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Vorwort

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In der Reihe »Berichte des Fraunhofer ITWM« soll die Arbeit des Instituts kontinuierlich einer interessierten Öffentlichkeit in Industrie, Wirtschaft und Wissenschaft vorgestellt werden. Durch die enge Verzahnung mit dem Fachbereich Mathematik der Universität Kaiserslautern sowie durch zahlreiche Kooperationen mit internationalen Institutionen und Hochschulen in den Bereichen Ausbildung und Forschung ist ein großes Potenzial für Forschungsberichte vorhanden. In die Berichtreihe werden sowohl hervorragende Diplom- und Projektarbeiten und Dissertationen als auch Forschungsberichte der Institutsmitarbeiter und Institutsgäste zu aktuellen Fragen der Techno- und Wirtschaftsmathematik aufgenommen.

Darüber hinaus bietet die Reihe ein Forum für die Berichterstattung über die zahlreichen Kooperationsprojekte des Instituts mit Partnern aus Industrie und Wirtschaft.

Berichterstattung heißt hier Dokumentation des Transfers aktueller Ergebnisse aus mathematischer Forschungs- und Entwicklungsarbeit in industrielle Anwendungen und Softwareprodukte – und umgekehrt, denn Probleme der Praxis generieren neue interessante mathematische Fragestellungen.

Dieter Prätzel-Wolters

Prof. Dr. Dieter Prätzel-Wolters
Institutsleiter

Kaiserslautern, im Juni 2001

A regime-switching regression model for hedge funds

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Abstract

The modelling of hedge funds poses a difficult problem since the available reported data sets are often small and incomplete. We propose a switching regression model for hedge funds, in which the coefficients are able to switch between different regimes. The coefficients are governed by a Markov chain in discrete time. The different states of the Markov chain represent different states of the economy, which influence the performance of the independent variables. Hedge fund indices are chosen as regressors. The parameter estimation for the switching parameter as well as for the switching error term is done through a filtering technique for hidden Markov models developed by Elliott (1994). Recursive parameter estimates are calculated through a filter-based EM-algorithm, which uses the hidden information of the underlying Markov chain. Our switching regression model is applied on hedge fund series and hedge fund indices from the HFR database.

Keywords: Switching regression model, Hedge funds, Optimal parameter estimation, Filtering

1 Introduction

The modelling of hedge funds poses a difficult problem since the available reported data sets are often small and incomplete. There are no obligations for hedge fund managers to report the hedge fund performances, therefore the reported returns are often biased. Hedge fund managers report their performances in good periods and in times when they would like to attract new investors, but the full spectrum of hedge fund performances remains uncertain. A performance analysis and forecast of hedge fund returns are therefore challenging tasks, a suitable modelling framework has to be found.

In recent years, empirical studies for hedge funds and their underlying strategies emerged, in which the authors tried to capture the characteristic features of time series for hedge funds. Due to their complicated structure a straightforward modelling approach has not yet been found. Hedge funds are typically not normal distributed and the performance is dependent on various factors in the markets but also on strategic decisions. Statistical properties were examined by Kat and Brooks [7], who described the highly negative skewness, kurtosis and the autocorrelation of hedge fund returns which is observable in the market. They conclude that the Sharpe ratio cannot be applied to estimate the hedge fund performance, the mean-variance performance is overestimated, since the hedge fund return distribution is not normal. Underlying trading strategies for hedge funds were first studied by Fung and Hsieh [4]. They characterised buy-and-hold and dynamic trading strategies. Amongst others, Schneeweis and Spurgin [9] and Lhabitant [8] develop multi-factor models where the hedge fund returns are regressed on hedge fund indices to model the specific characteristics and dependencies on different trading strategies. More recently, hedge fund time series were tested on change points and switching characteristics to capture a possible dependence on general market factors. Alexander and Dimitriu [1] analysed HFR hedge funds on switching strategies in single-factor models. Other regime-switching models were developed in Billio et at. [2], where a market index is chosen to model switching market regimes, which affect the hedge fund performance.

To understand the risk exposure of hedge funds to the market or to specific asset classes, it is important to further investigate the switching dependencies of trading strategies. One specific example is the case of the hedge fund Amaranth Advisors LLC, which was created in 2000 as a multi-strategy hedge fund but crashed in 2006 after misspeculations in natural gas. Gupta and Kazemi [6] analysed this case and came to the conclusion that investors could have detected the risk structure of the hedge fund by examining regression models for Amaranth on hedge fund indices and market indices. It became apparent in their study that Amaranth did not act as a multi-strategy fund but had too much exposure to one market sector.

In this paper, we would like to further investigate the risk exposures of hedge funds and develop a regime-switching model in order to capture switching trading strategies and dependencies to market risks. Our model approach is a regime-switching regression model where hedge fund returns are regressed on hedge fund indices representing different investment styles. The factors are able to switch between different regimes through time, therefore the risk exposure can vary. Goldfeld and Quandt [5] developed different regime-switching regression models, where the switching of factors is either modelled exogenously by a function or where the transition probabilities are known in advance. We would like to filter out the factors from the available data sets and develop an adaptive filter method for the regime-switching regression model. We suppose that the underlying economic situation is modelled through a hidden Markov chain, which is unobservable. The factors are governed by this Markov chain. In the next section we will develop the general model framework. Recursive filters for the Markov chain are developed in section 3, optimal parameter estimates are determined through a filter-based Expectation-Maximization algorithm. A simulation study is performed in section 4 whereas in section 6 the model is implemented on hedge fund returns. Through a correlation analysis we determine suitable regressors for each trading strategy, which are used to replicate single hedge funds within these strategies. Optimal parameter estimates are determined, over 3,000 single hedge funds from the HFR database are replicated within the regime-switching regression model, the classified trading strategy can be monitored. Section 7 gives conclusions and an outlook to future work.

2 Model framework

We develop a switching regression model for hedge fund returns. We work under the probability space $(\Omega, \mathcal{F}, P)$. Consider a dependent variable y_k, $k \in \mathbb{N}$, which models the hedge fund log returns, and p independent variables F_{ik}, $k \in \mathbb{N}$, $i = 1, ..., p$. The independent variables are log returns from selected hedge fund indices. The coefficients of the factors β_{ik} are supposed to be governed by a hidden Markov chain. The coefficients of the independent factors are therefore able to switch between different economic regimes. We assume that the observation at time k, y_k, is generated by one of the 'true' regression models with the coefficients β_i from the 'true' state j, $j = 1, ..., p$.

$$y_{k+1} = \sum_{i=1}^{p} \beta_i(\boldsymbol{x}_k) F_{i,k+1} + \sigma(\boldsymbol{x}_k)\epsilon_{k+1}. \tag{1}$$

The dynamics of the discrete-time Markov chain $\boldsymbol{x}$ are given by

$$\boldsymbol{x}_{k+1} = \Pi \boldsymbol{x}_k + v_{k+1} \tag{2}$$

where $\{\boldsymbol{x}_k, k \in \mathbb{N}\}$ is a finite state Markov chain, N denotes the number of states. The state space of $\boldsymbol{x}$ is represented by the set of unit vectors $\{\boldsymbol{e}_1, ...\boldsymbol{e}_N\}$, with $\boldsymbol{e}_j = (0, ..., 0, 1, 0, ...0)' \in \mathbb{R}^N$. The transition probability matrix of the homogenous Markov chain $\boldsymbol{x}$ is denoted by $\boldsymbol{\Pi} = (\pi_{ji})$ with $\pi_{ji} = P(\boldsymbol{x}_{k+1} = \boldsymbol{e}_j \mid \boldsymbol{x}_k = \boldsymbol{e}_i)$. We define v_k through $v_{k+1} := \boldsymbol{x}_{k+1} - \Pi\boldsymbol{x}_k$, and $E[v_{k+1} \mid \mathcal{F}_k] = 0$. So, $\{v_k\}, k \in \mathbb{N}$ is a sequence of martingale increments. Let $\mathcal{F}_k^{\boldsymbol{x}_0} = \sigma\{\boldsymbol{x}_0, ..., \boldsymbol{x}_k\}$ be the σ-field generated by $\boldsymbol{x}_0, ..., \boldsymbol{x}_k$ and let $\mathcal{F}_k^{\boldsymbol{x}}$ be the complete filtration generated by $\mathcal{F}_k^{\boldsymbol{x}_0}$. The error term is modeled through $\{\epsilon_k\}$, which is a sequence of $N(0, 1)$ iid random variables and the volatility $\sigma = (\sigma_1, \sigma_2, ..., \sigma_N)' \in \mathbb{R}^N$, $\sigma_j > 0, 1 \leq j \leq N$ which is also governed by the hidden Markov chain. We denote $\beta_i(\boldsymbol{x}_k) = \langle \beta_i, \boldsymbol{x}_k \rangle$ and $\sigma(\boldsymbol{x}) = \langle \sigma, \boldsymbol{x}_k \rangle$, where $\langle , \rangle$ is the scalar product in $\mathbb{R}^N$. Let $\mathcal{F}_k^y$ be the filtration generated by the $\sigma(y_1, y_2, ..., y_k)$ and $\mathcal{F}_k = \mathcal{F}_k^{\boldsymbol{x}} \vee \mathcal{F}_k^y$ is the global filtration.

Therefore the factor coefficients as well as the error terms are dependent on the underlying Markov chain. The hidden Markov chain represents underlying economic information and enables the parameters to react to economic changes. In the next section we would like to find a way to filter out the information from our observation process, the hedge fund returns. Utilising this information, we would like to derive recursive parameter estimates for the factor coefficients and the volatility. This will be done by applying a filtering technique to the observation process which was developed by Elliott [3].

3 Filtering

This section describes the derivation of an equivalent probability measure under which the observation process and the Markov chain are independent. It is utilised to derive recursive filters for processes of the Markov chain. We will derive the filter equation under the equivalent probability measure, the 'ideal' measure $\bar{P}$ and use a measure change back to the 'real world' measure P to estimate the parameters of the observation process. Under the equivalent reference measure, the Markov chain has the same dynamics as under the real measure, the observation process is independent form the Markov chain and $N(0,1)$iid. The reference probability measure $\bar{P}$ is derived through the Radon-Nikodŷm derivative $\frac{d\bar{P}}{dP}\ |_{\mathcal{F}_k}= \bar{\Lambda}_k$. We suppose we start with probability measure $\bar{P}$ on $(\Omega,\mathcal{F})$. We wish to construct a measure P, so that under P we have that $\epsilon_{k+1} := \frac{y_{k+1}-\sum_{i=1}^{p}\beta_i(\boldsymbol{x}_k)F_{i,k+1}}{\sigma(\boldsymbol{x}_k)}$ is a sequence of $N(0,1)$ iid random variables. Denote $\phi(\cdot)$ for the $N(0,1)$ density. We construct P from $\bar{P}$ by defining

$$
\begin{aligned}
\bar{\lambda}_l &= \frac{\phi\big(\frac{y_l-\sum_{i=1}^{p}\beta_i(\boldsymbol{x}_{l-1})F_{il}}{\sigma(\boldsymbol{x}_{l-1})}\big)}{\sigma(\boldsymbol{x}_{l-1})\phi(y_l)}\\
\bar{\Lambda}_0 &= 1\\
\text{and}\\
\bar{\Lambda}_k &= \prod_{l=1}^{k}\bar{\lambda}_l,\quad k\geq 1
\end{aligned}
$$

