Timing and Diversification: A State-Dependent Asset Allocation Approach

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Abstract

The influence of changing economic environment leads the distribution of stock market returns to be time-varying. This requires a dynamic adjustment of the asset allocation in order to enjoy a conditionally optimal investment. In this context, we examine the improvement of the portfolio performance by simulating portfolio strategies that are conditioned on the Markov regime switching behavior of stock market returns. Including a memory effect eliminates the empirical shortcoming of discrete state models that they produce a standard and an extreme state in stock returns. So far, this has prevented the regimes of being used as a valuable conditioning variable. Based on a discrete state indicator variable we present evidence of considerable performance improvement relative to the static model due to optimal shifting between aggressive and well diversified portfolio structures.

Keywords: Asymmetric stock return distribution, conditional asset pricing, dynamic diversification, Markov regime switching, timing.

JEL Codes: G12

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1 Introduction

Changing economic conditions cause the moments of stock returns to be time-varying. Investors require a premium for holding risks in times of recession and economy-wide financial distress and shocks to the market provoke persistently enhanced volatilities. These relations between economic activity and financial markets have direct and important effects on cross-sectional asset characteristics and hence, must be taken into account in portfolio management strategies.

In this paper, we propose a method that captures time-variation in the return distribution and we provide an accurate way of basing a traditional model on that information when the number of observations is limited. First, we describe the dynamic nonlinear stock market behavior with a univariate Markov regime switching model and so generate a valuable conditioning variable for asset allocation decisions. We then incorporate these regimes in a portfolio optimization process from where results a description of how the investors may actively manage their assets by exploiting time-variation in the return moments for portfolio restructuring.

Our model is designed in the spirit of the growing body of conditional asset pricing setups in the literature initiated by Gibbons and Ferson (1985). Discrete state models on the basis of the methodology proposed by Hamilton (1989) have proved to fit stock return properties well and they have intuitively very appealing characteristics. Hamilton and Susmel (1994) observe that a Markov regime-switching model provides a better statistical fit than ARCH models without switching and van Norden and Schaller (1997) find strong evidence of a regime switching behavior of U.S. stock returns. In the meantime, the use of regime-switching models for modelling dynamics and asymmetries in stock market returns has become very popular (e.g. Chauvet and Potter, 2000, Perez-Quiros and Timmermann, 2001, Ang and Bekaert, 2002 or Ang and Chen, 2002).

As a purely statistical method Markov switching models are able to provide interesting answers to economic questions. Recent studies confirm that the conditional moments of stock returns are business cycle related. Cecchetti, Lam and Mark (1990) show that switching in economic growth influences the distribution of stock returns. Hamilton and Lin (1996) report a dependency between return moments and economic recessions. Generally, researchers have found a strongly countercyclical effect of real activity on stock return volatility (e.g. Schwert, 1989 or Campbell et al., 2001). Ebell (2001) explains this particular linkage in a theoretical approach.

This study aims to take advantage of the empirical success and the eco-

nomic intuition of Markov regime switching models. We propose stock market regimes as a dynamic conditional information variable for a CAPM and we focus on two main objectives. On one hand our model attempts to account for the justified criticisms and to improve the standard version of CAPM by accommodating the need for "... factors, state variables or sources of priced risk, beyond movements in the market portfolio ..." (Cochrane, 1999). And on the other hand, it provides a potentially powerful tool for investors to enhance the portfolio performance by timing asset selection on conditional information about the moments of stock returns. We simulate several dynamic portfolio strategies of sector subindices and evaluate their performance to check for model accuracy.

Our version of a conditional CAPM represents a valuable complement to existing literature in that even though nonlinearities in stock returns are uncontested and increasingly receive attention most of today's empirical asset pricing studies still focus on single-state models. Within our framework we simulate and evaluate conditionally optimal timing and trading strategies for the case of Switzerland. We analyze how stock market regimes influence optimal dynamic investment decisions at a sector level. As a further innovation with respect to the existing literature which mainly focuses on strategies founded on optimized conditioning variables we also simulate more realistic investment decisions that are based on future regime forecasts.

The results show an improvement over standard strategies due to optimized timing in adjusting the portfolio structure based on switching Markov regimes. We show that the effectiveness of diversification varies over time and that therefore, investors should engage in an aggressive portfolio structure during turbulent periods whereas in calmer times they should hold a broader portfolio¹. These results are based on the accurate disentanglement of turbulent and calm periods in the stock market, which coincide with a shift in the covariance matrix between sector index returns. Out-of-sample simulation results only marginally improve standard CAPM results. The advantages of switching asset allocation is offset by identification problems of the regimes that lead to an enhanced trading activity and to portfolio structures that are much less distinct across the states.

The paper is organized as follows. Section 2 describes the Markov switch-

¹Our evidence of high comovement in turbulent times at a sector level of stock return is in line with similar observation at an individual stock level (e.g., Lamont et al., 2001; Perez-Quiros and Timmermann, 2001). On an international stock market level (e.g., Chesnay and Jondeau, 2001 and Ang and Bekaert, 2002) the findings are similar and frequently cited in the context of financial market contagion (e.g., Forbes and Rigobon, 2002).

ing regime model. Section 3 presents the data and provides evidence on the switching character of stock market returns. Section 4 describes the conditional CAPM methodology and the simulated investment strategies. Section 5 reports the results and section 6 concludes.

2 Markov Switching in Stock Returns

Backed by theoretical and empirical reports of the accuracy of switching-regime models we design a model based on the methodology by Hamilton (1989). We assume that the stock market returns r_t follow a stochastic process where in each period the returns will be drawn from a different conditional Gaussian distribution $f(r_t | \mathbf{r}_{t-1}, s_t = j; \boldsymbol{\theta})$ in which $\mathbf{r}_{t-1}$ denotes a vector of past returns, s_t represents a discrete state variable and $\boldsymbol{\theta}$ is a vector of parameters characterizing the distribution (i.e. μ, σ) and the state conditional probabilities, $\Pr(s_t = j | \mathbf{r}_{t-1}, \boldsymbol{\theta})$ for all j . Specifically, we model the stochastic process of the demeaned returns as an AR(1) process with regime-switching mean and variance:

$$\begin{aligned} r_t - \mu_0 - (\mu_1 - \mu_0) S_t &= \phi(r_{t-1} - \mu_0 - (\mu_1 - \mu_0) S_{t-1}) \\ &+ (\sigma_0 + (\sigma_1 - \sigma_0) S_t) \varepsilon_t, \end{aligned} \quad (1)$$

with $\varepsilon_t \sim Niid(0, 1)$ and where $S_t \in \{0, 1\}$ denotes the actual state in t . Note, that equation (1) implies that the actual state S_t represents fundamental market conditions and influences the entire distribution, the mean and the variance simultaneously.

