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TACTICAL ASSET ALLOCATION AND ESTIMATION RISK

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1. Introduction: Time-Varying Expected Returns

In investment practice and in modern financial economics, the classical assumption of identically and independently distributed (iid) returns over time, made by the basic version of the "efficient markets hypothesis," is called into question. Instead, expected returns are assumed to be time-varying. Instrumental variables like dividend yields or term spreads are employed to predict expected returns. Most empirical studies capture the relationship between instrumental variables and asset excess returns by linear regressions. They focus on assessing the level of predictability through statistical measures. The next step is to investigate whether profitable trading strategies can be built upon these predictive relationships. Most existing studies test market timing strategies, i.e. whether shifting between cash and stocks can systematically outperform the market portfolio.

However, most studies ignore the issue of estimation risk that surrounds the predictive relationships.[1] This is the primary reason for the high turnover that the investment strategies regularly produce. As there is a substantial amount of estimation risk (or, parameter uncertainty) attached to the predictive relationships, it is crucial to account for it. In this paper, we investigate several approaches to incorporate estimation risk in predictive regressions. We differentiate between approaches that adjust the forecasts and those that directly adjust the coefficients of the predictive regressions. For the latter ones, we apply Bayesian multivariate regression techniques. We show how to specify the relevant parameters, in particular the parameters of the prior distribution.

Furthermore, we do not focus on market timing but on tactical asset allocation (TAA). TAA involves several asset classes.[2] We implement sector rotation strategies. A sector-based approach is part of the investment process of most money managers, because, since the introduction of the Euro, sector effects are often considered as more important than country effects. We compare the different approaches in an out-of-sample study and find that incorporating estimation risk improves the risk-adjusted performance of dynamic and active asset allocation strategies and reduces turnover. The most promising strategies are based on Bayesian statistics. We also find that all the conditioning strategies outperform the unconditional strategies that operate under the iid setting. This holds also after correcting for estimation risk in the unconditional strategies.

2. The Predictability of Asset Returns

2.1 Linear Forecasting Models

There is a multitude of articles that model expected stock returns as time-varying. Some examples are those by FAMA and SCHWERT (1977), KEIM and STAMBAUGH (1986), CAMPBELL (1987), CAMPBELL and SHILLER (1988), FAMA and FRENCH (1988, 1989). The relationship between expected returns and instrumental variables is captured by linear regressions, called "predictive regressions". The asset excess returns (mostly, stock or stock market returns) are regressed on instrumental variables:

$$r_{it} = \alpha_i + \beta_{i1} z_{1,t-1} + \beta_{i2} z_{2,t-1} + \ldots + \beta_{iK} z_{K,t-1} + u_{it} \quad \forall \quad t = 1\ldots T, \; i = 1\ldots N \tag{1}$$

r_{it} denotes the excess return of the i^{th} asset class ($i = 1\ldots N$), which has been realized in the period from t-1 through t, z_{kt} is the k^{th} instrumental variable ($k = 1\ldots K$) at time t, and u_{it} is the residual term of the i^{th} regression. Usually, u_i is assumed to be normally distributed: $u_i \sim N(0, \sigma_i^2)$. The instrumental variables enter the regressions lagged by (at least) one period, because they must be known at the beginning of the period.[3]

The multivariate regression in equation (1) can be written more compactly in matrix notation. Let $X = (1_T\ Z)$ be a $T \times (K + 1)$ matrix that consists of a vector of ones, and of the $T \times K$ matrix Z of the realizations of the instrumental variables. The multivariate regression is given by

$$r = XB + U \tag{2}$$

where r denotes the $T \times N$ matrix of excess returns and B denotes the $(K + 1) \times N$ matrix of regression coefficients. B contains the N intercepts in the first row and the $K \times N$ slope coefficients in the other rows: $B = (\alpha', \beta')$. The $T \times N$ matrix U stores the residual terms of the N regressions. The normality assumption can be recast as

$$\mathrm{vec}(U) \sim N(0, \Sigma \otimes I_T)\ , \tag{3}$$

where the $N \times N$ matrix Σ includes the variances and covariances of the residual terms and I_T is the $T \times T$ identity matrix. The Maximum Likelihood estimator of the regression coefficients is given by

$$\hat{B} = (X'X)^{-1} X'r\ . \tag{4}$$

Given the values of the instrumental variables at time T and the estimated regression coefficients, the expected excess return of the next period can be estimated:

$$E(r_{i,T+1} | \Phi_T) = \hat{\alpha}_i + \hat{\beta}_{i1} z_{1,T} + \ldots + \hat{\beta}_{iK} z_{K,T} \tag{5}$$

or

$$E(r_{T+1} | \Phi_T) = \hat{B} x'_T, \tag{6}$$

where Φ_T denotes the information set available at time T and the $1 \times (K + 1)$ vector $x_T = (1\ z_T)$ stores the actual values of the instrumental variables. Usually, these expected excess returns are interpreted as point forecasts and imported to an algorithm for portfolio optimization. However, as the regression coefficients are estimated, they, as well as the expected returns for the next period, are subject to estimation error. Estimation error is the motivation for the Bayesian multivariate regression models in section 3.3.

The crucial question arises as to which instrumental or information variables show predictive power. Information variables that have forecasting abilities in existing studies are:

- valuation ratios as the dividend yield or price-earnings-ratio
- macroeconomic variables that reflect the business cycle, e.g. interest rates, changes in interest rates, term and default spreads.[4]

The choice of information variables should be based on economic grounds to prevent data mining and data snooping. Valuation ratios can be motivated by valuation models like the dividend discount model[5], while macroeconomic variables can be inferred from intertemporal asset pricing models.[6] Furthermore, the lagged market return is often included to utilize the existence of autocorrelation effects (mean reversion or momentum). In our empirical study, we determine 10 variables in advance and then always use these 10 variables, i.e. we do not test the regression model down. Our objective is not to assess which variables might be most helpful in predicting expected returns, but to investigate the impact of estimation risk in out-of-sample portfolio strategies.

2.2 Economic Versus Statistical Significance

Regressing stock excess returns on instrumental variables like the dividend yield or term spreads delivers a small, but often different from zero R-squared, and the regression coefficients are often significantly different from zero. A frequentist must make a decision in favor of one of both mutually exclusive alternatives: either, he rejects the notion of predictable returns and coefficients being different from zero due to the low coefficients of determination; or, he sets the estimated coefficients equal to the true values. A Bayesian investor, in contrast, explicitly accounts for the uncertainty (estimation error) in the regression coefficients and chooses a way in-between (see section 3.3 below).

