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Extracting global stochastic trend from non-synchronous data

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Abstract

We use a Kalman filter type model of financial markets to extract a global stochastic trend from the discrete non-synchronous data on daily stock market index returns of different stock exchanges. The model is tested for robustness. In addition, we derive "most important" hours of world financial market and estimate the relative importance of local versus global news for different stock markets. The model generates results that are consistent with intuition.

Key words: emerging stock markets, transition economies, financial market integration, stock market returns, global stochastic trend, state space model, Kalman filter, non-synchronous data.

JEL codes: C49, C58, G10, G15, F36, F65

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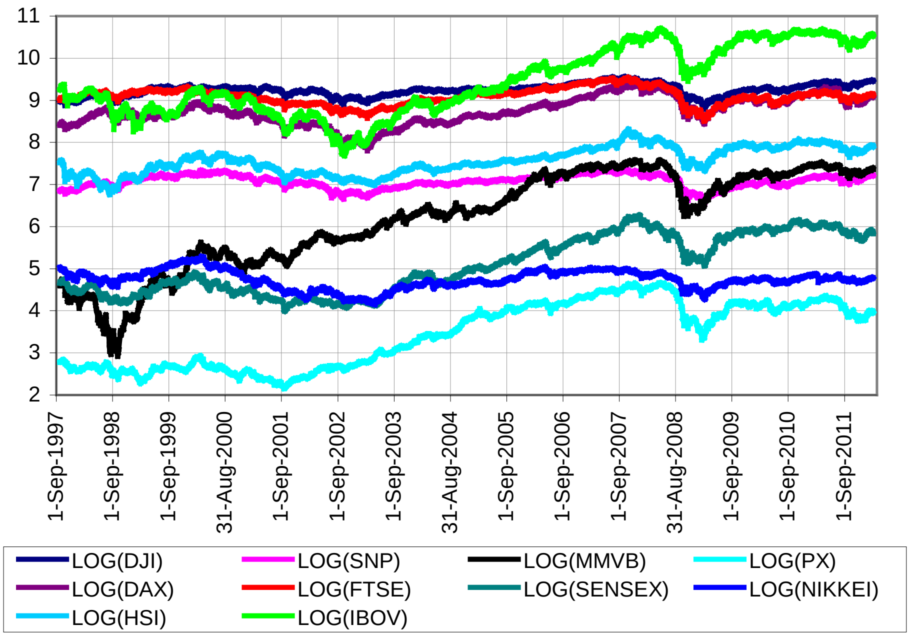
1 Introduction

Observing the scatterplot of stock market indices with the naked eye (Figure 1), one detects a common pattern, something that might be termed a “global stochastic trend”. Our idea here is that the value of a local stock market index is the sum of two components: (scaled) global stochastic trend and local fluctuation. Global stochastic trend is that common part of all local indices which absorbs all the news across the globe that is important for the global financial market and is determined at each point in time. But the trend is not directly observable; it exists only in the minds of traders. Local fluctuations depend partly on the local news, which is unimportant for the global financial market.

The purpose of this paper is to design a model that will extract the global trend from daily closing values of the stock market. These closing times differ but are distributed along the global time scale. For example, the closing times for stock exchanges in Moscow, Tokyo, and New York are respectively 6:00, 15:00, and 21:00 GMT. Thus the model should extract the common stochastic trend from non-synchronous data.

Figure 1 Stock market indices (in logs)



Our novel contribution is related to several strands of the literature. There are some papers which apply state-space models (Kalman filter) to extract common stochastic trend from *synchronous data*. Dungey, Martin, and Pagan (2000) use weekly data to study the spreads on long-term bonds for Australia, Japan, Germany, Canada and the UK, all relative to the USA, over the period 1991 to 1999. At weekly data frequency, the non-synchronous nature of the observations could be neglected. They use a dynamic factor model to decompose spreads into national and global factors. The factors are latent, and are assumed to have GARCH-type specifications and to exhibit serial dependence. The parameters of the model were computed using the indirect estimator of Gourieroux et al. (1993) and Gallant and Tauchen (1996), as well as a direct Kalman filter approach. They found that the world factor is the dominant influence for Australian and Canadian spreads, while both the UK and Germany display strong country-specific effects, albeit not as strong as does Japan.

Chang, Miller and Park (2009) investigate the statistical properties of estimators of parameters and unobserved series for state space models with integrated time series. In one such application, they use a Kalman filter model to derive latent common stochastic trend from daily observations on the 30 price series of the stocks that comprise the Dow Jones Industrial Average (DJIA). They found that the extracted common stochastic trend resembles the DJIA quite closely up to an affine transformation.

Cartea and Karyampas (2011) use Kalman filter-based methodology to decompose price series into the true efficient price and the microstructure noise. They found that the decomposition allows one to estimate the variance covariance matrix of assets returns in a more efficient way than the methods so far proposed in the literature, which is important for portfolio decision-making.

Bae and Kim (2011) use a two-step state space model and monthly data to examine the existence of global and regional factors and to analyze the effects of both factors on four Asian countries' yield curves. They found that the variation in the global and slope factor accounts for a significant fraction of the variation in Asian countries' bond yields. The Singapore level loading on the global level factor proved to be larger than those of the other countries, whereas the Hong Kong slope loading on the global slope factor was larger than those of the other countries.

