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Research article

Forecasting turbulence in the Asian and European stock market using regime-switching models

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Abstract: An early warning system to timely forecast turbulences in the Asian and European stock market is proposed. To ensure comparability, the model is constructed analogously to the early warning system for the US stock market presented by Hauptmann et al. (2014). Based on the time series of discrete monthly returns of the Nikkei 225 and the EuroStoxx 50, filtered probabilities are estimated by two successive Markov-switching models with two regimes each. The market is thus separated in three states: calm, turbulent positive and turbulent negative. Subsequently, a forecasting model using logistic regression and economic input factors is selected. In an empirical asset management case study it is illustrated that the investment performance is improved when considering the signals of the established warning system. Moreover, the US, Asian and European model are compared and interdependencies are highlighted.

Keywords: early warning system; logistic regression models; Markov-switching models
JEL classification numbers: C34, C53, G11, G15

1. Introduction

Financial crises such as Black Monday (1987), the Gulf War aftermath (1990), the Asian financial crisis (1997), the Russian financial crisis (1998), the bursting of the dotcom bubble (2000), the financial crisis (2007–2009) and the European debt crisis (since 2010) emphasize the need for early warning systems. For this reason, there exists abundant literature regarding the identification and prediction of crises. Various approaches include binary classification tree models (Duttagupta and Cashin, 2008), signal extraction (Demirgüc-Kunt and Detragiache, 2005 and Kaminsky and Reinhart, 1996), logit models (Barrell et al., 2010 and Li et al., 2015), logit and binomial trees (Davis and Karim, 2008b), logit and signal extraction (Davis and Karim, 2008a), probit models (Kamin et al., 2001 and Meichle et al., 2011) and Markov-switching models (Hamilton, 1989; Diebold et al., 1989; Martinez-Peria, 2002; Abiad, 2003; Maheu and McCurdy, 2000 and Hauptmann and Zagst, 2011). The prediction of turning points of time series was particularly treated in Wecker (1979) and Lahiri and Wang (1994).

In our paper Hauptmann et al. (2014), we developed an early warning system for the US stock market based on two Markov-switching models with two states each. In a comparison, this approach turned out to be more stable than the use of one Markov-switching model with three states. We now aim at developing early warning systems for the Asian and European stock market using the approach from Hauptmann et al. (2014). Furthermore, a detailed comparison of all three markets and models is drawn, shedding light on the underlying dependence structure. To the best of our knowledge, there are two main aspects that, in combination, separate our work from other approaches. First, in contrast to models using purely binary variables, the amount of incorporated information is increased by considering filtered probabilities. Second, we include macroeconomic variables, which as for example shown in Chen (2009), comprise a better predictive power than stock market movements when forecasting recessions.

The remainder of this article is structured as follows. Section 2 introduces the underlying Markov-switching models. Section 3 analyses interdependencies between the US, Asian and European market as well as the filtered probabilities. Subsequently in Section 4, logistic regression models are developed to predict the results of the Markov-switching models. The performance of the established warning system is illustrated in Section 5. Finally, Section 6 concludes.

2. Markov-switching models

Since the methodology of the construction of the early warning system is basically the same as for the US model proposed by Hauptmann et al. (2014), this section will only give a short summary of the relevant aspects. For a more detailed explanation as well as the results for the US market, the reader is kindly referred to Hauptmann et al. (2014). As e.g. Timmermann (2000) has shown, Markov-switching models are highly suitable for applications to economic time series, as they are able to comprise typical characteristics thereof such as fat tails, asymmetries, autocorrelation and volatility clustering. In the following, let $(r_t)_{t=1,\dots T}$ refer to the observed monthly returns (of the Nikkei 225 when considering the Asian setting or the EuroStoxx 50 for the European setting). Based on empirical results, we assume normally distributed returns with regime-dependent mean $\mu_{S_t} \in \mathbb{R}$ and regime-dependent volatility $\sigma_{S_t} > 0$. I.e.

$$r_t = \mu_{S_t} + \sigma_{S_t}\epsilon_t\,, \qquad \text{with } \epsilon_t \sim N(0,1) \text{ iid. } \forall t \in \{1,\dots,T\}, \tag{1}$$

where $(S_t)_{t=1,\dots,T}$ with $S_t \in \{0,1\}$ for all $t \in \{1,\dots,T\}$ denotes the unobservable state process with two regimes. S_t is supposed to be given by a time-homogeneous Markov chain with fixed transition probabilities $p, q \in [0,1]$, i.e.

$$\begin{pmatrix} p & 1-p \\ 1-q & q \end{pmatrix}, \tag{2}$$

where $p := \mathbb{P}(S_t = 0 \mid S_{t-1} = 0)$ and $q := \mathbb{P}(S_t = 1 \mid S_{t-1} = 1)$ and the initial distribution $(\delta, 1-\delta)$ with $\delta := \mathbb{P}(S_1 = 0) \in [0,1]$. Hence, the model is completely determined by the vector

$$\boldsymbol{\theta} = (p, q, \mu_0, \mu_1, \sigma_0, \sigma_1, \delta). \tag{3}$$

Since the underlying state process $(S_t)_{t=1,\ldots,T}$ cannot be observed, the parameter vector $\boldsymbol{\theta}$ is estimated by an expectation maximization (EM) algorithm for incomplete data as formulated by Dempster et al. (1977). More precisely, we use the Baum-Welch algorithm developed by Baum et al. (1970) for Markov-switching models. An advantage of this algorithm is that, due to the Gaussian setting, the optimal solution of the *M-step* of the EM algorithm can be analytically determined, which results in reduced calculation effort.