Most empirical studies follow the classical (frequentist) approach and make the conclusion that due to R-squared and coefficients being different from zero, returns are predictable and not independently distributed over time. At the same time, they emphasize that this does not necessarily mean that stock markets are not informationally efficient. Most authors express the view that the empirically detected predictive relationships reflect time-varying risk premia and can be explained by risk aversion change over time.[7]

The coefficients of determination are calculated in-sample. The crucial question, however, is whether returns can be predicted out-of-sample, and whether profitable trading strategies are possible. BOSSAERTS and HILLION (1999) as well as GOYAN and WELSCH (2003), show that popular information criteria, such as out-of-sample R^2 or mean-squared-error (MSE) cannot confirm predictability. But even with very low values of out-of-sample R^2's that are statistically not different from zero, investment strategies can be designed that lead to an economic profit and increase risk-adjusted return.[8] In the empirical section below, dynamic investment strategies based on a conditional information set are constructed to investigate the economic significance of time-varying expected returns.

The existing studies that shed light on the economic implications of return predictability can be classified according to various criteria:

- Which asset classes are taken into account? In particular: Is only one risky asset class (stocks) relevant, and hence, is the focus of *market timing* strategies, or are *tactical asset allocation* (TAA) strategies in the focus of attention?
- Which instrumental variables are used?
- Are *dynamic asset allocation* strategies designed that are not benchmark-related and that aim to produce a high absolute return with low absolute risk? Or are *active management* strategy pursuit, which target a high alpha and a low tracking error with respect to a pre-specified benchmark portfolio?

- Is estimation risk incorporated?

The majority of the existing studies can be classified in the category of dynamic asset allocation strategies. The first and seminal study is that of SOLNIK (1993). SOLNIK looks at 16 stock and bond markets. To forecast returns, he uses the local short rate, long rate, dividend yield and a January dummy variable. KLEMKOSKY and BHARATI (1995) allocate between US stocks, bonds, and cash. Their forecasting model is based on eleven macroeconomic variables. As SOLNIK, FLETCHER and HILLIER (2001) investigate dynamic asset allocation strategies in an international context and include 10 equity markets. In contrast to SOLNIK, they use global variables.

HARVEY's (1993) study comprises 20 developed stock markets and 21 stock markets of emerging markets. He uses the dividend yield and price-earnings-ratio of the world market portfolio, local valuation ratios and lagged market returns. BELLER et al. (1998), FLETCHER (1997), and ROBERTSSON (2000) study dynamic strategies of sector allocation. BELLER et al., includes 55 US sectors, FLETCHER, 10 UK sectors, and ROBERTSSON, 10 sectors in Sweden. They use common macroeconomic variables and valuation ratios. They consider only market-relevant, not sector-specific data. Finally, market timing strategies for Swiss stocks and bonds separately are the focus of SCHNEDLER (2002).

The majority of these studies comes to the conclusion that the dynamic strategies, which are conditioned on the instrumental variables, are superior to buy-and-hold investments and produce a higher risk-adjusted return (Sharpe ratio). This holds after transaction costs in BELLER et al. (1998), KLEMKOSKY and BHARATI (1995), and SOLNIK (1993); the remaining studies do not account for costs. Only FLETCHER and HILLIER (2001), and ROBERTSSON (2000) cannot confirm the superiority of the conditional strategies.

Studies that fall into the second category of active management strategies are those by KAHN et al. (1996) and CONNOR (1997). Both investigate TAA-strategies in an international context. CONNOR includes the eight largest stock markets, KAHN et al., look at 21 stock markets. Foreign currency exposure is hedged. They use similar instrumental variables. KAHN et al. exclude the lagged market return, because in their view, that would increase turnover. The active strategy outperforms the benchmark portfolio significantly.

Those studies which not only report performance statistics, but also portfolio weights show that the conditional strategies lead to a high turnover. The portfolio exists of only one or very few asset classes at a point of time. KLEMKOSKY and BHARATI (1995, p. 86) note:

"Interestingly, superior results are obtained by mostly ignoring the commonly accepted principle of diversification."

The primary reason for the low stability of portfolio weights is the fact that estimation risk is ignored in most of these studies. Exceptions are BELLER et al. (1998), CONNOR (1997), FLETCHER and HILLIER (2001), and KAHN et al. (1996). BELLER et al. employ Bayesian multivariate regression analysis and shrink towards the minimum-variance-portfolio (MVP), although they do not make this explicitly clear. CONNOR also utilizes Bayesian techniques. He shows that incorporating estimation risk leads to more stable and balanced portfolio structures. FLETCHER and HILLIER apply the method of resampled efficiency by MICHAUD (1998), while Kahn et al. employ the "alpha refinement" rule. These procedures are explained in more detail in the next section – except for resampled efficiency. Since this procedure has not lead to improved results in FLETCHER and HILLIER (2001), and since it has no decision-theoretic foundation (see SCHERER, 2002), it is not used in the empirical study.

3. Approaches to Incorporate Estimation Risk

3.1 Overview

The first way to incorporate estimation risk is to adjust the estimates for the expected returns with Bayesian techniques. This has been done by JORION (1986) and PASTOR (2000) under the iid setting. JORION sets expected returns to a common value over all assets in the prior, and hence, shrinks towards the minimum-variance-portfolio. PASTOR assumes a priori that an asset-pricing model holds and then shrinks towards the portfolio that is implied by that pricing model (e.g., the market portfolio in case of the CAPM). With time-varying expected returns, a second possibility opens up: Estimation errors are attached to the estimated coefficients of the multivariate regression given in equation (2). Hence, Bayesian techniques can directly adjust these coefficients to take the "parameter uncertainty" into account. Another issue is that of "model risk", which refers to the fact that the true return generating process is not known.[9]

3.2 Adjusting the Forecasts

The idea of these approaches is to estimate next period's expected returns based on the predictive regressions in a first step, and then to adjust them depending on the degree of estimation risk (or, forecast uncertainty) that is attached to these forecasts. In this section, the refinement rule of GRINOLD (1994) and GRINOLD and KAHN (2000) is reviewed; it is known as "alpha refinement".[10] It has been designed for benchmark-related portfolio construction, i.e. for active managers, and it is popular in investment practice. The essence is to shrink the raw forecasts towards the prior expected value of zero. An alpha/tracking error optimizer will deliver the benchmark portfolio when the alphas are set to zero. The alpha refinement rule can be classified as Bayesian.

