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ARE DIFFERENT NATIONAL STOCK MARKETS DRIVEN BY THE SAME STOCHASTIC HIDDEN VARIABLE?

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Abstract. The following contribution analyzes linkages between preselected national stock markets by a multivariate application of Markov-Switching models. This study shows evidence that the US-stock market and the German and Swedish stock markets are driven by the same unobservable stochastic variable. The latent variable causes these stock markets to switch between highly persistent Bull- and Bear-market regimes which offer strategic market timing opportunities. An out-of-sample experiment where stock market regimes are simultaneously forecasted on a monthly frequency (January 2008 – December 2010) shows that an actively managed equity funds being restricted to hold stocks permanently, dominates all passive trading strategies that account for internationally diversified equity portfolios.

1. Introduction

Analyzing the linkages between stock markets have been attracting increasing attention in the financial literature which in accordance to Voronkova (2004) may be in particular motivated by the global scale of the October 1987 stock market crash and the subsequent Asian and Russian crises of 1997–1998. Solnik, Boucrelle and Le Fur (1996) argue that low international correlation across markets may be the key determinant of global portfolio diversification as diversifying across national markets with low correlations allows the portfolio management to reduce the total portfolio risk. Koedijk, Campbell, and Kofman (2002) and Longin and Solnik (1995) analyze the correlation structure between markets. Furthermore, Forbes and Rigobon (2002) figure out that stock markets of developed countries have a high level of market co-movements, respectively, interdependence. Hardouvelis, Malliaropulous and Priestly (2006) analyze if the stock market integration across the countries that formed on January 1, 1999 the Economic and Monetary Union (EMU) has increased within the 1990s. Their results indicate that these stock markets converged towards full integration. Recent studies that focus on analyzing unconditional stock market correlations see strong evidence for an increase of correlations across national stock markets as suggested by Gklezakou and Mylonakis (2010), for instance.

Another strand of the literature, which is growing rapidly, focuses on the statistical concept of cointegration in order to analyze stock markets' interdependencies. Cointegration, as developed by Engle and Granger (1987) and Johansen (1988), refers to the fact that financial assets such as stock prices may have a common stochastic trend affecting in accordance to Lukas (1997) both tactical and strategic financial decision making. Evidence for cointegration relationships among European stock markets are found in Corhay et al. (1993), Rousova (2009),vErdinc and Milla (2009)and Grobys (2010), for instance. Rousova's (2009) results show furthermore that Central European stock markets became more integrated with the global economy in general which is also supported by Voronkova's (2004) findings. Furthermore, Francis and Leachman

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(1998) and Kasa (1992) find evidence for cointegration relationships between the developed European and the U.S. market.

Both directions of existing literature have in common that they state interdependencies across national stock markets. King, Sentana and Wadhwani (1990) figure out that changes in correlations between markets are driven primarily by movements in unobservable variables. But how can these unobservable variables which link national stock markets together be described, respectively, figured out? Does internationally focused portfolio management have any benefits from the knowledge of such unobserved variables? The following contribution should account for filling these gaps in the literature as the variable that is found to drive different national stock markets simultaneously is allowed for being unobservable. Furthermore, an international trading strategy is considered that takes into account preselected national stock markets that are driven into different market regimes by the same unobservable variable. The active trading strategy that takes into account regime switches and which is applied to the out-of-sample period from January 2008 – December 2010 exhibits even after transaction costs a Sharpe ratio being equal to 0.25 and, consequently, dominates all other passive strategies that do not account for regime switches.

2. Literature Review

Neither the concept of correlation nor the concept of cointegration gives any forecasts in which direction the financial assets are evolving over time. Moreover, Erdinc and Milla (2009) who investigate cointegration relationships among the EU major countries (i.e. France, Germany and United Kingdom) come to the conclusion that international financial diversification benefits are limited among France, Germany and the U.K. due to a common stochastic trend.