The stochastic process implies four distinct states $s_t \in \{1, 2, 3, 4\}$ following a first order univariate Markov chain that emerge from all possible combinations of S_t and S_{t-1} . We define the states as follows:

$$\begin{aligned} s_t &= 1 \text{ if } S_t = 0 \wedge S_{t-1} = 0, \\ s_t &= 2 \text{ if } S_t = 1 \wedge S_{t-1} = 0, \\ s_t &= 3 \text{ if } S_t = 0 \wedge S_{t-1} = 1, \\ s_t &= 4 \text{ if } S_t = 1 \wedge S_{t-1} = 1. \end{aligned} \quad (2)$$

The stochastic property of s_t is described in the transition probability matrix $\mathbf{P}$:

$$\mathbf{P} = \begin{bmatrix} p_{11} & 0 & p_{13} & 0 \\ 1 - p_{11} & 0 & 1 - p_{13} & 0 \\ 0 & 1 - p_{42} & 0 & 1 - p_{44} \\ 0 & p_{42} & 0 & p_{44} \end{bmatrix}, \quad (3)$$

where $p_{ij} = \Pr(s_t = j | s_{t-1} = i)$ lies in the unit interval. We assume that the transition probabilities that govern the changes of the random state variables s_t are constant and do not depend on any additional information at time t . The model thus identifies for the returns four different steady state distributions:

$$\begin{aligned} r_t | \mathbf{r}_{t-1}, s_t &= 1, \boldsymbol{\theta} \sim N(\mu_0, \sigma_0^2), \\ r_t | \mathbf{r}_{t-1}, s_t &= 2, \boldsymbol{\theta} \sim N\left(\frac{\mu_1 - \phi\mu_0}{1 - \phi}, \sigma_1^2\right), \\ r_t | \mathbf{r}_{t-1}, s_t &= 3, \boldsymbol{\theta} \sim N\left(\frac{\mu_0 - \phi\mu_1}{1 - \phi}, \sigma_0^2\right), \\ r_t | \mathbf{r}_{t-1}, s_t &= 4, \boldsymbol{\theta} \sim N(\mu_1, \sigma_1^2). \end{aligned} \quad (4)$$

We estimate the model parameters by maximizing the log likelihood function of the following Gaussian mixture distribution summed over the four states:

$$f(r_t | \mathbf{r}_{t-1}, \boldsymbol{\theta}) = \sum_{j=1}^4 \Pr(s_t = j | \mathbf{r}_{t-1}, \boldsymbol{\theta}) \times f(r_t | \mathbf{r}_{t-1}, s_t = j; \boldsymbol{\theta}) \quad (5)$$

The time series of $\Pr(s_t = j | \mathbf{r}_{t-1}, \boldsymbol{\theta})$ for $t = 1, 2, \dots, \tau, \dots, T$ is generated in an iterative process using a Bayesian updating mechanism. To optimize accuracy of these conditional probabilities we compute smoothed inferences based information until period T . For the out-of-sample portfolio simulation we take at each date τ , which is moving forward over time, an investment decision based on the one-step-ahead forecasts for the conditional state probabilities $\Pr(s_{\tau+1} = j | \mathbf{r}_{\tau}, \boldsymbol{\theta})$. Those are based on the information set until τ and calculated by premultiplying a (1×4) vector containing $\Pr(s_{\tau} = j | \mathbf{r}_{\tau}, \boldsymbol{\theta})$ by the transition matrix $\mathbf{P}$.

Our main objective, however, is to identify the conditional probability that the stock market is in state $S_t = i$ at period t , $\Pr(S_t = i | \mathbf{r}_{t-1}, \boldsymbol{\theta})$, which is calculated as the sum of the two related marginal probabilities, i.e.:

$$\begin{aligned} \Pr(S_t = 0 | \mathbf{r}_{t-1}, \boldsymbol{\theta}) &= \Pr(s_t = 1 | \mathbf{r}_{t-1}, \boldsymbol{\theta}) + \Pr(s_t = 3 | \mathbf{r}_{t-1}, \boldsymbol{\theta}), \\ \Pr(S_t = 1 | \mathbf{r}_{t-1}, \boldsymbol{\theta}) &= \Pr(s_t = 2 | \mathbf{r}_{t-1}, \boldsymbol{\theta}) + \Pr(s_t = 4 | \mathbf{r}_{t-1}, \boldsymbol{\theta}). \end{aligned} \quad (6)$$

These probabilities represent the information set for the optimal timing of asset diversification and enter the asset allocation model as conditioning variables in the spirit of McQueen and Roley (1993)².

²Note, that in this study S_t is of more interest than s_t as we adopt the standard CAPM assumption of well informed market participants. Hence, past period regimes are irrelevant for optimizing the asset allocation.

Importantly, this setup embodies a memory effect by modeling stock returns that depend on the current and the past regime and it augments a simple stochastic momentum model by a component accounting for jumps in lagged stock returns. This stickiness in state information transmission enters through the conditional demeaning of lagged returns in equation (1)³. Autoregressive setups are generally justified by the presence of noise traders who introduce serial correlation of an otherwise efficient stock market by slowly processing information⁴. Our model relies in addition on the realistic assumption that these traders do not simply look at past returns but in addition, they set them in relation to the market regime at those dates. Thus, they are able to make selective interpretations of past returns depending on the conditional mean $(\mu_1 - \mu_0) S_{t-1}$. A high proportion of such irrational traders enhances market momentum and may lead the regimes themselves to become more sticky, and hence, more persistent. This may represent a solution to the empirical problem that regime switching models tend to identify a normal and an extreme state of very short duration⁵. As such isolated events are not numerous, any in-sample analysis of the stock market based on such regimes will perform hardly any better than a static, time-invariant strategy. Moreover, as such erratic movements are almost unpredictable, they are neither of much use out-of-sample.

3 Data and Estimation

Our analysis uses monthly nominal log returns for the Datastream index representing the Swiss stock market and its 18 subindices. Returns at a higher frequency are more noisy and hence, make it more difficult to isolate cyclical variations. The observation period covers the sample from January 1973 to June 2001. We use the 1-month Euro Swiss francs rate as the return on a riskfree investment. Table 1 displays the estimation results for the regime switching model⁶. We find that the volatility is low when the point estimate of the mean return tends to be high and it is high otherwise, a

³In an analysis by Hess (2003) the employed second order Markov chain setup emerges as the most appropriate from a large number of specifications for the Swiss stock market.

⁴See Lo and MacKinlay (1999) for an overview of the causes of non-random stock market behavior.

⁵The nature of this problem is well illustrated in van Norden and Schaller (1997) who report a single state during most of the time interrupted by some isolated bursts of high volatility. Similar to the memory effect of higher order switching processes, switching ARCH models as in Hamilton and Susmel (1994) and Ang and Bekaert (2002) also produce persistent regimes.

⁶We perform the estimation with the EM-algorithm.

pattern that has repeatedly been reported in the literature (see e.g., Glosten et al., 1993). We denote the regime of high returns and low volatility $S_t = 0$ and $S_t = 1$, otherwise.

Table 1: Parameter Estimates for the Regime Switching Model

Volatility is 2.2 times higher during turbulent than during calm periods. This factor estimate is expectedly somewhat lower than in comparable studies but is not unexpected as none of our estimated regimes has the character of a short and isolated variance burst. The weakly significant autocorrelation of ds ($\rho = 0.10$) enforces the choice of the time-varying AR(1) model, originally chosen to incorporate sticky regimes. The transition probability matrix estimates and their standard errors (in parenthesis) for the state probabilities s_t are

$$\mathbf{P} = \begin{bmatrix} 0.99 (0.18) & 0 & 1.00 (0.18) & 0 \\ 0.01 (0.118) & 0 & 0.00 (0.18) & 0 \\ 0 & 0.00 (0.28) & 0 & 0.05 (0.28) \\ 0 & 1.00 (0.28) & 0 & 0.95 (0.28) \end{bmatrix}.$$

These switching probabilities imply a high regime persistence with an average duration of 1.2 years and 4.3 years for $S_t = 0$ and $S_t = 1$, respectively. Figure 1 illustrates on one hand the regime persistence and that the model identifies well the two actual states S_t with smoothed conditional probabilities $\Pr(S_t = 1 | \mathbf{r}_T, \boldsymbol{\theta})$ either close to zero or one.