The forecasts refer to the asset alphas. Alpha is defined as expected residual return, i.e. as a risk-adjusted expected return over the benchmark. The first step of the alpha refinement rule is to transform the raw forecasts or "signals" (e.g., "buy", "hold", and "sell" recommendations) into "scores". The signals are expressed in numerical terms (e.g., "+1", "0", and "–1") and then standardized. If cross-sectional signals are given, mean and standard deviation are computed with respect to the cross-section and used for standardization. Similar to KAHN et al. (1996), the signals that we exploit are extracted from time-series regressions and are given in units of excess returns. The standardizing procedure is then based on the mean and standard deviation of the raw forecasts separately for each time-series regression.

The alpha refinement rule transforms the scores into alphas:[11]

$$\alpha_i = IC_i \omega_i Score_i \,. \tag{7}$$

The alpha of asset i is equal to the information coefficient (IC), times residual volatility (ω), times score. By multiplying the scores with residual volatility, the standardized scores are transformed back into units of residual returns. GRINOLD (1994) points out that this step is essential to prevent "alpha eating". If the forecasts were not scaled by residual volatility, an optimizer would treat two assets that exhibit the same score (and the same IC) differently: The asset that has a lower residual volatility would be assigned a higher active weight than that with a higher residual volatility.

The information coefficient is defined as the correlation between alpha (expected residual return) and the realized residual return. It is a measure of forecasting ability. If the raw forecast does not contain any information with respect to future residual returns, the IC is zero, and alpha is zero as well. In our setting, the IC summarizes the information content of the i^{th} predictive regression. To compute the out-of-sample ICs and the scores in our empirical study, some data points must be reserved so that the investment strategies start a little later, as is explained in more detail in section 4. It is important to note that estimating the IC is subject to estimation risk, again.[12] CONNOR and KAHN (1997) argue for substituting an empirically estimated IC by a pre-determined value, or at least, to do a Bayesian adjustment.

Finally, the alphas from the refinement rule serve as input for the alpha/tracking error optimization:

$$\max_{h_{PA}}\left(h'_{PA}\alpha - \lambda_R h'_{PA} V h_{PA}\right), \tag{8}$$

where h_{PA} denotes the $N \times 1$ vector of active weights, λ_R is aversion to active or residual risk, and V is the $N \times N$ covariance matrix.

3.3 Adjusting the Regression Coefficients

Applying Bayesian techniques in econometrics goes back to TIAO and ZELLNER (1964a, 1964b), ZELLNER and CHETTY (1965), and ZELLNER (1971). In Bayesian regression models, a prior distribution of the regression coefficients and residual covariance matrix is specified and then combined with the likelihood function (i.e., the distribution of the sample estimates) to obtain the posterior distribution. Hence, the regression coefficients are adjusted directly. In this section, we give some more details about this Bayesian procedure. We focus on the specification of the prior distribution.

The Maximum Likelihood estimators for the multivariate regression (2), $r = XB + U$, are given by

$$\hat{B} = (X'X)^{-1}X'r \tag{9}$$

$$\hat{\Sigma} = \frac{1}{T}(r - X\hat{B})'(r - X\hat{B}). \tag{10}$$

Assuming normally distributed residual terms in equation (3), $\text{vec}(U) \sim N(0, \Sigma \otimes I_T)$, the ML estimator in equation (9) is normally distributed as well:

$$\text{vec}(\hat{B}) \sim N\left(\text{vec}(B), (\Sigma \otimes (X'X)^{-1}\right). \tag{11}$$

The natural-conjugate prior for B is given by

$$\text{vec}(B)|\Sigma \sim N\left(\text{vec}(B_0), \Sigma \otimes C\right), \tag{12}$$

where B_0 is the $(K + 1) \times N$ matrix of the means and C is the $(K + 1) \times (K + 1)$ covariance matrix of the regression coefficients B. Σ is specified non-informative (JEFFREY's Prior):

$$p(\Sigma) \propto |\Sigma|^{-(K+1)/2}. \tag{13}$$

Then, the mean of the posterior distribution of the regression coefficients is a matrix-weighted mean of B_0 and $\hat{B}$:

$$\tilde{B} = \left(C^{-1} + X'X\right)^{-1}\left(C^{-1}B_0 + X'X\hat{B}\right). \tag{14}$$

The crucial question is how to specify the parameters B_0 and C of the prior distribution in equation (12). A natural starting point is the efficient market hypothesis, which postulates stock prices to follow a random walk. Therefore, the slope coefficients are set to zero in the prior, implying non time-varying, non-predictable returns and information variables having no impact on expected returns. The Bayesian regression techniques can be employed both for dynamic asset allocation and active management. The intercept is set differently depending on the optimization mode: In the dynamic asset allocation case, it is set to a common value across all regressions that is equal to the expected return of the MVP. For active management (benchmark-related optimization), the intercepts are set to the implied benchmark returns of the assets. Thus, the optimal portfolio is shrunk towards the MVP in the first case, and towards the benchmark portfolio in the second case.

To specify the prior covariance matrix C, we apply the “Minnesota Prior“ technique. This procedure has been developed by the University of Minnesota and the Federal Reserve Bank of Minneapolis for Bayesian vector autoregressive (VAR) models in the 70s and 80s.[14] The variances of the regression coefficients are controlled by a “tightness parameter“, θ, and scaled by the (inverse) variances of the instrumental variables:[15]

$$C = \theta^2 \begin{pmatrix} \sigma_0^{-2} & 0 & \cdots & 0 \\ 0 & \sigma_1^{-2} & & \\ \vdots & & \ddots & \\ 0 & & & \sigma_k^{-2} \end{pmatrix}. \qquad (15)$$

C is a $(K + 1) \times (K + 1)$ diagonal matrix with $\sigma_0 = 1$. In the limit, $\theta \to \infty$, the values of the Bayesian regression coefficients equal those of the ML estimators. The prior specification in equation (15) is similar to ZELLNER’S (1986) “g-prior“, where the variances of the regression coefficients are also controlled by a “hyper parameter“. In the “g prior” however, the coefficients are not assumed to be independent in the prior, but as correlated; the correlations are set equal to those in the sample. This implies that all slope coefficients are scaled downwards by the same magnitude (they are multiplied by a parameter g_0). In contrast, the prior in (15) shrinks the coefficients towards zero at different magnitudes.

