Switching volatility in emerging stock markets:
Evidence from the new EU member countries

by

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Abstract

In this paper, we use weekly stock market data to examine whether the volatility of stock returns of ten emerging capital markets of the new EU member countries has changed as a result of their accession in the EU. In particular we are interested in understanding whether there are high and low periods of stock returns volatility and the degree of correlation across these markets. We estimate a Markov-Switching ARCH (SWARCH) model proposed by Hamilton and Susmel (1994) and we allow for the possibility that three volatility regimes may exist for stock returns volatility. The main finding of the present study is that the high volatility of stock returns of all new EU emerging stock markets is associated mainly with the 1997-1998 Asian and Russian financial crisis while there is a transition to the low volatility regime as they approach the accession to EU in 2004.

Keywords: Emerging European stock markets, stock return volatility, Markov-switching, financial crises.

JEL classification: C22, G15

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1. Introduction

In early 1990s a number of Central and Eastern European (CEE) countries established capital markets as part of their transition process towards adopting the mechanisms of a market economy. One of the main objectives of the reformers in the post-communist countries was the creation of private ownership via privatization of state-owned enterprises. As a result, a number of stock markets have been established in the region. The first stock exchange that reopened in the area was the Ljubljana Stock Exchange (LJSE), on March 29, 1990, followed by the Budapest Stock Exchange (BSE), on June 21, 1990, and the Warsaw Stock Exchange (WSE) on April 16, 1991.

In the aftermath of the establishment of the new stock markets in Central and Eastern Europe, their government in order to attract foreign capital implemented several measures such as, the improvement of disclosure practices of firms, order execution, ownership rights, and the abolishment of restrictions in capital movements. The accession of these countries to the European Union in May 1, 2004, as well as the recent accession of Romania and Bulgaria on January 1, 2007, gave a big boost on these markets and attracted the interest of many investors worldwide, who previously refrained from investing in legally open markets because of real or perceived political, liquidity and corporate governance risks.[1]

The first fifteen years of operation of the emerging European stock markets have been characterized by several events that may have affected the volatility of those markets. Such events, were the massive privatization programs that took place in early 1990s, the frequent exchange rate regime changes, the financial and currency

[1] The period between January to December of 2004, the examined CEE stock exchanges recorded significantly high returns. The Romanian stock exchange recorded a return of 103.5%, the Slovakian 83.9%, the Hungarian 57.2%, the Estonian 57.1%, the Czech 50.9%, the Polish 27.9% and the Slovenian recorded a return of 24.7%.

crises (i.e. the 1997-1998 Asian and Russian crises) and the European Union (EU) accession process. Understanding the channels the stock markets' volatility changes over time is important since the degree of risk of an asset is an important determinant of its price.

The most popular approaches to modeling volatility of stock returns is the autoregressive conditional heteroskedasticity (ARCH) specification proposed by Engle (1982) and the generalized autoregressive conditional heteroskedasticity (GARCH) specification introduced by Bollerslev (1986). However, there are some shortcomings in the use of such models for the study of the volatility in stock return data. A number of researchers [i.e. Diebold (1986), Lamoureux and Lastrapes (1990)] have shown that both ARCH and GARCH models would encounter high persistence in volatility and lower accuracy in the predicting performance due to low probability events (i.e. stock market Crash of 1987 and the 1997-1998 Asian and Russian crises) that reflect structural changes in the volatility process during the estimation period. Hamilton and Susmel (1994) introduced the SWARCH model incorporating Markov-switching and ARCH models. The idea behind the SWARCH model is the use of the Markov-switching specification to model these structural changes and identify breakpoints in an ARCH model of the conditional variance of stock market returns.

Within this framework Li and Lin (2003) argue that the SWARCH model is more appropriate in comparison with the ARCH and GARCH models in modelling the volatility of an emerging Asian stock market (Taiwan) during a period characterized by serious financial turmoil (such as the Asian crisis in 1997). Several studies (Turner *et al*. 1989; Hamilton and Lin, 1996; Van Norden and Schaller, 1997; Rydén *et al*. 1998) applied the Markov-switching framework to model returns on indices of mature stock markets. Although there is a great number of applications of the SWARCH specification to study the volatility of stock returns for several mature markets there is a limited number of studies of empirical application of Markov-switching models for modelling returns of Central and Eastern European stock market indices those of Linne (2002), Bialkowski (2004) and Moore and Wang (2007). However, none of these studies have applied the SWARCH model which this paper thoroughly analyses and applies.

This paper contributes to the literature since it examines the volatility patterns of stock returns of the stock markets of the Central and Eastern European countries by utilizing the Markov-switching ARCH (SWARCH) model proposed by Hamilton and Susmel (1994). This model allows the volatility of the stock returns of these emerging European markets to switch across different states, during the period of reconstruction of the underlying transition economies in the post communist era. Moreover, we investigate whether periods of increased stock market volatility identified by the SWARCH models coincide across countries and if they match the historical events (i.e. political and financial crises events).