Felices and Wieladek (2012) use monthly observations (1995–2007) on vulnerability indicators of financial crises, real exchange rate appreciation and international reserve growth, for 31 emerging market economies (EMEs) and 10 industrialized countries. They employ a Kalman filter-based model with time variation (Bayesian dynamic common factor model) to estimate the common component and find that a single common factor contributes on average up to 60% of the total variation in the vulnerability indicators. The exposure to global factors in most countries tends to fluctuate around the mean.

To the best of our knowledge, no one has yet suggested that one could extract common (global) stochastic trend from non-synchronous data such as daily returns on world stock markets. In this paper we offer a model for exploiting the Kalman filter approach to derive a global stochastic trend from non-synchronous discrete data.

2 The model

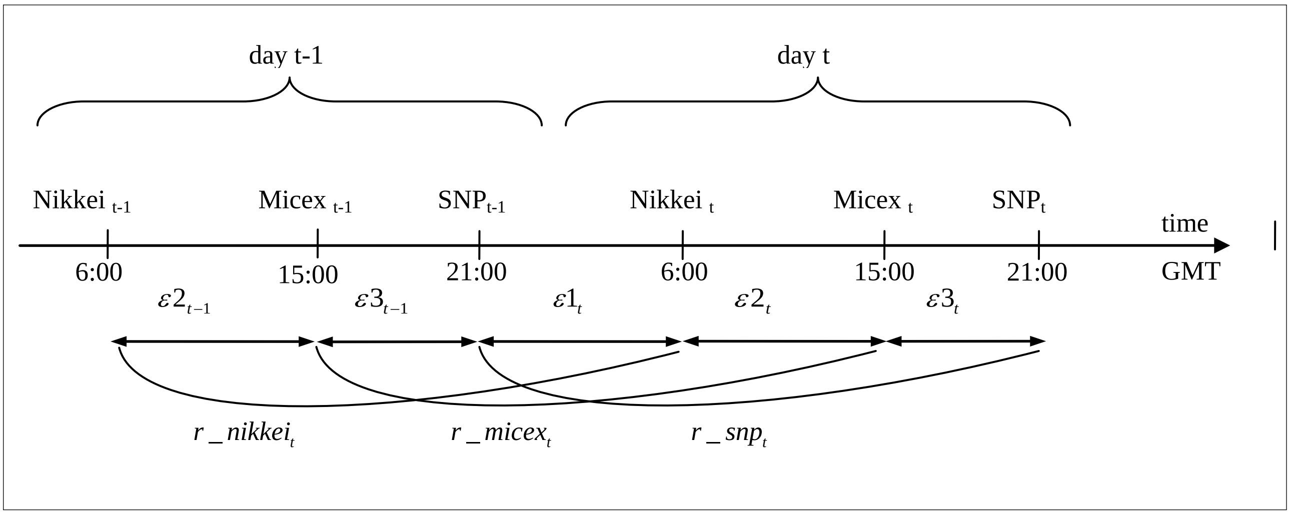
In an earlier paper (Korhonen and Peresetsky, 2013) we found that, as a result of globalization of the world economy and financial markets, a local stock market index return I_t could be split into two parts: the global stochastic trend IG_t , and the local part, specific to that market IL_t. The global trend IG_t absorbs all news from the world economy and world financial markets that is available at time t and important for all markets. The local stochastic trend IL_t absorbs local news that is important only to investors in the local market. The reason for this is globalization: more and more traders/financial firms operate, not in one but in many markets, and there is continuous 24 hours trading for many financial instruments. Thus we assume that

$$r\_I_t = r\_IG_t + r\_IL_t, \tag{1}$$

where prefix $r\_$ means log return: $r\_I_t = \ln(I_t / I_{t-1})$.

In order to describe the model we first consider an example with three stock-index daily returns: Japan (NIKKEI225), Russia (MICEX), US (S&P500). The value of each index is fixed at the closing time of the exchange, respectively 6:00, 15:00, and 21:00 GMT. Assuming there exists a common stochastic trend, we use the denotations $\varepsilon 1_t$, $\varepsilon 2_t$, $\varepsilon 3_t$ for log-returns of this trend in time intervals, respectively from 21:00 (day $t-1$) to 6:00 (day t); from 6:00 (day t) to 15:00 (day t); and from 15:00 (day t) to 21:00 (day t). Figure 2 illustrates the correspondence between the epsilons and the daily returns for the three indices.

Figure 2 Daily returns and state variables



The usual formulation for the Kalman filter model is given in (2):

$$\begin{aligned} y_t &= Ax_t + Hs_t + u_t \qquad \textit{observation equation} \\ s_t &= Fs_{t-1} + v_t \qquad \textit{state equation} \end{aligned} \tag{2}$$

where

$$\begin{aligned} & y_t \ -(n\times 1),\ \textit{observables}, \\ & s_t -(m\times 1),\ \textit{state variables}, \\ & A-(n\times k),\ H-(n\times m),\quad F-(m\times m),\quad \textit{matrices}, \\ & u_t \sim (0,\Sigma_u) - (n\times 1)\ \textit{random vector}, \\ & v_t \sim (0,\Sigma_v) - (m\times 1)\ \textit{random vector}. \end{aligned}$$