Following Elliott in [3] a filter for any adapted process H_k is given by

$$
\mathrm{E}\left[H_k \mid \mathcal{F}_k^{\boldsymbol{x}}\right] = \frac{\overline{\mathrm{E}}\big[H_k\bar{\Lambda}_k \mid \mathcal{F}_k^{\boldsymbol{x}}\big]}{\overline{\mathrm{E}}\big[\bar{\Lambda}_k \mid \mathcal{F}_k^{\boldsymbol{x}}\big]}
$$

and has the representation $\mathrm{E}\big[H_k \mid \mathcal{F}_k^{\boldsymbol{x}}\big] = \dfrac{\big\langle \mathbf{1}, \eta_k(H_k\boldsymbol{x}_k)\big\rangle}{\big\langle \mathbf{1}, \eta_k(\boldsymbol{x}_k)\big\rangle}$, where the conditional expectation of H_k given $\mathcal{F}_k^{y}$ is denoted by $\eta_k(H_k) := \bar{\mathrm{E}}[\Lambda_k H_k|\mathcal{F}_k^{y}]$. The filters for the state space process, the jump process, the occupation time process and auxiliary processes from the Markov chain can be derived through Elliott's theorem for general adapted processes. Suppose H_l is a scalar $\mathcal{F}-$adapted process, H_0 is $\mathcal{F}_0^{\boldsymbol{x}}$ measurable and

$$
H_l = H_{l-1} + a_l + \langle b_l, v_l\rangle + g_l f(y_l)
$$

where a, b and g are $\mathcal{F}$-predictable, f is a scalar-valued function and $v_l = \boldsymbol{x}_l - \Pi\boldsymbol{x}_{l-1}$. We denote by $\Gamma_j(y_k)$ the factor $\bar{\lambda}_k$ in component j,

$$
\Gamma_j(y_k) = \frac{\phi\big(\frac{y_k-\sum_{i=1}^{p}\beta_{ij}F_{ik}}{\sigma_j}\big)}{\sigma_j\phi(y_k)} \tag{3}
$$

A recursive relation for $\eta_k(H_k\boldsymbol{x}_k)$ is given by

$$
\begin{aligned}
\eta_k(H_k\boldsymbol{x}_k) &= \sum_{j=1}^{N}\Gamma^j(y_k)\big[\langle \boldsymbol{e}_j, \eta_{k-1}(H_{k-1}\boldsymbol{x}_{k-1})\rangle\Pi\boldsymbol{e}_j\\
&\quad +\langle \boldsymbol{e}_j, \eta_{k-1}(a_k\boldsymbol{x}_{k-1})\rangle\Pi\boldsymbol{e}_j\\
&\quad +(\mathrm{diag}(\Pi\boldsymbol{e}_j) - (\Pi\boldsymbol{e}_j)\otimes(\Pi\boldsymbol{e}_j))\eta_{k-1}(b_k\langle \boldsymbol{e}_j, \boldsymbol{x}_{k-1}\rangle)\\
&\quad +\eta_{k-1}(g_k\langle \boldsymbol{e}_j, \boldsymbol{x}_{k-1}\rangle)f(y_k)\Pi\boldsymbol{e}_j\big]
\end{aligned} \tag{4}
$$

Here, for any column vectors $\mathbf{z}$ and $\mathbf{y}$, $\mathbf{z}\otimes\mathbf{y}$ denotes the rank-one (if $\mathbf{z}\neq\mathbf{0}$ and $\mathbf{y}\neq\mathbf{0}$) matrix $\mathbf{z}\mathbf{y}^{\top}$. The proof of this formula can be found in Elliott [3], theorem 5.3. The estimator for the state $\boldsymbol{x}_k$ is derived from $\eta_k(H_k\boldsymbol{x}_k)$ by setting $H_k = H_0 = 1$, $a_k = 0$, $b_k = 0$ and $g_k = 0$. This implies that

$$
\eta_k(\boldsymbol{x}_k) = \sum_{j=1}^{N}\Gamma^j(y_k)\langle \boldsymbol{e}_j, \eta_{k-1}(\boldsymbol{x}_{k-1})\rangle\Pi\boldsymbol{e}_j \quad . \tag{5}
$$

The jump process

$$J_k^{(sr)} = J_{k-1}^{(sr)} + \langle \boldsymbol{x}_{k-1}, \boldsymbol{e}_r \rangle \pi_{sr} + \langle \boldsymbol{x}_{k-1}, \boldsymbol{e}_r \rangle \langle v_k, \boldsymbol{e}_s \rangle \tag{6}$$

which describes the number of jumps of the Markov chain $\boldsymbol{x}_k$ from state $\boldsymbol{e}_r$ to state $\boldsymbol{e}_s$ in time k leads to the filter equation

$$\begin{aligned} \eta_k(J_k^{sr} \boldsymbol{x}_k) &= \sum_{j=1}^{N} \Gamma^j(y_k) \langle \eta_{k-1}(J_{k-1}^{sr} \boldsymbol{x}_{k-1}), \boldsymbol{e}_j \rangle \Pi \boldsymbol{e}_j \\ &\quad + \Gamma^r(y_k) \eta_{k-1}(\langle \boldsymbol{x}_{k-1}, \boldsymbol{e}_r \rangle) \pi_{sr} \boldsymbol{e}_s \quad . \end{aligned} \tag{7}$$

The third process $O_k^{(r)} = \sum_{l=1}^{k} \langle \boldsymbol{x}_{l-1}, \boldsymbol{e}_r \rangle$ denotes the occupation time of the Markov process $\boldsymbol{x}$, which is the length of time $\boldsymbol{x}$ spent in state r up to time k. The obtained filter is

$$\begin{aligned} \eta_k(O_k^r \boldsymbol{x}_k) &= \sum_{j=1}^{N} \Gamma^j(y_k) \langle \eta_{k-1}(O_{k-1}^r \boldsymbol{x}_{k-1}, \boldsymbol{e}_j \rangle \Pi \boldsymbol{e}_j \\ &\quad + \Gamma^r(y_k) \langle \eta_{k-1}(\boldsymbol{x}_{k-1}), \boldsymbol{e}_r \rangle \Pi \boldsymbol{e}_r \quad . \end{aligned} \tag{8}$$

Finally, we consider auxiliary process $T_k^r(g)$, which occur in the maximum likelihood estimation of the model parameters. Specifically,

$$\begin{aligned} T_k^{(r)}(g) &= \sum_{l=1}^{k} \langle \boldsymbol{x}_{l-1}, \boldsymbol{e}_r \rangle g(y_l) \\ &= T_{k-1}^r(g) + \langle \boldsymbol{x}_{k-1}, \boldsymbol{e}_r \rangle g(y_k) \end{aligned} \tag{9}$$

where g is a function of the form $g(y) = y$ or $g(y) = y^2$. We apply formula (4) with the substitution $H_k = T_k^r(g)$, $H_0 = 0$, $a_k = 0$, $b_k = 0$ and $g_k = \langle \boldsymbol{x}_{k-1}, \boldsymbol{e}_r \rangle$ and get

$$\begin{aligned} \eta_k(T_k^r(g) \boldsymbol{x}_k) &= \sum_{j=1}^{N} \Gamma^j(y_k) \{ \langle \eta_{k-1}(T_{k-1}^r(g) \boldsymbol{x}_{k-1}), \boldsymbol{e}_j \rangle \Pi \boldsymbol{e}_j \\ &\quad + \Gamma^r(y_k) \langle \eta_{k-1}(\boldsymbol{x}_{k-1}), \boldsymbol{e}_r \rangle g(y_k) \Pi \boldsymbol{e}_r \,. \end{aligned} \tag{10}$$

3.1 Optimal parameter estimates

The recursive filters for the processes of the Markov chain are utilised in the maximum likelihood estimates for the model parameters. We apply a filtered-based EM algorithm to obtain optimal parameter estimates which can be updated when new information from the Markov chain is filtered out. The set of parameters ρ, which determines the regime-switching regression model is

$$\rho = \{\pi_{sr}, \beta_{ir}, \sigma_r, 1 \le r, s \le N, 1 \le i \le p\}. \tag{11}$$

The initial values for the parameter estimates are assumed to be given. The EM algorithm involves a change of measure from P^ρ to $P^{\widehat{\rho}}$. Under P^ρ, $\boldsymbol{x}$ is a Markov chain with transition matrix $\boldsymbol{\Pi} = (\pi_{ji})$. Under $P^{\widehat{\rho}}$, $\boldsymbol{x}$ is still a Markov chain with transition matrix $\widehat{\boldsymbol{\Pi}} = (\widehat{\pi}_{ji})$. Thus, $P^{\widehat{\rho}}(\boldsymbol{x}_{k+1} = \boldsymbol{e}_j | \boldsymbol{x}_k = \boldsymbol{e}_i) = \widehat{\pi}_{ji}$. Therefore, $\widehat{\pi}_{ji} \ge 0$ and $\sum_{j=1}^{N} \widehat{\pi}_{ji} = 1$. To find an estimate for the transition probability matrix $\boldsymbol{\Pi} = (\pi_{ji})$, where $\sum_{i=1}^{N} \pi_{ji} = 1$ we consider the Radon-Nikodŷm derivative

$$\begin{aligned} \left. \frac{d\hat{P}}{dP} \right|_{\mathcal{F}_k^y} := \Lambda_k^\pi &= \prod_{l=1}^{k} \left(\prod_{c,d=1}^{N} \left(\frac{\hat{\pi}_{dc}}{\pi_{dc}} \right)^{\langle \boldsymbol{x}_l, \boldsymbol{e}_d \rangle \langle \boldsymbol{x}_{l-1}, \boldsymbol{e}_c \rangle} \right) \\ \text{with} \quad \Lambda_0 &= 1 \end{aligned}$$

With $\hat{J}$, $\hat{O}$ and $\hat{T}$ denoting the best estimates for the processes J, O and T, respectively, the optimal parameter estimate $\hat{\pi}_{ji}$ is given by

$$\hat{\pi}_{ji} = \frac{\hat{J}_k^{ji}}{\hat{O}_k^i} = \frac{\eta_k(J_k^{ji})}{\eta_k(O_k^i)} \tag{12}$$

The optimal parameter estimate for the coefficients β_i are derived through the Radon-Nikodŷm derivative

$$\frac{d\hat{P}}{dP}\bigg|_{\mathcal{F}_k^y} := \Lambda_k^{\beta_i} = \prod_{l=1}^{k} \lambda_l^{\beta_i}$$

where

$$\begin{aligned}
\lambda_{l+1}^{\beta_i} &= \frac{\exp\Big[-\frac{1}{2\sigma(\boldsymbol{x}_l)}\big(y_{l+1} - \sum_{i=1}^p \hat{\beta}_i(\boldsymbol{x}_l)F_{i,l+1}\big)^2\Big]}{\exp\Big[-\frac{1}{2\sigma(\boldsymbol{x}_l)}\big(y_{l+1} - \sum_{i=1}^p \beta_i(\boldsymbol{x}_l)F_{i,l+1}\big)^2\Big]} \\
&= \exp\Big[\frac{1}{2\sigma(\boldsymbol{x}_l)}\big(2y_{l+1}\sum_{i=1}^p \hat{\beta}_i(\boldsymbol{x}_l)F_{i,l+1} - (\sum_{i=1}^p \hat{\beta}_i(\boldsymbol{x}_l)F_{i,l+1})^2 \\
&\qquad -2y_{l+1}\sum_{i=1}^p \beta_i(\boldsymbol{x}_l)F_{i,l+1} - (\sum_{i=1}^p \beta_i(\boldsymbol{x}_l)F_{i,l+1})^2\big)\Big]
\end{aligned}$$