The main findings that emerge from our analysis are summarized as follows. First, using the SWARCH-L specification we were able to identify two or in some cases three-state regimes for the ten Central and Eastern European countries. Second, with the exemption of Bulgaria, a 'low' and a 'high' volatility regime has been shown to be statistically significant. Third, based on the estimated transition probabilities we show that the estimated regimes are highly persistent. Fourth, The estimation of the three-state SWARCH specification also leads to the conclusion that apart from Slovenia all other stock markets have been experience very high volatility during the major financial crises during the period 1997-2001. Finally, we argue that the

European Union accession process has acted as a stabilizer for the smoothing of volatility of these emerging capital markets.

The rest of the paper is organized as follows. In section 2 we discuss the financial liberalization process and market characteristics of the CEE economies. Section 3 presents the econometric methodology. In section 4 we discuss the data and the empirical results and section 5 provides our conclusions.

2. Market characteristics and financial liberalization

Table 1 provides an overview of important characteristics of the examined stock markets in Central Eastern Europe. Therefore, it is shown that the larger stock markets in the CEE region, in terms of market capitalization at the end of 2005, are those of Poland, the Czech Republic and Hungary, with market capitalization of 93.60, 54.12 and 32.57 billion dollars respectively. Moreover, the smaller markets in the region are those of Estonia and Latvia with market capitalization of only 3.52 and 2.59 billion dollars respectively. As a result of the different approaches to privatization pursued by the CEE countries, the examined stock markets had substantially different patterns of growth, in terms of the listed firms. For instance, the number of firms listed on the Czech and Slovakian stock exchanges was initially large, following the first of several mass waves of privatization. [2] Since then, the majority of those firms have been delisted, because of the lack of liquidity and the overly stricter listing requirements.[3] However, in other exchanges, like the Polish one,

[2] Romania had also followed a mass privatization program, but all of the newly privatized companies listed on an over-the-counter market the RASDAQ. On December of 1998, 5946 companies are listed on the RASDAQ market. Moreover, Bulgaria and Lithuania had followed the same privatization strategy, a fact that is revealed by the initial large number of listed firms (see Table 1).

[3] At most CEE exchanges only a minority of the companies are listed at the official and regulated markets, where the listing requirements are much higher than other developed exchanges. On the contrary, there is large concentration of listings in the free market (unregulated) segments, since these listings impose no costs on the companies.

the number of listed firms has grown slowly, as a result of a steady approach to the implementation of the privatization scheme.

In Table 1, information is also presented regarding the date when the CEE capital markets opened to foreign investors, following the methodology proposed by Bekaert and Harvey (1995) and Bekaert (1995).[4] According to that information, most restrictions were lifted from the markets examined between 1996 and 1999. The Czech market was the first that made some steps towards official capital market liberalization, while the Lithuanian market was the last. However, it is important to point out that the legal restrictions on foreign participation were lifted gradually.

3. The SWARCH model

In this paper we apply the switching ARCH (SWARCH) model proposed by Hamilton and Susmel (1994), which has the following specification:

$$r_t = \mu + \alpha_1 r_{t-1} + \cdots + \alpha_{t-p} r_{t-p} + \varepsilon_t \tag{3.1}$$

$$u_t = \sqrt{h_t}\,\omega_t, \quad \omega_t \sim \text{Gaussian or Student t distribution} \tag{3.2}$$

$$\varepsilon_t = \sqrt{\gamma_{s_t}}\, u_t \tag{3.3}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 / \gamma_{s_{t-1}} + a_2 \varepsilon_{t-2}^2 / \gamma_{s_{t-2}} + \cdots + a_q \varepsilon_{t-q}^2 / \gamma_{s_{t-q}} \tag{3.4}$$

where r_t is the rate of return of the stock market index, and s_t is a latent variable (unobserved random variable) that can take the values 1, 2, …, or k. The variable s_t is considered as the ‘state’ or ‘regime’ that the process is in at time t and is described by a k-state Markov chain given by:

$$\text{Prob}(s_t = j \mid s_{t-1} = i, s_{t-2} = k, ..., r_{t-1}, r_{t-2}, ...) = \text{Prob}(s_t = j \mid s_{t-1} = i) = p_{ij} \tag{3.5}$$

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[4] Bekaert and Harvey (1995) proposed an indicator for characterizing the situation in which the emerging markets were opened to foreign investors considering a multitude of elements including: the official date of the capital market liberalization, the date of the ADR (American Depository Receipts) appearance on the market and the date of the first country fund.

where i,j = 1,2,….,K. Under this specification if the market is at time t-1 in state i it will change to state j with the fixed probability p_{ij}. The transition probabilities can be collected to the following k x k transition matrix:

$$P = \begin{bmatrix} p_{11} & p_{21} & \cdots & p_{K1} \\ p_{12} & p_{22} & \cdots & p_{K2} \\ \cdots & \cdots & \cdots & \cdots \\ p_{1K} & p_{2K} & \cdots & p_{KK} \end{bmatrix} \qquad (3.6)$$

where the sum of elements in each column in the above matrix should be equal to 1.[5]