In our case the observables are $y_t = [r\_nikkei_t,\ r\_micex_t,\ r\_snp_t]'$, and the epsilons are state variables. Since the indices have different scales, their returns have in common affine transformations of the common stochastic trend; hence the observation equation are (3):

$$\begin{aligned} & r\_nikkei_t = \alpha_1 + \beta_1(\varepsilon 2_{t-1} + \varepsilon 3_{t-1} + \varepsilon 1_t) + u1_t, \\ & r\_mmvb_t = \alpha_2 + \beta_2(\varepsilon 3_{t-1} + \varepsilon 1_t + \varepsilon 2_t) + u2_t, \\ & r\_snp_t = \alpha_3 + \beta_3(\varepsilon 1_t + \varepsilon 2_t + \varepsilon 3_t) + u3_t, \end{aligned} \tag{3}$$

where $\varepsilon 2_{t-1} + \varepsilon 3_{t-1} + \varepsilon 1_t$, $\varepsilon 3_{t-1} + \varepsilon 1_t + \varepsilon 2_t$, and $\varepsilon 1_t + \varepsilon 2_t + \varepsilon 3_t$ are returns for the global stochastic trend, corresponding to the three closing times. Local fluctuations $u1_t$, $u2_t$, $u3_t$ are presumed not to be correlated with the global stochastic trend. Intercepts α_i are not necessary, but are added to the model to account for possible local trend, we expect that their estimates will not be significantly different from zero. We also consider a model (3) without intercepts, and compare these two models to test for robustness.

Since the standard formulation of the state space model (1) does not allow for lagged state variables in the observation equations, it is necessary to increase dimensions of the state vector by introducing two additional components, $\varepsilon 2L_t, \varepsilon 3L_t$. Finally we arrive at the model (4)–(7):

Observation equations:

$$\begin{aligned} r\_nikkei_t = &\quad \alpha_1 + \beta_1(\varepsilon 2L_t + \varepsilon 3L_t + \varepsilon 1_t) + u1_t, \\ r\_mmvb_t = &\quad \alpha_2 + \beta_2(\varepsilon 3L_t + \varepsilon 1_t + \varepsilon 2_t) + u2_t, \\ r\_snp_t = &\quad \alpha_3 + \beta_3(\varepsilon 1_t + \varepsilon 2_t + \varepsilon 3_t) + u3_t, \end{aligned} \tag{4}$$

State equations:

$$\begin{aligned} \varepsilon 1_t = &\quad v1_t, \\ \varepsilon 2_t = &\quad v2_t, \\ \varepsilon 3_t = &\quad v3_t, \\ \varepsilon 2L_t = &\quad \varepsilon 2_{t-1}, \\ \varepsilon 3L_t = &\quad \varepsilon 3_{t-1}, \end{aligned} \tag{5}$$

where random vectors $u_t = [u1_t, u2_t, u3_t]'$ and $v_t = [v1_t, v2_t, v3_t]'$ are uncorrelated at all lags. Both vectors are vector white noise, and $Var(u_t) = \Sigma_u$, $Var(v_t) = \Sigma_v$. In our model we assume the simplest specification of these covariance matrices (5):

$$\Sigma_u = diag(\sigma_{u1}^2, \sigma_{u2}^2, \sigma_{u3}^2)\ ,\ \Sigma_v = diag(\sigma_{v1}^2, \sigma_{v2}^2, \sigma_{v3}^2)\ . \tag{6}$$

To make the model (4)–(6) identifiable we impose restriction (7) on the parameters:

$$\sigma_{v1}^2 + \sigma_{v2}^2, + \sigma_{v3}^2 = 1. \tag{7}$$

Thus we have the state-space model (4)–(7) with $n = 3$ observation equations and $m = 5$ state equations. Parameters of the model are $\alpha_1, \beta_1, \alpha_2, \beta_2, \alpha_3, \beta_3, \sigma_{u1}^2, \sigma_{u2}^2, \sigma_{u3}^2, \sigma_{v1}^2, \sigma_{v2}^2, \sigma_{v3}^2$ with the imposed restriction (7).

The model could be estimated using real observation on the market-index returns $y_t = [r\_nikkei_t, r\_micex_t, r\_snp_t]'$, using the Kalman filter procedure. We obtain parameter estimates $\hat{\alpha}_1, \hat{\beta}_1, \hat{\alpha}_2, \hat{\beta}_2, \hat{\alpha}_3, \hat{\beta}_3, \hat{\sigma}_{u1}^2, \hat{\sigma}_{u2}^2, \hat{\sigma}_{u3}^2, \hat{\sigma}_{v1}^2, \hat{\sigma}_{v2}^2, \hat{\sigma}_{v3}^2$, and predictions for the state variables $\hat{\varepsilon}1_t, \hat{\varepsilon}2_t, \hat{\varepsilon}3_t$. By summing the state variables one can estimate the evolution of the global stochastic trend. Also it is possible to split stock market returns into global and local parts (1) as shown in (8):

$$r\_nikkei_t = \hat{\alpha}_1 + \hat{\beta}_1(\hat{\varepsilon}2_{t-1} + \hat{\varepsilon}3_{t-1} + \hat{\varepsilon}1_t) + \hat{u}1_t = \hat{\alpha}_1 + \widehat{r\_nikkei}G_t + \hat{u}1_t,$$

$$r\_micex_t = \hat{\alpha}_2 + \hat{\beta}_2(\hat{\varepsilon}3_{t-1} + \hat{\varepsilon}1_t + \hat{\varepsilon}2_t) + \hat{u}2_t = \hat{\alpha}_2 + \widehat{r\_micex}G_t + \hat{u}2_t,$$

$$r\_snp_t = \hat{\alpha}_3 + \hat{\beta}_3(\hat{\varepsilon}1_t + \hat{\varepsilon}2_t + \hat{\varepsilon}3_t) + \hat{u}3_t = \hat{\alpha}_3 + \widehat{r\_snp}G_t + \hat{u}3_t. \qquad (8)$$

In a similar manner, one could build a model using k stock indices, each with its own closing time. In that case the number of observation equations would be $n = k$ and the number of state equations $m = 2k - 1$. If some of indices have identical closing times, the number of state equations decreases.

