourth of class size in Figure 3.
[30] Please notice again the different class size that is only the tenth part in Ffigure 2 of the class size in Figure 4.

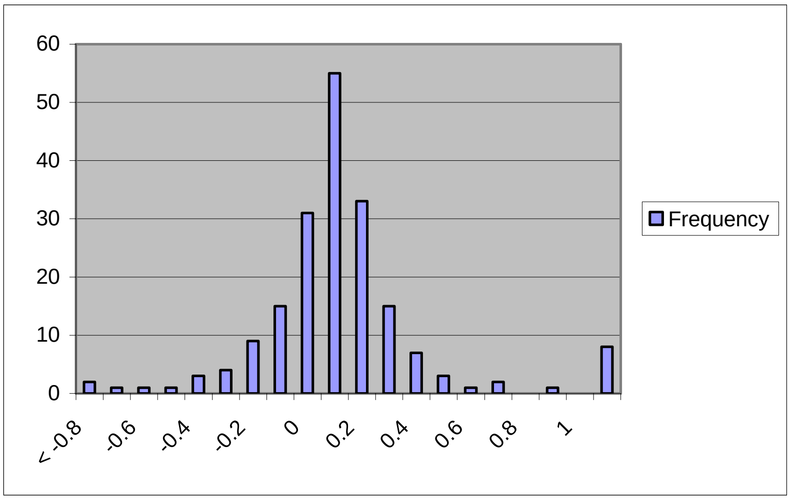

Figure 3: *Distribution of means of the time series estimators for the members of the HDAX*

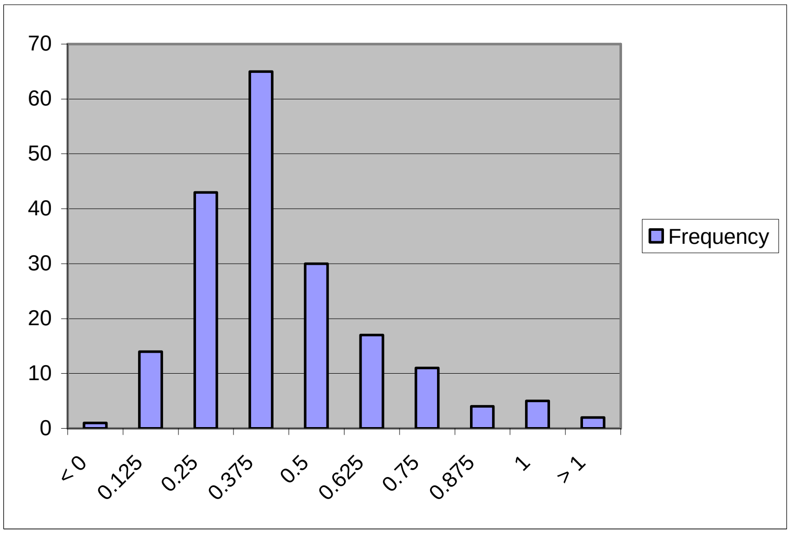

Figure 4: *Distribution of standard deviations of the time series estimators for the members of the HDAX*

To get further information about the characteristics of the RIM-estimator in comparison with the other estimators we also take a look at the Mean Squared Errors. For every company and every type of estimator we compute the mean squared difference between the estimated expected weekly return and the realized return for that week. Then we rank the different estimators for every single asset.[31] In Table 2 we report the mean ranks of the different estimators over all assets.[32]

	TSE	RIM	BAYES	CAPM	SHRK
Mean Rank	4.41	1.97	2.84	3.54	2.24

Table 2: *Mean ranks of the Mean Squared Errors of the different estimators*

[31] A similar approach was chosen by Jorion (1990).
[32] We do not report the results for each of the 206 stocks separately.

The RIM-estimator has the lowest MSE on average when compared to the other estimators. For about 46 per cent of all companies it has the lowest MSE of all estimators. The second best estimator regarding the average rank of the MSE over all assets is the shrinkage estimator followed by the combined estimator and the CAPM-estimator. The time series estimator is the worst. For most of the companies (about 72 per cent) it has the highest MSE of all estimators.

So the different estimators have apparently different properties that makes it seem promising to use the RIM-estimators as an alternative source of parameter estimates in Markowitz-optimization.

4 Results

The following table contains the average excess returns, the standard deviations and the empirical sharpe ratios of the different investment strategies when investing in the assets of the HDAX over the whole sample period from April 1994 to July 2004.