Figure 1: Regimes of the Swiss Stock Market

Narratively interpreted, figure 1 shows that the first structural break coincides with the end of the oil price shock and stock markets pick up and enjoy ten years of smooth and steady growth. Increased volatility due to large gains is shown by the regime switch in 1985 and the peaks in 1987 and 1990 indicate the respective crashes. The latest regime has been prevailing since 1997 when markets got to their all time high and weakened abruptly due to the Asian and Latin American crisis. The regimes are not clearly identified in periods with jointly high or low mean returns and variances. This is for example the case during the summer rally of 1987 preceding the crash or during the smooth decline in 1994. The raw returns in figure 2 illustrate these individual events.

Figure 2: Swiss Stock Market Returns

The investment set in the asset allocation analysis contains 18 Datastream sector indices. Table 2 reports the descriptive statistics for log returns in local currency for the sample period January 1973 to June 2001.

Tables 2: Descriptive Statistics

The figures exhibit considerable differences between the subindices, a fact that is relevant for the asset allocation. Monthly mean log returns range between -0.02% (*brw*) and 0.94% (*oth*) and monthly standard deviations between 4.19% (*elc*) and 8.08% (*met*). The autocorrelation of monthly returns exhibits some momentum for most of the indices and the correlations among the subindices (not reported) vary quite a lot with values between 0.34 and 0.79.

4 Conditional CAPM Methodology

4.1 Regimes as Conditioning Variable

Although time-varying moments of stock returns have now been generally accepted there does not exist an abundant but now rapidly growing literature of conditional asset pricing. Early examples conditioning asset pricing on an observed information set $\mathbf{\Omega}_t$ are presented by Mark (1988) and Ng (1991) who use an ARCH model to model time-varying betas. Further studies analyzing conditioning variables in the cross-section of asset returns (e.g., Ramchand and Susmel, 1998 and Ferson and Harvey, 1999) all come to the conclusion of a significantly superior explanatory power of these models over static, single state-models. Basing a traditional CAPM on conditioning information $\mathbf{\Omega}_t$ accounts for the time-varying risk premium of the stock market. The correctly priced return of asset i is

$$E \left[r'_{it} | \mathbf{\Omega}_{t-1} \right] = \frac{cov \left[r'_{it}, r'_{mt} | \mathbf{\Omega}_{t-1} \right]}{var \left[r'_{mt} | \mathbf{\Omega}_{t-1} \right]} E \left[r'_{mt} | \mathbf{\Omega}_{t-1} \right], \quad (7)$$

where r'_{it} and r'_{mt} denote excess returns of asset i and of the market over the riskfree rate, and $\mathbf{\Omega}_t = \Pr(S_t = j | \mathbf{r}_T, \boldsymbol{\theta})$ denotes the smoothed conditional state probabilities from the univariate Markov regime estimation of the market index.

Economically, it is more realistic to assume that the investor has a strong belief about the actual regime $\Pr^*(S_t = j | \mathbf{r}_T, \boldsymbol{\theta})$, which requires avoiding the mixture regimes presented in section 2. The discrete conditional probability $\Pr^*(S_t = j | \mathbf{r}_T, \boldsymbol{\theta})$ segregates the states at a natural cutoff point of

$\Pr(S_t = j|\mathbf{r}_T, \boldsymbol{\theta}) = 0.5$ and attributes probability 1 to the state $S_t = j$ which is conditionally the most probable at time t^7 , i.e.

$$\Pr^*(S_t = j|\mathbf{r}_T, \boldsymbol{\theta}) = \begin{cases} 1 & \text{if } \Pr(S_t = j|\mathbf{r}_T, \boldsymbol{\theta}) > 0.5 \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

The investor therefore optimizes a conditional Markowitz process with respect to his regime expectations. We use $\Pr^*(S_t = j|\mathbf{r}_T, \boldsymbol{\theta})$ as a dummy variable. This is equivalent to calculating a variance-covariance matrix V_{S_t} , and hence, a different optimal portfolio for each state.

Besides using the optimal in-sample conditional state probabilities as conditioning information we also simulate portfolios based on a binary state probability emerging from the one-step-ahead forecasts $\Pr(s_{\tau+1} = j|\mathbf{r}_\tau, \boldsymbol{\theta})$. In this case, we assume that in each period the investor repeats his optimization based on his one-step-ahead forecast $\Pr^*(S_{\tau+1} = j|\mathbf{r}_\tau, \boldsymbol{\theta})$ at the time of his investment decision.

$$\Pr^*(S_{\tau+1} = j|\mathbf{r}_\tau, \boldsymbol{\theta}) = \begin{cases} 1 & \text{if } \Pr(S_{\tau+1} = j|\mathbf{r}_\tau, \boldsymbol{\theta}) > 0.5 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

The performance of the out-of-sample model crucially depends on the quality of the regime forecasts. A key to the success of the investment strategies is how noisy the forecast estimates are when only a few historic observations are used to estimate the Markov switching parameters.

Our two-step approach of first identifying two regimes and then run the optimization process is subject to the observation of Boyer et al. (1997) who note that sample splits may cause spurious correlation breakdowns. However, besides the fact that time-varying correlations have been well documented, the number of coefficients in a full model estimation (as e.g., in Boyer et al., 1997, Chesnay and Jondeau, 2001) grows exponentially with the number of assets which in our case makes it an unfeasible option. Hence, given the number of assets and low-frequency data our procedure represents a tractable parsimonious alternative. Other suggestions in the literature to reduce the number of estimates that also rely on restrictive assumptions would, however, make us lose desirable properties such as persistent regimes⁸.

⁷The closeness of the solid and the dashed line in figure 1 shows that the introduction of discrete state probabilities does not represent a restrictive assumption.

⁸Billio and Pelizzon (2000) reduce the number of parameter estimates by restricting specific risk not to switch. Applied to our dataset their model requires a minimum of a 7-year historic period while our procedure theoretically needs less than 1 year for estimation allowing for robust estimates and a longer simulation period.

4.2 Portfolio Simulation

Our study examines a total number of five different investment strategies (3 in sample, 2 out-of-the sample) each of which is simulated under the assumption of time-varying market risk premium as implied by equation (1). It is a natural choice to analyze the performance of an investor who chooses to initially hold the tangency portfolio as it maximizes the Sharpe ratio. The optimal state dependent asset weights $\omega_{S_t}^*$ of the tangency portfolio emerge from a standard efficient set optimization problem^{9,10}, i.e.:

$$\omega_{S_t}^* = \frac{1}{\iota' V_{S_t}^{-1} (\mu_{S_t} - r_{f,t} \iota)} V_{S_t}^{-1} (\mu_{S_t} - r_{f,t} \iota), \quad (10)$$

where $\omega_{S_t}^*$ denotes the optimal state conditioned asset weights of the tangency portfolio in t , μ_{S_t} is a vector of the conditional means of N risky assets, $r_{f,t}$ denotes the risk free rate, V_{S_t} represents the conditional variance-covariance matrix based on $\Pr^*(S_{t+1} = j | \mathbf{r}_t, \boldsymbol{\theta})$ and ι a corresponding vector of ones. This setup implies that at each t there exists a variance-covariance matrix V_{S_t} and hence, a different optimal portfolio in each state. We estimate V_{S_t} from 30 preceding returns in the same state¹¹, i.e. $V_{S_t} = V_{S_t} | r_{S_t}, \dots, r_{S_{t-29}}$, and we simulate investment strategies that differ in two aspects. The difference of the five strategies lies in the assumptions about portfolio rebalancing, i.e. the choice of ω_{S_t} , and about the discrete state probabilities $\Pr^*(S_{t+1} = j | \mathbf{r}_t, \boldsymbol{\theta})$.