Thus we consider two other models:

Model 2 with 5 indices NIKKEI (6:00), MICEX (15:00), DAX, PX (16:30)[1], SNP (21:00), $n = 5$, $m = 7$; GMT closing time in parentheses.

Model 3 with 10 indices: NIKKEI (6:00), HSI (8:00), SENSEX (10:00), MICEX (15:00), DAX, PX, FTSE (16:30), IBOV (20:00), DJI, SNP (21:00), $n = 10$, $m = 13$[2].

[1] DAX is German index (Frankfurt), PX is Czech Republic index (Prague).
[2] HSI — Hong Kong, SENSEX — India (Bombay), FTSE — UK (London), IBOV — Brasil (Sao Paulo), DJI — New York.

3 Estimation of global stochastic trend

Consistency of the results for the different models

Part of the MICEX (NIKKEI, SNP) index return defined by the global trend $r\_\widehat{micex}G_t$ ($r\_\widehat{nikkei}G_t$, $r\_\widehat{snp}G_t$) could be estimated with any of the three models (Model 1, Model 2, Model 3). In that case, provided the general idea of the existence and role of the global trend is correct, all three estimates will be significantly correlated, and correlations between the results for Models 2 and 3 would likely be higher than the other correlations, since more information increases the likelihood that the estimate will be closer to the "true" global trend part of daily returns. Correlations among the three estimates of the global part and index return itself, presented in Table 1, are fairly high, 0.85–0.97. For MICEX correlation between Models 2 and 3, the estimate is higher than between the other two; for NIKKEI and SNP, the correlations are almost identical.

For SNP, the correlations between index return and its global part are very high (0.96–1.00) compared to the two other stock-index returns. This means that SNP is actually almost equal to the global trend. The NIKKEI runs closer to the global trend than does the MICEX.

Three estimates of the global trend at closing time for the Moscow exchange, corresponding to Models 1–3 are presented in Figure 3. The estimates seem to be very similar, which is quite remarkable, especially taking into account that these estimates of the global index are calculated as sums of the estimates of the global index daily returns.

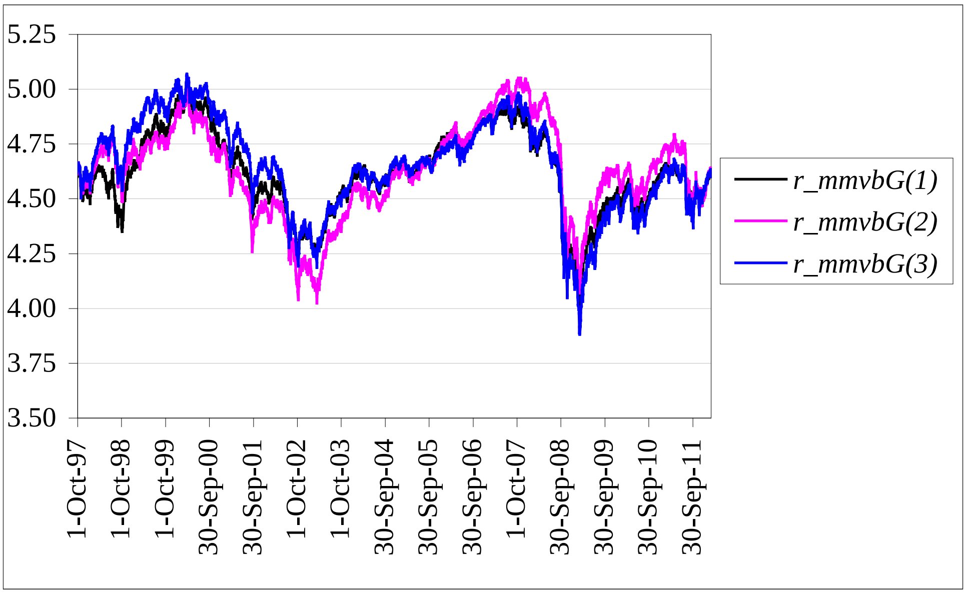
Table 1 Correlations between Model 1–3 estimates of the global part of returns

	r_micexG (1)	*r_micexG (2)*	*r_micexG (3)*
r_micexG (1)	1		
r_micexG (2)	0.851	1	
r_micexG (3)	0.876	0.944	1
r_micex	0.726	0.604	0.624

	r_nikkeiG (1)	*r_nikkeiG (2)*	*r_nikkeiG (3)*
r_nikkeiG (1)	1		
r_nikkeiG (2)	0.961	1	
r_nikkeiG (3)	0.926	0.931	1
r_nikkei	0.817	0.751	0.714

	r_snpG (1)	*r_snpG (2)*	*r_snpG (3)*
r_snpG (1)	1	0.973	
r_snpG (2)	0.973	1	
r_snpG (3)	0.972	0.964	1
r_snp	0.971	0.958	0.996

Figure 3 Three estimates of the global stochastic trend



Overall, we infer that the model provides robust estimates of the global stochastic trend.