4. Empirical Study: Tactical Sector Rotation Strategies

4.1 Data Set and Preliminary Regressions

Since the introduction of the Euro currency, sector allocation has attracted interest. There is an ongoing debate whether country or sector effects are dominant.[15] While this debate has not been resolved from an academic point of view, most institutional investors follow a sector-based approach in their investment process. In this section, we design investment strategies that allocate portfolio wealth to different Euroland sectors and those that dynamically change the industry exposures. We focus on two questions: First, is predictability of economic significance, i.e. can the market portfolio be systematically outperformed? Second, how important is it to incorporate estimation risk (with respect to performance and turnover) and which of the approaches introduced in section 3 is most promising?

The investment universe comprises the 10 Datastream sector indices for Euroland, which are conceived as tradable assets. The sector classification is given in Table 1, along with the sub-groups.

Table 1: Datastream Sector Classification

Sectors	Sub groups
Resources	Oil, Mining
Basic Industries	Chemicals, Construction & Building Materials, Forestry & Paper, Steel & other metals
General Industries	Aerospace & Defence, Diversified Industrials, Electronic & Electrical Equipment, Engineering
Cyclical Consumer Goods	Automobiles & Parts, Household (Clothing, Footwear), Goods & Textiles
Non-Cyclical Consumer Goods	Beverages, Food, Health, Pharmaceuticals & Biotechnology, Tobacco
Cyclical Services	Retailers, Leisure & Hotels, Media, Support Services, Transport
Non-Cyclical Services	Food & Drug Retailers, Telecom Services
Utilities	Electricity, Gas Distribution, Water
Information Technology	IT Hardware, Software & Computer Services
Financials	Banks, Insurance, Life Insurance, Investment Companies, Real Estates

The sample consists of monthly data from 12/88 to 9/02 (166 observations).[16] The performance indices are converted into excess returns, with the 3-month FIBOR proxying the risk-free rate. Table 2 summarizes the (arithmetic) means of monthly excess returns (in %), standard deviations (in %), autocorrelation coefficients of lags 1 to 4 and return correlations. The sectors are – as expected – relatively strongly correlated.

The instrumental variables comprise 10 macroeconomic variables and valuation ratios: the term spread between long-term bonds and the 3-month rate, the short-term spread between the 3-month rate and 1-month rate, the default spread, oil price, industrial production, Euroland inflation (CPI), OECD leading indicator, price-earnings-ratio (PER), dividend yield, and lagged market excess return. The default spread is defined as the yield differential between BBB- and AAA-rated bonds. Due to longer data availability, the US default spread is used.[17] Market return, PER, and dividend yield refer to the Datastream EMU index, which is made up of the 10 sector indices on a value-weighted basis. All variables are market-wide, none are industry-specific. Table 3 shows descriptive statistics for the instrumental variables over the full sample. Term spreads, default spread, and dividend yield are characterized by a strong persistence (slowly decaying autocorrelations). The correlation matrix is also given in

Table 2: Descriptive Statistics of Sector Returns

A) Means, standard deviations, and autocorrelation coefficients

	Mean	Volatility	Autocorrelation lag 1	lag 2	lag 3	lag 4
Resources	0.802	5.208	0.016	–0.007	0.039	0.013
Basic Industries	0.260	5.440	0.102	0.023	0.006	0.019
Industrials	0.285	5.824	0.128	0.049	0.067	0.037
Cyclical consumer goods	0.101	6.528	0.129	0.046	0.009	–0.038
Non-cyclical consumer goods	0.661	4.109	0.148	–0.052	–0.026	0.059
Cyclical services	0.254	5.669	0.146	0.121	0.062	0.036
Non-cyclical services	0.683	6.889	0.210	0.095	0.209	0.000
Utilities	0.561	4.183	0.114	0.068	0.050	–0.067
IT	0.938	9.096	0.238	0.104	0.115	0.063
Financials	0.190	5.509	0.123	0.095	0.020	0.081

B) Correlation matrix

	Resources	Basic Industries	Indus-trials	Cycl. consumer	Non-cycl. consumer	Cyclical services	Non-cycl. services	Utilities	IT	Finan-cials
Resources	1.000	0.696	0.637	0.633	0.620	0.546	0.398	0.506	0.486	0.630
Basic Industries		1.000	0.868	0.866	0.755	0.787	0.619	0.616	0.665	0.810
Industrials			1.000	0.834	0.715	0.894	0.759	0.624	0.802	0.842
Cyclical consumer goods				1.000	0.702	0.754	0.636	0.602	0.649	0.796
Non-cyclical consumer goods					1.000	0.642	0.494	0.646	0.509	0.776
Cyclical services						1.000	0.811	0.657	0.771	0.762
Non-cyclical services							1.000	0.602	0.782	0.642
Utilities								1.000	0.454	0.668
IT									1.000	0.705
Financials										1.000

(Arithmetic) means and standard deviations are expressed in monthly percentage terms. They are based on excess returns.
All statistics are computed over the full sample from 12/88 to 9/02 (166 observations).

Table 3: Descriptive Statistics of Instrumental Variables

A) Means, standard deviations, and autocorrelation coefficients

	Mean	Volatility	Autocorrelation lag 1	lag 2	lag 3	lag 4
term spread 10y-3m	0.772	1.396	0.983	0.962	0.939	0.907
term spread 3m-1m	0.066	0.182	0.684	0.500	0.567	0.534
default spread	0.930	0.452	0.971	0.942	0.901	0.868
oil price	20.009	5.029	0.873	0.760	0.651	0.518
industrial production	0.145	0.850	–0.229	–0.003	0.230	0.022
inflation (CPI)	0.218	0.196	0.308	0.004	0.112	0.047
OECD leading indicator	0.112	0.434	0.878	0.725	0.575	0.480
lagged market excess return	0.323	5.088	0.155	0.094	0.076	0.063
price-earnings-ratio	16.474	3.772	0.968	0.933	0.895	0.864
dividend yield	2.575	0.575	0.971	0.937	0.901	0.864

B) Correlation matrix

	Spread 10y-3m	Spread 3m-1m	Default Spread	Oil Pricer	Industrial Production	Inflation (CPI)	OECD Indicator	Lagged Return	PER	Dividend Yield
term spread 10y-3m	1.000	0.002	–0.308	–0.013	0.170	–0.263	0.348	0.104	0.322	–0.455
term spread 3m-1m		1.000	0.073	0.168	0.166	0.133	0.043	–0.093	–0.118	–0.036
default spread			1.000	0.484	–0.114	0.008	–0.327	–0.320	–0.121	0.140
oil price				1.000	–0.003	0.147	–0.213	–0.247	0.003	0.039
industrial production					1.000	–0.043	0.213	0.084	0.142	–0.209
inflation (CPI)						1.000	–0.066	0.053	–0.226	0.206
OECD leading indicator							1.000	0.081	0.346	–0.357
lagged market excess return								1.000	0.275	–0.273
price-earnings-ratio									1.000	–0.918
dividend yield										1.000

(Arithmetic) means and standard deviations are expressed in monthly terms.
All statistics are computed over the full sample from 12/88 to 9/02 (166 observations).