The system consists of equations (3.1) to (3.6) is called as the k-state, q-th order Markov switching ARCH model [SWARCH(k,q)]. Equation (3.1) describes the mean equation, while the residual of the mean equation is modelled by equation (3.3), where it is assumed that u_t follows an ARCH(q) process [described by equations (3.2) and (3.4)]. The underlying ARCH(q) variable u_t is then multiplied by the constant $\sqrt{\gamma_1}$ when $s_t = 1$, multiplied by $\sqrt{\gamma_2}$ when $s_t = 2$, and so on. The coefficient for regime 1 (γ_1) is normalized at unity, whereas $\gamma_i \geq 1$ for $i = 2,3,...,k$.[6] Moreover, we investigate both Gaussian ($\omega_t \sim N(0,1)$) and Student-t (with unit variance and ω degrees of freedom) versions of the model.

The estimation of the SWARCH model is done by the maximization of the following likelihood function:

$$L = \sum_{t=1}^{T} \ln f(r_t | r_{t-1}, r_{t-2}, ...)$$

[5] For reasons of simplicity we restrict our analysis so as not to allow state 2 to come after state 1 (p_{12}), and state 1 to come after state 3 (p_{31}), in the presence of three regimes in the SWARCH model.

[6] The SWARCH model in the presence of leverage effects is formulated as follows: $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 / \gamma_{s_{t-1}} + a_2 \varepsilon_{t-2}^2 / \gamma_{s_{t-2}} + \cdots + a_q \varepsilon_{t-q}^2 / \gamma_{s_{t-q}} + \xi L_{t-1} \varepsilon_{t-1}^2 / \gamma_{s_{t-1}}$
where $L_{t-1} = 1$ if $\varepsilon_{t-1} \leq 0$ and $L_{t-1} = 0$ if $\varepsilon_{t-1} > 0$

Byproducts of this estimation process are probability statements about the particular state/regime of the market under study, in time t. When these statements are based on information available through date t, the regime probability is called the 'filter probability' [$p(s_t, s_{t-1}, ..., s_{t-q} | r_t, r_{t-1}, ..., r_{-3})$]. On the other hand, if the information set includes the full sample period (up to date T), the regime probability is called the 'smooth probability' [$p(s_T | r_T, r_{T-1}, ..., r_{-3})$]. The 'smooth probability' represents the ex-post statement made by a financial analyst or an econometrician about the state of the market at time t, based on the entire time series.[7]

4. Data and empirical results

The data used in this paper are weekly stock-price indices from January 01, 1993, through November 25, 2005, for the equity markets of ten new European Union member states.[8] The data set consists of the local stock indices of Bulgaria (BSE), Czech Republic (PX50), Estonia (TALSE), Hungary (BUX), Latvia (RICI), Lithuania (LITIN), Poland (WIG), Romania (BET), Slovakia (SAX12) and Slovenia (SBI). All the national stock-price indices are used in local currency terms and based on weekly closing prices in each national market.[9, 10] These stock market indices are transformed into weekly rates of returns taking the first difference of the natural log of each stock-price index. The source of the data is the Datastream International.

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[7] For each model, the negative log-likelihood was minimized numerically using the optimization programme OPTIMUM in GAUSS 7.0 starting with steepest ascent and then switching to the BFGS algorithm.

[8] The sample period is not the same for the ten emerging European stock markets, since the opening date of the markets under inquiry range from market to market. Weekly data are used due to the presence of more noise with higher frequencies, such as daily data, which makes it more difficult to isolate cyclical variations and hence obscuresthe analysis of the driving moments of switching behavior.

[9] When data were unavailable, because of national holidays, bank holidays, or any other reasons, stock prices were assumed to stay the same as those of the previous day.

[10] Expressing the stock price indices in their national currencies restricts their changes to the movements in the stock prices only, avoiding distortions induced by numerous devaluations of the exchange rates that have taken place in the CEE region [see Voronkova (2004)].

4.1. Preliminary Statistics

The summary statistics of stock-index returns in the ten Central Eastern European markets are presented in Table 2. Specifically, we present information on the mean, standard deviation, skewness coefficient, kurtosis coefficient, the Jarque-Bera normality test, and the Ljung-Box test (LB). As expected with emerging equity markets, the index returns series are negatively skewed (with the exception of Romania and Slovakia) and leptokurtic. Moreover, the Jarque-Bera test statistic reveals the typical non-normality of high frequency financial time series. This finding suggests that for these markets, big shocks of either sign are more likely to be present and that the stock returns series may not be normally distributed. In addition most of the stock return series are found to exhibit significant autocorrelation as it is suggested by the Ljung-Box test statistic. The existence of this autocorrelation may be due to nonsynchronous trading of the stocks that form the index. Furthermore, it could be the result to price limitations imposed on the index or other types of market friction, producing a partial adjustment process.