The first simulation strategy (**fw**), in which the investor may engage assumes that the asset proportions of the initial tangency portfolio in each state are held fixed throughout the whole investment period. These fixed weights are maintained by rebalancing at the end of every month and they are based on the conditionally efficient investment set for each regime in the entire observation sample. The second strategy (**rbi**) is an investment in the tangency portfolio in t which is based on the efficient frontier computed from data from the preceding rolling 30-month period. For comparison we also report the results of a buy-and-hold strategy (**bh**) which is not purely passive as it implies rebalancing at regime switches¹². These three allocation strategies are all based on the binary in-sample regime estimates

⁹Any other portfolio is ad hoc and therefore omitted.

¹⁰See e.g., Huang and Litzenberger (1988) for the mathematics of the efficient frontier that lead to the asset weights.

¹¹There is a tradeoff between estimation accuracy and the length of the simulation period, which is severely limited if the historic period is chosen too long.

¹²The first asset allocation after a switch to regime j is set equal to the portfolio structure when state j was prevailing for the last time.

$\Pr^*(S_{t+1} = j | \mathbf{r}_T, \boldsymbol{\theta})$ as displayed in figure 1 and serve to evaluate the appropriateness of the regime-based CAPM and the information content of the regimes as a timing variable, respectively.

The out-of-sample simulations are similar to **rbi** in that there is an optimization at each t . They differ from each other with respect to the calculation of the regime forecasts. One strategy (**rbr**) uses a rolling 30-month historic window for estimating the regimes whereas the regime forecast of strategy (**rbg**) is based on a historic period which is growing over the whole sample. It is reasonable to assume that **rbg** is more promising as the transition probability estimates $\mathbf{P}$ are getting increasingly stable and come closer to the optimal in-sample probabilities over time. Therefore, and because the states are quite persistent, regime forecasts should be improving considerably over time. Table 3 summarizes the five strategies that emerge from the variation of the two key assumptions.

Table 3: Summary of Portfolio Strategies

To ensure that the simulation results are realistic and not driven by extreme sector allocations we also run the optimization process for **rbr** and **rbg** under the constraint that a sector share may not deviate more than 10% from its average weight in the sector.

5 Empirical Results

5.1 In-sample Analysis

Two main observations emerge from the state-dependent portfolio optimizations and simulations. First, the results in panel A of table 4 from the optimization procedure indicate that the two Markov regimes represent important timing signals for each strategy as the conditional moments are superior to the unconditional ones¹³. Second, panel B displays that simulating regime-switching based dynamic investment strategies also substantially improves the risk-adjusted performance relative to the static case.

Table 4: Performance of Optimized Portfolios

The annualized mean return improvement of all three conditional in-sample strategies denoted by 1&0 relative to the unconditional investment (no) in the tangency portfolio is between 1.3% (**rbi**) and 3.6% (**bh**). The

¹³The model is estimated under the restriction of no short sales.

active return with respect to the market, r_a , is markedly higher for conditional strategies. Hence, the theoretical argument in favor of a regime switching approach seem to hold empirically and are well fitted as a timing signal to alter the portfolio's risk exposure while trading activity increases only slightly. The marginally higher average sales volume (SV) stem from the complete portfolio restructuring at regime switches. The sales volume in **rbi** approaches 20% of the actual wealth, which on one hand illustrates the variability of the efficient frontier and suggests on the other hand that net of transaction costs adjusting each period to the new efficient set is detrimental to portfolio performance.

The figures in panel B show that the higher returns of state-dependent asset allocation are not the result of substantially riskier strategies by exhibiting a clearly improved risk-adjusted performance for the regime-switching CAPM. Various performance measures generally display the same positive results. Only for **rbi** the Graham and Harvey (1996) measures (GH1, GH2), punishing untimely and too frequent rebalancing, exhibit negative values¹⁴.

The main reason for the robustly positive results lies in the characteristics of the asset covariances which dramatically change across the two regimes. They are substantially higher during turbulent periods (i.e. $S_t = 0$) where none of 153 correlation coefficients lies below 0.5 whereas in peaceful times 145 cross-correlations are below this limit¹⁵. Ignoring this between-sector asymmetry, which to our knowledge has not yet been documented, would lead to an overestimation of the diversification properties in a bearish and turbulent market and to an underestimation, otherwise¹⁶. In order to account for this varying environment it is optimal to dynamically adjust the weights of the subindices within the portfolio.

The figures in table 5 clearly show that as a consequence optimal asset proportions change markedly across the regimes.

Table 5: Asset Proportions

When correlations are high the optimal portfolio is composed of less, in some strategies just one, assets than in the time-invariant model and reflects the algorithm's ability to adapt to the changing efficiency of diversification¹⁷.

¹⁴Nevertheless, despite of the larger readjustment volume of the time-varying strategies they generally exhibit outperformance even net of transaction costs (not reported) and may be further improved by lowering the rebalancing frequency.

¹⁵Detailed results available from the author upon request.

¹⁶On an individual firm level, Ang and Chen (2002) report asymmetric patterns that are similar to our observations on the sector level.

¹⁷The **bh** and the **fw** strategy reveal that the optimal strategy is to not diversify sector

A shift of the market regime towards low correlation translates into conservative portfolios composed of numerous assets which take advantage of the more efficient diversification.

In summary, the time variation in the effectiveness of portfolio diversification leads to the apparently paradox result that the investor should seek high diversification in times of high returns and low volatility and of low diversification during turbulent periods when returns tend to be low. While this contradicts Campbell et al. (2001) who consider that diversification is more important when the economy turns down, our conclusion is in line with Ang and Chen (2002) who warn from overestimating the benefits of diversification in falling markets.

5.2 Out-of-sample Analysis

The statistics of the simulated conditional CAPM strategies based on regime forecasts $\Pr^*(S_{\tau+1} = j | \mathbf{r}_\tau, \boldsymbol{\theta})$ in table 6 still show a slightly improved performance relative to the unconditional in-sample results (see **rbi** no regimes in table 4). The annualized excess returns over the standard case are 0.6% and 0.8% for **rbr** and **rbg**, respectively and are mainly due to the loss in fit.

Table 6: Statistics of Out-of-Sample Simulations

However, transaction costs make this advantage disappear¹⁸. The reason is a relatively higher average trading volume of roughly 25% (as compared to 18.3% in the unconditional case) due to the uncertainty of future regimes, which are less persistent and hence, lead to more frequent asset reallocation. Optimizing under constrained sector allocations, i.e. **rbr(10)** and **rbg(10)**, however improves the relative performance. While the exclusion of extreme sector weights hardly lowers the performance it reduces the sales volume by more than half. Hence, net of transaction costs constrained portfolios outperform unconstrained ones while at the same time considerably reducing the tracking error with respect to the market and makes them more attractive to practitioners¹⁹.

specific risk by allocating 100% to the insurance sector. This extreme allocation is a mere product of the optimizing process at the 30th observation which then, due to the definition of the **bh** and the **fw** strategy remains, unlike **rbi**, unchanged. Note, that as the investment opportunities are industry indices, firm-specific risk of the individual shares is diversified away and, hence, the variance of riskier strategies does not explode.