Let $\hat{\boldsymbol{\theta}}_t$ be the estimate of $\boldsymbol{\theta}_t$, derived from the information available up to time t, which is given by $\boldsymbol{r_t} = (r_t, \ldots, r_t)$. Then the filtered probabilities for the two states $j \in \{0, 1\}$ are defined by

$$p_t^j := \mathbb{P}(S_t = j \mid \boldsymbol{r_t}; \hat{\boldsymbol{\theta}}_t). \tag{4}$$

Regarding the monthly returns of the Nikkei 225, the characteristics of the two regimes are summarized in Table 1.*

Table 1. Sample characteristics of the monthly returns of the Nikkei 225 derived from a single two-state Markov-switching model based on the time period from 01/1992 to 10/2015.

	calm	**turbulent**
Mean (ann.)	0.1854	−0.1136
Standard deviation (ann.)	0.1291	0.2202

The Markov-switching model identifies two regimes with different volatilities, leading us to the classification of a calm and turbulent market. In the following, let $S_t = 0$ denote a calm and $S_t = 1$ a turbulent market state. Since the turbulent market state is of special interest, we decided to further analyse this regime through a second Markov-switching model. Therefore let $\mathbb{T} = \{1, \ldots, T\}$ be the complete time period under consideration and $\mathbb{T}^D = \{t \in \mathbb{T} : \mathbb{P}(S_t = 1 \mid \boldsymbol{r_t}; \hat{\boldsymbol{\theta}}_t) > 0.5\}$ (D indicates Distress) the turbulent market periods. Furthermore, let $(S_t^D)_{t\in\mathbb{T}^D}$ denote the regime process restricted to the turbulent phases. Then the filtered probabilites of the second Markov-switching model are given by $j \in \{0, 1\}$

$$p_t^{D,j} := \mathbb{P}(S_t^D = j \mid S_t = 1; \boldsymbol{r_t}; \hat{\boldsymbol{\theta}}_t). \tag{5}$$

The second filtered probabilities essentially represent conditional probabilities, since they are conditioned on the characterization of a turbulent market. Therefore we define

$$p_t^G := p_t^0\,, \qquad p_t^Y := p_t^1 \cdot p_t^{D,0} \quad \text{and} \qquad p_t^R := p_t^1 \cdot p_t^{D,1}\,, \tag{6}$$

where G, Y and R stand for Green, Yellow and Red, referring to the traffic light system introduced in Hauptmann et al. (2014). Note that $p_t^G + p_t^Y + p_t^R = 1$ holds.

The empirical results of all three states of the Nikkei 225 are given in Table 2. The denomination of a turbulent negative and a turbulent positive market state stems from the difference in the mean.

*The analysis regarding the Asian market was chosen to focus on the years after the Japanese bubble economy, since it marked a massive change in the Japanese market with very different economic characteristics.

Table 2. Sample characteristics of the monthly returns of the Nikkei 225 derived from a step-by-step combination of two two-state Markov-switching models based on the time period from 01/1992 to 10/2015.

	calm	turbulent negative	turbulent positive
Mean (ann.)	0.1854	−0.4639	0.5867
Std. dev. (ann.)	0.1291	0.0784	0.3501

The corresponding results for the European market are presented in Table 3 and Table 4. Note that the extreme values in Table 4 are due to the short time period that exhibits only 27 turbulent negative and 21 turbulent positive states.

Table 3. Sample characteristics of the monthly returns of the EuroStoxx 50 derived from a single two-state Markov-switching model based on the time period from 01/1987 to 10/2014.

	calm	turbulent
Mean (ann.)	0.2080	−0.2848
Standard deviation (ann.)	0.1485	0.2119

Table 4. Sample characteristics of the monthly returns of the EuroStoxx 50 derived from a step-by-step combination of two two-state Markov-switching models based on the time period from 01/1987 to 10/2014.

	calm	turbulent negative	turbulent positive
Mean (ann.)	0.2080	−0.5758	0.9475
Std. dev. (ann.)	0.1485	0.0610	0.2927

3. Comparison of market turbulences

In this section we compare the US, Asian and European market according to the filtered probabilities for market turbulences.†

The scatterplots of the considered indices (see Figure 1) reveal a clear dependency. The ‘lost decade’ of Japan is the only phase that does not indicate any similarity of the markets, which makes sense since the Japanese economy was internationally less integrated at that time. It is interesting to see whether this dependency can also be found in the filtered probabilities. Pearson’s linear correlation coefficient and Kendall’s tau are given in Table 5 for different periods in time. Overall the results of both correlation coefficients embody the same findings. During the financial crisis positive dependence is highest. In addition, all three markets move very similar within the US real estate upswing period. The European debt crisis is closely related to the US market, while the Asian market behaves rather

†Note that a comparison of the second filtered probabilities is only possible in months which are marked as turbulent by the first models in **all** three markets. Moreover, a reliable prediction of the second regression model requires a sufficiently large training data set. For these reasons, reliable and available data points start only in mid–2004, leaving just about 50 turbulent months which is too small for a data set to permit a meaningful comparison. Therefore, we will focus the analysis on the first filtered probabilities for now.

different. Furthermore, the fact that the Asian market was very loosely tied to the US and the European market during its 'lost decade' is also reflected in the correlation coefficients.

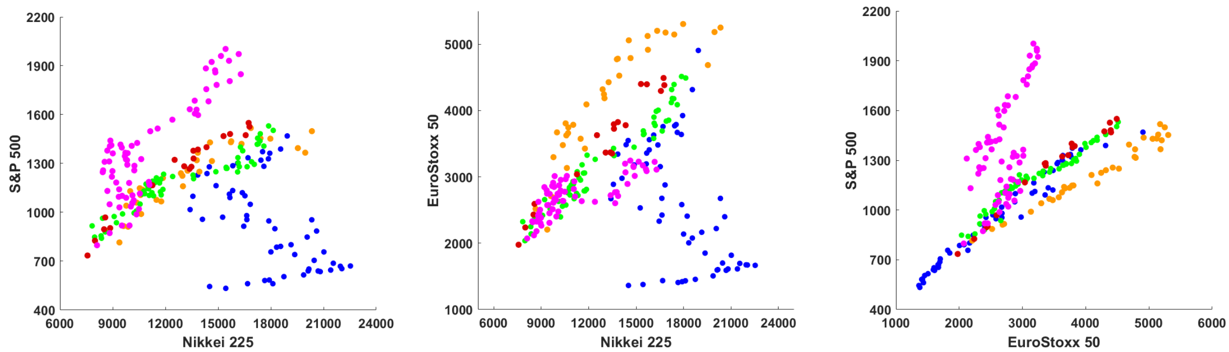

Figure 1. Scatterplots of the Nikkei 225, the S&P 500 and the EuroStoxx 50 from 05/1995–09/2014. Japan's lost decade is marked in blue (05/1995–12/1999). The burst of the dotcom bubble is marked in orange (01/2000–10/2002). The US real estate upswing is marked in green (11/2002–07/2007). The financial crisis is marked in red (08/2007–02/2009). The European debt crisis is marked in magenta (02/2009–09/2014).