HDAX

Strategy:	TSE	RIM	BAYES	CAPM	SHRK	EQUAL	GMVP	HDAX
Av.excess return:	0.20533	0.01377	0.11006	0.00541	0.01369	0.0442	0.0356	0.04488
Std. deviation:	0.1903	0.02642	0.09458	0.0156	0.02967	0.17869	0.1165	0.22463
Sharpe Ratio:	1.07898	0.52118	1.16363	0.34713	0.46145	0.24734	0.30559	0.19978

Table 3: *Sharpe-Ratios; Assets: HDAX; Investment Period: 14.04.1994-01.07.2004*

The results show a noticeable superiority of the investment strategy based on the time series estimator (TSE) with a sharpe ratio of about 1.08. In contrast, the second best strategy based on the RIM-estimator (RIM) has a sharpe ratio of 0.52 which is only half as high. But most importantly we find that through a combination of both of these estimators (BAYES) we can achieve a sharpe ratio of 1.16 that is superior to the performance when using both estimators independently.

To test the statistical significance of the differences in the sharpe ratios we use the test of Jobson and Korkie. The results are summarized in Table 4.

	TSE	SHRK	GMVP	HDAX	EQUAL	RIM	BAYES	CAPM
TSE	NA	0.61753	**0.77339***	**0.87919****	**0.83163***	0.5578	**-0.08465***	**0.73185****
SHRK	NA	NA	0.15586	0.26167	0.21411	-0.05973	**-0.70217***	0.11433
GMVP	NA	NA	NA	0.10581	0.05825	-0.21558	**-0.85803***	-0.04153
HDAX	NA	NA	NA	NA	-0.04756	-0.32139	**-0.96384****	-0.14734
EQUAL	NA	NA	NA	NA	NA	-0.27383	**-0.91628****	-0.09978
RIM	NA	NA	NA	NA	NA	NA	-0.64245	0.17405
BAYES	NA	NA	NA	NA	NA	NA	NA	**0.8165****
CAPM	NA	NA	NA	NA	NA	NA	NA	NA

Table 4: *Pairwise differences in Sharpe Ratios; Significance test according to Jobson-Korkie (*** Significance at 1 per cent-level, ** 5 per cent-level, * 10per cent-level); Assets: HDAX; Investment Period: 14.04.1994-01.07.2004*

The superiority of the combined estimator is statistically significant in six out of seven cases. Also when comparing the strategy based on the combined estimator with the strategy based on the RIM-estimator we find the performance of the combined estimator to be higher even though this difference is not statistically significant. The results show that the best investment strategy an investor could choose for the asset universe of the HDAX is an investment strategy based on the estimator of expected returns that combines the information contained in time series data about past returns and the information contained in analysts' forecast about the future development of an asset.

However, the result that the time series estimator performs well is astonishing and stands in contrast to earlier studies like Jorion (1991) or Jobson and Korkie (1980) who find the time series estimator to perform relatively bad.[33] To analyze these results in detail we ask whether they are valid also for different segments of the market and for different time periods. Therefore we generate sub-samples: first, we divide the sample according to the membership of the companies to the sub-indices DAX 30 and MDAX and secondly, we split the sample in two time periods.

4.1 Split of the sample in sub-indizes: DAX 30 and MDAX

In our following analysis we will use the sub-samples of the DAX 30 and the MDAX. The DAX 30 contains the biggest German companies regarding the volume of the order book and

[33] The performance of the time series estimator is also surprising when we compare the ranking of the sharpe ratios (TSE, RIM, BAYES, CAPM, SHRK) and the mean ranks of the MSE contained in Table 2. While within the mean ranks of the MSE the time series estimator was last, within the ranking of the sharpe ratios the time series estimator is second to the Bayes-estimator. However, also in Jorion (1990) the MSE-ranking and the sharpe ratio-ranking do not correspond exactly to each other.

the market capitalization. The MDAX contains the companies which are biggest next to the DAX 30.[34]

With respect to the RIM-estimate the following hypothesis can be developed. Usually, bigger companies with a higher turnover in shares are followed by more financial analysts than smaller ones. According to the empirical findings that there is a positive relationship between the number of analysts who follow a company and the precision of their forecasts we expect the forecasts for the members of the DAX 30 to have a higher accuracy than the forecasts for the members of the MDAX.[35] Therefore we would expect the investment strategy that is based on the estimators of the residual income model to have a better performance when applied for the assets contained in the DAX 30 than for the assets contained in the MDAX.

With respect to the time series estimate we would expect to find a violation of the weak form market efficiency according to Fama (1970) to be more likely for the smaller companies of the MDAX than for the companies of the standard segment. This inefficiency in turn would imply a good performance of the time series estimator: if returns are positively autocorrelated, a strategy based on the time series estimator, i.e. a momentum strategy, shows a high performance.