¹⁸This observation also holds net of transaction costs of a conservative 1%. Results are available from the author upon request.

¹⁹We use the mean absolute deviation of the investment return relative to the market index as a measure of tracking error. See Rudolf et al. (1999) for a discussion of further

The performance measures in table 7 confirm the previous results of a marginal improvement of the conditional CAPM out-of-sample simulations over the standard case. As the volatility of the conditional strategies is lower, none of its performance values falls below the static strategy with Sharpe, Treynor and two GH measures of 0.11, 0.59, -1.73 and -1.42, respectively. Hence, the timing component of the forecasted regimes still outweighs the loss of fit out of sample and underpins the accurateness of our approach.

Table 7: Out-of-sample Performance

Notably, the **rbg** strategy values come close to the outperformance of the **rbi** in-sample values which suggests that for large samples the regime forecasts are accurate enough to provide a reliable timing signal for portfolio restructuring. Table 5 points to the origin of performance loss relative to the dynamic in-sample **rbi** strategy. While the average asset allocations of **rbi** are very different across the two states, errors in regime forecasts lead **rbr** and **rbg** allocations to be similar and prevent them to fully exploit the advantage of switching sector weights.

What other factors that could negatively influence the out-of-sample performance of this dynamic method should be taken into account? First, despite the fact that the switching-regime model corrects for biases in the standard model it increases the variation of the coefficient estimates and hence, allows for a less exact strategy formulation. In the **rbg** model, this occurs especially at the beginning of the simulation period when the sample is very short but then dampens as more observations are included. In the **rbr** model it occurs over the whole period as the rolling window of 30 observations is very short for robustly estimating all parameters which results in a regime forecast error frequency of more than twice than that of **rbg**.

Second, a wrong regime forecast may not only lead to a non-optimal but to a detrimental allocation in the contrary direction relative to the 'neutral' single state. Several overperformances relative to the standard formulation are on average necessary to make up the damage caused by one single wrong regime forecast²⁰.

Third, there may be more than just two regimes. The algorithm estimates show for short periods regimes of jointly high (low) returns and high (low) volatility which are difficult to classify under the present specification.

measures and a method for minimizing the tracking error.

²⁰ A similar observation in a time-series dimension is made by Dacco and Satchell (1999) who show that only a small out-of-sample regime misclassification is sufficient to lose any advantage of a superior model.

Given the limited number of observations introducing more regimes is not recommendable as these states are not frequent enough to robustly condition the CAPM optimization.

Finally, a full model estimation incorporating time-varying correlations may improve the accurateness of the regimes and avoid the correlation breakdown problem. But because of the large number of assets relative to the sample the degrees of freedom are lacking for this approach that would require high frequency data or very few assets for a robust estimation if not additional model constraints are to be considered.

6 Conclusion

To account for the time-variation in the return distribution of stock markets we suggest a conditional CAPM and evaluate whether the conceptual innovation translates into a better performance for a Swiss investor. Encouraged by theoretical, empirical and practical arguments we design a Markov switching regime stock market model in order to extract stylized discrete states with changing mean and variance. We propose the use of a function of the conditional state probabilities as conditioning variable in a dynamic CAPM. We introduce sticky regimes to circumvent the empirical problem of identifying two states of very different persistence and hence, duration and so avoid the problem of an insufficient number of observations in one state.

Simulation results show that the persistent character of each of the states makes regime switches a valuable timing signal for portfolio rebalancing. The performance relative to the single-state benchmark increases considerably without incurring any more risk. The optimal strategy is to diversify in periods calm and prosperous stock markets and to invest aggressively in turbulent times. The reason for this apparently surprising result is the fact that in high-volatility periods the assets tend to comove closely which puts a severe limitation on the effectiveness of diversification. The out-of-sample strategies only slightly outperform the benchmark. Noisy parameter estimates, regime forecast errors and difficulties with correctly classifying the regimes tend to partly offset the gain of the regime-dependent setup. The outperformance, however, tends to increase with historic periods as the parameter estimates are more similar to the in-sample values, which hence, improves the dynamic strategy performance.

References

- [1] Ang A and G Bekaert (2002) International Asset Allocation with Regime Shifts, *Review of Financial Studies*, **15**, 1137-87.
- [2] Ang A and J Chen (2002) Asymmetric Correlations of Equity Portfolios, *Journal of Financial Economics*, **63**, 443-94.
- [3] Billio M and L Pelizzon (2000) Value-at-Risk: A Multivariate Switching Regime Approach, *Journal of Empirical Finance*, **7**, 531-554.
- [4] Boyer BH, MS Gibson and M Loretan (1997) Pitfalls in Tests for Changes in Correlations, Board of Governors of the Federal Reserve System, International Finance Discussion Paper 597.
- [5] Campbell JY, M Lettau, BG Malkiel and Y Xu (2001) Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk, *Journal of Finance*, **56**, 1-43.
- [6] Chauvet M and S Potter (2000) Coincident and Leading Indicators of the Stock Market, *Journal of Empirical Finance*, **7**, 87-111.
- [7] Chesnay F and E Jondeau (2001) Does Correlation Between Stock Returns Really Increase During Turbulent Period?, *Economic Notes*, **30**, 53-80.
- [8] Cecchetti SG, P-S Lam and NC Mark (1990) Mean Reversion in Equilibrium Asset Prices, *American Economic Review*, **80**, 398-418.
- [9] Cochrane JH (1999) New Facts in Finance, *Economic Perspectives*, **23**, 36-58.
- [10] Dacco R and S Satchell (1999) Why Do Regime-switching Models Forecast so Badly?, *Journal of Forecasting*, **18**, 1-16.
- [11] Ebell MC (2001) Why Are Asset Returns More Volatile during Recessions? A Theoretical Explanation, Study Center Gerzensee Working Paper 01.
- [12] Ferson WE and CR Harvey (1999) Conditioning Variables and the Cross Section of Stock Returns, *Journal of Finance*, **54**, 1325-60.
- [13] Forbes K and R Rigobon (2002) No Contagion, Only Interdependence: Measuring Stock Market Co-Movements, *Journal of Finance*, **57**, 2223-61.