Table 5. Pearson's linear correlation coefficient and Kendall's tau for the filtered probabilities of the turbulent state with respect to the US, Asian and European market for different periods in time.

Pearson's linear correlation coefficient	**Asia - US**	**Asia - Europe**	**Europe - US**
Lost Decade in Japan (05/95–12/99)	0.2876	0.3071	0.6727
Burst of Dotcom Bubble (01/00–10/02)	0.2635	0.0503	0.7656
US Real Estate Upswing (11/02–07/07)	0.7302	0.7695	0.7496
Financial Crisis (08/07 - 02/09)	0.9354	0.8413	0.8517
European Debt Crisis (03/09–09/14)	0.4851	0.5113	0.7848
Kendall's tau	**Asia - US**	**Asia - Europe**	**Europe - US**
Lost Decade in Japan (05/95–12/99)	0.0922	0.2610	0.0506
Burst of Dotcom Bubble (01/00–10/02)	0.0553	-0.0089	0.6364
US Real Estate Upswing (11/02–07/07)	0.4474	0.5489	0.6353
Financial Crisis (08/07–02/09)	0.6023	0.6842	0.7661
European Debt Crisis (03/09–09/14)	0.3885	0.3704	0.6852

Figure 2 visualizes the dependence structure by exhibiting the corresponding copula plots (generated via the empirical distribution function).

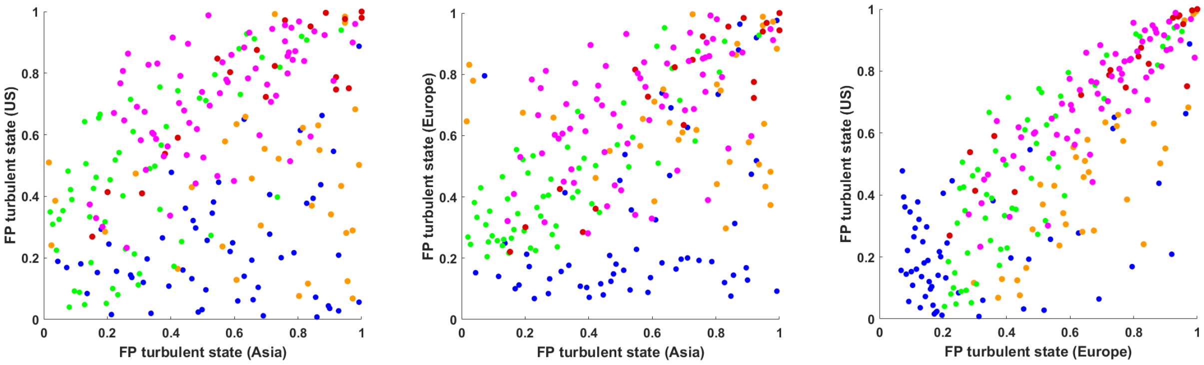

Figure 2. Scatterplots of the copulas of the filtered probabilities for the turbulent state (derived via the empirical distribution function) with respect to the US, Asian and European market from 05/1995–09/2014. Japan's lost decade is marked in blue (05/1995–12/1999). The burst of the dotcom bubble is marked in orange (01/2000–10/2002). The US real estate upswing is marked in green (11/2002–07/2007). The financial crisis is marked in red (08/2007–02/2009). The European debt crisis is marked in magenta (02/2009–09/2014).

Table 6. Correlation coefficient for the filtered probabilities of the turbulent state of the US market at time $t-1$ and the Asian/European market at time t for different periods in time.

Pearson's linear correlation coefficient	**Asia**$_t$ **- US**$_{t-1}$	**Europe**$_t$ **- US**$_{t-1}$
Lost Decade in Japan (05/95–12/99)	0.2804	0.4714
Burst of Dotcom Bubble (01/00–10/02)	0.1869	0.3462
US Real Estate Upswing (11/02–07/07)	0.6917	0.6988
Financial Crisis (08/07–02/09)	0.7464	0.6326
European Debt Crisis (03/09–09/14)	0.4382	0.7147
Kendall's tau	**Asia**$_t$ **- US**$_{t-1}$	**Europe**$_t$ **- US**$_{t-1}$
Lost Decade in Japan (05/95–12/99)	0.1130	0.0143
Burst of Dotcom Bubble (01/00–10/02)	-0.0089	0.3262
US Real Estate Upswing (11/02–07/07)	0.4624	0.5589
Financial Crisis (08/07–02/09)	0.2164	0.3801
European Debt Crisis (03/09–09/14)	0.3119	0.5636

All three scatter plots reveal that, with the exception of the Japanese lost decade and the burst of the dotcom bubble regarding the Asian market, the filtered probabilities are clearly concordant. Moreover, months of crises seem to gather in the upper right quadrant. In fact, the more severe the crisis the closer are the points to the upper right corner. For example during the burst of the dotcom bubble, the EuroStoxx 50 was hit harder than the S&P 500 and the Nikkei 225 (as one can see by simply comparing the indices). Therefore, the orange dots spread on the upper part of the European axis, while regarding the US and the Asian axis some dots can also be found on the lower part. The financial crisis, as the biggest here considered downturn, is exclusively located in the upper right corner. With respect to Japan's lost decade the Nikkei 225 was highly volatile, while the S&P 500 and the EuroStoxx

50 stayed very calm. Accordingly the blue dots spread along the Asian axis, while gathering on the lower half of the US and European axis. In addition, it was tested whether the US market as a globally leading economy is one month ahead of the Asian and European market. The correlations of the filtered probabilities of the US market at time $t-1$ and the Asian/European market at time t are displayed in Table 6 for different periods in time. Comparing these linear coefficients with the ones regarding all markets at the same points in time (see Table 5), an advance of one month of the US market cannot be confirmed.