In addition to our main results concerning the global stochastic trend, we provide some robustness checks. We estimated models with and without intercepts α_i, and obtained virtually identical results.

We also experimented with shorter time sample, i.e. leaving out the most recent crisis. To check this, the initial sample, covering 23 September 1997 – 7 March 2012 and including two financial crises, is reduced to the relatively calmt period of 1 July 1999 – 1 July 2008. Model 1 was estimated on both samples; the correlations for the estimated global parts of the three indices at the common time interval are presented in Table 2.

Table 2 Correlations between Model 1 estimates of the global part of the returns for two periods

micexG	*nikkeiG*	*snpG*
0.987	0.992	0.999

Figure 4 presents the log of the SNP index and two estimates of the global stochastic trend. The first one is for estimation over the whole period 23 September 1997 – 7 March 2012 (global2), and the second refers to the short period of 1 July 1999 – 1 July 2008 (global1). Both estimates are calculated at the closing time of the New York stock exchange. Note that the global trend could be identified only up to an affine transformation. Both estimates in Fig.4 are normalized to coincide with log SNP at July 1, 1999.

In Figures 5 and 6 similar plots are presented for the NIKKEI and MICEX indices. Plots of the global index are presented for the closing times of the correspondent exchanges. Note that the Russian index MICEX is less closely related to the global trend compared with Japanese or US indices.

Figure 4 Log(SNP) and two estimates of the global stochastic trend

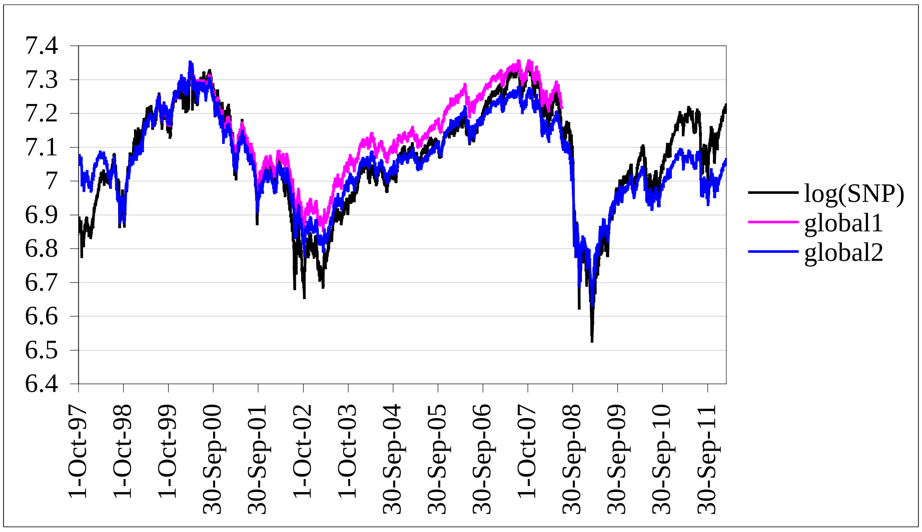


Figure 5 Log(NIKKEI) and two estimates of the global stochastic trend

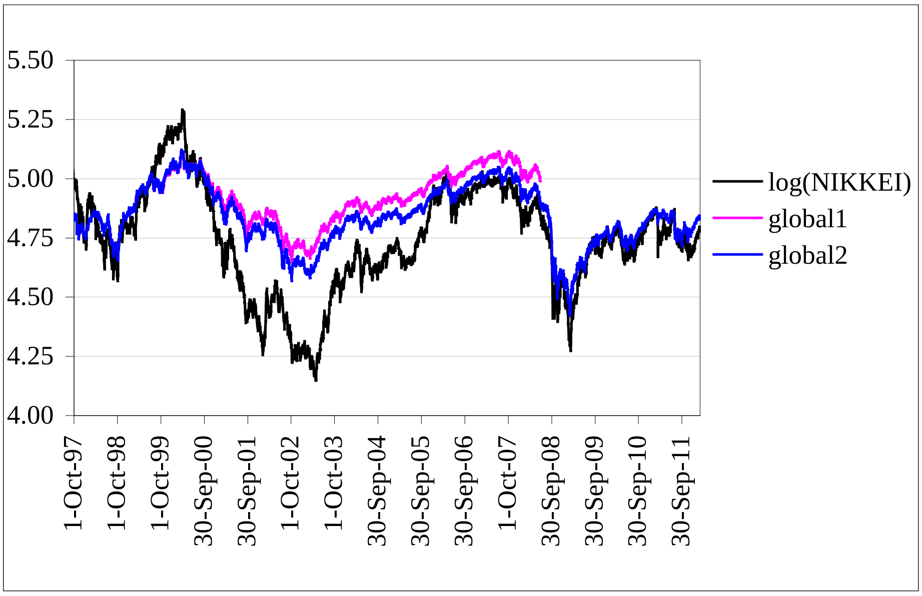
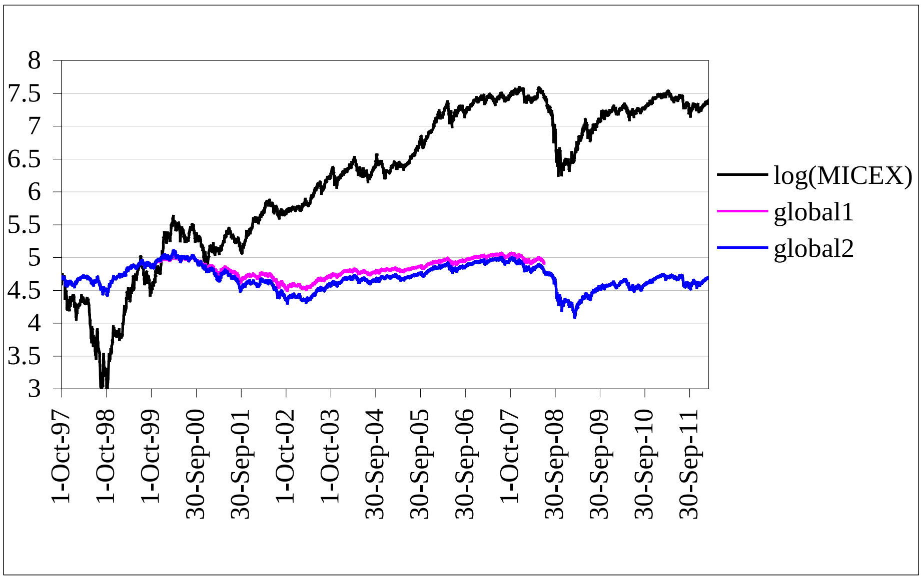