The log-likelihood of $\bar{\Lambda}_k^{\beta_i}$ is then given by

$$\begin{aligned}
\log \bar{\Lambda}_k^{\beta_i} &= \sum_{l=1}^{k}\Big(\big(2y_l\sum_{i=1}^p \hat{\beta}_i(\boldsymbol{x}_{l-1})F_{il} - (\sum_{i=1}^p \hat{\beta}_i(\boldsymbol{x}_{l-1})F_{il})^2 + R(\beta_i)\big)/2\sigma(\boldsymbol{x}_{l-1})\Big) \\
&= \sum_{l=1}^{k}\Big(\sum_{j=1}^{N}\langle \boldsymbol{x}_{l-1}, \boldsymbol{e}_j\rangle(2y_l\sum_{i=1}^p \hat{\beta}_{ij}F_{il} - \sum_{i=1}^p \hat{\beta}_{ij}^2 F_{i,l}^2 \\
&\qquad -2\sum_{\substack{1\le i<p \\ i<m\le p}} \hat{\beta}_{ij}F_{il}\beta_{mj}F_{ml}))/2\sigma_j\Big) + R(\beta_{ij}) \\
&= \sum_{j=1}^{N}\Big(2(\sum_{i=1}^p T_k^j(y_kF_{il})\hat{\beta}_{ij}) - \sum_{i=1}^p T_k^j(F_{il}^2)\hat{\beta}_{ij}^2 \\
&\qquad -2\sum_{\substack{1\le i<p \\ i<m\le p}} T_k^j(F_{ik}F_{mk})\hat{\beta}_{ij}\beta_{mj})/2\sigma_j\Big) + R(\beta_{ij}),
\end{aligned}$$

where $R(\beta_i)$ denotes a remainder which does not contain $\hat{\beta}_i$. Now we calculate the conditional expectation of the log-likelihood $L(\hat{\beta}_i) := \mathrm{E}[\log \bar{\Lambda}_k^{\beta_i} \mid \mathcal{F}_k^y]$ and take the derivative for each $\hat{\beta}_{ij}$.

$$\frac{\partial L(\hat{\beta}_i)}{\partial \hat{\beta}_{ij}} = \Big(\hat{T}_k^j(y_kF_{ik}) - \hat{T}_k^j(F_{ik}^2)\hat{\beta}_{ij} - \sum_{i<m\le p}\hat{T}_k^j(F_{ik}F_{mk})\beta_{mj}\Big)/2\sigma_j \tag{13}$$

We equate $\frac{\partial L(\hat{\beta}_i)}{\partial \hat{\beta}_{ij}}$ to zero and get the following optimal parameter estimate for $\hat{\beta}_{ij}$

$$\beta_{ij} = \frac{\hat{T}_k^j(y_kF_{ik}) - \sum_{i<m\le p}\hat{T}_k^j(F_{ik}F_{mk})\beta_{mj}}{\hat{T}_k^j(F_{ik}^2)} \tag{14}$$

The optimal parameter estimate for σ is derived in the same manner. We first define the Radon-Nikodŷm derivative $\frac{d\hat{P}}{dP}\Big|_{\mathcal{F}_k^y} := \Lambda_k^\sigma = \prod_{l=1}^k \lambda_l^\sigma$ with

$$\begin{aligned}
\lambda_l^\sigma &= \frac{\frac{1}{\sqrt{\hat{\sigma}(\boldsymbol{x}_l)}}\exp\big(-\frac{1}{2\hat{\sigma}(\boldsymbol{x}_l)}(y_{l+1} - \sum_{i=1}^p \beta_i(\boldsymbol{x}_l)F_{i,l+1})^2\big)}{\frac{1}{\sqrt{\sigma(\boldsymbol{x}_l)}}\exp\big(-\frac{1}{2\sigma(\boldsymbol{x}_l)}(y_{l+1} - \sum_{i=1}^p \beta_i(\boldsymbol{x}_l)F_{i,l+1})^2\big)} \\
&= \sqrt{\frac{\sigma(\boldsymbol{x}_l)}{\hat{\sigma}(\boldsymbol{x}_l)}}\exp\Big(-\frac{1}{2\hat{\sigma}(\boldsymbol{x}_l)}(y_{l+1} - \sum_{i=1}^p \beta_i(\boldsymbol{x}_l)F_{i,l+1})^2 + \frac{1}{2\sigma(\boldsymbol{x}_l)}(y_{l+1} - \sum_{i=1}^p \beta_i(\boldsymbol{x}_l)F_{i,l+1})^2\Big)
\end{aligned}$$

The log-likelihood is then

$$\begin{aligned}
\log \Lambda_l^\sigma &= \sum_{l=1}^k \big(-\frac{1}{2}\log(\hat{\sigma}(\boldsymbol{x}_{l-1})) - \frac{1}{2\hat{\sigma}(\boldsymbol{x}_{l-1})}(y_l - \sum_{i=1}^p \beta_i(\boldsymbol{x}_{l-1})F_{i,l})^2\big) + R(\sigma) \\
&= \sum_{l=1}^k \sum_{j=1}^N \langle \boldsymbol{x}_{l-1}, \boldsymbol{e}_j\rangle \Big(-\frac{1}{2}\log(\hat{\sigma}_j) - \frac{1}{2\hat{\sigma}_j}\big(y_l^2 - 2y_l\sum_{i=1}^p \beta_{ij}F_{il} + (\sum_{i=1}^p \beta_{ij}F_{il})^2\big)\Big) + R(\sigma) \\
&= \sum_{j=1}^N \Big(-\frac{1}{2}O_k^j \log(\hat{\sigma}_j) - \frac{1}{2\hat{\sigma}_j}\big(T_k^j(y_k^2) - 2\sum_{i=1}^p T_k^j(y_kF_{ik})\beta_{ij} + \sum_{i=1}^p T_k^j(F_{ik}^2)\beta_{ij}^2 \\
&\quad +2\sum_{\substack{1\le i<p \\ i<m\le p}} T_k^j(F_{ik}F_{mk})\beta_{ij}\beta_{mj}\big)\Big) + R(\sigma)
\end{aligned}$$

where $R(\sigma)$ does not contain $\hat{\sigma}$. Now we calculate the conditional expectation $L(\hat{\sigma})$ and take the derivative w.r.t. $\hat{\sigma}_j$ and get

$$\begin{aligned}
\frac{\partial L(\hat{\sigma})}{\partial \hat{\sigma}_j} &= -\frac{1}{2\hat{\sigma}_j}\hat{O}_k^j + \frac{1}{\hat{\sigma}_j^2}\big(\hat{T}_k^j(y_k^2) - 2\sum_{i=1}^p \hat{T}_k^j(y_kF_{ik})\beta_{ij} + \sum_{i=1}^p \hat{T}_k^j(F_{ik}^2)\beta_{ij}^2 \\
&\quad +2\sum_{\substack{1\le i<p \\ i<m\le p}} \hat{T}_k^j(F_{ik}F_{mk})\beta_{ij}\beta_{mj}\big)
\end{aligned}$$

With that we have

$$\hat{\sigma}_j = \frac{1}{\hat{O}_k^j}\big(\hat{T}_k^j(y_k^2) - 2\sum_{i=1}^p \hat{T}_k^j(y_kF_{ik})\beta_{ij} + \sum_{i=1}^p \hat{T}_k^j(F_{ik}^2)\beta_{ij}^2 + 2\sum_{\substack{1\le i<p \\ i<m\le p}} \hat{T}_k^j(F_{ik}F_{mk})\beta_{ij}\beta_{mj}\big)$$

4 Simulation

In order to assess applicability of our filtering procedure we first perform a simulation study on a two-state switching regression model with two regressors. We simulate an underlying two-state Markov chain as well as the two independent regressor processes $F1$ and $F2$. The regressor processes are normal distributed random variables with mean -0.2 and 0.5, respectively. The simulated observation process is then calculated through

$$y_{k+1} = \sum_{i=1}^2 \beta_i(\boldsymbol{x}_k)F_{i,k+1} + \sigma(\boldsymbol{x}_k)\epsilon_{k+1}. \tag{15}$$

The model parameters in the two states are set to $\beta_{11} = 0.5$, $\beta_{12} = 1.5$, $\beta_{21} = -0.4$, $\beta_{22} = 0.3$, $\sigma = (0.11, 0.07)$. In Figure 1, we can see the simulated observation process and the replicated process using the filtered parameter estimates. The lower graph shows the residuals of the observation process and the replication utilising the filtered parameter estimates. Figure 2 shows the

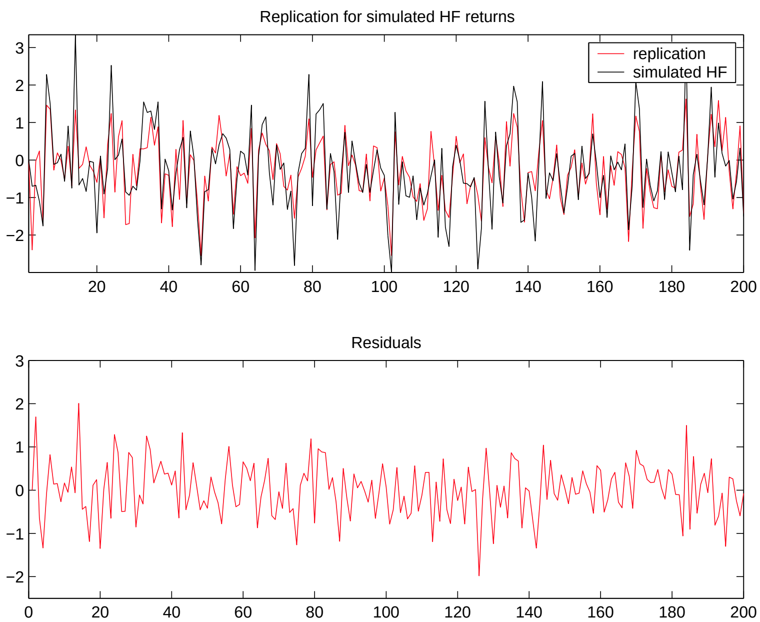

Figure 1: Replication of simulated observation process with two regressors

parameter estimates for the factors β_1 and β_2, the transition probabilities and the error term σ. We further simulate a switching regression model with three regressors F_1, F_2 and F_3. The three

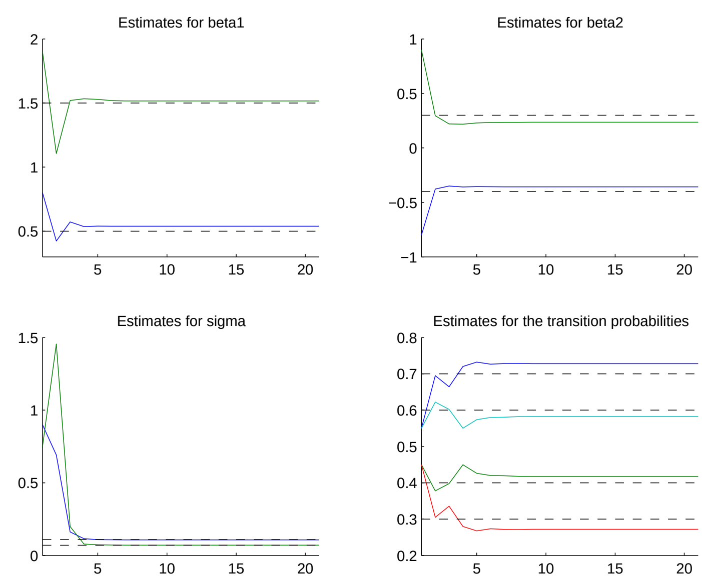

Figure 2: Filtered optimal parameter estimates

regressors are simulated as normal distributed returns with different means. The simulated underlying Markov chain takes again two possible states. The parameters in the simulation process