Table 5 and Table 6 contain the average realized returns p.a., the standard deviations and the empirical sharpe ratios of all investment strategies based on the DAX 30 and the MDAX, respectively, for the whole sample period. Splitting the sample in this way shows that the high performance of the strategy based on the time series estimator for the HDAX is mainly due to the performance of the members of the MDAX. Whereas in the standard segment the sharpe ratio of the strategy based on the time series estimator is similar to the performance of the index, in the mid-cap segment the sharpe ratio is much higher than the sharpe ratio of the corresponding index. The reason for the difference in accuracy could be a less efficient market for smaller companies.

[34] We will not use the TecDAX in our further analysis which is part of the HDAX since March 2003 as there is only a very short history available for this index.

[35] Alford/Berger (1999), for example, find a positive relationship between analysts following a company and forecast accuracy. Furthermore, they find a positive relationship between turnover of shares and analysts following a company which implies an indirect positive relationship between turnover and forecast accuracy. Eddy/Seifert (1992) find a significantly positive relationship between company size and forecast accuracy.

DAX30

Strategie:	TSE	RIM	BAYES	CAPM	SHRK	EQUAL	GMVP	DAX 30
durch. Rendite:	0.02338	0.00784	0.01642	0.00726	0.00774	0.07528	0.08012	0.04954
Standardabw.:	0.09584	0.01355	0.0505	0.01534	0.01209	0.231	0.19577	0.23861
Sharpe Ratio:	0.24395	0.57855	0.32511	0.47319	0.64036	0.32587	0.40925	0.20762

Table 5: *Sharpe-Ratios; Assets: DAX 30; Investment Period: 14.04.1994-01.07.2004*

MDAX

Strategie:	TSE	RIM	BAYES	CAPM	SHRK	EQUAL	GMVP	MDAX
durch. Rendite:	0.16682	0.00309	0.08836	3.91E-04	0.00932	0.03211	0.04289	0.04186
Standardabw.:	0.12947	0.01874	0.06436	0.01403	0.02055	0.16184	0.11516	0.15974
Sharpe Ratio:	1.28854	0.16485	1.37301	0.02784	0.45363	0.19839	0.37242	0.26203

Table 6: *Sharpe-Ratios; Assets: MDAX; Investment Period: 14.04.1994-01.07.2004*

Regarding the strategy based on the RIM-estimator we obtain the opposite result: while we have a remarkably good performance when investing in the assets of the DAX 30 we do not have a performance that is above average when investing in the assets of the MDAX. This result is an accordance to empirical studies that found a positive relationship between company size and forecast accuracy. The greater the analysts' following the higher the precision of the return estimators based on these forecasts and the higher the performance based on the return estimators.

The pairwise tests of the statistical significance of the difference in the sharpe ratios give the following results for the DAX 30:

	TSE	SHRK	GMVP	HDAX	EQUAL	RIM	BAYES	CAPM
TSE	NA	-0.3964	-0.1653	0.03634	-0.08192	-0.3346	**-0.08116***	-0.22924
SHRK	NA	NA	0.23111	0.43274	0.31449	0.06181	0.31524	0.16717
GMVP	NA	NA	NA	0.20164	0.08338	-0.1693	0.08414	-0.06394
HDAX	NA	NA	NA	NA	-0.11826	-0.37093	-0.1175	-0.26558
EQUAL	NA	NA	NA	NA	NA	-0.25268	7.58E-04	-0.14732
RIM	NA	NA	NA	NA	NA	NA	0.25343	0.10536
BAYES	NA	NA	NA	NA	NA	NA	NA	-0.14808
CAPM	NA	NA	NA	NA	NA	NA	NA	NA

Table 7: *Pairwise differences in Sharpe Ratios; Significance test according to Jobson-Korkie (*** Significance at 1 per cent-level, ** 5 per cent-level, * 10per cent-level); Assets: DAX 30; Investment Period: 14.04.1994-01.07.2004*

As we can see the pairwise tests identify only one strategy that is significantly better than another with respect to the sharpe ratio. This is the strategy based on the combined estimator when compared to the time series estimator.

The remarkable difference in the sharpe ratios of the strategies based on the RIM-estimator and the time series estimator shows these two strategies are obviously based on different sets of information. Through the combination of both of these estimators these different sets of information can be aggregated in a single estimator and estimation errors can be diversified away. The combination of both estimators results in an investment strategy that has a sharpe ratio that 8 per cent higher than the strategy based on the time series estimator alone with a marginal significance at the 10 per cent level.