Table 3. The variables are weakly correlated, with some exceptions.

In a first step, the predictive regressions of the 10 sector returns on the 11 independent variables (including an intercept) are performed in-sample, over the full period from 12/88 to 9/02. Table 4 summarizes the regression coefficients, along with p-values corrected for heteroskedasticity (WHITE, 1980), R^2's, and Durbin-Watson statistics. Industrial production, inflation, and OECD leading indicators are lagged by 3 months to account for the publication lag. All other variables are lagged by 1 month. The signs of the coefficients correspond by-and-large to economic intuition. For example, the PER has a negative sign in most cases, and the default spread has an adverse impact on returns. The R^2's are between 7.3% and 19.4%, the adjusted R^2's fall in the range of 1.3% to 14.1%.

4.2 Investment Strategies

To assess whether the forecasting ability of the information variables can be exploited in tactical asset allocation, we implement investment strategies in an out-of-sample context. The expected returns for the next period are derived from the predictive regressions. At the beginning of each month, the regression model is re-estimated, based on data available at that point in time. Using the actual values of the instrumental variables, expected returns are predicted.

Table 4: In-Sample Predictive Regressions

	Intercept	Spread 10y-3m	Spread 3m-1m	Default Spread	Oil Price	Industrial Production	Inflation (CPI)	OECD indicator	Lagged Return	PER	Dividend Yield	R^2	adj. R^2	Durbin/Watson
Resources	**11.294**	**0.027**	**1.263**	**–1.373**	**–0.046**	**–1.048**	**–3.836**	**0.649**	**0.018**	**–0.236**	**–1.403**	**0.073**	**0.013**	**2.045**
	0.239	*0.940*	*0.577*	*0.261*	*0.706*	*0.046*	*0.064*	*0.557*	*0.856*	*0.461*	*0.444*			
Basic Industries	**10.047**	**–0.221**	**–1.667**	**–0.531**	**0.018**	**0.239**	**–6.568**	**0.772**	**0.170**	**–0.301**	**–1.242**	**0.078**	**0.019**	**2.001**
	0.384	*0.561*	*0.520*	*0.680*	*0.868*	*0.653*	*0.004*	*0.464*	*0.141*	*0.388*	*0.586*			
Industrials	**5.255**	**–0.190**	**2.504**	**–1.943**	**–0.009**	**–0.005**	**–7.670**	**0.601**	**0.146**	**–0.074**	**–0.105**	**0.106**	**0.048**	**1.965**
	0.656	*0.656*	*0.306*	*0.227*	*0.941*	*0.992*	*0.002*	*0.605*	*0.228*	*0.834*	*0.964*			
Cyclical consumer	**13.924**	**–0.258**	**–2.897**	**–0.324**	**–0.034**	**–0.007**	**–7.946**	**1.094**	**0.214**	**–0.400**	**–1.688**	**0.091**	**0.032**	**1.992**
	0.293	*0.541*	*0.373*	*0.827*	*0.791*	*0.991*	*0.002*	*0.407*	*0.091*	*0.326*	*0.527*			
Non-cyclical consumer	**6.552**	**–0.132**	**1.314**	**–2.226**	**0.106**	**0.009**	**–3.252**	**–0.610**	**0.096**	**–0.166**	**–0.966**	**0.074**	**0.014**	**1.932**
	0.495	*0.646*	*0.479*	*0.011*	*0.193*	*0.980*	*0.039*	*0.492*	*0.264*	*0.567*	*0.604*			
Cyclical services	**–0.889**	**0.098**	**2.742**	**–1.703**	**–0.113**	**0.233**	**–7.948**	**–0.276**	**0.165**	**0.133**	**1.623**	**0.150**	**0.094**	**2.067**
	0.943	*0.794*	*0.293*	*0.231*	*0.332*	*0.627*	*0.001*	*0.797*	*0.131*	*0.725*	*0.492*			
Non-cyclical services	**–10.199**	**0.382**	**5.384**	**–1.882**	**–0.265**	**–0.025**	**–8.081**	**–0.104**	**0.097**	**0.486**	**4.276**	**0.157**	**0.102**	**1.826**
	0.517	*0.442*	*0.177*	*0.267*	*0.052*	*0.969*	*0.006*	*0.940*	*0.447*	*0.300*	*0.172*			
Utilities	**7.874**	**–0.025**	**0.631**	**–2.162**	**–0.020**	**–0.094**	**–2.390**	**–1.228**	**0.065**	**–0.157**	**–0.665**	**0.081**	**0.022**	**1.989**
	0.280	*0.935*	*0.701*	*0.024*	*0.812*	*0.792*	*0.113*	*0.204*	*0.408*	*0.489*	*0.639*			
IT	**–11.448**	**0.323**	**8.303**	**–3.462**	**–0.178**	**–0.569**	**–15.457**	**0.250**	**0.140**	**0.581**	**4.725**	**0.194**	**0.141**	**1.777**
	0.569	*0.622*	*0.069*	*0.141*	*0.384*	*0.525*	*0.001*	*0.893*	*0.456*	*0.330*	*0.256*			
Financials	**7.061**	**–0.213**	**1.588**	**–3.057**	**0.043**	**–0.200**	**–5.936**	**–0.425**	**0.122**	**–0.093**	**–0.780**	**0.103**	**0.045**	**2.009**
	0.532	*0.580*	*0.459*	*0.060*	*0.709*	*0.703*	*0.010*	*0.711*	*0.333*	*0.782*	*0.728*			

The regressions of sector excess returns on lagged instrumental variables are based on the full sample from 12/88 to 9/02 (166 observations).
The p-values, corrected for heteroskedasticitiy (White, 1980), are given in italics.

The estimation period to compute the regression coefficients and the remaining input parameters is initially set to 30 months. The first estimation period is from 7/91 to 12/93, because the sample data in advance from 12/88 to 6/91 is needed for the alpha refinement strategy. Then, excess returns for 1/94 are predicted. The covariance matrix is also based on the period from 7/91 to 12/93. Portfolios are constructed with these expected returns and covariance matrix. Then, the estimation period is rolled one month forward (8/91 to 1/94), and forecasts for 2/94 are generated. Hence, the forecast horizon is equal to one month. This procedure is repeated 105 times, resulting in 105 out-of-sample returns for each strategy.