Figure 1 provides plots of log stock price indices for each market over the sample period. These plots reveal that all the CEE markets are characterized by upward sloping trends, particularly in the period after the November 2001 announcement of the EU enlargement. Furthermore, the top panel of figures 2-10 plots the weekly stock returns for each market. These plots show a clustering of larger return volatility around and after mid-1997 when the Asian financial crisis was taking place as well as in mid-1998 during the Russian currency crisis.

4.2. The MS-ARCH model and estimation results

We now move to modeling the volatility of the CEE stock markets with the estimation of an AR(1)-GARCH(1,1)-t model for each country case.[11] Table 3 reports the estimates of the returna and conditional variance equations. The AR(1) term in the mean equation is significantly positive for Czech The results indicate that the volatility persistence measure is close to one for the majority of the markets examined.[12] These results reveal that the volatility in the GARCH models has the high persistence problems, that according to Lamoureux and Lastrapes (1990) and Hamilton and Susmel (1994) are caused by the structural changes in the statistical process generating the volatility.

Given that the Markov-switching ARCH (SWARCH) model proposed by Hamilton and Susmel (1994) can incorporate these structural changes, we estimated a panel of different SWARCH specifications in order to see which specification captures most of the dynamics in the stock returns examined. We estimated models with q = 0 to 2 autoregressive terms in the ARCH process and for K = 2 or 3 different volatility states, under the Gaussian and Student-t distribution, and with and without the leverage parameter ξ proposed by Glosten et al. (1993).[13]

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[11]Prior to the estimation of the SWARCH models we conduct unit root and stationarity tests to determine the stochastic properties of the data. We employ the Elliot *et al*. (1996) and Elliot (1999) GLS augmented Dickey-Fuller and Ng and Perron (2001) GLS versions of the modified Phillips-Perron (1988) unit root tests. For robustness we also apply the Kwiatkowski *et al*. (1992) KPSS stationarity test. The results show that we are unable to reject the null hypothesis of a unit root in the data for the levels of all five series, whereas the first difference of the series are I(0) processes. Te results are available upon request.

[12] Hamilton and Susmel (1994) provide a rigorous and comprehensive analysis of the of the volatility persistence measure. The estimation results of the ten AR(1)-GARCH(1,1)-t models are not reported to save space, but they are available upon request.

[13] In this paper we report the results with q=1, since the use of more than one ARCH terms in the SWARCH specification did not improve the results and proved extremely difficult (and sometimes impossible) to maximize, leading to a non-positive definite Hessian matrix. Moreover, we focus on discussing the SWARCH specifications with the Student-t distribution for the subsequent analysis, since the specifications under the Student-t distribution turn out better than those under the Gaussian distribution (the likelihood ratio tests rejected the Gaussian in favor of the Student-t formulation).

Following Hamilton and Susmel (1994) and Li and Lin (2003), we statistically test the null hypothesis of no regime switch by using the standard likelihood-ratio (LR) test proposed by Davies (1987). For this purpose we estimat an AR(1)-ARCH(1)-t model, since the GARCH specifications are not strictly nested with the SWARCH specifications.[14] The ARCH process could be described as a special case of SWARCH under the constraint of $\gamma_1 = \gamma_2 = 1$.[15] The LR test statistics are reported in Table 3, together with the estimates of the two-state Markov-switching ARCH models. The results strongly suggest that for most of the stock markets under examination, with the exception of Bulgaria and Lithuania, the hypothesis of no regime switch is rejected.[16] Moreover, the LR test statistics suggest that for some markets the three-state SWARCH specifications may be appropriate.[17]

Given the rejection of the hypothesis of no regime switch, we continue our analysis with the discussion of the estimation results, as reported in Table 3. In most cases, the Ljung-Box Q-statistic suggests that there is no autocorrelation in the level of the standardized residuals or in the squared standardized residuals. Thus the two-state SWARCH model captures most of the dynamics in the stock returns examined. Furthermore, several other interesting findings emerge from the present analysis.

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[14] According to Hamilton and Susmel (1994), is not feasible to combine the Markov-switching and GARCH model.

[15] However, with the constraint of $\gamma_1 = \gamma_2 = 1$, one would encounter an unidentified problem when testing the model, since the parameter γ_2 is unidentified under the null hypothesis that there is only one state. Hansen (1991, 1992) has proposed asymptotically valid tests, though yet its implementation is computationally expensive in this case. Nevertheless, despite the fact that the Likelihood Ratio statistics under this condition no longer follows the standard χ^2 distribution, we report critical values for the likelihood ratio tests as if the χ^2 approximation were valid.