When we turn to the MDAX we find the results of the sharpe ratio difference tests to have a totally different structure:

	TSE	SHRK	GMVP	HDAX	EQUAL	RIM	BAYES	CAPM
TSE	NA	**0.83491****	**0.91612****	**1.02651*****	**1.09015*****	**1.12369*****	**-0.08447***	**1.2607*****
SHRK	NA	NA	0.08121	0.1916	0.25524	0.28878	**-0.91938****	0.42579
GMVP	NA	NA	NA	0.11039	0.17403	0.20757	**-1.00059****	0.34458
HDAX	NA	NA	NA	NA	0.06364	0.09718	**-1.11097*****	0.23419
EQUAL	NA	NA	NA	NA	NA	0.03354	**-1.17461*****	0.17055
RIM	NA	NA	NA	NA	NA	NA	**-1.20816*****	0.13701
BAYES	NA	NA	NA	NA	NA	NA	NA	**1.34517*****
CAPM	NA	NA	NA	NA	NA	NA	NA	NA

Table 8: *Pairwise differences in Sharpe Ratios; Significance test according to Jobson-Korkie (*** Significance at 1 per cent-level, ** 5 per cent-level, * 10per cent-level); Assets: MDAX; Investment Period: 14.04.1994-01.07.2004*

The strategy based on the time series estimator leads to a very good performance that is significantly better at the 5 per cent and 1 per cent level compared to all other strategies that do not use the time series estimator. However, when we combine the time series estimator with the RIM-estimator and invest based on this combined estimator we can realize a performance that is again significantly better than all other strategies – even significantly better than the strategy based on the time series estimator alone.

As we can see even if the strategy based on the RIM-estimator derived from the analysts' forecasts performs poorly when used separately it still contains enough information in addition to the time series estimator to improve its performance significantly.

Analysis of the performance of the time series estimator: Comparison of autocorrelations for the members of the DAX30 and the members of the MDAX

We want to analyze if the excellent performance of the time series estimator for the MDAX is due to a violation of the weak form of market efficiency according to Fama (1970). We use a regression based approach as presented in (19). For every firm i we do a regression of the quarterly returns on the quarterly returns of the preceeding period

$$\sum_{\tau=t+1}^{t+13} r_{\tau,i} = \gamma_i \cdot \sum_{\tau=t}^{t-12} r_{\tau,i} + \varepsilon_{\tau,i}. \qquad (19)$$

$\hat{\gamma}_i$ is the estimator of the autocorrelation coefficient between the quarterly returns. The distribution of the t-statistics of the adjusted estimated autocorrelation coefficients[36] is represented in Figure 5. As Figure 5 shows we find a slight increase in positive autocorrelations.

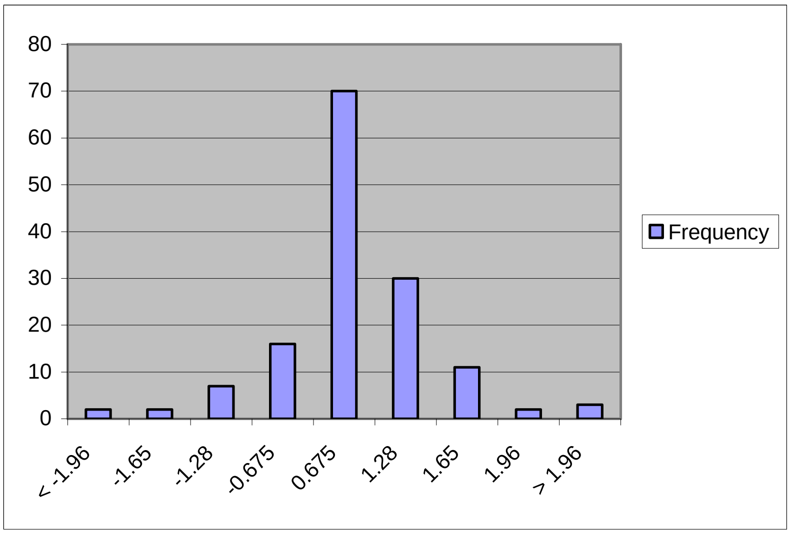

Figure 5: *Distribution of t-statistics of adjusted estimated autocorrelation coefficients*

As the investment over the quarter starting at time t is based on the mean return of the preceeding 4 quarters we also analyze the correlation between the return of the quarter starting in t with the returns of the preceeding 4 quarters according to the regression approach in (20).