However, Guidolin and Timmerman (2008) consider the asset allocation problem from an investor's point of view that faces the traditional asset allocation decision where the investor decides how much to invest in major asset classes such as cash, stocks and bonds. Their studies give evidence that the asset allocation problem may be depending on the current stock market's regime and that regimes offer different investment opportunities. As a consequence

investors' asset allocations vary over time as they revise their beliefs about the underlying state probabilities. For instance, Guidolin and Timmerman (2008) figure out that the optimal weight on stocks increases in the investment horizon only when the investor initially assigns a high weight to the crash state. Thereby, the traditional investment advice of increased exposure to stocks the longer the investment horizon is consequently rather an exception than a rule if potential regime switches are taken into account.

Investors, academics and practitioners share the common view that low frequency trends in stock markets do exist being often referred to as bull and bear markets respectively. This common view has been affirmed by studies of Perez-Quiros and Timmermann (2000), Ang and Bekaert (2002), Guidolin and Timmernann (2005, 2008). Regime switching models as being employed in these studies can in accordance to Guidolin and Timmermann (2008) capture several properties of the return distribution as they typically identify regimes such as bull and bear markets with different means, variances and correlations across assets. Since underlying state probabilities change over time, this may lead to time variations in expected returns, volatility persistence and changing correlations. Furthermore, Timmermann (2000) argues that regime switching models are capable of modeling even complicated forms of heteroskedasticity, fat tails and the skews in the underlying distribution of returns.

Apart from Ang and Bekaert (2002) the literature mentioned above is basically focused on figuring out the traditional optimal asset allocation of investors that have the possibility to decide between cash, bonds and stock portfolios. To the best of my knowledge though there are no studies available that are explicitly aimed at the international management of equity funds which are restricted, respectively, supposed to hold stocks even in bear markets and thus cannot decide on switching from stocks to bonds, for instance. If bull and bear markets occur across global stock markets at the same time, investing internationally offers investment opportunities as each stock market then, offers different risk and return patterns given different states.

The concept of different market regimes suggest cycles or trends that get reversed after some time. Identifying turning points in the data generating processes of stock returns is a challenging issue due to the latent nature of bull and bear markets. For active portfolio management that shifts between offensive and defensive asset allocation strategies a probability model for asset returns and their corresponding regime depending distributions is required. In line with Guidolin and Timmermann (2008) markov-switching models meet these requirements and can be used for extracting low frequency trends in financial stock market data and for purposes of statistical inference, too.

While this contribution shares a similar regime switching setup as in Guidolin and Timmermann (2008) a very different question will be addressed, namely the linkages between international stock markets being also a subject of Ang and Bekaert's (2002) studies. In contrast to Ang and Bekaert's (2002) who treat the regime switching variable as observable, the following study accounts for the latter criticism being mentioned by Guidolin and Timmermann (2008), as the stochastic variable is assumed to be unobservable. Thereby, it will be analyzed which implications these results may involve concerning an internationally positioned portfolio managements' asset allocation decision. The experiment being performed is in line with Guidolin and Timmermann (2008) an out-of-sample experiment of investment strategies that consider the impact of regimes to the optimal allocation decision under usually imposed restrictions such as being continuously invested in stocks.

3. ECONOMETRIC METHODOLOGY

Following Guidolin and Timmermann (2008) it will be supposed that the assets' mean and covariances in returns (i.e. international stock market returns) are driven by a common state variable, S_t that takes integer values from $1, ..., k$:

$$\begin{pmatrix} r_{1t} \\ \vdots \\ r_{Nt} \end{pmatrix} = \begin{pmatrix} \mu_{1S_t} \\ \vdots \\ \mu_{NS_t} \end{pmatrix} + \sum_{j=1}^{p} A_{j,S_t} \begin{pmatrix} r_{1t-j} \\ \vdots \\ r_{Nt-j} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \vdots \\ \varepsilon_{Nt} \end{pmatrix} \tag{3.1}$$

In this model $\left(\mu_{1S_t}, ..., \mu_{NS_t}\right)^{'}$ is the mean, respectively, expectation vector for the return-vector $(r_{1t}, ..., r_{Nt})^{'}$ in the state S_t and $(\varepsilon_{1t}, ..., \varepsilon_{Nt})^{'} \sim N(0, \sum_{S_t})$, where $\sum_{S_t}$ and A_{j,S_t} are (NxN) matrices and are depending on the state S_t. As the studies here are focused on figuring out rather the stochastic linkages between stock markets as their time varying correlations and in order to hold the model as parsimonious as possible, the matrix $\sum_{S_t}$is restricted to be a diagonal (NxN) matrix.Consequently, each element of the diagonal corresponds to the stock market's variance. If $k = 1$,equation (3.1) will in line with Guidolin and Timmermann (2008) simplify to a standard vector-autoregression. In the following, regime switching in the state variable S_t (i.e. from"bear market" to "bull market" for instance) are governed by the transition probability matrix, $\mathbf{P}$, where $\mathbf{P}$ is a (kxk) matrix with elements.