[16] The p-values for the LR tests are so small that we have little doubt that the null hypothesis would be rejected by any more rigorous testing procedures. Despite the acceptance of the null hypothesis of no regime switch for the markets of Bulgaria and Lithuania, we will continue our analysis taking into account these markets as well.

[17] The null hypothesis of a two-state SWARCH model against the three-state model is rejected, with the exception of Estonia and Poland at the 1% significance level. However, the use of the standard likelihood ratio tests is not the most appropriate, since the parameters P_{ij}, for the third state, are unidentified under the null hypothesis of two states.

Firstly, the coefficients of the lagged innovation-squared in the ARCH process of the conditional volatility are all insignificantly different from zero, with the exception of Poland, Slovakia and Slovenia. Therefore, when we take into account the likelihood for the existence of a switching regime in the volatility generating process, the ARCH effect seems to be reduced or even disappear in most markets examined.[18] Secondly, the switching parameters (the γ_2's) are in all cases significantly different than one, with the exception of Bulgaria where the switching parameter is not statistically significant at the 5% level of significance. These results reveal that we are able to distinguish for all the markets, except for Bulgaria, a 'low' and a 'high' volatility regime, while the γ_2 parameter is the ratio between the two states. Specifically, in our two-state case, the 'high' volatility regime is on average 6.42 times higher than in the 'low' volatility regime. Moreover, in two extreme cases, for Estonia's stock market returns the 'high' volatility regime is on average 10.6 times higher than that in the 'low' volatility regime, while for Czech Republic's stock market returns the 'high' volatility regime is only 2.3 times higher than that in the 'low' volatility regime.

Finally, the estimated transition probabilities (p_{11} and p_{22}) suggest that the estimated regimes are highly persistent. Particularly, the 'low' volatility regime would be expected to last on average for $(1\text{-}\hat{p}_{11})^{-1} = 100.33$ weeks, while the 'high' volatility regime last on average for 48.22 weeks. Thus, the CEE stock markets remain in the 'low' volatility state relatively more than in the 'high' volatility state. In Figures 2-10, we present the emerging smoothed probabilities of the 'high' and the 'low' volatility regimes based on the estimates of the MS-ARCH model for each CEE stock market.

[18] We also estimated a SWARCH model which incorporates a leverage effect in the volatility process. The results indicate that, with the exception of Czech Republic, there is no evidence for an asymmetric effect of negative news on conditional volatility. Thus, the unexpected negative surprises to returns do not cause a bigger impact on volatility than positive news.

The regime identification have been done following the methodology proposed by Hamilton (1989), according to which an observation belongs to regime i if the smoothed probability $p(s_t = i | r_T, r_{T-1}, ..., r_{-3})$ is higher than 0.5.

We now move to the discussion of our results. With respect to the Czech Republic, the estimated smoothed probabilities in Figure 2 reveal that the Czech stock returns are in the high volatility state during the first years of the period examined. This period seems to be associated with the increased instability observed in the emerging CEE stock markets during the first years after the transition. Following a period of almost two years (mid-1995 to mid-1997) that characterized by low volatility, the Czech stock returns switch to the high volatility state during the period between 1997 and 2001. This period coincides with the currency crisis, which began in the Czech Republic in May 1997, the financial crises prevalent around this time in Southeast Asia (late 1997), Russia (August-September 1998), Brazil (January 1999), Turkey (February-March 2001) and Argentina (January-February 2001) as well as the terrorist attacks in US (September 2001). Finally, the low volatility regime noticed from the beginning of 2002 can be attributed to the EU accession process.[19]

According to Figure 3, stock market returns in Estonia are mainly in the high volatility state during the period between November 1996 and February 1999. This period coincides with the significant rise of the TALSE index in 1996-1997, the first years after the establishment of the Tallinn stock exchange, and the 1997-1998 Asian and Russian financial crises. Afterwards, Estonian stock returns tend to have long

[19] In November 2001, the European Commission outlined the timing and named countries involved in the enlargement.

stays in the low volatility state, in a period that characterized by exchange rate stability, since a currency board exchange rate system was introduced in 1999.[20]

As for the case of Hungary, the low volatility in the first years of the period examined is not surprising, since the BUX index did not present (see Figure 1) the extreme volatility observed in most of the other emerging CEE stock markets around this time. The Hungarian stock returns stayed in the low volatility state, with few exceptions, until October 1997, when the Southeast Asian financial crisis expanded.[21] Moreover, the high volatility regime observed in the period between May 1998 and April 1999, may be attributed to spill-over effects of the Czech, the Russian and the Brazilian crises. The returns evolved into a low volatility regime from 2001 onwards.