$$\sum_{\tau=t+1}^{t+13} r_{\tau,i} = \gamma_{i,1} \cdot \sum_{\tau=t}^{t-12} r_{\tau,i} + \gamma_{i,2} \cdot \sum_{\tau=t-13}^{t-25} r_{\tau,i} + \gamma_{i,3} \cdot \sum_{\tau=26}^{t-38} r_{\tau,i} + \gamma_{i,4} \cdot \sum_{\tau=39}^{t-51} r_{\tau,i} + \varepsilon_{\tau,i}. \qquad (20)$$

The Ljung-Box test-statistics for the approach according to (20) shows a slight increase in significant autocorrelations, too. The number of the significant autocorrelations at the 10 per cent level is 22 instead of 14 to be expected. To summarize we find – even though weak –

[36] The estimated autocorrelation coefficient is biased downwards for a small number of observations, see Campbell/Lo/MacKinlay (1997), p. 46. The adjustment of the test-statistic is done according to Fuller (1976): $\tilde{\rho} = \hat{\rho} + \frac{1}{T-1}\left(1-(\hat{\rho})^2\right)$.

evidence for a violation of the weak form of market efficiency in the market segment of the MDAX.

4.2 Split of the sample in sub-periods: April 1994-July 1999 and July 1999-July 2004

We split our sample in two sub-periods of equal length. The first half encompasses the period from April 14, 1994 till July 8, 1999 and the second half the period from July 8, 1999 till July 1, 2004. As we can see in Figure 6 the first half of our sample period is characterized by a

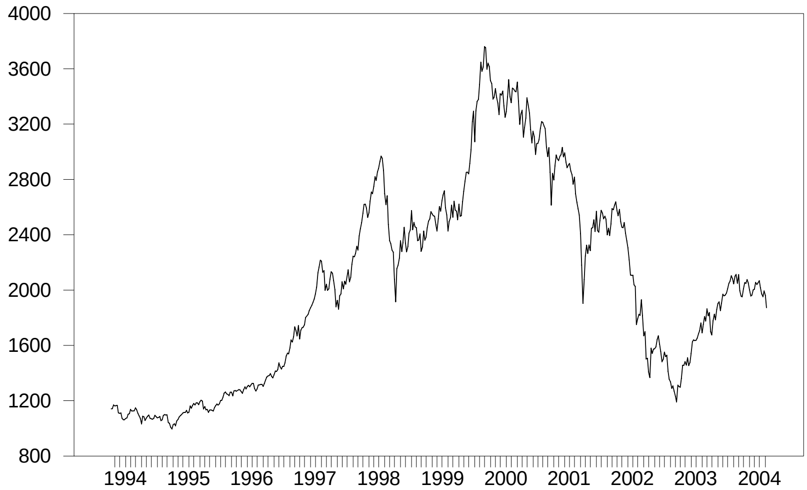

Figure 6: *Development of the DAX100/HDAX in the sample Period 14.4.1994-1.7.2004*

general upward trend of the market whereas in the second half we have a downward trend. The all-time high in our sample period was realized on March 2, 2000.

HDAX

Strategie:	TSE	RIM	BAYES	CAPM	SHRK	EQUAL	GMVP	HDAX
durch. Rendite:	0.23763	6.57E-04	1.17E-01	0.01012	0.0159	0.08056	0.0264	0.14347
Standardabw.:	0.20177	0.02345	0.10104	0.01898	0.0293	0.14812	0.11626	0.1817
Sharpe Ratio:	1.17771	0.02803	1.15775	0.53297	0.54261	0.54391	0.22709	0.78959

Table 9: *Sharpe-Ratios; Assets: HDAX; Investment Period: 14.04.1994-08.07.1999*

HDAX

Strategie:	TSE	RIM	BAYES	CAPM	SHRK	EQUAL	GMVP	HDAX
durch. Rendite:	0.17063	0.02748	0.10238	4.58E-04	0.01132	0.00586	0.04512	-0.05879
Standardabw.:	0.17694	0.02904	0.08709	0.01089	0.02999	0.20553	0.11652	0.2611
Sharpe Ratio:	0.96434	0.94623	1.17557	0.04205	0.37746	0.02849	0.38728	-0.22517

Table 10: *Sharpe-Ratios; Assets: HDAX; Investment Period: 08.07.1999-01.07.2004*

The splitting of our sample into two sub-periods leads to the following results: The strategy based on the RIM-estimator shows a weak performance compared to the other strategies in the first sub-period. This inferiority in performance is even significant when compared to the performance of the strategy based on the time series estimator and on the combined estimator.