$$Pr(S_t = i/S_{t-1} = j) = p_{ji}, \ \ with \ i, j = 1, ..., k \tag{3.2}$$

Hence, each regime is the realization of a first-order Markov chain with constant transition probabilities. As the state variable S_t is hidden, respectively, unobservable a filtered estimate has to be computed from the datavector $\mathbf{r}_t$. The model thus allows the return and volatility to vary across states which may have strong asset allocation implications for a portfolio management. For instance, knowing that the current state is a bear state, the management will invest in the stock market exhibiting the lowest expected losses and thus exhibiting the most defensive properties. Estimation will be performed by maximizing the likelihood function being associated with (3.1)-(3.2). As S_t is assumed to be unobservable, it has to be treated as latent variable which requires the EM algorithm as described in detail by Hamilton (1989) and discussed further by Guidolin and Timmermann (2005).

The matrix of transition probabilities is in line with Alexander and Dimitriu (2005) given by

$$S = \begin{pmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{pmatrix} = \begin{pmatrix} p_{11} & 1-p_{22} \\ 1-p_{11} & p_{22} \end{pmatrix} = (p_{ij}) \tag{3.3}$$

Let a Markov chain be given by η_t with $\eta_t = (1,0)'$ when $S_t = 1$ and $\eta_t = (0,1)'$ when $S_t = 2$ then the conditional expectation of η_{t+1} given for $S_t = i$ may be given by

$$E = \left[\eta_{t+1}/S_t = i\right] = \begin{pmatrix} p_{i1} \\ p_{i2} \end{pmatrix} = S\eta_t \tag{3.4}$$

The conditional probability density function of $\mathbf{r}_t$ is assumed to be normal and collected in a $(N\text{x}1)$ vector $\theta_t = (\vartheta_{1t,\ldots,}\vartheta_{Nt})$ where $\vartheta_{1t} = f(r_t/S_t = i, \theta)$ is the normal density function where the parameter vector θ is conditional on the state so that $\vartheta_{it} = \left[(2\pi)^{1/2}\sigma_i\right]^{-1} \cdot \exp(-(r_t - \mu_i)^2/2\sigma_i^2)$.The conditional state probabilities are in line with Alexander and Dimitriu (2005) be obtained recursively by

$$\widehat{\eta}_{t/t} = \frac{\widehat{\eta}_{t/t-1} \otimes \vartheta_t}{\mathbf{1}'(\widehat{\eta}_{t/t-1} \otimes \vartheta_t)} \qquad with \quad \widehat{\eta}_{t+1/t} = S\widehat{\vartheta}_{t/t} \tag{3.5}$$

where
$\widehat{\eta}_{t/t}$ = vector of conditional probabilities for each state estimated at time t
$\widehat{\eta}_{t+1/t}$ = prediction of the same conditional probabilities for time $t+1$
$\mathbf{1}$ = vector of ones

In equation (3.5) the symbol $\otimes$ denotes the element by element multiplication. Furthermore, the i th element of the product $\widehat{\eta}_{t/t-1} \otimes \vartheta_t$ can be considered as the conditional joint distribution of the vector $\mathbf{r}_t$ and $S_t = i$ whereas the numerator in equation (3.5) denotes the density of the observed vector $\mathbf{r}_t$ conditional on the current information set. The conditional density of the error vector is then given by

$$L(\theta, S) = \sum_{t=1}^{T} \log f(r_t/\theta, S) = \sum_{t=1}^{T} \log \mathbf{1}'(\widehat{\eta}_{t/t-1} \otimes \vartheta_t) \tag{3.6}$$

Furthermore, the model will be restricted in two ways: First $p_{ij} > 0.50$ for i=j that is, the probability of each state is restricted to be higher than 50% in order to guarantee the regimes' persistence. The second point is that the minimum duration of each state is also restricted in to be equal or longer than one quarter (i.e. three months). The latter restriction rests upon the argument that near time stock market crashes such as of October 1987 last three months as highlighted by Gonzalez et al (2005). Consequently, an adequate model should provide bear markets that last at least three months.