4. Logistic regression

In order to forecast the filtered probabilities p_t^1 and $p_t^{D,1}$, as derived in Section 2, we develop a linear regression model for each of them. To end up with an ordinary linear regression, the probabilities are first transformed with the logistic function, i.e. for $j = 1$ and $t \in \mathbb{T}$ or respectively for $j = (D, 1)$ and $t \in \mathbb{T}^D$ we define

$$y_t^j := \ln\left(\frac{p_t^j}{1 - p_t^j}\right). \tag{7}$$

Then, the relation between the transformed response variable y_t^j and a set of covariates x_t^j is given by

$$y_{t+1}^j := \boldsymbol{\beta}^{\boldsymbol{j}\prime} \boldsymbol{x}_{\boldsymbol{t}}^{\boldsymbol{j}} + \epsilon_t^j. \tag{8}$$

Furthermore, the regression model is extended by an ARMA(p, q) process to capture time-dependency, possibly inherent in the error term of equation (8). This leads to

$$y_{t+1}^j := \boldsymbol{\beta}^{\boldsymbol{j}\prime} \boldsymbol{x}_{\boldsymbol{t}}^{\boldsymbol{j}} + \sum_{l=1}^{p} \phi_l \cdot \epsilon_{t-l}^j + \sum_{k=1}^{q} \theta_k \cdot \delta_{t-k}^j + \delta_t^j , \tag{9}$$

where ϕ_l and θ_k denote the coefficients of the ARMA(p, q) process, ϵ_t^j the error terms of the regression models and δ_t^j the error term of the ARMA(p, q) process.[‡]

Regarding the Asian model, a set of 37 different economic factors was tested as explanatory variables, as well as various transformations thereof.[§] The set covers various economic aspects such as interest rates (e.g. MUTAN, TIBOR, LIBOR, Government and Corporate bonds), stock market data (e.g. historical volatility of the Nikkei 225, 10 days momentum), factors reflecting the Japanese economy (e.g. monetary base, GDP, debt level, unemployment rate, purchasing manager's index, producer price index, consumer price index) plus indicators of the global economic situation (e.g. OECD CLI, oil price, exchange rates, Ifo Weltwirtschaftsklima Index). To account for interdependencies between the variables, bivariate products are also admitted as additional factors. All time series are shifted to their date of publication, such that for the regression of y_{t+1}^j only data available at time period t is used. Model selection is based on the AIC criterion (cf. Akaike, 1974) and the Bonferroni correction (see e.g. Shao, 2003) to the significance level $\alpha = 0.05$. Because of the large number of tested factors and products thereof, the resulting model is heavily overfitted with a high adjusted R^2 but also an enormous number of covariates. In order to identify a well performing model with a reasonable number of economically interpretable factors, the data set was reduced to a

[‡]For further details, see e.g. Hamilton (1994) or Brockwell and Davis (1991).
[§]See Appendix A for a list of all significant factors.

minimal set of relevant factors based on knowledge from the US model. Precisely, the starting set comprised the Nikkei 225 Volatility Index, the Corporate Bond Spread, the Termspread 5Y-1Y and the Termspread 10Y-1Y. Afterwards, this data set was successively increased by the variable leading to the highest increase of the adjusted R^2 and suiting the combination of included economic factors best. This procedure was stopped when no significant improvement could anymore be achieved by model extension. The resulting model is reported in Table 7.[¶] The adjusted R^2 of this model is 53.17%.

Table 7. Summary of the estimated Asian regression model of the transformed turbulent filtered probabilities y^1_{t+1}. Significance at the level of 5% (1% and 0.1% resp.) is denoted by '*' ('**' and '***' resp.).

	estimate	std. error	p value
(Intercept)	-1.10^{***}	0.23	0.000004
Monetary Base (in PCH)	-0.10^{***}	0.03	0.000860
Nikkei 225 10 Days Momentum	-0.0006^{***}	$1.521e{-04}$	0.000206
OECD CLI (in PCH)	-8.26^{***}	1.26	0.000000
TANKAN (small enterprises manufacturing)	-0.11^{***}	0.01	0.000000
Trade Balance (in PCH)	0.0004^{***}	0.0001	0.000150
Corporate Bond Spread * Mutan	3.00^{***}	0.37	0.000000
Corporate Bond Spread * Spread TIBOR 1Y - Gov. Bond 1Y	5.99^{***}	1.02	0.000000
TANKAN (small enterprises manufacturing) * Termspread 5Y-1Y	0.08^{***}	0.01	0.000000
Corporate Bond Spread * Nikkei 225 Volatility Index	0.12^{***}	0.02	0.000000
Mutan * Asia CLI (in PCH)	-9.06^{***}	1.65	0.000000
OECD CLI (in PCH) * Mutan	5.37^{***}	1.00	0.000000
Spread TIBOR 1Y - Gov. Bond 1Y * Asia CLI (in PCH)	-16.20^{***}	3.45	0.000004
Corporate Bond Spread * Asia CLI (in PCH)	8.68^{***}	2.55	0.000776
OECD CLI (in PCH) * Spread LIBOR 6M - TIBOR 6M	-14.43^{**}	4.45	0.001348
Nikkei 225 1M Volatility Index * Termspread 10Y-1Y	0.04^{***}	0.008	0.000003
Nikkei 225 10 Days Momentum * Spread TIBOR 1Y - Gov. Bond 1Y	-0.0008^{**}	0.0002	0.001233
OECD CLI (in PCH) * Trade Balance (in PCH)	-0.01^{**}	0.003	0.005425

Table 8 summarizes the second regression model which forecasts the turbulent negative

[¶]PCH stands for percentage change.

probabilities.[‖] The adjusted R^2 of this model is 53.23%. In summary, both models contain factors covering sentiment, liquidity, leading economic indicators and market confidence.