- [14] Gibbons MR and WE Ferson (1985) Tests of Asset Pricing Models with Changing Expectations and an Unobservable Market Portfolio, *Journal of Financial Economics*, **14**, 217-36.
- [15] Glosten LR, R Jagannathan and DE Runkle (1993) On the Relation Between the Value and the Volatility of the Nominal Excess Return on Stocks, *Journal of Finance*, **48**, 1779-1801.
- [16] Graham JR and CR Harvey (1996) Market Timing Ability and Volatility Implied in Investment Newsletters' Asset Allocation Recommendations, *Journal of Financial Economics*, **42**, 397-421.
- [17] Hamilton JD (1989) A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, *Econometrica*, **57**, 357-84.
- [18] Hamilton JD and R Susmel (1994) Autoregressive Conditional Heteroskedasticity and Changes in Regime, *Journal of Econometrics*, **64**, 307-33.
- [19] Hamilton JD and G Lin (1996) Stock Market Volatility and the Business Cycle, *Journal of Applied Econometrics*, **11**, 573-93.
- [20] Hess MK (2003) What Drives Markov Regime Switching Behavior of Stock Markets? The Swiss Case, *International Review of Financial Analysis*, forthcoming.
- [21] Huang C-F and RH Litzenberger (1988) *Foundations for Financial Economics*, Prentice Hall, Englewood Cliffs.
- [22] Karolyi GA and RM Stulz (1996) Why Do Markets Move Together? An Investigation of U.S.-Japan Stock Return Comovements, *Journal of Finance*, **51**, 951-86.
- [23] Lamont O, C Polk and J Saá-Requejo (2001) Financial Constraints and Stock Returns, *Review of Financial Studies*, **14**, 529-54.
- [24] Lo AW and AC MacKinlay (1999) *A Non-Random Walk Down Wall Street*, Princeton.
- [25] Mark NC (1988) Time-Varying Betas and Risk Premia in the Pricing of Forward Foreign Exchange Contracts, *Journal of Financial Economics*, **22**, 335-54.

- [26] McQueen G and VV Roley (1993) Stock Prices, News and Business Conditions, *Review of Financial Studies*, **6**, 683-707.
- [27] Ng L (1991) Tests of the CAPM with Time-Varying Covariances: A Multivariate GARCH Approach, *Journal of Finance*, **46**, 1507-21.
- [28] van Norden S and H Schaller (1997) Regime Switches in Stock Market Returns, *Applied Financial Economics*, **7**, 177-91.
- [29] Perez-Quiros G and A Timmermann (2001) Business Cycle Asymmetries in Stock Returns: Evidence from Higher Order Moments and Conditional Densities, *Journal of Econometrics*, **103**, 259-306.
- [30] Ramchand L and R Susmel (1998) Variances and Covariances of International Stock Returns: The International Capital Asset Pricing Model Revisited, *Journal of International Financial Markets, Institutions and Money*, **8**, pp. 39-57.
- [31] Rudolf M, H-J Wolter and H Zimmermann (1999) A Linear Model for Tracking Error Minimization, *Journal of Banking & Finance*, **23**, 85-103.
- [32] Schwert GW (1989) Why Does Stock Market Volatility Change over Time?, *Journal of Finance*, **44**, 1115-53.

Figure 1: Regimes of the Swiss Stock Market

Notes: The dashed line shows the smoothed conditional probabilities $\Pr(S_t = 1|\mathbf{r}_T, \boldsymbol{\theta})$ for the sample 1973:01 to 2001:06. The solid line shows the assumedly observed state probabilities of the stock market $\Pr^*(S_t = j|\mathbf{r}_T, \boldsymbol{\theta})$, defined by the cutoff probability $\Pr(s_t = j|\mathbf{r}_T, \boldsymbol{\theta}) = 0.5$ (see equation (8)). It illustrates the investors' expectations about the prevailing regime.

Figure 2: Monthly Returns of Swiss Stock Market

Notes: The figure shows monthly continuous returns of the Datastream Swiss stock market index for the sample 1973:01 to 2001:06.

Table 1: Parameter Estimates for the Markov-Switching Model

	μ_{S_t}	σ_{S_t}	ϕ
$S_t = 1$	1.00** (0.41)	3.37** (0.26)	0.10* (0.06)
$S_t = 0$	-1.25 (1.82)	7.38** (0.61)	

Notes: The displayed figures are regime-dependent maximum likelihood moment estimates of Swiss stock market index returns in equation (1) for the period 1973:01 to 2001:06. Standard errors in parenthesis. ** and * denote significance at a 95% and a 90% level, respectively.

Table 2: Descriptive Statistics of Stock Returns

	μ	med	max	min	σ	ρ_1	Sk	Kt
<i>bmt</i>	0.42	0.76	16.74	-31.77	5.24	0.10*	-1.23	8.77
<i>bnk</i>	0.49	0.82	29.08	-47.70	6.29	0.09*	-1.55	16.34
<i>brw</i>	-0.02	-0.39	22.81	-23.00	4.55	0.16**	-0.03	6.94
<i>cgd</i>	0.83	1.06	17.68	-24.56	5.13	0.08	-0.33	4.74
<i>elc</i>	0.35	0.19	15.95	-24.11	4.19	0.14**	-0.33	7.30
<i>elt</i>	0.63	0.47	28.54	-40.37	6.65	0.24**	-0.57	8.83
<i>eng</i>	0.34	0.90	17.00	-34.71	6.23	0.21**	-1.14	7.06
<i>fdp</i>	0.81	1.03	27.59	-20.87	5.25	-0.02	0.06	5.80
<i>fdr</i>	0.27	-0.08	20.21	-33.06	6.02	0.02	-0.36	6.89
<i>ins</i>	0.86	1.11	20.20	-26.03	5.63	0.11**	-0.54	5.53
<i>lsr</i>	0.64	0.68	50.88	-28.71	7.17	-0.01	0.81	11.03
<i>met</i>	0.65	0.67	27.69	-31.24	8.08	0.16**	0.05	4.28
<i>mul</i>	0.16	0.32	24.16	-39.45	6.23	0.14**	-0.61	7.92
<i>oth</i>	0.94	0.42	30.00	-29.22	7.23	0.15**	0.03	5.72
<i>pap</i>	0.31	0.39	18.22	-29.70	5.78	0.09*	-0.62	5.83
<i>phr</i>	0.69	1.01	16.23	-30.96	5.66	0.12**	-0.62	5.79
<i>trs</i>	0.20	0.11	25.28	-23.29	6.62	0.09*	0.06	4.49
<i>uts</i>	0.42	0.16	17.29	-21.61	4.19	0.14**	0.05	6.48
<i>ds</i>	0.73	1.03	14.71	-23.95	4.55	0.14**	-0.79	6.43
<i>rf</i>	0.35	0.32	0.94	0.00	0.22	0.95**	0.67	2.57

Note: Descriptive statistics are calculated for monthly returns in the sample 1973:01 to 2001:06. The sector indices are *bnk* = Banks, *bmt* = Building Materials, *brw* = Breweries, *cgd* = Consumer Goods, *elc* = Electricity, *elt* = Electronic Equipment, *eng* = Engineering, *fdr* = Food Retailers, *fdp* = Food Producers, *ins* = Insurances, *lsr* = Leisure&Hotels, *met* = Metallurgy, *mul* = Department Stores, *oth* = Other Businesses, *pap* = Paper&Packaging, *phr* = Pharma, *trs* = Transportation, *utl* = Utilities, *ds* = DS stock market index, *rf* = 1-month Euro Swiss franc rate. Source: Datastream. μ = mean, med = median, max = maximum value, min = minimum value, σ = standard deviation, Sk = skewness, Kt = kurtosis, ρ_1 = first-order autocorrelation. Jarque-Bera tests reject the null of normal distribution for all series at a 99% confidence interval and are therefore not displayed. ** and * denote significance at the 95% and a 90% level, respectively.