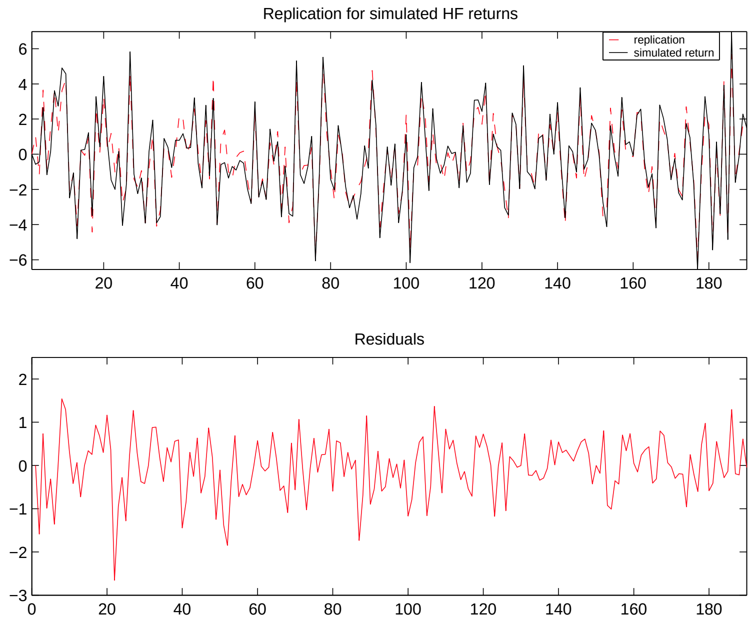

Figure 3: Replication of simulated observation process with three regressors

are set to $\beta_{11} = 2$, $\beta_{12} = 2.5$, $\beta_{21} = -0.5$, $\beta_{22} = 0.5$, $\beta_{31} = -0.3$, $\beta_{32} = 0.3$, $\sigma_1 = 0.1$, $\sigma_2 = 0.06$ and the transition probability matrix is set to $\Pi = \begin{pmatrix} 0.4 & 0.3 \\ 0.6 & 0.7 \end{pmatrix}$. Figure 4 shows the parameter estimates after 20 algorithm runs. In these example paths, parameter estimates converge very closely to the parameter values in the simulated observation process.

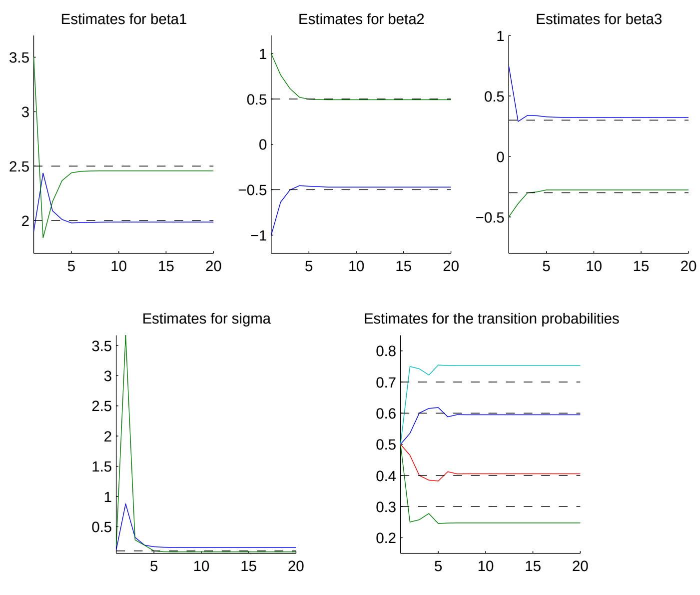

Figure 4: Filtered optimal parameter estimates

5 Simulation of short time series

Our particular focus in this paper are short time series. We therefore adapt our the simulation study to this special case. We consider again a regression model with two regressors, where the factors can take values in two states, which are governed by a hidden Markov chain.

This simulation of filtering parameter estimates on short time series requires the optimal parameter estimates to be updated after shorter batches than in the previous simulation. Here, we simulate time series containing 90 and in a second simulation study 50 data points, the parameter estimates are updated after batches of three or four data points. The filter for the processes of the Markov chain therefore contain less new information for parameter updates than in the case of longer time series. The choice of initial values for the parameters is done through a standard regression on the first ten data points of the simulated time series. The obtained factors $\overline{\beta}_1$ and $\overline{\beta}_2$ from the standard regression model are chosen as the initial values for the first state of β_1 and β_2 in the regime-switching regression setting, the second state is chosen as $\overline{\beta}_1 - 0.8$ and $\overline{\beta}_2 + 0.8$, respectively. The initial value for σ is set according to the standard deviation of the residuals from the standard regression model, $\sigma(1) = 0.6 * \text{std}(reg_res)$, $\sigma(2) = 1.5 * \text{std}(reg_res)$.

First, we simulate 10,000 time series for the Monte Carlo experiment where the length of the series is set to $T = 80$. For each simulation the factor β_1 is set to $\beta_1 = (1.5, 0.5)$ and the second factor in the simulation is $\beta = (-0.4, 0.3)$. We perform two set of experiments, in the first one σ is set constant, the second one allows σ to vary, the parameter estimate is updated through the filtering approach. Figure 5 shows a sample simulation of the time series and the evolution of the filtered parameter estimates with constant σ. A sample path for the simulation with varying σ is shown in Figure 6.

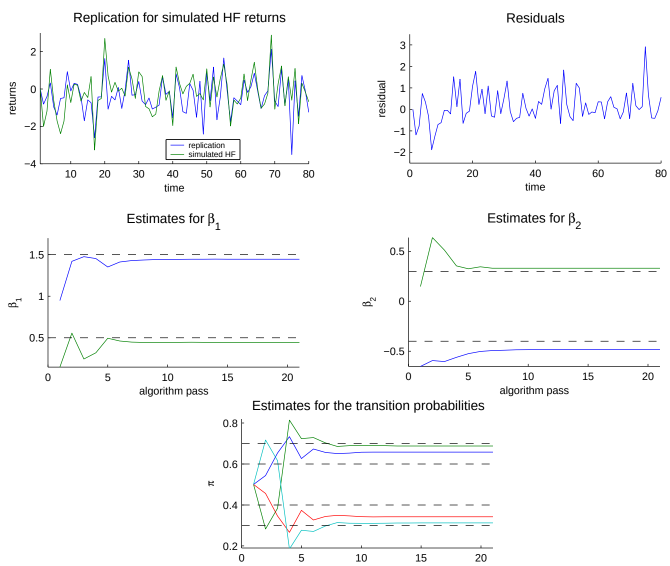

Figure 5: Regression for hedge fund returns in a 2-state HMM, $\sigma = (0.1, 0.2)$

The mean value of the optimal filtered parameter estimates of 10,000 simulations are shown in Table 5. We consider two cases of frequency of the parameter update. First the parameters are updated in batches of four data points, secondly we consider batches of three data points. These small batches are necessary in parameter estimation for short time series since the parameters have to be updated to converge to local maxima. Our results show that a less frequent update

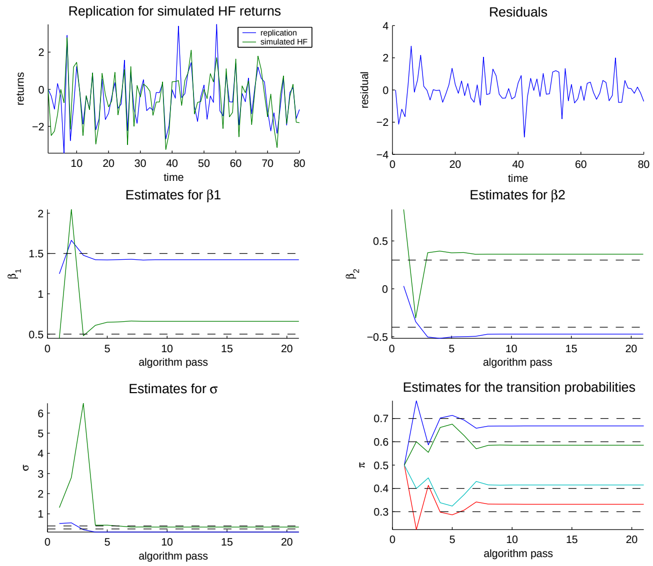

Figure 6: Regression for hedge fund returns in a 2-state HMM, $\sigma = (0.08, 0.04)$

	T = 50, batch: 3	T = 50, batch: 4	T = 90, batch: 3	T = 90, batch: 4
$\beta_1(1)$	1.2730 (0.525)	1.3285 (0.399)	1.2680 (0.830)	1.3279 (0.4161)
$\beta_1(2)$	0.7815 (0.793)	0.7143 (0.559)	0.7902 (1.694)	0.6926 (0.4838)
$\beta_2(1)$	-0.2754 (0.313)	-0.3048 (0.258)	-0.2736 (0.315)	-0.3050 (0.2604)
$\beta_2(2)$	0.1800 (0.395)	0.2039 (0.339)	0.1530 (0.365)	0.1982 (0.315)
π_{11}	0.6460 (0.272)	0.6603 (0.225)	0.6103 (0.295)	0.6531 (0.227)
π_{21}	0.3540 (0.272)	0.3397 (0.225)	0.3897 (0.295)	0.3469 (0.227)
π_{12}	0.6135 (0.352)	0.5849 (0.310)	0.5115 (0.289)	0.5354 (0.273)
π_{22}	0.3865 (0.352)	0.4151 (0.310)	0.4885 (0.289)	0.4646 (0.273)

Table 1: Parameter estimates for short time series with constant σ

with batches of four data points lead to parameter estimates closer to the chosen ones. This is due to the fact that the filters, which are used in the MLE's for the parameters, rely on new information from the observed data series, an update every three time steps does not include enough new information to update the filters.

The optimal parameter estimates from simulations with varying σ are stated in Table 5. We simulate short time series of $T = 50$ and $T = 90$ data points and filter out the optimal parameter estimates. The parameters are set to the same values as above, σ is set to $\sigma = (0.25, 0.4)$. The parameter estimates in the setting with varying σ lead to slightly higher RMSE, the additional uncertainty increases the variations of the parameters.
The simulations are repeated on longer time series to compare the resulting parameter estimates and RMSEs to those for shorter time series. We simulate again 10,000 observation time series, this time with a length of T=200, so that the algorithm can run 19 times with batches of 10 data points. Although the number of paramter updates stays roughly the same, the information processed within a data batch prior to the next parameter update is enlarged. The resulting parameters estimates and RMSEs for varying as well as constant σ's are depcited in table 5.
The next simulation includes a constant term in the regression model, the first factor $F_{1,k}$,

	T = 50, batch:3	T = 50, batch:4	T = 90, batch:3	T = 90, batch:4
$\beta_1(1)$	1.1719 (1.286)	1.2087 (0.563)	1.253 (1.382)	1.1909 (0.667)
$\beta_1(2)$	0.8796 (0.987)	0.8384 (0.599)	0.9084 (0.945)	0.8389 (0.728)
$\beta_2(1)$	-0.1974 (0.382)	-0.2284 (0.337)	-0.1627 (0.393)	-0.2122 (0.348)
$\beta_2(2)$	0.0632 (0.445)	0.0861 (0.396)	0.0255 (0.440)	0.0722 (0.392)
$\sigma(1)$	0.3499 (1.170)	0.2202 (0.290)	0.3048 (0.411)	0.2176 (0.216)
$\sigma(2)$	0.4549 (1.120)	0.3992 (0.399)	0.4148 (0.755)	0.3896 (0.346)
π_{11}	0.5764 (0.339)	0.5779 (0.299)	0.5592 (0.359)	0.5562 (0.330)
π_{21}	0.4236 (0.339)	0.4221 (0.299)	0.4408 (0.359)	0.4437 (0.330)
π_{12}	0.5168(0.341)	0.4832 (0.294)	0.4952 (0.346)	0.4607 (0.302)
π_{22}	0.4834 (0.341)	0.5168 (0.294)	0.5048 (0.346)	0.5393 (0.302)

Table 2: Parameter estimates for short time series with varying σ

	T = 200, batch of 10	
	constant σ	varying σ
$\beta_1(1)$	1.4413 (0.167)	1.2579 (0.440)
$\beta_1(2)$	0.5751 (0.231)	0.8159 (0.447)
$\beta_2(1)$	-0.3652 (0.132)	-0.2564 (0.288)
$\beta_2(2)$	0.2881 (0.171)	0.1012 (0.306)
$\sigma(1)$	constant	0.1345 (0.134)
$\sigma(2)$	constant	0.4268 (0.245)
π_{11}	0.6799 (0.114)	0.5538 (0.244)
π_{21}	0.3201 (0.114)	0.4462 (0.244)
π_{12}	0.5149 (0.198)	0.3964 (0.188)
π_{22}	0.4851 (0.198)	0.6036 (0.188)

Table 3: Parameter estimates for longer time series

$k = 1, ..T$ is therefore set to a vector of ones. Again, 10,000 simulations are run, we set $\beta_1 = (0.05.0.1)$, $\beta_2 = (1.5, 0.5)$, $\beta_3 = (-0.4, 0.3)$, $\sigma = (0.25, 0.4)$ and the transition probability matrix is set to $\Pi = \begin{pmatrix} 0.7 & 0.4 \\ 0.3 & 0.6 \end{pmatrix}$. After 29 runs of the algorithm with batches of ten data points, the last update of the parameter estimations lead in the mean to the parameter values which are depicted in the first columns of table 5. RMSE is stated in parentheses.