With respect to the Baltic countries Lithuania and Latvia we observed a similar behavior of the stock returns volatility. Thus, between March 1998 and December 1998, the stock returns moved to the high volatility state, reflecting the political and financial crises in Russia.[22] The volatility remained in the low volatility regime from 1999 onward. However, this was disrupted by short-lived high volatility pattern in 2003, which may be, in part, caused by the euphoria arose among the market participants after the signature of the Treaty of Accession in April 16 2003.[23]

In Poland, the initial period of high volatility in 1993-1995 seems to be associated with the burst of the speculative bubble, which according to Bolt and Milobedzki (1994) was caused by the change in the monetary policy implemented by

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[20] Estonian stock returns switched to the high volatility state only for few weeks at the end of 1999 (EU confirmed Estonia as a tier-one candidate),in the fall of 2001 (11th September terrorist attacks in US) and in September 2003 (Estonians vote overwhelmingly to join the European Union in a referendum).

[21] The high volatility regime in 1994 and also 1996 coincides with the start of the privatization of the banking sector and the dramatic increase in foreign direct investments respectively.

[22] Russia threatened trade sanctions against Latvia in response to political disputes during the spring of 1998. Furthermore, the Latvian market was seriously affected by financial crisis in Russia since Latvian companies had large exposures to Russia.

[23] The period between March to May 2003 the RICI index raised by about 65%.

the National Bank of Poland.[24] In May 1995, Poland's exchange rate system moved from a crawling peg to less restrictive crawling bands, a fact that may explain the low volatility regime in the subsequent period.[25] The increased probability to remain on the high volatility regime in 1998 corresponds to the Russian financial crisis.

Turning our attention on the Romanian stock market we observe that the stock market returns switched from the low volatility regime to the high volatility regime during the first five years of the sample. This is shown in Figure 8. Thus, we argue that the period of high volatility in 1997-1998 can be attributed to the financial crises in Southeast Asia and Russia and the period of high volatility in 1999 coincides with the large depreciation of the lev against the US dollar. The low volatility regime it appears to prevail from 2000 onwards which may be due to the beginning in February 2000 of the formal discussion between Romania and the European Union for the potential accession as well as to the official talks on Romanian's application to join NATO.

According to Figure 9, stock market returns in Slovakia appear to remain in the low volatility regime for most of the period under examination. The stock returns volatility is in the high volatility regime in 1994, reflecting the instability of the young Slovakian stock market in the first years after the transition. Furthermore, the period of high volatility in 1999 may be associated with the large depreciation of the Slovak Koruna and the political instability observed around this time.

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[24] In 1993, the National Bank of Poland reduced substantially the interest rates which made investments on the Warsaw Stock Exchange very attractive, given that the high inflation rates made returns on all commercial bank accounts negative. The burst of the bubble occurred since the trading on the WSE was based not on future corporate profits, but on hopes of increased share prices.

[25] The low volatility regime observed in the period after the beginning of 1999, may be attributed to the floating exchange rate system introduced officially in April 2000 [unofficially the floating exchange rate system have been instituted in July 1999, according to Kierzenkowski (2005)], and the increase of institutional ownership after the appearance of Polish pension funds on 19 May 1999 [see Bohl and Brzeszczynski (2006)].

Finally, as for Slovenia, the early period of high volatility in 1994-1999 coincides with the financial crises in south-Asia (late 1997) and Russia (August-September 1998), as well as the large amount of restrictions for foreign portfolio investors imposed by the Slovene central bank in February 1997. Slovenian stock returns switched to the low volatility regime from 1999 onwards, reflecting the lift of most restrictions on foreign portfolio investments in Slovenian capital market. A high probability of high volatility in 2002 corresponds to the rapid increase of the participation of foreign institutional investors in the share capital of the Slovenian listed firms.

A common feature emerges from the results of the estimation of the SWARCH model and the derived smoothed probabilities. As it is clear from Figures 2-10 the Central Eastern European stock market returns, with the exception of the Slovakian stock returns, switch to the high volatility regime during the period 1997-1998, a period that coincides with the financial crises in Southeast Asia and Russia. This finding may imply that the emerging European stock markets might be affected by some kind of "volatility contagion" throughout the crises turmoil. Following Edwards and Susmel (2001), we investigate this issue further by estimating, for the markets examined, a three-state SWARCH specification. The third state is named as "unusually high volatility" and the results are reported in Table 4. According, to these results the most CEE stock returns have a long stay in the "unusually high volatility" regime around the 1998 Russian crisis period. Moreover, the Baltic markets are those that seem to be affected more by that crisis event, since the Baltic States have relatively stronger political, financial and trade relationships with Russia as being former Soviet Union member states (see Black *et al*., 2000). Moreover, it is observed that the Southeast Asia crisis had a smaller impact on the emerging CEE stock markets.[26] Finally, the fact that most of these stock markets experienced a significant increase in the stock returns volatility ("unusually high volatility" regime) particularly around the period of the 1998 Russian crisis is indicative, but does not constitute statistical evidence in favor of the "volatility contagion" hypothesis.[27]

An additional interesting feature of our results is that the European Union accession process appears to be an important factor that acts as a stabilizer in the volatility of these stock markets. Stock returns seem to be in the low volatility regime from the early 2000's, much before the time of entry to the EU in May 2004, since the date of entry was known among the market participants prior to that date.[28] Moreover, the lift of the restrictions on foreign investors seem to cause a switch to the high volatility regime in the short-run but acts as another stabilizer factor of stock markets' volatility in the long-run. This result is in line with the finding of Bohl and Brzeszczynski (2006), who concluded that the increase of institutional ownership after the establishment of Polish pension funds on 19 May 1999 reduced the Polish returns volatility.