Figure 6 Log(MICEX) and two estimates of the global stochastic trend

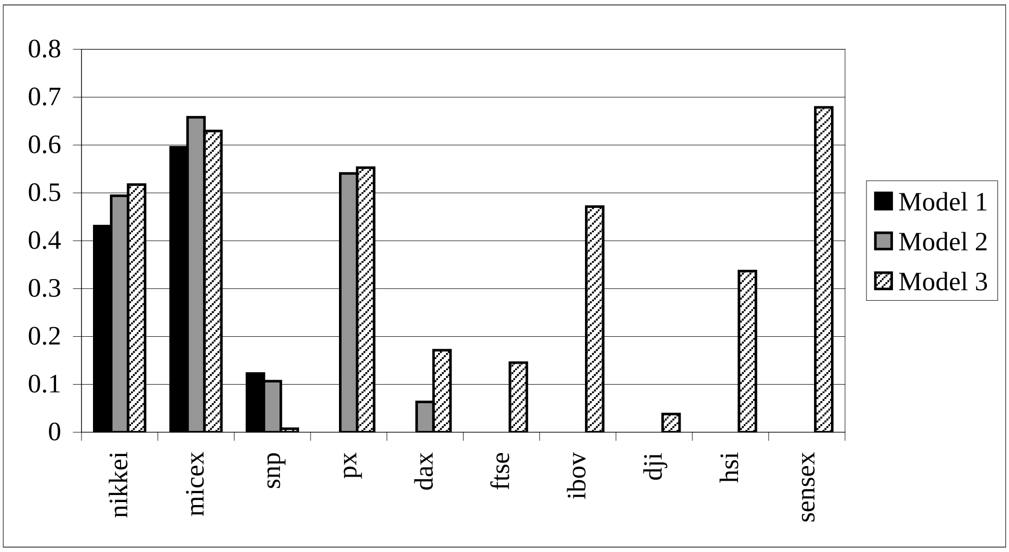


4 Relative importance of local and global news

Local news. The relative importance of local news could be measured as the ratio of the local-part variance of the index return to total variance of the index return $Var(r\_IL)/Var(r\_I)$. Such ratios were calculated via three models (results in Fig. 7). As expected, local news is highly important for emerging markets: Russia (MICEX), India

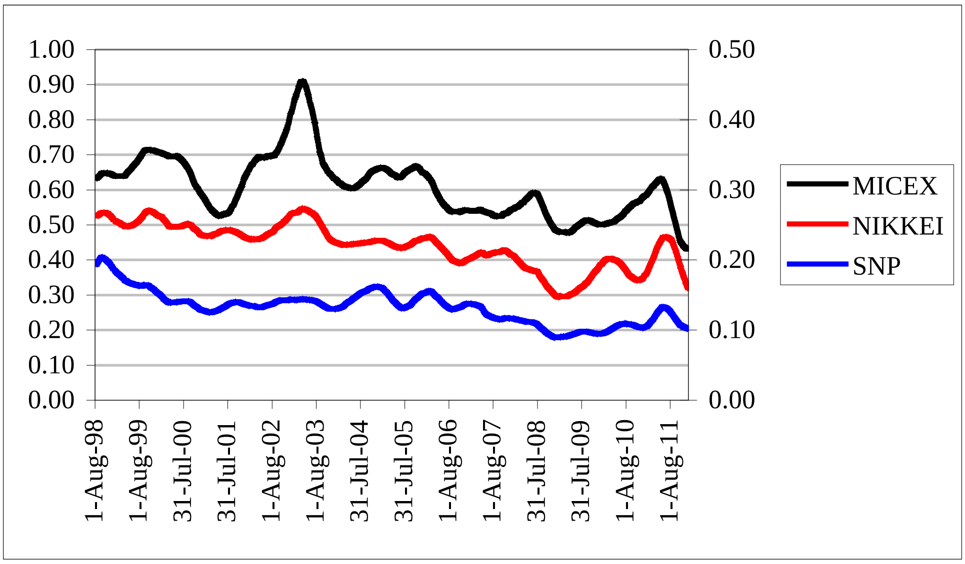
(SENSEX), Brasil (IBOV), Czech Republic (PX). And for Japan (NIKKEI), the local news appears to be relatively important. This result may be explained by the disappointing and highly idiosyncratic performance of the Japanese economy during the past two "lost" decades. And importance of local news is relatively small for the US (DJI, SNP), the UK (FTSE), and Germany (DAX), since most news in these countries is actually global news.