The results are different, however, in the second sub-period: There the RIM-estimator shows an excellent performance. The time series estimator shows a very good performance in the first as well as in the second sub-period. According to the different quality of the RIM-estimator in the first and the second sub-period a significant improvement through the combination of the time series estimator with the RIM-estimator in comparison to the separate use of the time series estimator can be detected only in the second but not in the first sub-period as it can be seen in Table 11 and Table 12.

	TSE	SHRK	GMVP	HDAX	EQUAL	RIM	BAYES	CAPM
TSE	NA	0.6351	0.95062	0.38812	0.6338	**1.14968***	0.01996	0.64473
SHRK	NA	NA	0.31552	-0.24698	-0.00129	0.51458	-0.61514	0.00964
GMVP	NA	NA	NA	-0.5625	-0.31682	0.19906	-0.93066	-0.30589
HDAX	NA	NA	NA	NA	0.24568	0.76156	-0.36816	0.25661
EQUAL	NA	NA	NA	NA	NA	0.51587	-0.61384	0.01093
RIM	NA	NA	NA	NA	NA	NA	**-1.12972***	-0.50494
BAYES	NA	NA	NA	NA	NA	NA	NA	0.62477
CAPM	NA	NA	NA	NA	NA	NA	NA	NA

Table 11: *Pairwise differences in Sharpe Ratios; Significance test according to Jobson-Korkie (*** Significance at 1 per cent-level, ** 5 per cent-level, * 10per cent-level); Assets: HDAX; Investment Period: 14.04.1994-08.07.1999*

	TSE	SHRK	GMVP	HDAX	EQUAL	RIM	BAYES	CAPM
TSE	NA	0.58688	0.57706	**1.18951***	0.93585	0.01811	**-0.21122****	**0.92229****
SHRK	NA	NA	-0.00983	0.60263	0.34897	-0.56877	-0.7981	0.33541
GMVP	NA	NA	NA	0.61245	0.35879	**-0.55894***	-0.78828	0.34523
HDAX	NA	NA	NA	NA	-0.25366	**-1.17139****	**-1.40073****	-0.26722
EQUAL	NA	NA	NA	NA	NA	**-0.91773****	-1.14707	-0.01356
RIM	NA	NA	NA	NA	NA	NA	-0.22934	0.90417
BAYES	NA	NA	NA	NA	NA	NA	NA	**1.13351****
CAPM	NA	NA	NA	NA	NA	NA	NA	NA

Table 12: *Pairwise differences in Sharpe Ratios; Significance test according to Jobson-Korkie (*** Significance at 1 per cent-level, ** 5 per cent-level, * 10per cent-level); Assets: HDAX; Investment Period: 08.07.1999-01.07.2004*

A possible explanation for the fact that there cannot be achieved an improvement in performance in the first sub-period through a combination of the estimators could be that the accuracy of the analysts' forecasts and therefore the accuracy of the RIM-estimators is relatively low when compared to the second sub-period. The presumably increased accuracy of analysts' forecasts could be due to a better corporate information policy vis-á-vis financial analysts[37] as well as to the empirically positive relationship between the number of analysts following a company and forecast accuracy.[38] In our sample period the number of analysts increased from an average of 720 analysts employed in 55 brokerage houses between 1995

[37] For the positive relationship between information disclosure and forecast accuracy see for example, Hope (2003) or Higgins (1998).
[38] See e.g. Alford/Berger (1999).

and 1999 to an average of 1.090 analysts of 77 brokerage houses between 1999 and 2002. [39] However, our results do not support the empirical findings of Higgins (2002) who reports a deterioration of forecast accuracy in periods of economic downturns for the Japanese market.

5 Summary

In this paper we analyzed if the use of analysts' forecasts to estimate expected stock returns in the context of Markowitz portfolio optimization results in a better performance when compared to "traditional" estimation and investment strategies. In an empirical study for the German stock market we used analysts' forecasts to implement the Residual Income Model and inferred the implied cost of equity capital from the model. In a next step we combined the estimator obtained from the RIM with the time series estimator in an optimal way. As alternative investment strategies we considered three strategies that were based on estimators of expected returns, too: the time series estimator, the CAPM-estimator, and a shrinkage estimator proposed in the literature on estimation risk. Furthermore, we employed three other strategies for comparison that are not based on estimations of expected returns: the equally weighted portfolio, the global minimum variance portfolio and the market index.

Our basic result is that for the universe of the largest 110 German stocks, the HDAX, the strategy based on the estimator that combines the information of analysts' forecasts and time series data is superior to all other strategies – in all except of one cases even statistically significant.