After estimating the model, an out-of-sample analysis will be considered. That is, the boundary probabilities will be estimated where only information until the previous time period will be taken into account. Then, the model is updated and in the next time period the additional information will be affiliated and so on. In this manner the current estimate will forecast the regime that will be taken into account concerning the asset allocation decision. A probability threshold concerning the regime forecast assures that there has to be a certain reliability about the regime forecast. This approach is also in line with Guidolin and Timmermann (2008) as the current parameter estimation does not employ any data that was unavailable at the time of the forecast. The choice of the asset allocation could itself have been benefited from full-sample information.

4. Results

In line with Guidolin and Timmermann (2008) monthly stock market data (i.e. in log-returns) is employed being downloaded from yahoo.com and nasdaqomxnordic.com which is available for free. The overall sample being considered is December 1994 – January 2011, as stock market data of European stock indices is limited. In line with Erdinc and Milla (2009) the major European stock markets in Germany (i.e. DAX 30), U.K. (i.e. FTSE) and France (i.e. CAC 40) are considered as well as the US-stock market (i.e. S&P 500) and the Swedish stock market (i.e. OMX 30) which is the leading stock market index within the Scandinavian countries in Europe. The model is estimated for k=2, where k=1 denotes the bull state and k=2 denotes the bear state. The lag order p is in accordance to the HQ-and SC chosen to be *0* which is also in line with the common finding that stock market returns of developed countries do not exhibit autocorrelation. Due to the restrictions being imposed, the most distinctive estimates can be ascertained for a multivariate model that accounts for the S&P 500, DAX 30 and OMX 30. Combinations of estimated multivariate models involving other countries' stock indices like the French and/or the British stock indices showed only little persistent regimes (i.e. a duration being less than three months concerning the bear markets) and a low state probability of bear market regime (i.e. below 0.50). The numerical maximum-likelihood optimization procedure for estimating the multivariate model being provided by Perlin (2009), gives the following estimates concerning the 2-State-Markov-Switching model accounting for the US, German and Swedish stock markets (standard deviations are given in parenthesis):

$$\begin{pmatrix} \mu_{S\&P500,S_1} \\ \mu_{DAX30,S_1} \\ \mu_{OMX30,S_1} \end{pmatrix} = \begin{pmatrix} \underset{(0.0016)}{0.0091} \\ \underset{(0.0011)}{0.0070} \\ \underset{(0.0017)}{0.0094} \end{pmatrix} + \begin{pmatrix} \epsilon_{S\&P500,t} \\ \epsilon_{DAX30,t} \\ \epsilon_{OMX30,t} \end{pmatrix}$$

$$\text{with volatility vector} \begin{pmatrix} \sigma_{S\&P500,S_1} \\ \sigma_{DAX30,S_1} \\ \sigma_{OMX30,S_1} \end{pmatrix} = \begin{pmatrix} \underset{(0.0000)}{0.0173} \\ \underset{(0.0000)}{0.0122} \\ \underset{(0.0001)}{0.0171} \end{pmatrix}, \tag{4.1}$$

$$\begin{pmatrix} \mu_{S\&P500,S2} \\ \mu_{DAX30,S2} \\ \mu_{OMX30,S2} \end{pmatrix} = \begin{pmatrix} \underset{(0.0055)}{-0.0091} \\ \underset{(0.0040)}{-0.0062} \\ \underset{(0.0054)}{-0.0083} \end{pmatrix} + \begin{pmatrix} \epsilon_{S\&P500,t} \\ \epsilon_{DAX30,t} \\ \epsilon_{OMX30,t} \end{pmatrix}$$

$$\text{with volatility vector} \begin{pmatrix} \sigma_{S\&P500,S2} \\ \sigma_{DAX30,S2} \\ \sigma_{OMX30,S2} \end{pmatrix} = \begin{pmatrix} \underset{(0.0000)}{0.0400} \\ \underset{(0.0000)}{0.0277} \\ \underset{(0.0001)}{0.0387} \end{pmatrix}, \tag{4.2}$$

$$\text{where } \; S_t = \begin{pmatrix} \underset{(0.11)}{0.94} & \underset{(0.05)}{0.12} \\ \underset{(0.03)}{0.06} & \underset{(0.20)}{0.88} \end{pmatrix} \tag{4.3}$$