Table 8. Summary of the estimated Asian regression model of the transformed turbulent negative filtered probabilities $y^{D,1}_{t+1}$. Significance at the level of 5% (1% and 0.1% resp.) is denoted by '*' ('**' and '***' resp.).

	estimate	std. error	p value
(Intercept)	-43.77^{***}	6.40	0.000000
Consumer Confidence Index	-3.16^{**}	1.01	0.002058
Producer Price Index (in PCH)	-23.13^{***}	5.93	0.000141
Termspread 5Y-1Y	33.68^{***}	6.17	0.000002
Termspread 10Y-1Y	6.87^{***}	2.03	0.000885
OECD CLI (in PCH) * Trade Balance (in PCH)	0.04^{***}	0.01	0.000000
Termspread 5Y-1Y * US Dollar/JPY	-0.28^{***}	0.04	0.000000
US Dollar/JPY * PMI	0.06^{***}	0.00	0.000000
Consumer Confidence Index * Corporate Bond Spread	9.49^{***}	2.26	0.000044
Termspread 10Y-1Y * Corporate Bond Spread	-12.94^{***}	3.30	0.000129
US Dollar/JPY * Corporate Bond Spread	0.19^{***}	0.05	0.000149
Termspread 10Y-1Y * Brent	0.15^{***}	0.04	0.000185
Corporate Bond Spread * Asia CLI	-8.31^{***}	2.38	0.000607
Producer Price Index (in PCH) * Brent	0.06^{***}	0.02	0.000372
US Dollar/JPY * Asia CLI	0.03^{**}	0.01	0.001102
Producer Price Index (in PCH) * US Dollar/JPY	0.16^{**}	0.05	0.002158
US Dollar/JPY * Nikkei 225 10 Days Momentum	$8.457e{-}06^{**}$	$3.032e{-}06$	0.005943
Termspread 5Y-1Y * Brent	-0.19^{*}	0.07	0.011189

The European logistic regression models were constructed in a similar way and are presented in Table 9 and Table 10.[**] The adjusted R^2 of the first European model is 62.09% and of the second 67.99%.

[‖]PCH stands for percentage change.
[**]See Appendix B for a list of all significant factors.

Table 9. Summary of the estimated European regression model of the transformed turbulent filtered probabilities $y^{D,1}_{t+1}$. Significance at the level of 5% (1% and 0.1% resp.) is denoted by '*' ('**' and '***' resp.).

	estimate	std. error	p value
(Intercept)	-0.40	0.31	0.199096
Termspread 10Y-6M	1.82^{***}	0.25	0.000000
Termspread 5Y-1M	-3.63^{***}	0.50	0.000000
EONIA	-3.93^{***}	0.52	0.000000
Consumer Confidence Index	0.10^{***}	0.02	0.000000
EuroStoxx 50 10 Days Momentum	-0.003^{***}	0.0008	0.000666
VSTOXX	-0.04^{**}	0.01	0.002299
EONIA * CPI	0.04^{***}	0.01	0.000000
VSTOXX * Corporate Bond Spread	0.03^{***}	0.01	0.000000
EONIA * OECD CLI	-0.13^{***}	0.03	0.000007
Corporate Bond Spread * LIBOR Spread	-0.50^{***}	0.13	0.000189
Corporate Bond Spread * EuroStoxx 50 10 Days Momentum	0.002^{***}	0.0006	0.000730
Termspread 5Y-1M * VSTOXX	0.05^{***}	0.01	0.000101

Table 10. Summary of the estimated European regression model of the transformed turbulent negative filtered probabilities $y^{D,1}_{t+1}$. Significance at the level of 5% (1% and 0.1% resp.) is denoted by '*' ('**' and '***' resp.).

	estimate	std. error	p value
(Intercept)	13.87^{***}	2.45	0.000001
VSTOXX	-0.32^{***}	0.07	0.000010
EONIA * LIBOR Spread	4.00^{***}	0.70	0.000001
LIBOR * EuroStoxx 50 10 Days Momentum	0.01^{***}	0.002	0.000007
OECD CLI * EuroStoxx 50 1M Volatility	0.16^{***}	0.03	0.000000
VSTOXX * Ifo Geschäftsklima Index	-0.02^{***}	0.004	0.000022
EONIA * LIBOR-OIS 3M	-0.03^{**}	0.01	0.002730

The first regression models for both the Asian and the European market contain an ARMA (p, q) extension. To fit the parameters, several values for p and q were tested using the Akaike information criterion (AIC) and Bayesian information criterion (BIC). As in Hauptmann et al. (2014), we find that based on these criteria, the choice of $p = 1,\ q = 0$ leads to a better fit than models of higher order. Also as in Hauptmann et al. (2014), no ARMA (p, q) extension is performed for the second regression models.

Comparing the covariates of the US, Asian and European model, we find that a broad range of economic aspects are reflected in the models. Concerning interest rates, all three models contain termspreads (displaying the form of the yield curve) and corporate bond spreads. In the first model for the European market, the term spreads can be identified measuring the concavity of the term structure in the same way as in the US model (see Hauptmann et al., 2014). In both the model for the European market and for the US market, the corporate bond spreads are included in the first model, but they are not included in the second model. The liquidity in the inter-bank market is reflected by the MUTAN, EONIA and LIBOR in the different markets. Information about the respective stock markets are included via implicit and historical volatility as well as the momentum. While the historical volatility in the US model is both a measure of the current volatility of the market and the market movements from the recent past, it is substituted by the forward looking implied volatility to capture the expected market movements and the momentum to capture the past trading days in the European model and the Asian model. The global economic situation is covered in all three models by the OECD CLI. Additionally, the Major Five Asia CLI accounts especially for the regional influences on the Japanese economy. Other specific factors that reflect the local economies are included by the Trade Balance, the YEN/US Dollar exchange rate, the Producer Price Index, the Consumer Confidence Index and the TANKAN in the Asian model as well as the Consumer Confidence Index and the ifo Geschäftsklima Index in the European model. In the forecasting models, we observe that less input factors are needed to forecast the US stock market compared to the European and Asian market. This can be interpreted by the leading role of the US economy which influences the European and Asian economies as studied in Section 3 using the example of the real estate upswing and subsequent financial crisis originating in the US. On the other hand, the presence of indicators of financial stability such as the LIBOR spread and LIBOR-OIS spread in the European model can be interpreted by the big influence of the financial crisis and European debt crisis as well as the risk emerging from the greater heterogenity of the economies. Finally, the existence of regional economic indicators in the Asian model mentioned above can be interpreted by greater regional characteristics such as Japan's lost decade, which is not reflected in the other markets.