Table 5 gives an overview of the implemented investment strategies and the abbreviations that are used below. The unconditional strategies are based on historical (excess) returns only. They comprise the benchmark portfolio (the Datastream EMU Index), minimum-variance-portfolio (MVP), equally-weighted portfolio (EWP), and tangency portfolio (TP). To incorporate estimation risk, one could use the approach of JORION (1986) or PASTOR (2000) and shrink the TP to the MVP or to the market portfolio. Neither approach can improve on the TP in our study and hence these strategies are omitted in the tables.[18] The unconditional strategies, of course, use a very limited data set compared to the conditional strategies, thus they serve as a reference point. The more complex conditional strategies are only of interest for investment practice if they can perform better than simple strategies like the MVP or the index portfolio.

The conditional strategies include the instrumental variables and are based on the predictive regressions. As explained above, they can be classified into non-benchmark-related approaches (dynamic asset allocation) and benchmark-related approaches (active management). In the "raw forecasts strategy," the predicted excess returns in equation (6) are transformed into portfolio weights without any adjustment. The risk aversion parameter, λ_T, in the mean/variance objective function

$$\max_{h_P}\left(h'_P\mu - \lambda_T h'_P V h_P\right) \tag{16}$$

is set to 2. h_P is the $N \times 1$ vector of portfolio weights, μ denotes the $N \times 1$ vector of expected excess returns. To account for estimation risk in the regression coefficients, the Bayesian techniques from above are employed. The optimal portfolio is shrunk towards the MVP ("Bayes_ MVP" strategy). The tightness parameter, θ, in the Minnesota prior is set to 0.2, as suggested by DOAN et al. (1984).

Table 5: Investigated Investment Strategies

A) Unconditional strategies

- Benchmark portfolio (BM)
- Minimum-variance-portfolio (MVP)
- Equally-weighted-portfolio (EWP)
- Tangency portfolio (TP)

B) Conditional strategies

1. *Dynamic asset allocation (non benchmark-related)*
   - Portfolio based on raw forecasts (Raw forecasts)
   - Bayes approach, shrinking towards MVP (Bayes_MVP)
2. *Active management (benchmark-related)*
   - Portfolio based on raw alphas (Raw alphas)
   - Bayes approach, shrinking towards benchmark (Bayes_BM)
   - Alpha refinement (GK)

Then, raw alphas are extracted from the raw forecasts.[19] The raw alphas are used as an input for the alpha/tracking error optimization (8) first ("Raw alphas"). Active risk aversion is set to 2.5. To incorporate estimation risk, the Bayesian regression techniques are applied again, with the benchmark portfolio as shrinkage target this time ("Bayes_BM"). Finally, the alpha refinement rule is applied. The data from 12/88 to 6/91 are used to produce a history of raw forecasts ("signals") by performing 30 rolling regressions.[20] They are needed to standardize the signal of the first out-of-sample period (7/91) and to compute the empirical information coefficients. It turns out, however, that the empirical information coefficients have large estimation errors, which confirms the presumption of CONNOR and KAHN (1997). Therefore, we only report results for a constant information coefficient. The IC that enters in equation (7) is always set to 0.5.[21]

For all investment strategies, the sample covariance matrix, based on the last 30 observations, is used. It is given by

$$\hat{V} = (r - 1_T \hat{r}')'(r - 1_T \hat{r}')/(T-1) \tag{17}$$

with

$$\hat{r} = r' 1_T / T .$$

Since portfolio weights are much more sensitive to changes in expected returns compared to risk parameters, and since we want to evaluate different estimators for expected returns, it seems reasonable to use the same covariance matrix for all strategies.[22]

The comparison of the dynamic asset allocation strategies is based on the Sharpe ratio, that of the active strategies on the information ratio. Furthermore, monthly turnover is computed, and the weight structures are analyzed to assess which strategy leads to more stable weights over time and hence, lower transaction costs.

4.3 Results

With Short-Selling

The portfolio optimizations are performed with short-selling permitted first. This is not very relevant from a practical point of view, because most investors must not or do not want to sell short. Nevertheless, this case is interesting, because it reveals which strategies are most promising when estimation risk exists. Imposing restrictions dilutes the results, since restrictions reduce the impact of estimation risk.

First, we will discuss the results for the non-benchmark-related strategies. Panel A of Table 6 displays the (arithmetic) means (in %), standard deviations (in %), Sharpe ratios of the monthly out-of-sample returns and the one-way monthly turnover (in %). The benchmark exhibits a (monthly) Sharpe ratio of 0.067, the EWP one of 0.098. The MVP can significantly outperform both passive strategies. In contrast, the TP fails: the monthly volatility exceeds 60% and the Sharpe ratio becomes negative. The conditional strategies are superior to the passive strategies and the MVP. The Sharpe ratio of the "raw forecasts strategy" is higher, while its volatility is about the same as the benchmark. Incorporating estimation risk reduces volatility; the Sharpe ratio slightly increases. Hence, turnover falls. The turnover of the "Bayes_MVP strategy" is only half of that of the "Raw forecasts strategy".

The active strategies produce a respectable monthly information ratio of about 0.15, as is shown in Panel B of Table 6. Both strategies that take estimation risk into account can enhance risk-adjusted performance, while reducing tracking error and turnover by about two-thirds.

A note concerning the non-benchmark related strategies: They are not the result of an alpha/ tracking error optimization, but they could be used for active management. For example, the MVP generates a monthly average active return of 0.484%, the "raw forecasts strategy" even of

Table 6: Performance Statistics with Short Sales Allowed

A) Non-benchmark related strategies

Strategy	Mean	Standard deviation	Sharpe ratio	Turnover
Minimum-variance	0.846	4.840	0.175	40.67
Tangency portfolio	–3.244	61.902	<0	2527.65
Equally-weighted	0.516	5.270	0.098	1.35
Benchmark	0.362	5.434	0.067	–
Raw forecasts	1.302	6.172	0.211	127.11
Bayes_MVP	1.143	5.121	0.223	55,85

B) Active management strategies

Strategy	Realized active return	Tracking error	Information ratio	Correlation to BM	Turnover
Raw alphas	0.241	2.080	0.116	0.143	93.01
Bayes_BM	0.118	0.730	0.161	0.132	30.32
Alpha refinement	0.156	0.835	0.187	0.232	35.32

"Pseudo alphas" of non-benchmark related strategies

Strategy	Realized active return	Tracking error	Information ratio	Correlation to BM
Minimum-variance	0.484	5.070	0.095	–0.577
Raw forecasts	0.940	5.905	0.159	–0.410
Bayes_MVP	0.781	5.065	0.154	–0,526

(Arithmetic) mean and standard deviation as well as realized alpha and tracking error are expressed in percent per month.
Sharpe ratio and information ratio are also monthly statistics.
"correlation to BM" denotes the correlation of active returns to benchmark returns.
"turnover" is the monthly one-way turnover in percentage terms.