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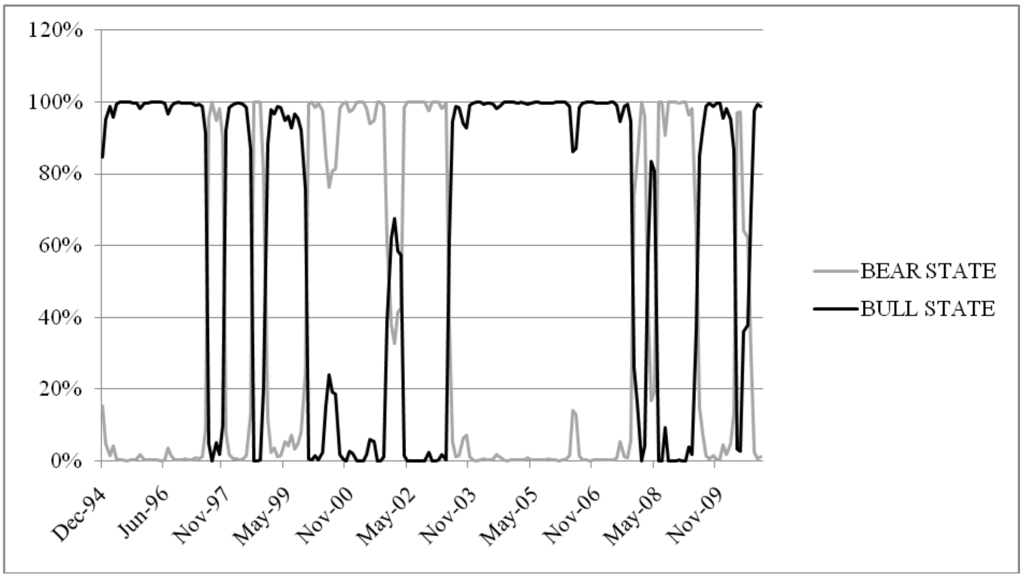
The expected duration of regime "bull-market" is estimated as 15.67 months, whereas the corresponding figure of the regime "bear market" is estimated as 8.46 months. The volatility of the bear markets is considerably higher for all stock markets as shown in equation (4.1). In bull markets the OMX 30 exhibits the highest estimated log-returns, whereas the DAX 30 shows the highest expected returns during bear markets. As a consequence, knowing that the current state is a persistent bull state will make the stock market most attractive offering the highest expected returns (i.e. OMX 30). Figure 2 plots the time varying state probabilities of the two-state model (see equation (4.3)). In line with Guidolin and Timmermann (2008), in the following out-sample experiment the boundary probabilities for each month are estimated such that the current state probability does not involve any information after time t. In contrast to Guidolin and Timmermann (2008) the out-of-sample period being analyzed here does account for the challenging bear market in the year 2008 as a consequence of the financial crises. Furthermore, the associated bull market starting in 2009 will be accounted for, too. The active trading strategy takes into account the updated current state probability and rebalances the international portfolio (i.e. switches from one stock market to another) as soon as the probability threshold is exceeded. This active trading strategy is compared with $N!$ different buy and hold strategies that involve different combinations of N=3 different stock markets.

If the current probability threshold $\widehat{P}(\text{"}bull\text{"}) \geqslant 0.90$, the management's decision is to invest in the stock market exhibiting the highest expected returns (i.e. OMX 30), otherwise the portfolio does only account for the most defensive stock index (i.e. DAX 30). Figure 3 and 4 show the forecasted state probabilities from January 2008 – December 2010. The deviation between forecasted and realized bull and bear market regimes respectively is on average 14%.