5. Prediction results

The estimation results of the two Asian regression models derived in Section 4 are illustrated in Figure 3, whereas the forecast results of the European model can be found in Figure 4.

As can be seen, calm and bullish months are mostly colored in green and yellow while most bearish months are marked red. To measure the quality of the out-of-sample prediction results, various forecast accuracy measures of the filtered probabilities (p derived by the Markov-switching models) and the estimates ($\hat{p} = 1/(1 + \exp(y))$ derived by the logistic regression models) are calculated. Besides the root mean squared error (RMSE), defined as

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(p_i - \hat{p}_i)^2}{n}},$$

we also consider the mean absolute error and the median absolute error. The results are shown in Table 11.

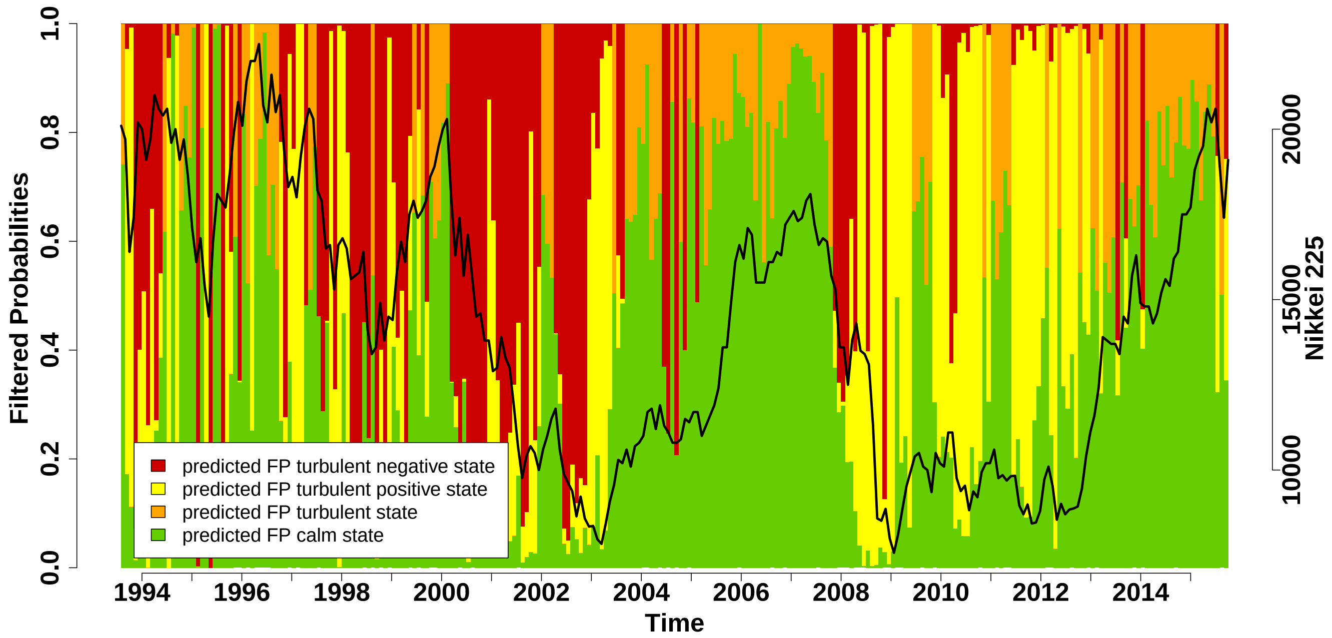

Figure 3. One-month-ahead prediction of the two Asian regression models derived in Section 4 from 09/1993–10/2015.

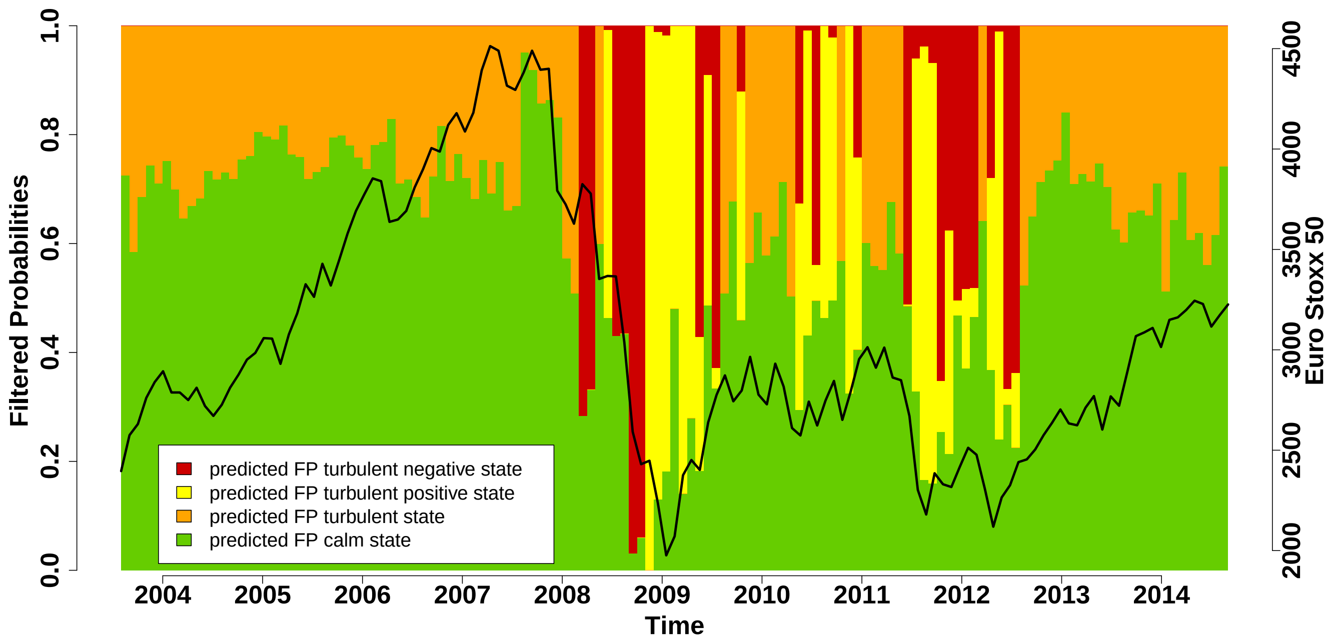

Figure 4. One-month-ahead prediction of the two European regression models derived in Section 4 from 09/2003–09/2014.