When we divide our sample in the sub-samples of the Blue Chip index DAX 30 and the mid-cap index MDAX we find the RIM-estimator to perform very well for the DAX 30 and very poorly for the MDAX. The different structure of the results within the different market segments could be caused by the different accuracy of analysts' forecasts in the different segments. This is in line with empirical studies that find analysts' forecasts to be more precise for stocks in the standard segment than for second-line stocks.

Nevertheless, the combination of the time series estimator with the RIM-estimator results in a significant improvement in performance compared to the time series estimator for both

[39] See Henze/Röder (2005). The authors report the yearly number of analysts and brokerage houses between 1987 and 2002. We compute the average analyst number for sub-period 1 only from 1995 on because the unusual small number of analysts in 1994 could be due to an error in the process of data collection as the authors notice.

market segments. Even if the RIM-estimator performs poorly for the mid-cap index when used separately it still contains enough valuable information to lead to a significant enhancement in performance when combined with the time series estimator. Furthermore, for the mid-cap index the combination of the estimators leads to a performance that is significantly superior to all other strategies.

When we check the robustness of our results with respect to the time period we find that it is not possible to yield a higher performance when investing based on the combined estimator in the first half of our sample. In the second half instead we get an improvement of the sharpe ratio that is significant at the 5 per cent level. The reason for this result could be an increased precision of analysts' forecasts throughout the whole sample period.

Overall our results confirm that the information contained in analysts' forecasts helps to reduce the severe negative consequences of estimation risk in portfolio optimization.

Appendix

No.	HDAX	MDAX	DAX30
1	AAREAL BANK	x	
2	ADIDAS-SALOMON	x	x
3	AEG DAIMLER-BENZ	x	
4	AGIV REAL ESTATE	x	
5	AIXTRON		
6	ALLIANZ		x
7	ALTANA	x	x
8	AMB GENERALI HDG.	x	
9	ARMSTRONG DLW	x	
10	ASKO	x	
11	AT & S AUSTRIA TECH		
12	AVA	x	
13	AWD HOLDING	x	
14	AXA KONZERN	x	
15	BAADER WERTPAH.	x	
16	BABCOCK BORSIG	x	x
17	BANKGES. BERLIN	x	
18	BARMAG	x	
19	BASF		x
20	BAYER		x
21	BAYER.HYPBK.		x
22	BAYER.HYPO-UND-VBK.		x
23	BB BIOTECH		
24	BEATE UHSE	x	
25	BEIERSDORF	x	
26	BERU	x	
27	BEWAG	x	
28	BHW HOLDING	x	
29	BILFINGER BERGER	x	
30	BMW		x
31	BOSS (HUGO)	x	
32	BRAU UND BRUNNEN	x	
33	BREMER VULKAN	x	
34	BUDERUS	x	
35	CARGOLIFTER	x	
36	CELANESE	x	
37	CELESIO	x	
38	COMDIRECT BANK	x	
39	COMMERZBANK		x
40	COMPUTER 2000	x	
41	CONTINENTAL	x	x
42	DAIMLER-BENZ AG		x
43	DAIMLERCHRYSLER		x
44	DBV-WINTERTHUR HLDG	x	
45	DEGUSSA	x	x
46	DEPFA DEUTSCHE	x	
47	DEUTSCHE BANK		x
48	DEUTSCHE BOERSE	x	x
49	DEUTSCHE LUFTHANSA		x
50	DEUTSCHE POST		x
51	DEUTSCHE TELEKOM		x
52	DEUTZ	x	
53	DIALOG SEMICON.		
54	DIDIER-WERKE	x	
55	DIS DT.INDUSTRIE SVS.	x	
56	DOUGLAS HOLDING	x	
57	DRAEGERWERK	x	
58	DRESDNER BANK		x
59	DSL HOLDING	x	
60	DUERR	x	
61	DYCKERHOFF	x	
62	E ON		x
63	EADS	x	
64	ELMOS SEMICON.		
65	EPCOS	x	x
66	ERGO VERSICHERUNG	x	
67	ESCADA AG	x	
68	EVOTEC OAI		
69	FAG KUGELFISCHER	x	
70	FELTEN&GUIL. ENERGIE	x	
71	FIELMANN	x	
72	FJH		
73	FPB HOLDING		x
74	FRAPORT	x	
75	FREENET		
76	FRESENIUS MED.CARE	x	x
77	FRESENIUS	x	
78	GEA	x	
79	GERRESHEIMER GLAS	x	
80	GFK	x	
81	GILDEMEISTER	x	
82	GOLD-ZACK	x	
83	GPC BIOTECH		
84	GROHE FRIEDR.	x	
85	HANNOVER RUCK.	x	
86	HEIDELB.DRUCK.	x	
87	HEIDELBERGCEMENT	x	
88	HENKEL		x
89	HERLITZ	x	
90	HOCHTIEF	x	
91	HOECHST		x
92	HOLZMANN PHILIPP	x	
93	HORNBACH HLDG	x	
94	HORNBACH-BAUMARKT	x	
95	HORTEN DEAD	x	
96	HYPO RLST.HLDG.	x	
97	IDS SCHEER		
98	IKB DT.INDSTRBK.	x	
99	INDUS HOLDING	x	
100	INFINEON		x
101	ING BHF-BANK	x	
102	IVG IMMOBILIEN	x	
103	IWKA	x	
104	IXOS SOFTWARE		
105	JENOPTIK	x	
106	JUNGHEINRICH	x	
107	K + S	x	
108	KAMPA-HAUS	x	
109	KAMPS	x	
110	KARSTADT QUELLE	x	x