Figure 7 Relative importance of local news



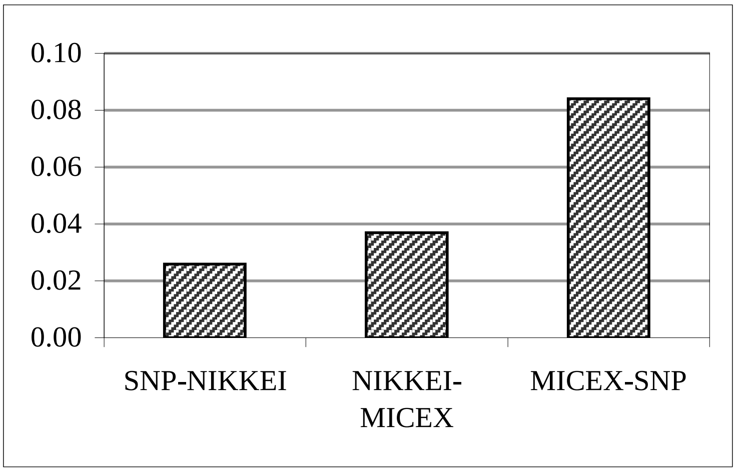
It is possible to study the evolution of these ratios over time. For this, we calculated the ratios $Var(r\_IL)/Var(r\_I)$ for moving windows of size 150 trading days, Time series $rel\_var\_I_t$ denotes the ratio $Var(r\_IL)/Var(r\_I)$ calculated for the window $(t-149, t)$. The next series, $rel\_var\_I_t$, was smoothed using the 51-point centered moving average. The resulting plots for Model 1 are presented in Fig. 8. The three plots reveal a decreasing importance of local news for the three markets. This is in line with the conclusion of Korhonen and Peresetsky (2013), who found an increasing trend of globalization of the world financial markets, especially after 2003. A bit of relative importance of the local news is observed for the 2008–2009 crisis, during which the markets are more highly correlated with each other.

Figure 8 Relative importance of the local news: Trend
(MICEX, NIKKEI — left scale, SNP — right scale)



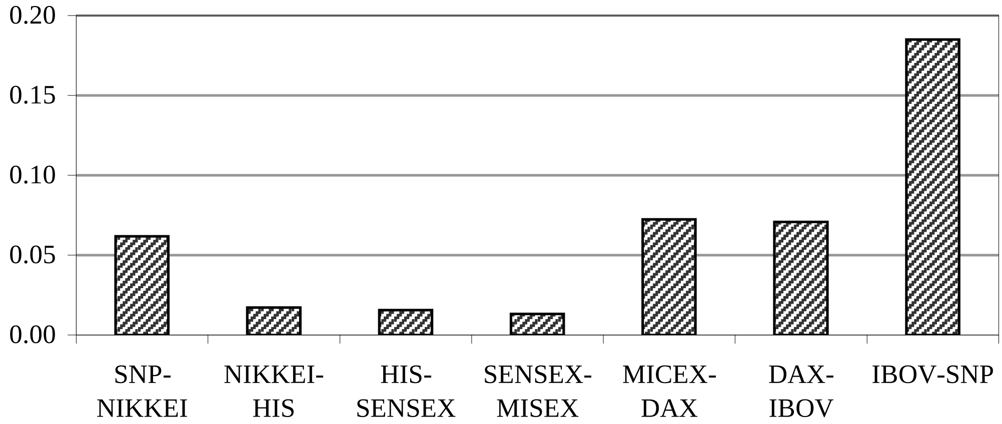
Global news density. In Figure 2 the variance of the global index return between 15:00 and 20:00 GMT, $V(\varepsilon 3)$ can be interpreted as the amount of news during this 6-hour interval of the global time scale. If the global trend is a random walk, this variance should be proportional to the length of the interval. Thus we interpret $V(\varepsilon 3)/6$ as the average density of news per hour in this time interval. Similar calculations could be done for all time intervals used in models 1–3. Closing-to-closing time intervals of the markets, which are used in this paper, are presented in Figure A1 in the Appendix.

Figure 9 Density of global news, Model 1



Density of global news, estimated with Model 1, is presented in Fig. 9. Results for Model 3 estimations are presented in Figure 10. From Figures 9 and 10 one may conclude that the most important hour for the global financial market news is 20:00–21:00 GMT, one hour before closing time of the New York Stock Exchange.