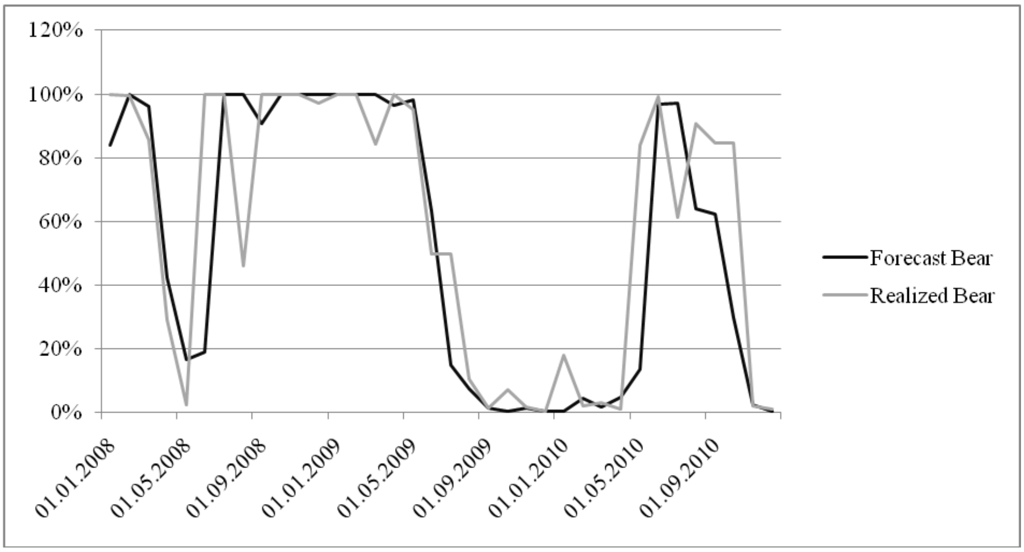
Figure 1. State probabilities of the overall sample (December 1994-January 2010)



The international portfolio management decides to invest in the German index DAX 30 from January 1, 2008 – September 3, 2008 as the German stock market exhibits the lowest expected loss in bear markets. As the forecasted probability of a bull regime exceeds 90% (i.e.$\widehat{P}(\text{"}bull\text{"}/t) = 93\%$) on September 3, 2008, the management switches the from the German to the Swedish stock market OMX 30 as the latter is expected to generate the highest returns in bull-markets. As the forecasted probability of bull-market state declines on May 3, 2010 below 90% (i.e.$\widehat{P}(\text{"}bull\text{"}/t) = 86\%$ on May, 2010 against $\widehat{P}(\text{"}bull\text{"}/t) = 95\%$ on April 1, 2010), the management switches the invested volume again to the German stock market. This position will be hold until November 1, 2010 as the probability of "bull-market" exceeds again the probability threshold $\widehat{P}(\text{"}bull\text{"}/t) = 98\%$ as on November 1, 2010 (in comparison to $\widehat{P}(\text{"}bull\text{"}/t) = 70\%$ on the previous month).

Table I shows that the actively managed international portfolio that takes low frequency trends into account clearly dominates all other international investment strategies that account for the stock markets being involved. This outcome even holds after transaction costs. The actively managed international portfolio exhibits a Sharpe-ratio of 0.25 corresponding to a Sharp ratio of 0.31 before trading costs.