0.94% (see Panel C of Table 6). However, these strategies produce an extremely high monthly tracking error of more than 5%. Furthermore, active returns are highly negatively correlated to benchmark returns. This is intuitively clear: The MVP invests into defensive sectors with a low beta. It under-performs the market in a rising market, while in a falling market, it outperforms. However, active management should produce uncorrelated (orthogonal) returns.[23] Therefore, these strategies are not suitable for active management. The active returns of the explicitly benchmark-related strategies are almost uncorrelated to the benchmark (see Panel B of Table 6).

Without Short-Selling

The analysis is repeated with the short-selling restriction in place. Restrictions should increase the performance of those strategies that are very vulnerable to estimation errors like the TP. The impact of the remaining strategies cannot be determined ex ante. Restrictions dampen the impact of estimation risk, too, but they also cut off performance potential. Table 7 confirms that the Sharpe ratio of the TP significantly increases. It now exceeds that of the EWP and benchmark portfolio. At the same time, volatility and turnover decline. The remaining strategies – MVP, "raw forecasts," and Bayes_MVP – are a little inferior now than before, but turnover reduces substantially. The two conditional strategies are still superior to the MVP, with about the same volatility. Incorporating estimation risk yields Sharpe ratios of similar magnitude, but lower turnover. Employing these strategies for active management again results in a high tracking error and negative correlations to the benchmark (see Panel C of Table 7).

With the short-selling restriction in place, the active strategies still outperform the benchmark (see Panel B of Table 7). The information ratio

Table 7: Performance Statistics Without Short Sales

A) Non-benchmark related strategies					
Strategy	Mean	Standard deviation	Sharpe ratio		Turnover
Minimum-variance	0.576	3.980	0.145		6.56
Tangency portfolio	0.748	6.189	0.121		16.82
Equally-weighted	0.516	5.270	0.098		1.35
Benchmark	0.362	5.434	0.067		—
Raw forecasts	0.735	4.244	0.173		25.16
Bayes_MVP	0.657	4.067	0.162		9.73
B) Active management strategies					
Strategy	Realized active return	Tracking error	Information ratio	Correlation to BM	Turnover
Raw alphas	0.230	1.279	0.180	0.110	43.46
Bayes_BM	0.135	0.629	0.215	0.092	22.08
Alpha refinement	0.117	0.642	0.182	0.244	24.01
C) "Pseudo alphas" of non-benchmark related strategies					
Strategy	Realized active return	Tracking error	Information ratio	Correlation to BM	
Minimum-variance	0.214	3.018	0.071	–0.695	
Raw forecasts	0.373	2.718	0.137	–0.640	
Bayes_MVP	0.296	2.899	0.102	–0.679	

(Arithmetic) mean and standard deviation as well as realized alpha and tracking error are expressed in percent per month.
Sharpe ratio and information ratio are also monthly statistics.
"correlation to BM" denotes the correlation of active returns to benchmark returns.
"turnover" is the monthly one-way turnover in percentage terms.

Table 8: Weight Structures of Active Strategies

Strategy Weight measures	Resources	Basic Industries	Industrials	Cycl. consumer	Non-cycl. consumer	Cyclical Services	Non-cycl. Services	Utilities	IT	Financials
Raw alphas										
mean active weight	–3.51%	–0.99%	0.59%	2.34%	0.14%	1.76%	1.35%	0.48%	2.71%	–4.88%
standard deviation	8.05%	10.47%	14.29%	10.38%	9.59%	10.16%	12.32%	7.61%	8.20%	14.23%
minimum	–10.86%	–12.28%	–13.59%	–6.55%	–9.88%	–9.65%	–15.61%	–5.52%	–10.06%	–31.10%
maximum	26.59%	32.39%	42.01%	45.73%	53.02%	31.58%	45.05%	28.17%	24.97%	23.85%
Bayes_BM										
mean active weight	–2.71%	–0.99%	–1.11%	1.09%	–0.09%	1.83%	1.51%	–0.04%	1.07%	–0.58%
standard deviation	4.61%	6.89%	7.22%	5.99%	7.13%	6.68%	5.92%	3.86%	3.91%	7.40%
minimum	–10.51%	–12.21%	–12.98%	–6.35%	–9.53%	–7.42%	–13.26%	–5.21%	–5.31%	–18.00%
maximum	4.60%	18.39%	16.26%	25.21%	34.88%	20.22%	23.67%	11.00%	16.81%	20.56%
Alpha refinement (GK)										
mean active weight	–1.50%	0.49%	–1.61%	–0.66%	0.45%	0.87%	–0.14%	–0.11%	2.09%	0.11%
standard deviation	4.71%	5.42%	10.05%	3.93%	6.89%	7.53%	5.21%	4.69%	4.43%	5.86%
minimum	–10.14%	–11.67%	–13.59%	–6.50%	–9.52%	–8.88%	–13.90%	–5.52%	–7.32%	–14.16%
maximum	10.31%	15.07%	32.93%	11.10%	18.75%	22.66%	18.62%	15.41%	14.85%	15.87%

"mean active weight", "standard deviation", "minimum" and "maximum" refer to mean, standard deviation, minimum, and maximum of active weights over all 105 out-of-sample periods.

even rises, and turnover is reduced. The strategy based on the Bayesian multivariate regression model turns out to be best.

Table 8 displays the portfolio weights of the active strategies. The mean active weight of all sectors, the standard deviation over the out-of-sample periods, and the minimum and maximum weight are shown. Those strategies that incorporate estimation risk result in smaller standard deviations and lower maximum positions. The minimum weights are about the same. This indicates that the short-selling restriction is binding in all three strategies.[24]

5. Conclusions

Expected returns are time-varying and can be partly explained by valuation ratios and macroeconomic variables. This can be exploited by investment strategies, which was shown in a case study of sector rotation strategies in this article. Such conditional strategies can be designed either to achieve high total return and low total risk (dynamic asset allocation), or a high alpha and low tracking error (active management). They are, by far, superior to unconditional strategies that operate under the classical iid setting. Their performance could even be further enhanced if market-wide variables were replaced by sector-specific ones, e.g., the dividend yield or PER of each individual sector could be used. Also, the lagged sector returns could be included to exploit the autocorrelation patterns (see Table 2).