The three factor model is now simulated with three simulated regressors and no constant term. The resulting parameter estimates for $T = 300$ after 29 algorithm runs is given in table 5. The true value for β_1 is $(0.5, 0.1)$, the transition probability matrix is set to $\Pi = \begin{pmatrix} 0.7 & 0.4 \\ 0.3 & 0.6 \end{pmatrix}$ and the other parameter values are chosen as stated above.

Overall, the parameters estimated from long time series lead to smaller RMSEs than those from short time series. Since the available hedge fund time series are often short, one has to find a compromise of a medium batch length and enough runs of the algorithm, so parameters can converge to a local maximum. In the following empirical study, we model hedge fund return series with batches of six data points, the algorithm runs at least twice.

	T=300, batch of 10, intercept		T=300, batch of 10, no intercept	
	constant σ	varying σ	constant σ	varying σ
$\beta_1(1)$	0.0617 (0.136)	0.0549 (0.149)	0.4673 (0.153)	0.3976 (0.228)
$\beta_1(2)$	0.0562 (0.111)	0.0675 (0.116)	0.1242 (0.116)	0.1941 (0.186)
$\beta_2(1)$	1.3934 (0.286)	1.2394 (0.448)	1.4060 (0.270)	1.2506 (0.441)
$\beta_2(2)$	0.6043 (0.276)	0.8027 (0.444)	0.5950 (0.254)	0.7629 (0.426)
$\beta_3(1)$	-0.3372 (0.193)	-0.2105 (0.299)	-0.3438 (0.178)	-0.2218 (0.291)
$\beta_3(2)$	0.2513 (0.183)	0.0859 (0.313)	0.2493 (0.169)	0.1146 (0.296)
$\sigma(1)$	constant	0.2718 (0.147)	constant	0.2759 (0.132)
$\sigma(2)$	constant	0.4269 (0.190)	constant	0.3885 (0.177)
π_{11}	0.6301 (0.115)	0.5538 (0.232)	0.6345 (0.119)	0.5773 (0.215)
π_{21}	0.3699 (0.115)	0.4462 (0.232)	0.3655 (0.119)	0.4227 (0.215)
π_{12}	0.4515 (0.097)	0.4069 (0.192)	0.4513 (0.104)	0.4204 (0.193)
π_{22}	0.5485 (0.097)	0.5931 (0.192)	0.5487 (0.104)	0.5796 (0.193)

Table 4: Parameter estimates for longer time series with three regression factors

6 Model implementation

The model introduced in sections 2 and 3 is now implemented on hedge fund returns regressed on hedge fund indices obtained from Hedge Fund Research (HFR). The data series from the indices are monthly returns between 1998 and 2009 for nine different investment strategies. A statistical analysis can be seen in Table 5. In general, the monthly returns of these hedge fund indices are leptokurtic and highly skewed.

Trading strategy	Min	Max	Median	Mean	Std	Skewness	Kurtosis
Equity Hedge (EH)	-0.0999	0.0978	0.0006	0.0058	0.0254	-0.3460	6.7159
Event Driven (ED)	-0.0902	0.0479	0.0008	0.0040	0.0206	-1.4864	7.7399
Macro (M)	-0.0738	0.0854	0.0005	0.0079	0.0274	0.1285	3.7676
Relative Value Arbitrage (RVA)	-0.1411	0.0407	0.0006	0.0009	0.0211	-3.3777	20.7480
Merger Arbitrage (MA)	-0.0456	0.0329	0.0007	0.0035	0.0108	-0.7418	6.2439
Equity Market Neutral (EMN)	-0.0275	0.0292	0.0002	0.0009	0.0103	-0.0561	4.1592
Distressed Securities (DS)	-0.1169	0.0611	0.0004	0.0032	0.0216	-1.9453	12.2267
Convertible Arbitrage (CA)	-0.3468	0.0590	0.0006	-0.0015	0.0374	-6.5970	57.5095
Absolute Return (AR)	-0.0439	0.0231	0.0005	0.0026	0.0109	-1.2985	6.9018

Table 5: Statistical analysis of HFR indices

The performance of most hedge fund indices was heavily impacted by the financial crisis, which hit the financial markets in September 2008. The value of the HFRX Index Convertible Arbitrage fell from 984.66 points on 31 August 2008 to 436.18 points on 31 December 2008, the index of the trading strategy Relative Value declined over the same period from 1131.2 points to 788.5 points. Surprisingly, the indices from trading strategies Macro and Merger Arbitrage were nearly unaffected from this crisis. The values of nine different HFRX indices between 2003 and 2010 are depicted in Figure 7.

The return series of single hedge funds are also obtained from HFR. Here, we examine monthly time series from four main trading strategies. We will consider in our analysis the trading strategies Equity Hedge, Event Driven, Relative Value and Macro, which are further divided into sub-trading strategies. Table 7 in the Appendix shows descriptive statistics of the return series for hedgefunds within the considered trading strategies, mean values of mean, standard deviation,

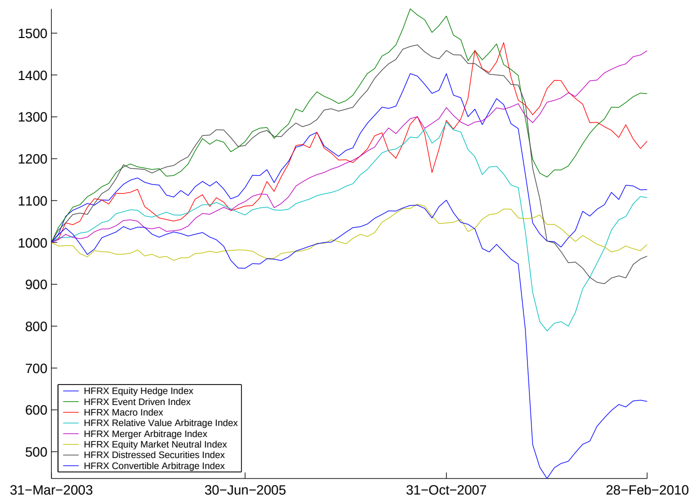

Figure 7: HFRX indices

kurtosis and skewness over series in each strategy are stated. The majority of hedgefund which we will model through our regression model is classified as funds coming from the Equity Hedge strategy. The return series within our database are leptokurtic and negatively skewed, the mean return is positive.

For each trading strategy and substrategy, three regressors are chosen, which are used for each single hedgefund within that strategy. The choice of the regressors for each trading strategy is based on a correlation analysis between hedgefunds and hedgefund indices as well as hedgefunds and market indices. A correlation analysis of hedgefund indices and market indices furthermore ensures, that the regressors taken for each trading strategy are not highly correlated. Table 17 in the Appendix shows the correlation table of hedgefunds and hedgefund indices. The hedge fund time series in this correlation analysis are considered up to December 2007. A correlation analysis of the complete data set showed, that time series in 2008 depict higher correlations to indices due to the financial crisis. Analysing hedge fund returns up to 2007 gives us a clearer picture of strategy-specific correlations with indices.

The choice of the regressors for each trading strategy class is based on the results from the correlation analysis. Both HF index regressors are chosen according to the correlation table from data sets up to December 2007. The three indices with the highest correlation to the hedge funds in each class are chosen, from these the two indices with the lowest correlation to each other are set as regressors. The third regressor is the market index with the highest correlation to the hedge fund strategy class. Table 6 shows the three chosen regressors, which are used to replicate the single hedge fund time series within one trading strategy.

We perform a regression analysis with three possible regressors modelling the risk exposure in different investment strategies. The factors β_j and the variance σ_j are herby able to switch between two different regimes. We only model those hedge funds with a minimum size of 20 data points, shorter time series cannot be model with our algorithms. Our simulation study showed, that standard errors of short batches are larger, the algorithm needs information to update parameters in a reasonable way. We therefore set the batch length to six, the filter algorithm is updated after every sixth data point. Each hedge fund return series which we model is divided into two

Trading strategy	Regressors
ED Activist:	EH, MA, MSCI
ED Credit Arbitrage:	CA, EV, MSCI
ED Distressed Restructuring:	DS, EH, MSCI
ED Merger Arbitrage:	MA, EH, MSCI
ED Multi Strategy:	EMN, ED, MSCI
ED Private Issue:	EH, MA, MSCI
ED Special Situation:	EV, AR, MSCI
EH Basic Materials:	ED, M, MSCI
EH Equity Market Neutral:	ED, M, MSCI
EH Fundamental Growth:	ED, M, MSCI
EH Fundamental Value:	ED, M, MSCI
EH Multi Strategy:	ED, M, MSCI
EH Quantitative Directional:	ED, M, MSCI
EH Short Bias:	EH, MA, MSCI
EH Technology Healthcare:	EH, MA, MSCI
RV FI-Asset Backed:	CA, ED, TBill
RV FI-Convertible Arbitrage:	CA, AR, MSCI
RV FI-Corporate:	EH, DS, MSCI
RV FI-Sovereign:	M, ED, MSCI
RV Multi Strategy:	RV, EH, MSCI
RV Volatility:	EMN, ED, TBill
RV Yield Alternatives:	DS, ED, MSCI
M Active Trading:	M, CA, TBill
M Commodity-Systematic:	M, EMN, TBill
M Currency-Discretionary:	M, CA, MSCI
M Currency-Systematic:	M, CA, MSCI
M Discretionary Thematic:	M, EH, MSCI
M Multi Strategy:	M, ED, MSCI
M Systematic Diversified:	M, AR, MSCI

Table 6: Regressors for each trading strategy

intervals, one fitting and one forecast interval. The forecast interval is always one third of the whole length of the time series. Within the first two thirds, the parameters are estimated and the state of the hidden Markov chain is estimated. For the forecast interval, we keep the parameter estimates fixed and use them to replicate the hedge fund time series. The estimated transition probabilities for the Markov chain are kept constant too. An example for one hedge fund of the strategy "Equity Hedge - Multi Strategy" is depicted in Figure 8. Here, the fitting interval has a length of 40 data points, the forecast is calculated for 20 data points. The figure depicts the model within a two-state setting. We see that the parameter estimates converge after about 10 algorithm runs. The transition probability of the Markov chain is estimated after six algorithm runs as $\Pi = \begin{pmatrix} 0.3097 & 0.3082 \\ 0.6903 & 0.6918 \end{pmatrix}$, the second state has a higher probability than the first one. It is interesting to note, that the parameter estimate converge in one state more or less to the estimate from a standard linear regression (depicted as slashed line).