Table 11. Various measures of forecast accuracy of the one-month-ahead prediction of the regression models proposed for the Asian and European market.

	Asia	**Europe**
RMSE	0.3756	0.3469
Mean absolute error	0.2678	0.2682
Median absolute error	0.1707	0.2023
Time period	09/93–10/15	09/03–09/14

Furthermore, the performance of all three forecasting models is illustrated by a simple asset management case study. We consider the options to invest in the Nikkei 225, the EuroStoxx 50, the S&P 500 and a risk–free asset. For simplicity we take the 1–month US Treasury Constant Maturity Rate[††] as risk–free asset and neglect transaction costs. The investment strategy $\mathcal{S}$ consists of investing the relative proportion of the forecasted green probability $FC^{I,G}$ plus the forecasted yellow $FC^{I,Y}$ probability in each index I under the condition that the forecasted probability of red $FC^{I,R}$ is not the largest. I.e. the investment ratio invested in index $I \in$ {Nikkei 225, EuroStoxx 50, S&P 500} at time t equals

$$V_t^I = \begin{cases} \frac{FC_t^{I,G}+FC_t^{I,Y}}{3} & \text{if } \max\left\{FC^{I,G}, FC^{I,Y}, FC^{I,R}\right\} \neq FC^{I,R} \\ 0 & \text{if } \max\left\{FC^{I,G}, FC^{I,Y}, FC^{I,R}\right\} = FC^{I,R} \end{cases} \tag{10}$$

and the investment in the risk–free asset r_f is given by

$$V_t^{r_f} = 1 - \left(V_t^{\text{Nikkei 225}} + V_t^{\text{S\&P 500}} + V_t^{\text{EuroStoxx 50}}\right). \tag{11}$$

The results of the investment strategy are summarized in Table 12 and illustrated in Figure 5. For comparison the results of a Buy–and–Hold–Strategy of the risk–free asset and a $1/n$ portfolio with respect to the Nikkei 225, the S&P 500 and the EuroStoxx 50 are also listed. Including the information from the warning systems in a simple strategy already increases the return to 5.58% (in contrast to 3.85% for the $1/n$ portfolio and to 1.41% for the risk-free investment) while reducing the volatility and especially the downside risk compared to the $1/n$ portfolio essentially. Furthermore, Figure 5 reveals a substantial investment protection by the strategy during the global downturn of the financial crisis.

[††]The 1–month US Treasury Constant Maturity Rate is available at the Federal Reserve Bank of St. Louis, `https://research.stlouisfed.org/fred2/series/DGS1MO`.

Table 12. Comparison of different investment strategies based on the period 08/2004–09/2014 and with an initial portfolio value of 100.

	Risk–free investment	1/n **portfolio**	**Strategy S**
Terminal value	115.32	147.76	173.68
Return (% p.a.)	1.41	3.85	5.58
Volatility (% p.a.)	5.25	15.59	9.85
mod. Sharpe ratio (p.m.)[a]	–	0.0697	0.1326
Omega measure Ω (p.m.)[b]	–	1.2055	1.4129
95%–VaR (p.m.)	0	−0.0897	−0.0454
95%–CVaR (p.m.)	0	−0.1094	−0.0631
Maximum drawdown	0	−0.5544	−0.3089

Note: [a] The modified Sharpe ratio measures the expected excess return of a strategy in terms of the 1–month US Treasury Constant Maturity Rate divided by the standard deviation of the excess returns. [b] The Omega measure denotes the ratio between the expected upside and the expected downside of the excess returns, where the upside (downside) is defined as the positive (negative) excess returns.

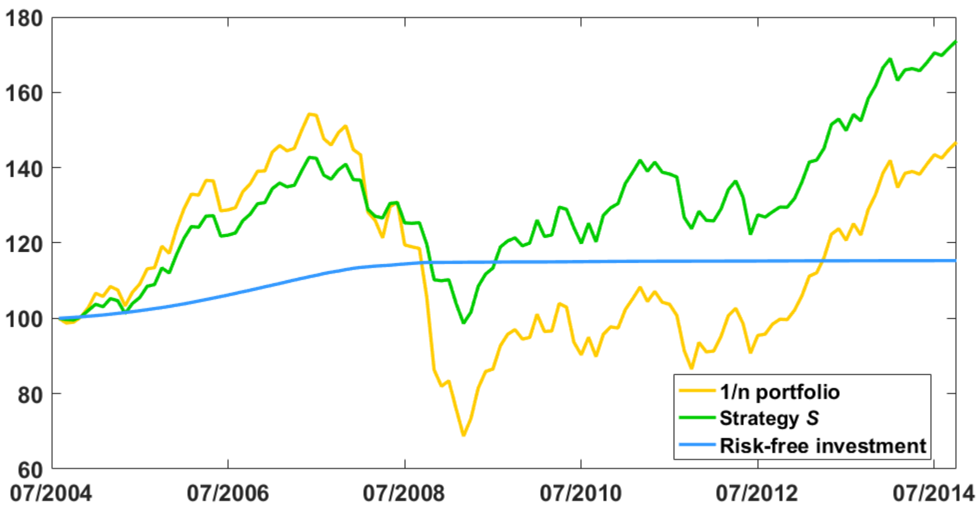

Figure 5. Plot of the development of all three investment strategies compared in Table 12.