Figure 2. Forecasted and realized bear market



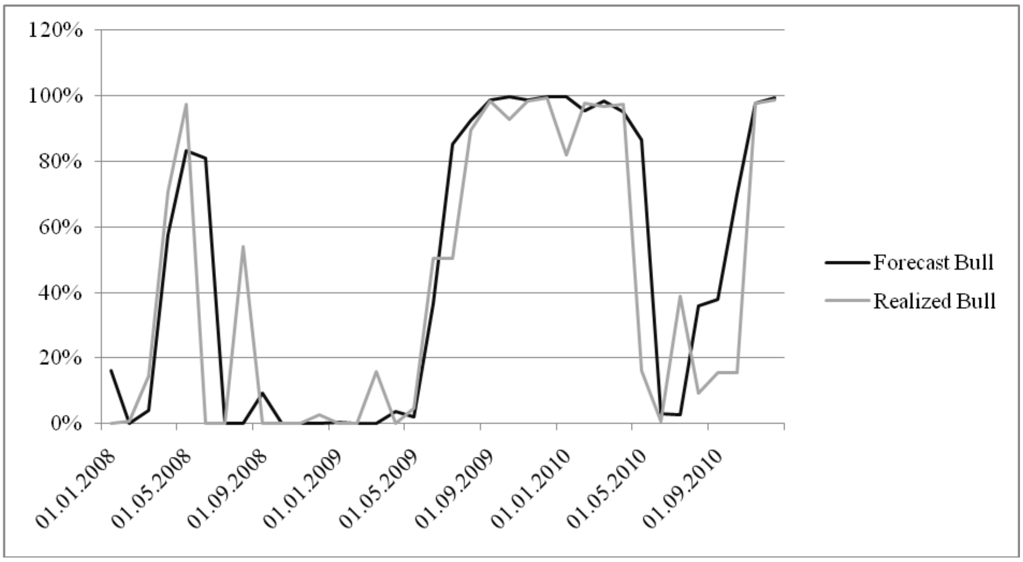
5. DISCUSSION

Next to the concept of correlation and cointegration, the 2-State-Markov-Switching model treats the driving variable which links the stock markets as unobservable. The model estimates show that the S&P 500, the DAX 30 and the OMX 30 are driven by the same hidden stochastic process which causes switches of the stock markets' means and covariances. Interestingly, Erdinc and Milla (2009) find evidence for a cointegration relationship between the British stock market, FTSE, and the German stock market, DAX 30. They argue that UK stock returns' movements explain and can also be explained by the variations in the French and Germans' stock exchange returns, making in this way U.K. a leading indicator between these three EU countries. This conclusion may be supported by the generally unidirectional causality confirmed by the Granger causality test. However, estimating a 2-State-MS model involving these three countries shows non-persistent bear market regimes where the estimated state probability of the bear market regime is estimated at S_2 =0.34 while the expected duration of the latter regime is estimated as 1.52 months, whereas the corresponding figures of the bull market regime are, S_1 =0.74 and 3.86 months respectively. Francis and Leachman (1998) and Kasa's (1992) findings can be supported in the sense that European stock markets (i.e. the German and Swedish stock markets) and the US- stock markets are driven by the same stochastic process. However, the stochastic process that links financial assets together in the context of cointegtaion theory is different from the stochastic process being found in this study here, as the latter causes these stock markets simultaneously to switch from a bull- to a bear market regime and vice versa.

In contrast to Erdinc and Milla (2009) who conclude that international financial diversification benefits are limited in the presence of a cointegration relationship, the studies here suggest that it is rather the market timing that matters. Thus, Ang and Bekaert's (2002) studies can be supported. Each stock market shows different statistical properties depending on the regime. An international investor can benefit from the knowledge of regimes as different stock markets are transmitting from bull to bear market and vice versa at the same time being associated with different investment opportunities. A high degree of correlation, however, seems to be the key determinant of the hidden variable driving the stock market returns simultaneously.

Unlike Guidolin and Timmermann (2008) who employ a 4-State-Markov model, the studies here do only account for two regimes, namely bull- and bear markets which is also in line with Ang and Bekaert (2002) for instance. As the 4-State-Model accounts also for two additional states being referred to as "crash state" and "recovery state", the overall state probabilities become smaller. However, Guidolin and Timmermann's (2008) finding that exists from the crash state are almost always to the recovery state and occur with close to 50% chance may also be an interesting item concerning the market timing opportunities in the context of international portfolio management, as the crash state offers both a signal that a regime switch will occur soon, and, due to its high volatility, a good opportunity to go out of the market. The crash and recovery states are in accordance to Guidolin and Timmermann (2008) transitory states while the bull state and the slow growth state are found to be persistent. The latter point seems to be not plausible as in the literature it is reported that also the crash state (i.e. "bear state") is persistent which can be found in Claessens, Kose and Terrones (2009), for instance.[1]