The focus of this study was the issue of estimation risk or forecast uncertainty. Most existing articles studying the economic implications of return predictability ignore estimation errors, although the coefficients of the predictive regressions must be estimated from the sample. These studies often come to the conclusion that exogenous variables can increase performance but also lead to non-diversified portfolios and a high turnover, so that these strategies can hardly be implemented in practice. Here, we explicitly account for estimation risk. We show that portfolio weights become more stable over time and turnover is substantially reduced. There is no adverse impact on performance, measured by the Sharpe and information ratio. In contrast, performance often is even enhanced. In particular, Bayesian multivariate regression models, combined with the Minnesota prior, turn out to be promising.[25]

ENDNOTES

[1] Studies do exist that examine the issue of estimation risk in the context of strategic asset allocation; cf. BARBERIS (2000). In contrast, we focus on a short-term period environment. The Bayesian adjustment that BARBERIS uses (he employs a diffuse prior) would have a negligible impact in tactical asset allocation strategies.

[2] While market timing aims at controlling the beta of the portfolio, TAA is about over- and underweighting asset classes in a balanced portfolio or countries and sectors in a stock portfolio, cf. GRINOLD/KAHN (2000).

[3] The iid setting is a special case of (1), where asset returns are regressed on an intercept only. Then, expected returns are based only on realized returns, and the estimated intercept coefficient is equal to the sample mean, cf. DAHLQUIST/ HARVEY (2001).

[4] See, among others, ANG/BEKAERT (2003), CHEN et al. (1986), FAMA (1991), FERSON/ HARVEY (1991, 1993), HARVEY (1995), HODRICK (1992).

[5] For recent discussions about the usefulness of dividend yields to predict risk premia, cf. GOYAN/ WELSCH (2003) and the literature survey by REY (2003).

[6] FAMA/FRENCH (1989) argue that risk premia are higher during recessions because investors are interested in smoothing their consumption stream. When their income is low, they need an incentive to invest their money.

[7] See, e.g., COCHRANE (1999), FAMA (1991) and FERSON/HARVEY (1991, 1993). BOSSAERTS/ HILLION (1999) and GOETZMANN/JORION (1993) disagree; for them, predictability is just a statistical artifact.

[8] An information coefficient of 0.1, which can be classified positively according to GRINOLD/KAHN (2000), corresponds to an out-of-sample R^2 of 0.1^2 = 1%. Skill is not the only "ingredient" for performance; the other is the number of opportunities or (independent) "bets". See GRINOLD/KAHN (2000) for the "fundamental law of active management". See also DROBETZ/HOECHLE (2003).

[9] Even if the model structure was known and linear regressions were appropriate to model time-varying expected returns, the relevant instrumental variables would not be known. With k potential variables, there are 2^k possibilities to combine the variables. BOSSAERTS/HILLION (1999) and PESARAN/TIMMERMANN (1995) perform all 2^k possible regressions and then pick out one based on a statistical measure (which has been calculated in-sample). A theoretically more appealing approach is to apply Bayesian modeling selection criteria. CREMERS (2002) and AVRAMOV (2002) weight the regression coefficients over all 2^k regressions in accordance with their posterior probability.

[10] An alternative is the BLACK/LITTERMAN (1992) model.

[11] For a mathematical proof of this equation, cf. GRINOLD/KAHN (2000, Ch. 10).

[12] If the IC is estimated from a sample of 120 periods and if it takes on a value of 0.05, the a 95% confidence interval is [–0.129; +0.229], i.e. the true IC falls in this range with a probability of 95%. With shorter sample, the range increases. The confidence interval is based on the estimation error of the IC, $1/T^{0.5}$, and on the assumption of normality; cf. KAHN (1996).

[13] Cf. DOAN et al. (1984), LITTERMAN (1986), and TODD (1984).

[14] This is a simple version of a Minnesota Prior that has initially been developed for more complex Bayesian VAR models.

[15] Cf. BECKERS et al. (1996), GRINOLD et al. (1989), HESTON/ROUWENHORST (1995), ROUWENHORST (1999), RUDOLF/ZIMMER-MANN (1998).

[16] The Datastream indices start 12/73. The starting point 12/88 is due to the instrumental variables, which were partly not available before.

[17] Corporate bond yields are available from 12/88 for the U.S. and from 12/95 for Euroland. Euroland and U.S. default spreads are strongly correlated (the correlation coefficient is larger than 0.95).

[18] The results can be obtained from the authors. The finding that accounting for estimation risk but

sticking to the iid setting cannot systematically improve over the MVP or TP is also made by HEROLD/MAURER (2003).

[19] We do this by re-running the regressions with demeaned data and without an intercept. Alternatively, one could subtract the benchmark impact from the raw forecasts.

[20] The first is based on the estimation period from 1/89 to 7/91 (and lagged instrumental variables from 12/88 to 6/91), the second is based on 2/89–8/91, etc., and the last on 6/91–11/93.

[21] This value has been chosen because the alpha refinement strategy leads to portfolios with tracking errors of the same magnitude as the "Bayes_BM" strategy. This makes the portfolios and their turnover better comparable, because the impact of long-only constraints heavily depends on the level of active risk, as is shown by GRINOLD/KAHN (2000).

[22] From a theoretical point of view, the unconditional, sample covariance matrix should be replaced by the conditional covariance matrix (i.e., the covariance matrix based on the forecast errors). Our empirical results, however, show that the performance statistics do not improve.

[23] This is a cornerstone of active management; cf. TREYNOR/BLACK (1973) and GRINOLD/KAHN (2000). For an illustration, cf. HEROLD (2001).

[24] The results explained in the main text are robust to parameter variations. When setting the estimation window length to 45 or 60 months, the conditional strategies still outperform their unconditional counterparts. The (monthly) information ratio even rises to values around 0.4 to 0.5. These and some additional results (varying risk aversion or the tightness parameter) can be obtained from the authors.

[25] If forecasts are given in a qualitative manner (e.g., "the dollar will depreciate versus the Euro," or "Telco stocks will outperform utilities") and not quantitatively, Bayesian methods still play an important role in portfolio construction, as shown by HEROLD (2003).

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