The replication of the hedge fund series in the forecast interval is close to the actual performance of the hedge fund. The residuals from the forecast interval, which can be seen in the second plot in Figure 9 are smaller than the residuals from a linear regression. A Jarque-Bera test on the residuals of the HMM forecast confirms, that the hypothesis of normal distributed residuals cannot be rejected for a significance level of 5 %.

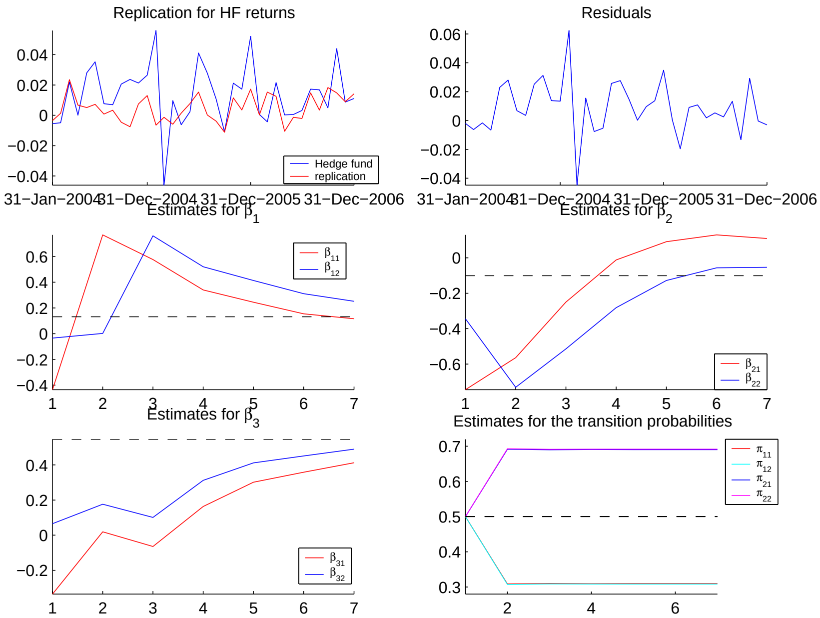

Figure 8: Regression in a 2-state HMM

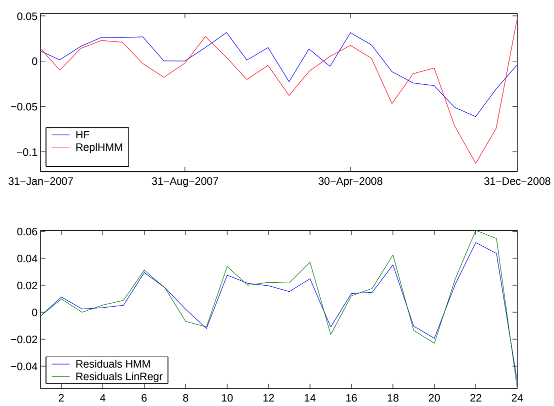

Figure 9: Regression in a 2-state HMM

In the following implementation we look at an example from the strategy “Event Driven-Activist” and let the factors β_{ip} be estimated through the HMM filter in a two-state model. We choose initial values for the factors β through a linear regression on the first six data points, the initial transition probability matrix Π has equal probabilities for each state. On this data set, the algorithm is run 30 times and the data is processed in batches of six data points.

6.1 Model performance for hedgefund strategies

We now analyse the performance of the switching-regression model on classes of hedgefunds, classified through their trading strategy. The performance of the switching model within a fitting and a forecast time series interval is examined. Time series are chosen, where the algorithm runs

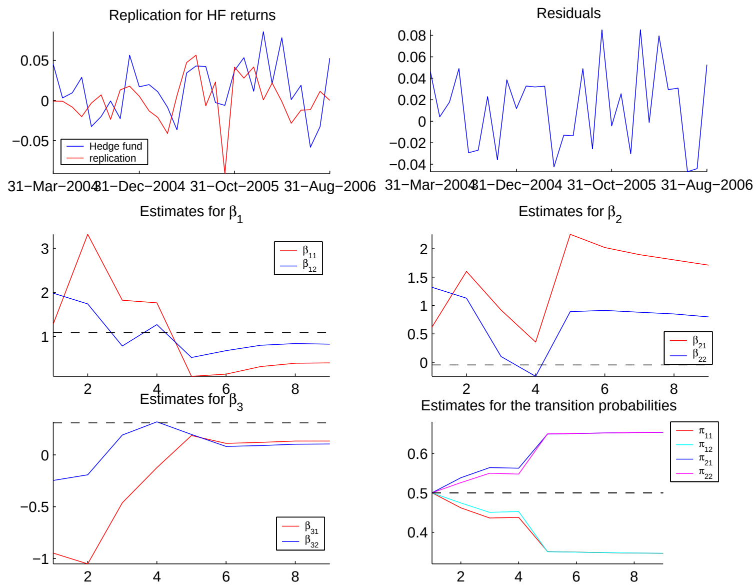

Figure 10: Regression in a 2-state HMM

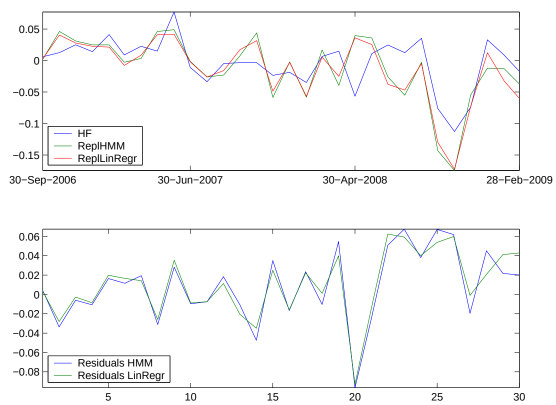

Figure 11: Regression in a 2-state HMM

at least twice (therefore, a minimum of 20 data points are considered). All time series from our database are replicated with the regime-switching regression model. For each trading strategy and substrategy we calculate error measures (RMSE, MdRAE and MdAPE) for a hidden Markov chain with one, two or three possible states. The performance of the algorithm is highly dependent on the initial values for the parameter estimates. We choose to perform a classical OLS estimate for each data set on the first ten data points and use these estimates as initial values. Initial values for the additional states are chosen as these OLS +/- a small value, chosen reasonably. The initial transition probability matrix is set to equal distributed values. Since the choice of the initial values effects the results from the filter-based EM-algorithm and since additional states are roughly based on the OLS estimate, the resulting model results for different states are not necessarily nested. Better error measures for a higher state model are certainly the aim of the model setting, nevertheless, they are not necessary.

The results of our analysis are depicted in two tables for each main trading strategy. The first

	Mean RMSE for Model 1,2 and 3					
Equity Hedge	Fit sample			Forecast sample		
Energy Basic Materials	0.04848	0.04846	0.04834	0.07386	0.07364	0.07378
Equity Market Neutral	0.02396	0.02381	0.02371	0.03657	0.03626	0.03628
Fundamental Growth	0.04965	0.04951	0.04947	0.06359	0.06332	0.06333
Fundamental Value	0.03357	0.03348	0.03341	0.05154	0.05119	0.05121
Multi Strategy	0.04171	0.04128	0.04124	0.06077	0.06070	0.06069
Quantitative Directional	0.04497	0.04505	0.04496	0.06674	0.06611	0.06615
Short Bias	0.054297	0.05449	0.05444	0.06558	0.06587	0.06585
Technology Healthcare	0.04420	0.04439	0.04432	0.05603	0.05576	0.05577
	Mean MdRAE for Model 1,2 and 3					
Equity Hedge	Fit sample			Forecast sample		
Energy Basic Materials	0.86825	0.85605	0.84623	0.98255	0.92589	0.92905
Equity Market Neutral	0.87968	0.88053	0.87227	1.0407	1.02090	1.0208
Fundamental Growth	0.74698	0.75575	0.75004	0.86649	0.86250	0.86372
Fundamental Value	0.75301	0.74558	0.73893	0.81094	0.79970	0.80031
Multi Strategy	0.81248	0.80563	0.79762	1.5804	1.51670	1.5229
Quantitative Directional	0.74977	0.7775	0.76559	0.99215	0.97723	0.97786
Short Bias	0.63803	0.65745	0.65352	1.1480	1.1390	1.1406
Technology Healthcare	0.83635	0.83183	0.82626	1.1165	1.1065	1.1075
	Mean MdAPE for Model 1,2 and 3					
Equity Hedge	Fit sample			Forecast sample		
Energy Basic Materials	0.85331	0.83402	0.82775	1.16	1.1288	1.1307
Equity Market Neutral	1.0001	0.98557	0.97809	1.2811	1.2786	1.2779
Fundamental Growth	0.87432	0.8675	0.86716	1.4359	1.4293	1.4298
Fundamental Value	0.87395	0.86569	0.86324	1.0517	1.0359	1.0371
Multi Strategy	0.93338	0.91204	0.91332	1.1488	1.1414	1.1431
Quantitative Directional	0.8551	0.87324	0.86677	1.1489	1.1235	1.125
Short Bias	0.84587	0.91393	0.90801	2.781	2.7227	2.732
Technology Healthcare	0.98737	0.97748	0.97819	1.3975	1.3841	1.3857

Table 7: Model comparison for Equity Hedge strategies

table shows the mean error measure for a hidden Markov chain with one, two or three possible states. Error measures are calculated separately for the fitting and the forecast interval. The mean is taken over each substrategy. It is clearly visible, that the two-state HMM leads to the best results for almost all trading strategies in the forecast interval. Adding of a possible third state does not lead to significantly better error measures, the additional uncertainty coming from the initial values is visible. The second table of each trading strategy shows the number of hedgefunds modelled and the percentage of a better performance of the HMM with a higher number of states compared to the lower state setting. In all strategies we can see that that the 2-state HMM outperforms the 1-state HMM within the forecast sample in around 80% of modelled hedgefund series.

The first trading strategy we examine is the Equity Hedge strategy and its eight substrategies. Table 7 depicts the error measures for the fitting and forecast sample. We can see that the RMSE is quite small for all substrategies. The forecast sample depicts smaller mean RMSE for the 2-state HMM.

The comparison of the model performance of 2- and 3-state model is shown in Table 8. For a total of 1578 hedgefunds, the second model outperforms the first in about 80% of the modelled time series. The lowest RMSE is reached for the substrategy "Equity Market Neutral", where 194 hedgefund series were modelled.

Model 2 to 1	#	better MSE Fit	better MSE Forecast
Energy Basic Materials	114 HF	50.88 %	64.91 %
Equity Market Neutral	194 HF	54.64%	66.50 %
Fundamental Growth	357 HF	50.14 %	62.47 %
Fundamental Value	643 HF	53.97 %	60.03 %
Multi Strategy	50 HF	66.00 %	56.00 %
Quantitative Directional	93 HF	51.61 %	53.76 %
Short Bias	29 HF	48.28 %	44.83 %
Technology Healthcare	98 HF	42.86 %	63.27 %
Model 3 to 2	#	better MSE Fit	better MSE Forecast
Energy Basic Materials	114 HF	69.30%	38.60 %
Equity Market Neutral	194 HF	81.44 %	33.51 %
Fundamental Growth	357 HF	68.91 %	42.58 %
Fundamental Value	643 HF	75.12 %	41.37 %
Multi Strategy	50 HF	70.00 %	46.00 %
Quantitative Directional	93 HF	73.12 %	45.16 %
Short Bias	29 HF	62.07 %	55.17 %
Technology Healthcare	98 HF	74.49 %	39.80 %

Table 8: Outperformance (in %) of models in terms of error measures in fit and forecast interval for Equity Hedge strategies

The second trading strategy which is examined is the strategy ”Event Driven”. Here, we model in total 348 hedgefund return series. The lowest RMSE in the fit and forecast samples is reached within a 2-state model for the substrategy ”Merger Arbitrage”. All error measures are reasonably low, the RMSE is here slightly better than the one of the other trading strategies.