6. Conclusions

An early warning system for the Asian and European stock market was developed, analogously to the US forecasting model proposed by Hauptmann et al. (2014). The model is based on two Markov-switching models with two regimes each. The thus derived filtered probabilities separate the market in a calm, turbulent positive and turbulent negative market while maintaining the dependence structure of the underlying stock indices. In general, a strong linear dependency of the stock markets can be observed in periods of no locally restricted crisis. Furthermore, logistic regression models using economic covariates were constructed to forecast the filtered probabilities. Via an empirical asset management case study it was shown that the integration of the signs of the warning systems leads to a significantly higher return and reduced volatility and downside risk.

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Conflict of Interest

All authors declare no conflict of interest.

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Appendix

A. Underlying data set for the Asian model

In the following, all economic factors that turned out to be significant for the Asian model are given as well as their data sources. If reasonable, some transformations such as the absolute and relative change or the spread between two different variables etc. were also considered.[‡‡]

TANKAN
Bank of Japan (http://www.stat-search.boj.or.jp/index_en.html#)
US Dollar/JPY
Bank of Japan (http://www.stat-search.boj.or.jp/index_en.html#)
Mutan ON Call Rate JPY
Reuters (JPONMU=RR)
TIBOR-OIS Spread 6M
Reuters (JPYTIB3-OS6M=R)
OECD Composite Leading Indicator (OECD + Major 6 NME)
OECD Statistics (http://stats.oecd.org/index.aspx?datasetcode=MEI_CLI)
Major Five Asia Composite Leading Indicator
OECD Statistics (http://stats.oecd.org/index.aspx?datasetcode=MEI_CLI)
Producer Price Index, All commodities
Bank of Japan (http://www.stat-search.boj.or.jp/index_en.html#)
Brent Crude Spot FOB Sullom Voe North SeaUSD
Reuters (BRT-)
Corporate Bonds - Government Bond 4Y
Reuters (Merrill Lynch Japan Corporate Index - JPGOV4YZ=R)
Nikkei 225 10 Days Momentum
Federal Reserve Bank of St. Louis
(https://research.stlouisfed.org/fred2/series/NIKKEI225#)
(https://research.stlouisfed.org/fred2/series/NIKKEI225#)
Spread TIBOR 1Y - Government Bond 1Y
Reuters (TIJPY1YD= - JPGOV1YZ=R)
Termspread Government Bonds 5Y - 1Y
Reuters (TIJPY5YD= - JPGOV1YZ=R)
Termspread Government Bonds 10Y - 1Y
Reuters (TIJPY10YD= - JPGOV1YZ=R)
Consumer Confidence Index (CCI)
OECD Statistics
(https://data.oecd.org/leadind/consumer-confidence-index-cci.htm#)
Nikkei Volatility Index
Reters (.JNIV)
Monetary Base
Bank of Japan (http://www.stat-search.boj.or.jp/index_en.html#)

[‡‡]For a complete list of all tested economic factors, please contact us.

Real Trade Balance
Bank of Japan (http://www.stat-search.boj.or.jp/index_en.html#)

B. Underlying data set for the European model

In the following, all economic factors that turned out to be significant for the European model are given as well as their data sources. If reasonable, some transformations such as the absolute and relative change or the spread between two different variables etc. were also considered.

Termspread Government Bonds 10Y - 6M
ECB Statistical Data Warehouse
(http://sdw.ecb.europa.eu/browseTable.do?node=qview&SERIES_KEY=165.YC.B.U2.EUR.4F.G_N_A.SV_C_YM.SR_10Y&start=01-01-1999&end=01-10-)
(http://sdw.ecb.europa.eu/browseTable.do?node=qview&SERIES_KEY=165.YC.B.U2.EUR.4F.G_N_A.SV_C_YM.SR_6M&start=01-01-1999&end=01-10-)

Termspread Government Bonds 5Y - 1Y
ECB Statistical Data Warehouse
(http://sdw.ecb.europa.eu/browseTable.do?node=qview&SERIES_KEY=165.YC.B.U2.EUR.4F.G_N_A.SV_C_YM.SR_5Y&start=01-01-1999&end=01-10-)
(http://sdw.ecb.europa.eu/browseTable.do?node=qview&SERIES_KEY=165.YC.B.U2.EUR.4F.G_N_A.SV_C_YM.SR_1Y&start=01-01-1999&end=01-10-)

EURO STOXX 50 Volatility (VSTOXX)
STOXX (https://www.stoxx.com/index-details?symbol=V2TX

Corporate Bond Spread
iBoxx Eur Corporate BBB Index - iBoxx Eur Corporate AAA Index
Reuters (.IBBEU005E) - (.IBBEU0057)

LIBOR Spread
LIBOR 3M - Euro Yield Curve 3M
global-rates
(http://www.global-rates.com/interest-rates/libor/european-euro/1989.aspx
ECB Statistical Data Warehouse
(http://sdw.ecb.europa.eu/browseTable.do?node=qview&SERIES_KEY=165.YC.B.U2.EUR.4F.G_N_A.SV_C_YM.SR_3M&start=01-01-1999&end=01-10-)

OECD Composite Leading Indicator (OECD + Major 6 NME)
OECD Statistics (http://stats.oecd.org/index.aspx?datasetcode=MEI_CLI)

Consumer Surveys, Confidence indicator, SA
Reuters ('EUCONS=ECI')

EuroStoxx 50 10 Days Momentum
STOXX (https://www.stoxx.com/index-details?symbol=SX5E)

EuroStoxx 50 1 Month Volatility
STOXX (https://www.stoxx.com/index-details?symbol=SX5E)

Euro Zone CPI, All Items
Reuters (aXZCPI)

EONIA
ECB Statistical Data Warehouse
(http://sdw.ecb.europa.eu/quickview.do?SERIES_KEY=198.EON.D.EONIA_TO.RATE)
Ifo Geschäftsklima Index
CES ifo Group
(http://www.cesifo-group.de/de/ifoHome/facts/Time-series-and-Diagrams/Zeitreihen.html)
LIBOR-OIS Spread 1M and 3M
Reuters (EURL-O1M=R) (EURL-O3M=R)