Figure 3. Forecasted and realized bull market



The 2-State-MS model as suggested here estimates highly persistent state probabilities that can be employed in order to select stock markets in accordance to their expected defensive respectively offensive properties. A drawback may be that switching whole positions from one stock market to the other is associated with high trading costs. Each time when the portfolio is rebalanced the overall portfolio turnover is 200% per definition. While the rebalancing frequency increases linear with the frequency of regime switches, the net return decreases with every rebalancing. High persistent regimes are therefore an essential requirement for the trading strategy and the introduced restrictions such as lower bounds concerning the state probability of $p_{ij} > 0.50$ for i=j and a minimum expected duration of equal or higher than three months may even be sharpened. However, the portfolio performances can even be improved if the asset allocation given each stock market, respectively, each regime is optimized, too. This may involve methodologies such as enhanced index tracking as well as employing stock selection methods

[1]Claessens, Kose and Terrones (2009) who analyze the linkages between key macroeconomic and financial variables around business and financial cycles over the period 1960-2007 estimate the average duration of equity price declines to be 4.93 quarters. However, equity price busts (i.e. strong price declines or "crash states" as in Guidolin and Timmermann's (2008) notation) are much longer, in particular, if the underlying economy faces a recession. Their estimate of the crash state's duration is 11.79 quarters and statistically significant even on a 1% significance level which clearly shows evidence of the crash regime's persistence.

in order to figure out the best defensive (offensive) stock allocation when the regime switches from a bull state (bear state) to a bear state (bull state).

However, the results show evidence for the dominance of an active trading strategy which accounts for different market regimes even though the volatility of the constructed actively managed equity portfolio is marginal higher compared to the passive trading strategies. The dominance can be lead back to higher annual returns being gained (see table I).

Table I. Statistical properties of international investment strategies

Weight allocation			**Return p.a.**	**Volatility p.a.**	**Trading costs p.a.**	**Sharpe-ratio**
S&P 500	DAX 30	OMX 30				
2/6	2/6	2/6	3.25%	19.38%	-	0.17
3/6	1/6	2/6	2.69%	19.44%	-	0.14
2/6	1/6	3/6	3.84%	19.64%	-	0.20
2/6	3/6	1/6	2.65%	20.25%	-	0.13
3/6	2/6	1/6	2.10%	20.15%	-	0.10
1/6	2/6	3/6	4.39%	19.55%	-	0.22
1/6	3/6	1/6	3.80%	19.45%	-	0.20
Active trading strategy with 2-State-MS-Model**			6.71%***	21.85%	1.20%*	0.25

* Assuming 0.60% costs per 100% trading volume.
** Takes into account a probability threshold of 0.90.
*** 6.71% p.a. corresponds to the net return (i.e. after transaction costs). The corresponding gross return is 7.91% p.a.

6. CONCLUSION

Even though the academic literature concludes that the effectiveness of international diversification benefits may be lowered the higher the degree of correlation or, in particular, in the presence of a cointegration relationship that ties international stock markets together, these studies here find evidence for beneficial market timing opportunities regarding the management of internationally focused equity funds. The knowledge of major international stock markets being linked together by unobservable variables may establish a wide area of research. The data being employed to estimate the model is on monthly base and therewith in line with other academic research. Empirically, stock markets price declines are the strongest in the early beginning of such busts. Higher frequented data such as weekly data may be more adequate to extract regime changes much earlier. However, a drawback of high frequented data may be to distinguish between long-run trends and price adjustments which may happen if the price decline (increase) during a bear (bull) market drifts too far away from the long-run expected return during the corresponding market regime. Then, a short-run adjustment process which causes the market returns to revert back to the market's conditional mean return may be estimated as regime switching even though the regime has not changed.

Moreover, there is evidence for some association between cointegration and the unobservable stochastic variable driving the market regimes. The studies here show evidence that a cointegration relationship does not necessarily presuppose that markets are also driven by an unobservable variable into different market regime. A more technical question may be to assert if the converse argument also holds. In other words, does an unobservable variable that links stock markets together presuppose a cointegration relationship?

Furthermore, the asset allocation decision of an equity portfolio management is not only limited to the decision in which stock market to invest and when to invest, but a further question may be which stocks should be selected given the investor faces a bear or bull market regime in the stock markets? Thus, the 2-State-MS model may be imbedded in a sequence of decision rules aiming at maximizing the profit in bull market regimes, respectively, minimizing the losses in bear market regimes.

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