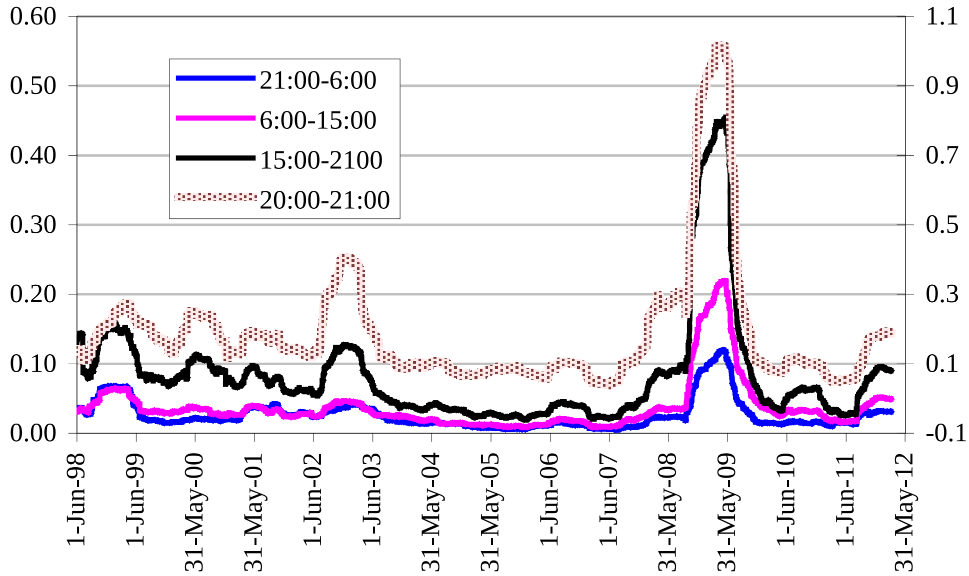
Figure 10 Density of global news, Model 3



The evolution of news densities over time is presented in Figure 11. The densities are calculated for moving windows of 150 trading days. A point on the time scale corresponds to the right side of the window. The time series of densities are smoothed using the 51 point centered moving average. Results are presented for the three intervals based on Model 1 and for the last hour before NYSE closing based on Model 3.

All four plots reveal huge jumps of news density during the 2008–2009 crisis. In all periods the highest news density is for the last hour before NYSE closing, 20:00-21:00 GMT.

Figure 11 Density of global news, Trend
(intervals 21:00–6:00, 6:00–15:00, 15:00–21:00 — left axis, 20:00–21:00 — right axis)



5 Conclusions

In this paper we present a model of global stock market returns based on the concept of global market index, which is not observable. The market return is split into the two parts, the first being defined by the global market index, which accumulates all relevant information from the global markets, and the second being driven by local news, which is not important for the global market.

We build a Kalman-filter type model which enables us to estimate the unobservable global market index from observations on daily returns of the various markets distributed over the globe. The highlight of this model, in contrast to models that extract a common stochastic trend, is that it can deal with non-synchronous data. Our model is applied to returns of three, five, and ten stock indices. It is shown that the results are robust with respect to the chosen set of indices and time intervals for estimation. Furthermore, the results agree with intuition.

The density of news is highest in the interval between closing times in Moscow and New York (15:00–21:00 GMT). For model 3 the highest news density is in the timeframe 20:00–21:00 GMT — the last hour of trading before closing of the New York Stock Exchange.

The indices for the large markets, DJI, S&P, DAX, are the main determinants of the global trend. Small markets, such as those of Russia, India, Czech, Brazil, may deviate widely from the global trend.

From the year 2003 increasing integration of the stock markets is observed, meaning that the importance of local news decreases with time. This is in line with results of the Korhonen and Peresetsky (2013), where quite different models lead to the same conclusion.

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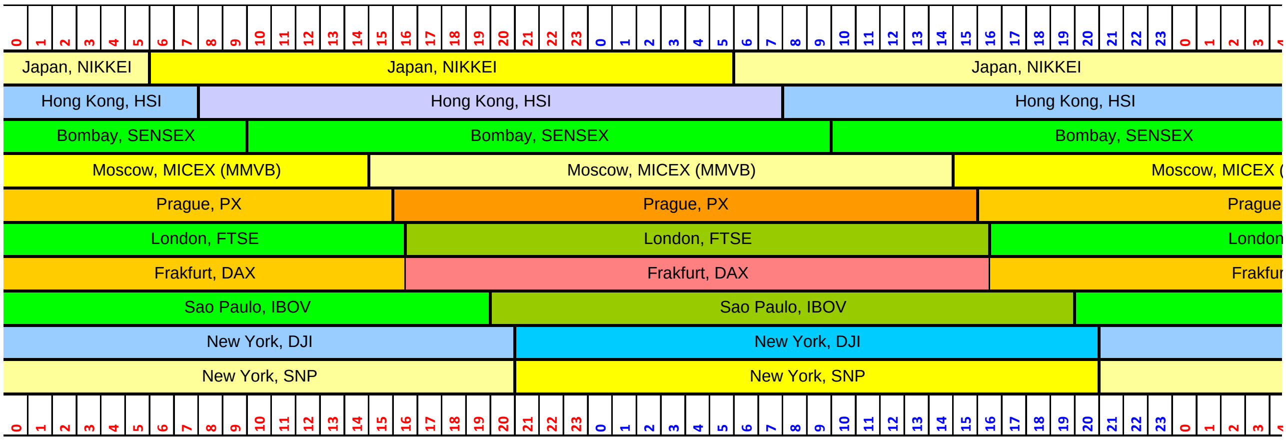
Appendix

Figure A1 Closing-to-closing time interval for different stock markets (GMT)



Source: http://www.marketclocks.com/ and stock market websites.

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