No.	HDAX	MDAX	DAX30
111	KAUFHOF		x
112	KIEKERT	x	
113	KLOECKNER-WERKE	x	
114	KOENIG & BAUER AG	x	
115	KOLBENSCHMIDT PIERB.	x	
116	KONTRON		
117	KRONES AG	x	
118	KRUPP STAHL	x	
119	KSB	x	
120	LAHMEYER	x	
121	LEIFHEIT	x	
122	LEONI	x	
123	LINDE		x
124	LINOTYPE-HELL	x	
125	LION BIOSCIENCE		
126	LOEWE	x	
127	MAN		x
128	VODAFONE		x
129	MANNHEIMER AG HLDG.	x	
130	MEDIGENE		
131	MEDION	x	
132	MERCK KGAA	x	
133	METRO		x
134	MG TECHNOLOGIES	x	x
135	MICRONAS SEMICON.		
136	MLP AG	x	x
137	MOBILCOM		
138	MOKSEL A	x	
139	MPC MUENCHMAYER C.	x	
140	MUNCH.RUCK.REGD.	x	x
141	NORDDEUTSCHE AFFIN.	x	
142	NORDEX		
143	PFEIFFER VAC TECH.		
144	PHOENIX	x	
145	PLAMBECK NEUE ENGE.		
146	PLETTAC	x	
147	PORSCHE	x	
148	PROSIEBEN SAT 1	x	
149	PUMA	x	
150	QIAGEN		
151	QSC		
152	REICHELT OTTO	x	
153	REPOWER SYSTEMS		
154	RHEINMETALL	x	
155	RHOEN-KLINIKUM	x	
156	ROFIN SINAR TECHS.		
157	RUETGERS	x	
158	RWE		x
159	SALAMANDER	x	
160	SALZGITTER	x	
161	SAP AG	x	x
162	SAP SYSTEMS		
163	SCA HYGIENE PROD.	x	
164	SCHERING		x
165	SCHMALBACH-LUBECA	x	

No.	HDAX	MDAX	DAX30
166	SCHWARZ PHARMA	x	
167	SCM MICROSYSTEMS		
168	SGL CARBON	x	
169	SIEMENS		x
170	SIEMENS NIXDORF AG		x
171	SINGULUS TECH.		
172	SIXT	x	
173	SKW TROSTBERG	x	
174	SOFTWARE	x	
175	SPAR HANDELS-AG	x	
176	STADA ARZNEIMITTEL	x	
177	STINNES	x	
178	STRABAG	x	
179	SUEDZUCKER AG	x	
180	SUESS MICROTECH		
181	TARKETT	x	
182	TECHEM	x	
183	TECIS HOLDING	x	
184	TELEPLAN INTL.	x	
185	TELES		
186	THIEL LOGISTIC	x	
187	THYSSENKRUPP		x
188	T-ONLINE		
189	TUI		x
190	UNITED INTERNET		
191	VARTA	x	
192	VCL FILM + MEDIEN	x	
193	VEW	x	
194	VIAG		x
195	VILLEROY& BOCH	x	
196	VOLKSFUERSORGE HD.	x	
197	VOLKSWAGEN		x
198	VOSSLOH	x	
199	WAYSS & FREYTAG	x	
200	WCM BETEILIGUNG	x	
201	WEB DE		
202	WEBER (GERRY) INTL.	x	
203	WEDECO WATER TECH.	x	
204	WELLA	x	
205	WERU	x	
206	ZAPF CREATION	x	
$\sum$	206	143	45

Table 13: *Companies contained in the indices HDAX, MDAX, and DAX 30 between 14.04.1994 and 01.07.2004.*

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