The comparison of the one-, two- and three-state HMM in Table 10 leads to similar conclusion as the one above. The 2-state HMM outperforms the 1-state HMM in the forecast samples in approximately 80 % of modelled time series, roughly 65% are outperformed in the fitting sample. The best outperformance number is obtained for the substrategy ”Multi Strategy”, where 100 % of time series lead to better RMSE’s in fit and forecast sample.

Error measures for the trading strategy ”Macro” are depicted in Table 11, 591 time series are modelled. Here, we can see the best performance in terms of low error measures for the substrategy ”Currency Discretionary”, which leads to a RMSE in the fitting sample of 0.03 and in the forecast sample of 0.04. Error measures for Macro strategies are slightly higher than those for the other strategies, but they are still very low. The highest RMSE in a 2-state HMM setting is 0.067 for the fitting sample and 0.13 for the forecast sample, both obtained from the substrategy ”Active Trading”. The 25 time series from this substrategy seem to be the hardest to replicate with our regression model, still the error measures are rather low.

The comparison of 1-, 2- and 3-state HMM in table 12 leads again to similar results, a better MSE is reached in roughly 80% to 84% of hedgefund return series.

The last trading strategy we examine is the ”Relative Value” strategy and its seven substrategies. Best RMSE is reached for the strategy ”FI Corporate”, the numbers can be seen in table 13.

In total, we model here 572 hedgefund series. Nearly 90% have a lower forecast RMSE in a 2-state HMM than in a 1-state HMM as can be seen in table 14. The inclusion of a possible regime switch helps to reach smaller errors, the chosen regressors are a good choice to replicate the

	Mean RMSE for Model 1,2 and 3					
Event Driven	Fit sample			Forecast sample		
Activist Return	0.042207	0.042523	0.042468	0.049113	0.049721	0.049669
Credit Arbitrage	0.043194	0.041611	0.041685	0.036069	0.036053	0.036081
Distressed Restructuring	0.028263	0.028635	0.028529	0.040548	0.040482	0.040487
Merger Arbitrage	0.014182	0.014002	0.013915	0.021665	0.021488	0.021497
Multi Strategy	0.050907	0.048394	0.048486	0.050012	0.049725	0.049759
Private Issue	0.068553	0.06923	0.069084	0.085498	0.084336	0.084446
Special Situations	0.032162	0.031988	0.031924	0.046428	0.046243	0.046248
	Mean MdRAE for Model 1,2 and 3					
Event Driven	Fit sample			Forecast sample		
Activist Return	0.77427	0.81874	0.79972	0.81771	0.80063	0.80083
Credit Arbitrage	1.6086	1.5977	1.554	1.9578	1.9669	1.9673
Distressed Restructuring	1.1249	1.1166	1.0943	2.5115	2.4678	2.4704
Merger Arbitrage	0.78791	0.79589	0.79335	0.7874	0.79389	0.79302
Multi Strategy	1.3066	1.3047	1.2907	1.0885	1.0807	1.0814
Private Issue	1.6536	1.7236	1.6903	3.2688	3.2454	3.2466
Special Situations	0.81346	0.8177	0.80888	0.98556	0.96592	0.9664
	Mean MdAPE for Model 1,2 and 3					
Event Driven	Fit sample			Forecast sample		
Activist Return	0.86936	0.91237	0.90125	0.86724	0.90208	0.90181
Credit Arbitrage	0.88127	0.88337	0.89288	1.1045	1.1042	1.1049
Distressed Restructuring	0.88358	0.87136	0.86558	1.0611	1.0558	1.0561
Merger Arbitrage	0.84106	0.83076	0.82707	0.92834	0.91897	0.91952
Multi Strategy	0.92346	0.88355	0.90401	1.2961	1.2631	1.2642
Private Issue	1.2594	1.2768	1.2665	3.0782	3.0922	3.0974
Special Situations	0.85978	0.84336	0.84116	1.0991	1.0874	1.0889

Table 9: Model comparison for Event Driven strategies

Model 2 to 1	#	better MSE Fit	better MSE Forecast
Activist Return	19 HF	73.68 %	42.11%
Credit Arbitrage	14 HF	64.28%	57.14%
Distressed Restructuring	95 HF	44.21 %	58.95%
Merger Arbitrage	40 HF	62.50 %	57.5%
Multi Strategy	8 HF	100.00 %	62.5 %
Private Issue	23 HF	30.43 %	86.96 %
Special Situations	149 HF	63.76 %	51.68 %
Model 3 to 2	#	better MSE Fit	better MSE Forecast
Activist Return	19 HF	73.68 %	63.16 %
Credit Arbitrage	14 HF	71.43 %	35.71%
Distressed Restructuring	95 HF	83.16%	44.21%
Merger Arbitrage	40 HF	90.00 %	47.5 %
Multi Strategy	8 HF	12.50 %	37.5 %
Private Issue	23 HF	86.96 %	21.73%
Special Situations	149 HF	73.15 %	46.98 %

Table 10: Outperformance (in %) of models in terms of error measures in fit and forecast interval for Event Driven strategies

hedge funds.

To further compare the replicability of the major trading strategies, we compare the means of

	Mean RMSE for Model 1,2 and 3					
Macro	Fit sample			Forecast sample		
Active Trading	0.054521	0.055354	0.055272	0.10281	0.10109	0.10409
Commodity Systematic	0.063026	0.063102	0.063081	0.059794	0.059822	0.059801
Currency Discretionary	0.031107	0.032049	0.031844	0.043957	0.043851	0.045293
Currency Systematic	0.042479	0.042	0.041926	0.0718	0.067271	0.06984
Discretionary Thematic	0.040521	0.040462	0.040394	0.0621	0.061246	0.061997
Multi Strategy	0.038297	0.037993	0.037932	0.055218	0.054381	0.054665
Systematic Diversified	0.047053	0.04703	0.046997	0.061396	0.060426	0.061285
	Mean MdRAE for Model 1,2 and 3					
Macro	Fit sample			Forecast sample		
Active Trading	0.86219	0.89603	0.88237	1.5115	1.5807	1.5263
Commodity Systematic	0.80008	0.79524	0.79828	0.76908	0.76141	0.76964
Currency Discretionary	0.81594	0.86675	0.84714	1.3594	1.2247	1.3449
Currency Systematic	1.1106	1.0557	1.0355	1.4173	1.3587	1.4023
Discretionary Thematic	0.76058	0.76382	0.7576	0.91545	0.91	0.91944
Multi Strategy	0.80352	0.79323	0.79524	1.0105	0.98081	0.98235
Systematic Diversified	0.74554	0.73942	0.73909	1.1369	1.0889	1.138
	Mean MdAPE for Model 1,2 and 3					
Macro	Fit sample			Forecast sample		
Active Trading	1.0291	1.0224	1.0122	1.8825	1.9693	1.9298
Commodity Systematic	1.0461	1.0336	1.0299	0.98988	0.98232	0.99101
Currency Discretionary	0.99073	0.99668	0.98062	1.3486	1.3615	1.3355
Currency Systematic	1.2861	1.2425	1.2027	1.949	1.8521	1.9356
Discretionary Thematic	0.91396	0.92053	0.91478	1.1123	1.1352	1.1164
Multi Strategy	0.91711	0.89693	0.89697	1.2181	1.2032	1.1946
Systematic Diversified	0.9489	0.9464	0.94039	1.4544	1.3863	1.4477

Table 11: Model comparison for Macro strategies

Model 2 to 1	#	better MSE Fit	better MSE Forecast
Active Trading	25 HF	52.00 %	52.00 %
Commodity Systematic	45 HF	48.89 %	62.22%
Currency Discretionary	16 HF	31.25 %	43.75 %
Currency Systematic	70 HF	35.71 %	58.57 %
Discretionary Thematic	127 HF	46.46%	46.46 %
Multi Strategy	86 HF	56.98%	53.49 %
Systematic Diversified	222 HF	52.70 %	55.86%
Model 3 to 2	#	better MSE Fit	better MSE Forecast
Active Trading	25 HF	64.00 %	44.00 %
Commodity Systematic	45 HF	62.22%	44.44%
Currency Discretionary	16 HF	81.25 %	62.50 %
Currency Systematic	70 HF	82.86 %	54.29 %
Discretionary Thematic	127 HF	73.23 %	62.50 %
Multi Strategy	86 HF	70.93 %	46.51%
Systematic Diversified	222 HF	65.32 %	49.10 %

Table 12: Outperformance (in %) of models in terms of error measures in fit and forecast interval for Macro strategies

the RMSEs from the 2-state model for each main trading strategy. Table 15 shows the mean errors over all sub-strategies for each main trading strategy for the fit and the forecast part. The smallest error is reached by replication of Relative Value strategies, followed by the Event

Relative Value	Mean RMSE for Model 1,2 and 3 Fit sample			Forecast sample		
FI Asset Backed	0.018661	0.01643	0.016413	0.02739	0.027111	0.02712
FI Convertible Arbitrage	0.025036	0.02467	0.02463	0.05859	0.058514	0.058534
FI Corporate	0.017139	0.017121	0.016993	0.044263	0.043885	0.043912
FI Sovereign	0.021206	0.021116	0.021037	0.048098	0.04770	0.047727
Multi Strategy	0.023076	0.022969	0.022873	0.045797	0.045374	0.045396
Volatility	0.040639	0.040453	0.040456	0.07698	0.076983	0.076974
Yield Alternatives	0.028444	0.02834	0.028287	0.058359	0.058077	0.058096
Relative Value	Mean MdRAE for Model 1,2 and 3 Fit sample			Forecast sample		
FI Asset Backed	2.4003	2.6651	2.5445	3.0389	3.0324	3.0319
FI ConvertibleArbitrage	1.0828	1.0716	1.0635	1.1974	1.1966	1.1968
FI Corporate	1.2498	1.28	1.214	1.311	1.2949	1.2958
FI Sovereign	1.0868	1.0609	1.0544	1.0785	1.0741	1.0747
Multi Strategy	1.4237	1.4386	1.4223	1.7672	1.7566	1.7584
Volatility	0.95947	0.96082	0.95072	0.985065	0.98191	0.98211
YieldAlternatives	1.1407	1.1593	1.1598	1.1958	1.17910	1.1798
Relative Value	Mean MdAPE for Model 1,2 and 3 Fit sample			Forecast sample		
FI Asset Backed	0.72798	0.71771	0.71049	0.89549	0.87538	0.8774
FI ConvertibleArbitrage	0.83926	0.83766	0.83047	0.89124	0.89182	0.89192
FI Corporate	0.86883	0.88316	0.86717	1.0656	1.0552	1.0556
FI Sovereign	0.93637	0.97242	0.9718	1.1764	1.1778	1.179
Multi Strategy	0.91964	0.9081	0.89762	1.37	1.3524	1.3525
Volatility	0.94795	0.95199	0.94728	1.0106	1.0108	1.0109
YieldAlternatives	0.95778	0.95541	0.96167	1.1897	1.1995	1.1979