Table 3: Summary of Portfolio Strategies

Strategy	asset weights	cond. state probabilities
fw	$\omega_{S_t} = \omega_{S_1}^*$	$\Pr^*(S_{t+1} = j \mathbf{r}_T, \boldsymbol{\theta})$
bh	$\omega_{S_1} = \omega_{S_1}^*$	$\Pr^*(S_{t+1} = j \mathbf{r}_T, \boldsymbol{\theta})$
rbi	$\omega_{S_t} = \omega_{S_t}^*$	$\Pr^*(S_{t+1} = j \mathbf{r}_T, \boldsymbol{\theta})$
rbr	$\omega_{S_t} = \omega_{S_t}^*$	$\Pr^*(S_{\tau+1} = j r_\tau, \dots, r_{\tau-29}, \boldsymbol{\theta})$
rbg	$\omega_{S_t} = \omega_{S_t}^*$	$\Pr^*(S_{\tau+1} = j \mathbf{r}_\tau, \boldsymbol{\theta})$

Note: The table indicates the key assumptions of the different investment strategies. Strategies based on in-sample regimes: **bh** = buy and hold; **fw** = fixed weights of all assets over the whole investment period; **rbi** = rebalancing strategy based on new optimization in-sample in every period. Strategies based on one-step-ahead regime forecasts: **rbr** = rebalancing strategy with historic period in rolling 30-month window; **rbg** = rebalancing strategy with historic period in growing window. $\omega_{S_1}^*$ denotes a vector of optimal asset weights for regime S . The discrete conditional state probabilities $\Pr^*(S_t = j | \mathbf{r}_t, \boldsymbol{\theta})$ are based on smoothed in-sample probabilities for **fw**, **bhr**, **rbi** and on one-step ahead forecasts of state probabilities for **rbr**, **rbg**. Subscript 1 indicates the starting date of the simulation period. Boldfaced $\mathbf{r}_t$ indicates a return series from the beginning of the sample to date t of the simulation period. No portfolio rebalancing in the **bh** strategy.

Table 4: Performance of Optimized Portfolios

Panel A: Descriptive Statistics									
Strategy	Regime	Obs.	μ	σ	ρ_1	SV	EW	r_a	TE
bh	no	286	1.00	4.62	0.17**	0	1252.5	0.01	1.42
	1&0	286	1.28	5.30	0.15**	2.3	2499.8	0.30	1.95
	1	231	1.13	3.61	0.15**				
	0	55	1.91	9.61	0.14				
fw	no	286	1.07	4.54	0.15**	1.2	1527.1	0.08	1.27
	1&0	286	1.33	5.24	0.14**	3.5	2912.4	0.36	1.72
	1	231	1.19	3.49	0.14**				
	0	55	1.07	9.61	0.14				
rbi	no	286	0.95	5.45	0.14**	18.2	967.5	-0.02	2.12
	1&0	286	1.06	5.02	0.04	19.3	1422.3	0.10	2.03
	1	231	1.11	3.81	0.05				
	0	55	0.44	8.47	0.18**				

Panel B: Risk-adjusted Performance Measures										
Strategy	Regime	S	T	$GH1$	$GH2$	α	$se(\alpha)$	β	$se(\beta)$	R^2
bh	no	0.00	0.01	-0.14	-0.13	0.05	0.11	0.95	0.02	0.85
	1&0	0.06	0.30	2.21	1.86	0.28	0.16	1.03	0.04	0.74
fw	no	0.02	0.08	0.83	0.82	0.12	0.10	0.95	0.02	0.87
	1&0	0.07	0.34	2.98	2.53	0.33	0.15	1.04	0.03	0.78
rbi	no	0.11	0.59	-1.73	-1.42	-0.02	0.18	1.01	0.04	0.69
	1&0	0.15	0.78	-0.70	-0.62	0.06	0.17	0.94	0.03	0.70

Notes: Strategies based on in-sample regimes: **bh** = buy and hold; **fw** = fixed weights of all assets over the whole investment period; **rbi** = rebalancing strategy based on new optimization in-sample in every period. no = unconditional CAPM; 1&0 = conditional CAPM based on separate simulations within regimes 1 and 0. The investment period is 1977:09 - 2001:06. The historic period for the portfolio optimization is a moving window of 30 periods. The statistics are based on monthly returns. μ = mean; σ = standard deviation; ρ_1 = AR(1) coefficient, SV = average sales volume, in percents of actual portfolio value, EW = end wealth of an initial investment of 100, r_a = active return vs. DS-index, TE = tracking error, mean absolute deviation vs. DS-index, S = Sharpe ratio, T = Treynor ratio, GH = Graham-Harvey (1996) performance measure (with annualized figures), α and β are the coefficients of a Jensen alpha regression. ** and * denote significance at a 95% and a 90% level, respectively.

Table 5: Asset Proportions

	bh				fw				rbi			
	no	1&0	1	0	no	1&0	1	0	no	1&0	1	0
<i>bnk</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	2.0	2.5	0.0
<i>bmt</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.4	0.5	0.0
<i>brw</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.3	2.5	2.1	4.7
<i>cgd</i>	17.9	24.4	30.2	0.0	25.0	29.6	36.7	0.0	13.9	10.2	12.6	0.0
<i>elc</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.6	0.7	0.0
<i>elt</i>	0.0	17.7	23.4	0.0	0.0	20.9	25.9	0.0	6.4	6.0	7.3	0.0
<i>eng</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	3.3	4.1	0.0
<i>fdr</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.4	2.7	3.3	0.0
<i>fdp</i>	16.9	10.7	14.5	0.0	21.2	13.4	16.6	0.0	6.9	3.8	4.7	0.0
<i>ins</i>	35.6	19.2	0.0	100.0	28.3	19.2	0.0	100.0	6.6	15.6	5.8	61.2
<i>lsr</i>	0.0	0.6	0.8	0.0	0.0	0.6	0.7	0.0	2.9	2.6	2.1	5.2
<i>mul</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.8	3.4	4.1	0.3
<i>oth</i>	29.6	25.1	31.0	0.0	25.5	16.2	20.1	0.0	11.6	11.3	11.1	13.7
<i>pap</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.7	6.6	3.3	14.8
<i>phr</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	11.3	10.2	12.6	0.0
<i>met</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	9.6	4.4	5.4	0.0
<i>trs</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.3	4.1	5.1	0.0
<i>uts</i>	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	10.5	10.4	12.8	0.0