5. Summary and concluding remarks

In this paper, we used a Markov-switching ARCH (SWARCH) model to examine the volatility patterns through time for a group of ten, new EU members, Central Eastern European stock markets. For this purpose we employed weekly stock price data for the period January 1993 to November 2005 for the following CEE countries: Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. The Markov-switching specification of the

[26] Only the stock returns in Estonia, Hungary, Lithuania and Romania are in the "unusually high volatility" regime during the Southeast Asia crisis period.
[27] See Edwards and Susmel (2001) for a more detailed discussion.
[28] Romania joined the EU in January 2007.

SWARCH model is shown to describe better the dynamics of the stock market returns under examination, since it reduces the high volatility persistence problems faced by standard ARCH models.

The main findings that emerge from our analysis are summarized as follows. First, using the SWARCH-L specification we were able to identify two or in some cases three-state regimes for the ten Central and Eastern European countries. Second, with the exemption of Bulgaria, a 'low' and a 'high' volatility regime has been shown to be statistically significant. Third, based on the estimated transition probabilities we show that the estimated regimes are highly persistent. Fourth, the estimation of the three-state SWARCH specification also leads to the conclusion that apart from Slovenia all other stock markets have been experience very high volatility during the major financial crises during the period 1997-2001. Finally, we argue that the European Union accession process has acted as a stabilizer for the smoothing of volatility of these emerging capital markets.

These results may be of interest to academic researchers and practitioners who study the workings of emerging markets as well as to investors and portfolio managers who are active in emerging markets and they consider the inclusion in their portfolios equities from the CEE stock markets.

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Table 1: Market Characteristics for CEE stock exchange markets

Country	Stock market established	Restrictions lifted	1st ADR	Market Capitalization (billions of US dollar)				Nº of listed firms			
				96	98	01	05	96	98	01	05
Bulgaria	October 1997*	1998[9]	January 1998	0.01	0.14	0,50	5,13	9	998	402	331
Czech	June 1992	September 1994[1]	January 1994	19.3	13.9	9,4	54,1	1670	304	102	39
Estonia	May 1996	1996[5]	April 1998	0.69	0.51	1,73	3,52	11	22	17	19
Hungary	July 1990	1996[2]	December 1992	5.18	13.7	10,3	32,5	45	54	58	44
Latvia	January 1996	1996[7]	December 1997	0.15	0.38	0,69	2,59	34	68	63	46
Lithuania	January 1996	June 1999[6]	January 1996	0.90	1.07	1,19	8,12	410	60	45	43
Poland	January 1991	February 1997	December 1992	8.41	20.4	26,1	93,6	83	198	230	241
Romania	April 1995	March 1998[8]	January 1998	0.06	0.35	1,22	18,1	17	126	60	59
Slovakia	January 1994	April 1998[4]	January 1996	5.77	4.11	3,46	4,74	970	833	888	306
Slovenia	December 1989	1999[3]	January 1996	0.89	2.98	3,46	7,89	45	90	151	116

Sources: Bekaert and Harvey: "chronology of economic, political and financial events in emerging markets", Dvorak και Podpiera (2006), National stock exchanges and WFOE (World Federation of Exchanges).
1) More restrictions lifted in 1999
2) More restrictions lifted in 1998
3) Until 1999 foreign sales within 7 years taxed 12%. 25% foreign ownership limit.
4) More restrictions lifted in 2000
5) More liberalization in 2000. Restrictions on certain industries.
6) Some restrictions have been lifted since 1991, when the new FDI law (No. 35/1991) came into effect, while more restrictions lifted on 2001.
7) All restrictions lifted in 1999
8) More restrictions lifted in 2000
9) All restrictions lifted in 2004
* Trading on the Bulgarian stock exchange was suspended for one year on 23 October 1996, while the first trading session on the regulated market took place on October 21, 1997.