Table 13: Model comparison for Relative Value strategies

Model 2 to 1	#	better MSE	better MSE
FI Asset Backed	89 HF	51.69 %	58.43 %
FI Convertible Arbitrage	86 HF	37.21 %	45.35 %
FI Corporate	94 HF	48.94 %	72.34 %
FI Sovereign	22 HF	54.55 %	72.73 %
Multi Strategy	183 HF	53.55 %	67.21 %
Volatility	60 HF	53.33 %	53.33 %
Yield Alternatives	38 HF	63.16 %	65.79 %
Model 3 to 2	#	better MSE	better MSE
FI Asset Backed	89 HF	85.39 %	48.32 %
FI Convertible Arbitrage	86 HF	80.23%	53.49 %
FI Corporate	94 HF	86.17 %	31.92 %
FI Sovereign	22 HF	68.18 %	18.18%
Multi Strategy	183 HF	85.25 %	37.16%
Volatility	60 HF	61.67 %	53.33 %
Yield Alternatives	38 HF	68.42%	39.47 %

Table 14: Outperformance (in %) of models in terms of error measures in fit and forecast interval for Relative Value strategies

Driven strategies. The smallest RMSE are obtained from the Event Driven substrategy Merger Arbitrage (RMSE Fit: 0.014, RMSE Forecast: 0.021), followed by the Relative Value substrategy FI-Asset Backed (RMSE Fit: 0.016, RMSE Forecast: 0.027). The largest RMSE were obtained

	RMSE Fit sample	RMSE Forecast sample
Equity Hedge	0.04256	0.05910
Event Driven	0.03948	0.04686
Macro	0.04543	0.06505
Relative Value	0.02444	0.05109

Table 15: Mean RMSE for main trading strategies

for a Macro substrategy, namely Active Trading (RMSE Fit: 0.055, RMSE Forecast: 0.104).We can conclude from this error analysis that a 2-state HMM is a reasonable model choice for all trading strategies. The chosen regressors can be utilized as typical independent variables for each trading strategy. If a single hedge fund follows a claimed substrategy it can be replicated through the typical regressors within this model setup. In general, the substrategies from the Relative Value strategy have the smallest forecast errors.

7 Conclusion

We developed a regime-switching regression models to replicate hedge fund return series. The optimal parameter estimates are derived through a filtered-based EM-algorithm. The parameter estimates are recursive and use hidden information from the Markov chain. Our findings show that the model is well suited to replicate hedge funds through hedge fund indices as well as market indices within that regime-switching setting. The regime-switching model is more flexible, the parameters can be updated when the market situation changed, a forecast within this model framework is therefore more reliable. Our simulation study showed that the model leads to small confidence intervals for the parameter estimates when the algorithm is run with batches of at least six data points. Short time series can therefore be modelled.

The empirical analysis on a hedge funds database lead to good results, showing a good forecast performance of the model when a 2-state HMM is chosen. Furthermore, an analysis of different trading strategies lead to strategy-specific characteristics of the regression model. Modelling of hedgefunds of the trading strategy Relative Value leads to the smallest RMSE's. The risk analysis of single hedgefunds can be further examined in future work through the calculation of risk measures within the framework of this regime-switching regression model.

Table 16: Descriptive statistics of single hedge fund series from the HFR database.

Strategy	Substrategy	Total	Living	Dead	GMean	Mean	Std Dev	Kurtosis	Skewness
Event Driven	all	389	278	111	0.48	0.58	3.58	8.17	-0.61
	Activist	22	16	6	-0.56	-0.26	6.22	7.36	-0.69
	Credit Arbitrage	16	10	6	0.17	0.23	2.57	8.91	-1.38
	Distressed Restructuring	110	81	29	0.52	0.61	3.46	9.47	-0.81
	Merger Arbitrage	40	27	13	0.69	0.71	1.82	8.86	-0.32
	Multi Strategy	16	10	6	0.43	0.55	3.86	7.78	-0.65
	Private Issue	26	14	12	1.85	2.01	4.84	7.29	0.90
	Special Situation	159	120	39	0.36	0.44	3.62	8.17	-0.61
Equity Hedge	all	1750	1261	489	0.23	0.41	4.83	5.54	-0.35
	Basic Materials	132	100	32	-0.08	0.28	6.59	5.23	-0.20
	Equity Market Neutral	214	142	72	0.47	0.51	2.61	5.72	-0.20
	Fundamental Growth	413	310	103	-0.05	0.20	6.04	5.15	-0.38
	Fundamental Value	679	475	204	0.28	0.42	4.39	5.58	-0.45
	Multi Strategy	61	52	9	0.30	0.50	5.13	7.54	-0.31
	Quantitative Directional	112	84	28	0.29	0.49	4.97	5.96	-0.21
	Short Bias	30	17	13	1.28	1.49	6.02	5.40	0.59
	Technology Healthcare	109	81	28	0.46	0.59	4.50	5.33	-0.02
Relative Value	all	641	388	263	0.33	0.47	3.42	11.93	-1.27
	FI-Asset Backed	113	67	46	0.56	0.62	2.27	12.76	-1.21
	FI-Convertible Arbitrage	92	51	41	-0.03	0.13	3.74	14.27	-1.83
	FI-Corporate	104	70	34	-0.03	0.11	3.33	13.41	-1.93
	FI-Sovereign	22	18	4	0.56	0.63	3.31	16.50	-1.50
	Multi Strategy	187	109	78	0.45	0.52	2.81	11.18	-1.20
	Volatility	78	48	30	0.55	0.97	6.11	9.82	-0.56
	Yield Alternatives	45	25	20	0.33	0.43	3.79	6.14	-0.12
Macro	all	666	524	142	0.59	0.88	4.63	5.43	-0.025
	Active Trading	28	24	4	1.29	1.37	3.70	6.81	-0.19
	Commodity-Systematic	57	39	18	0.43	0.64	5.89	4.43	0.08
	Currency-Discretionary	19	14	5	0.73	0.79	2.60	7.44	-0.20
	Currency-Systematic	79	61	18	0.77	0.92	3.89	6.07	-0.01
	Discretionary Thematic	146	106	40	0.43	0.60	4.81	5.50	-0.32
	Multi Strategy	101	80	21	0.77	0.89	4.20	5.79	-0.14
	Systematic Diversified	236	200	36	0.88	1.03	4.91	4.93	0.21

Substrategy	AR	CA	DS	EH	EMN	ED	M	MA	RVA
ED all	0.337	0.303	0.345	0.420	0.125	0.464	0.265	0.341	0.315
ED Activist	0.254	0.219	0.262	0.465	0.195	0.418	0.247	0.292	0.273
ED Credit Arbitrage	0.239	0.327	0.263	0.280	0.113	0.326	0.201	0.230	0.334
ED Distressed Restructuring	0.327	0.292	0.431	0.382	0.104	0.455	0.232	0.283	0.290
ED Merger Arbitrage	0.391	0.264	0.253	0.435	0.194	0.504	0.202	0.562	0.351
ED Multi Strategy	0.421	0.303	0.346	0.321	0.413	0.363	0.338	0.281	0.327
ED Private Issue	0.199	0.214	0.160	0.267	0.011	0.282	0.218	0.243	0.101
ED Special Situation	0.368	0.342	0.363	0.483	0.111	0.518	0.314	0.360	0.360
EH all	0.269	0.251	0.187	0.401	0.054	0.381	0.321	0.238	0.275
EH Energy Basic Materials	0.365	0.360	0.222	0.482	0.025	0.490	0.466	0.312	0.369
EH Equity Market Neutral	0.203	0.188	0.104	0.239	0.125	0.213	0.225	0.162	0.208
EH Fundamental Growth	0.325	0.302	0.212	0.479	0.051	0.456	0.399	0.243	0.356
EH Fundamental Value	0.283	0.256	0.217	0.441	0.058	0.420	0.326	0.265	0.277
EH Multi Strategy	0.191	0.179	0.123	0.316	-0.011	0.290	0.262	0.154	0.213
EH Quantitative Directional	0.251	0.263	0.203	0.406	0.071	0.389	0.313	0.273	0.232
EH Short Bias	-0.185	-0.248	-0.299	-0.545	-0.027	-0.489	-0.292	-0.341	-0.172
EH Technology Healthcare	0.187	0.201	0.183	0.402	-0.028	0.351	0.241	0.288	0.199
RV all	0.212	0.246	0.197	0.221	0.046	0.227	0.181	0.169	0.215
RV FI-Asset Backed	0.028	0.084	0.045	0.036	-0.041	0.061	0.037	0.013	0.069
RV FI-Convertible Arbitrage	0.399	0.540	0.349	0.357	0.135	0.353	0.273	0.301	0.372
RV FI-Corporate	0.249	0.299	0.302	0.321	0.100	0.352	0.234	0.252	0.243
RV FI-Sovereign	0.183	0.135	0.159	0.188	-0.049	0.184	0.200	0.122	0.181
RV Multi Strategy	0.285	0.289	0.233	0.296	0.064	0.303	0.254	0.226	0.299
RV Volatility	0.022	-0.017	-0.005	-0.013	-0.070	-0.056	0.040	-0.013	-0.028
RV Yield Alternatives	0.123	0.125	0.138	0.174	0.071	0.179	0.074	0.112	0.176
M all	0.177	0.175	0.078	0.204	0.016	0.174	0.296	0.113	0.168
M Active Trading	0.032	0.085	0.006	0.038	-0.027	0.025	0.099	0.057	0.083
M Commodity-Systematic	0.064	0.085	0.027	0.064	-0.085	0.054	0.231	0.006	0.043
M Currency-Discretionary	0.157	0.177	0.107	0.118	0.026	0.107	0.305	0.091	0.155
M Currency-Systematic	0.107	0.162	0.060	0.126	0.109	0.104	0.169	0.051	0.132
M Discretionary Thematic	0.272	0.262	0.147	0.324	0.004	0.305	0.354	0.175	0.277
M Multi Strategy	0.193	0.204	0.090	0.246	0	0.224	0.273	0.140	0.209
M Systematic Diversified	0.177	0.143	0.054	0.194	0.025	0.143	0.345	0.113	0.134

Table 17: Correlation analysis of hedgefunds and hedgefund indices

References

[1] C. Alexander and A. Dimitriu. Detecting switching strategies in equity hedge funds returns. *Journal of Alternative Investments*, 8(1):7–13, 2005.

[2] M. Billio, M. Getmansky, and L. Pelizzon. Dynamic risk exposure of hedge funds: a regime-switching approach. Technical report, Department of Economics, Ca' Foscari University of Venice, 2007.

[3] R.J. Elliott. Exact adaptive filters for Markov chains observed in Gaussian noise. *Automatica*, 30(9):1399–1408, 1994.

[4] W. Fung and DA Hsieh. Empirical characteristics of dynamic trading strategies: the case of hedge funds. *Review of Financial Studies*, 10(2):275–302, 1997.

[5] S.M. Goldfeld and R.E. Quandt. A Markov model for switching regressions. *Journal of Econometrics*, 1(1):3–15, 1973.

[6] B. Gupta and H. Kazemi. Factor exposures and hedge fund operational risk: the case of Amaranth. Technical report, University of Massachusetts, 2007.

[7] H.M. Kat and C. Brooks. The Statistical Properties of Hedge Fund Index Returns and Their Implications for Investors. Technical report, Cass Business School, 2001.

[8] F.S. Lhabitant. Hedge funds investing: a quantitative look inside the black box. *Journal of Financial Transformation*, 1(1):82–90, 2001.

[9] T. Schneeweis and R. Spurgin. Multi-factor models in managed futures, hedge fund and mutual fund return estimation. *Journal of Alternative Investments*, 1:1–24, 1998.

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