Table 5: continued

	rbr			rbg			rbr(10)			rbg(10)		
	1&0	1	0	1&0	1	0	1&0	1	0	1&0	1	0
<i>bnk</i>	0.6	0.2	1.3	3.4	4.4	0.0	2.6	2.1	3.4	4.6	4.6	4.7
<i>bmt</i>	0.2	0.1	0.4	0.5	0.6	0.0	2.2	1.7	3.0	0.4	0.6	0.0
<i>brw</i>	3.8	5.9	0.8	2.2	2.7	0.4	1.8	1.6	2.1	1.5	1.3	2.1
<i>cgd</i>	12.0	19.2	1.2	9.0	11.4	1.1	7.3	10.6	2.0	6.9	6.2	9.4
<i>elc</i>	0.3	0.0	0.8	0.4	0.6	0.0	3.2	4.8	0.6	6.1	7.7	0.7
<i>elt</i>	5.5	3.1	9.3	6.4	8.3	0.0	5.4	4.5	7.0	4.5	5.7	0.0
<i>eng</i>	0.4	0.4	0.3	2.7	3.5	0.0	1.1	0.9	1.5	1.4	1.6	0.5
<i>fdr</i>	2.7	0.0	7.1	1.3	1.7	0.0	2.1	0.0	5.4	1.3	1.4	1.2
<i>fdp</i>	9.2	13.6	2.7	5.3	5.3	5.7	11.9	13.7	9.0	11.0	9.9	15.1
<i>ins</i>	12.9	9.9	15.6	17.6	9.7	41.0	7.5	8.0	6.7	9.1	6.6	17.8
<i>lsr</i>	4.0	6.4	0.3	2.5	2.0	4.5	3.2	3.0	3.6	2.2	1.9	3.5
<i>mul</i>	4.2	0.1	10.8	3.5	4.6	0.0	1.9	0.3	4.4	1.8	2.1	0.8
<i>oth</i>	10.6	5.1	19.5	10.3	10.5	10.6	4.6	3.4	6.7	10.5	12.6	3.1
<i>pap</i>	2.9	2.3	2.2	5.3	3.3	11.5	2.1	1.7	2.7	2.4	1.9	4.2
<i>phr</i>	10.3	16.5	1.2	9.3	11.8	1.1	29.7	33.6	23.7	27.7	28.1	26.5
<i>met</i>	9.1	4.9	16.1	6.4	1.6	24.1	3.2	2.9	3.8	2.9	2.1	5.7
<i>trs</i>	3.4	5.3	0.6	4.2	5.4	0.0	1.7	2.5	0.5	1.4	1.7	0.5
<i>uts</i>	7.9	7.0	9.7	9.7	12.6	0.0	8.5	4.9	14.3	4.2	4.2	4.2

Notes: The table reports average percentage shares of the sector subindices in the simulated portfolios. Strategies based on in-sample regimes: **bh** = buy and hold; **fw** = fixed weights of all assets over the whole investment period; **rbi** = rebalancing strategy based on new optimization in-sample in every period. Strategies based on one-step-ahead regime forecasts: **rbr** = rebalancing strategy with historic period in rolling 30-month window; **rbg** = rebalancing strategy with historic period in growing window. (10) indicates optimization under the restriction of asset weights of a 10% band around the average share of the sector in the market index. no = unconditional CAPM with no regimes; 1&0 = conditional CAPM based on separate simulations within regimes 1 and 0. The investment period is 1977:09 - 2001:06. The historic period for the portfolio optimization is a moving window of 30 periods. See footnote of table 2 for variable definitions.

Table 6: Descriptive Statistics of Out-of-Sample Portfolios

Panel A: Strategies without Transaction Costs										
Strategy	Regime	Obs.	μ	σ	ρ_1	SV	TC	EW	r_a	TE
rbr	1&0	286	1.00	5.20	0.12**	26.1	0	1149.6	0.04	1.99
	1	171	0.75	4.85	0.07					
	0	115	1.37	5.68	0.18**					
rbg	1&0	286	1.02	4.93	0.15***	23.6	0	1264.1	0.05	1.98
	1	220	1.22	3.89	0.14**					
	0	66	0.42	7.40	0.18**					
rbr(10)	1&0	286	0.94	4.63	0.12**	9.8	0	1003.4	-0.05	1.17
	1	171	0.85	4.62	0.12					
	0	115	1.07	4.68	0.14					
rbg(10)	1&0	286	0.96	4.53	0.10*	9.1	0	1099.0	0.05	1.29
	1	220	1.29	3.65	0.11					
	0	66	-0.20	6.74	0.20*					

Panel B: Strategies with Transaction Costs										
Strategy	Regime	Obs.	μ	σ	ρ_1	SV	TC	EW	r_a	TE
rbr	1&0	286	0.55	5.24	0.13**	24.9	146.8	318.9	-0.41	2.06
	1	171	0.33	4.89	0.09					
	0	115	0.84	5.74	0.20					
rbg	1&0	286	0.59	4.92	0.16**	23.7	147.1	372.7	-0.38	1.98
	1	220	0.83	3.89	0.16**					
	0	66	-0.27	7.38	0.18					
rbr(10)	1&0	286	0.75	4.63	0.13**	10.2	102.4	596.1	-0.24	1.19
	1	171	0.68	4.62	0.13*					
	0	115	0.86	4.67	0.14					
rbg(10)	1&0	286	0.78	4.46	0.09	9.0	116.7	673.2	-0.13	1.15
	1	220	1.11	3.52	0.08					
	0	66	-0.40	6.75	0.21*					

Notes: Strategies based on one-step-ahead regime forecasts: **rbr** = rebalancing strategy with historic period in rolling 30-month window; **rbg** = rebalancing strategy with historic period in growing window. (10) indicates optimization under the restriction of asset weights of a 10% band around the average share of the sector in the market index. 1&0 = conditional CAPM based on separate simulations within regimes 1 and 0. The investment period is 1977:09 - 2001:06. The historic period for the portfolio optimization is a moving window of 30 periods. The statistics are based on monthly returns. The results of the unconditional standard case (i.e., **rbi**, no regimes) are reported in table 4. μ = mean; σ = standard deviation; ρ_1 = AR(1) coefficient, SV = average sales volume, in percents of actual portfolio value, TC = transaction costs in Swiss francs, EW = end wealth of an initial investment of 100, EW = end wealth of an initial investment of 100, r_a = active return vs. DS-index, TE = tracking error, mean absolute deviation vs. DS-index. Transaction costs are 1%. ** and * denote significance at a 95% and a 90% level,

respectively.

Table 7: Out-of-sample Performance Measures

Panel A: Strategies without Transaction Costs									
Strategy	S	T	$GH1$	$GH2$	α	$se(\alpha)$	β	$se(\beta)$	R^2
rbr	0.12	0.67	-0.78	-0.67	0.06	0.17	0.97	0.04	0.69
rbg	0.14	0.73	-0.15	-0.13	0.10	0.16	0.92	0.04	0.70
rbr(10)	0.12	0.59	-0.86	-0.83	-0.03	0.10	0.96	0.02	0.88
rbg(10)	0.13	0.65	0.20	0.20	0.08	0.11	0.94	0.02	0.88
Panel B: Strategies with Transaction Costs									
Strategy	S	T	$GH1$	$GH2$	α	$se(\alpha)$	β	$se(\beta)$	R^2
rbr	0.05	0.24	-6.23	-5.30	-0.41	0.17	0.98	0.04	0.69
rbg	0.05	0.25	-5.38	-4.87	-0.34	0.16	0.93	0.04	0.71
rbr(10)	0.07	0.34	-3.30	-3.18	-0.22	0.10	0.97	0.02	0.88
rbg(10)	0.10	0.46	-1.83	-1.82	-0.09	0.09	0.94	0.02	0.88

Notes: Strategies based on one-step-ahead regime forecasts: **rbr** = rebalancing strategy with historic period in rolling 30-month window; **rbg** = rebalancing strategy with historic period in growing window. (10) indicates optimization under the restriction of asset weights of a 10% band around the average share of the sector in the market index. All results are for a conditional CAPM (i.e., 1&0). The investment period is 1977:09 - 2001:06. The historic period for the portfolio optimization is a moving window of 30 periods. The results of the unconditional standard case (i.e., **rbi**, no regimes) are reported in table 4. S = Sharpe ratio, T = Treynor ratio, GH = Graham-Harvey (1996) performance measures (with annualized figures), α and β are the coefficients of a Jensen alpha regression. Transaction costs are 1%.