Table 2: Descriptive statistics of weekly index return series

	Bulgaria	Estonia	Latvia	Lithuania	Hungary	Poland	Romania	Slovakia	Slovenia	Czech
	Descriptive Statistics									
Mean	0.002	0.0038	-0.0006	-0.0012	0.0047	0.0051	0.0044	0.0023	0.0024	0.0005
Standard Deviation	0.057	0.045	0.0368	0.0358	0.040	0.0543	0.046	0.040	0.0295	0.029
Skewness	-0.075	-0.809	-0.470	-0.053	-0.861	-0.015	0.1144	2.841	-0.0794	-0.423
Kurtosis	14.348	7.215	3.481	2.834	8.954	5.720	3.5803	30.720	7.946	1.998
Jarque-Bera Normality test	3457.63*	1125.46*	194.57*	130.75*	2331.76*	917.53*	229.00*	25864.9*	1631.81*	119.18*
LB(6)	6.47	39.76*	55.80*	25.76*	33.27*	17.89*	10.51	112.70*	21.84*	23.19*
LBS(6)	24.98*	189.69*	93.70*	64.41*	39.28*	372.32*	11.42	71.15*	63.76*	32.68*
Obs.	403	494	359	390	673	673	427	636	620	607

Notes: All variables are first differences of the natural log of stock indices; JB is the statistic for the null of normality; LB(6) denotes the Ljung-Box test statistic for serial correlation with 6 lags respectively, LBS(6) denotes the Ljung-Box test statistic for squared returns with 6 lags. (*) denotes statistical significance at the 5 percent critical level.

Table 3: Estimation of the AR(1)-SWARCH(2,1)-t model

$$r_t = \mu + \alpha_1 r_{t-1} + \varepsilon_t, \ \ u_t = \sqrt{h_t}\omega_t, \ \ \omega_t \sim \mathrm{t}(\omega), \ \ \omega > 2 \ \ \text{και} \ \varepsilon_t = \sqrt{\gamma_{s_t}} u_t$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 / \gamma_{s_{t-1}} \ , \ S_t = 1,2$$

	Bulgaria	Czech	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Slovakia	Slovenia
μ	0.0018 [0.0016]	0.0026* [0.0010]	0.0037* [0.0011]	0.0043* [0.0012]	0.0013 [0.0014]	-0.0005 [0.0014]	0.0031* [0.0013]	0.0053* [0.0016]	0.0004 [0.0009]	0.0014* [0.0007]
α_1	0.0716 [0.0491]	0.1346* [0.0451]	0.1371* [0.0435]	0.0894* [0.0440]	0.0642 [0.0576]	0.1600* [0.0554]	0.0670 [0.0436]	0.1082* [0.0483]	0.1378* [0.0430]	0.1648* [0.0424]
α_0	0.0013* [0.0004]	0.0004* [0.0000]	0.0005* [0.0001]	0.0007* [0.0001]	0.0006* [0.0000]	0.0006* [0.0001]	0.0009* [0.0001]	0.0007* [0.0001]	0.0006* [0.0001]	0.0001* [0.0000]
α_1	0.3023 [0.2030]	0.1526 [0.1017]	0.0251 [0.0747]	0.1073 [0.1037]	0.0581 [0.0621]	0.1275 [0.1156]	0.2255* [0.0806]	0.0014 [0.0331]	0.2819* [0.1210]	0.1306* [0.0649]
ω	3.5814* [1.1130]	7.8711* [2.4049]	4.0171* [1.0857]	7.3666* [2.9415]	9.7567* [5.0177]	8.0586* [4.3099]	6.3578* [1.7411]	7.1852* [3.0389]	3.4740* [0.6098]	6.4739* [1.6254]
γ_2	22.8780 [15.6818]	2.3744* [0.4961]	10.609* [2.3251]	5.5673* [1.5739]	6.6237* [1.8280]	5.3494* [1.6697]	7.3329* [1.6944]	5.3802* [1.0508]	8.2193* [3.4675]	6.3250* [0.9865]
p_{11}	0.9842	0.9903	0.9848	0.9779	0.9913	0.9806	0.9953	0.9640	0.9906	0.9943
p_{22}	0.7705	0.9892	0.9602	0.9040	0.9528	0.9125	0.9821	0.9553	0.9245	0.9945
L	698.89	1311.02	977.12	1300.82	730.97	787.98	1184.07	756.45	1328.67	1463.36
LB(6)	7.55	7.39	21.15*	29.38*	45.23*	9.91	14.08	3.06	49.44*	3.74
LBS(6)	3.21	5.02	10.36	27.14*	31.79*	5.26	12.52	0.59	44.15*	1.58
L^*	698.40	1305.03	949.20	1291.125	717.83	785.21	1164.56	745.18	1324.55	1421.11
L^{**}	698.89	1313.53	977.15	1301.01	732.93	788.91	1184.15	756.50	1329.01	1463.59
L^{***}	700.91	1315.39	985.47	1304.42	735.35	788.63	1197.78	758.55	1332.66	---
LR1	0.98^{+} [0.80]	11.98 [0.007]	55.84 [0.000]	19.40 [0.000]	26.28 [0.000]	5.54^{+} [0.13]	39.02 [0.000]	22.54 [0.000]	8.24 [0.04]	84.5 [0.000]
LR2	4.04^{+} [0.25]	8.74^{++} [0.03]	16.70 [0.000]	7.20^{+} [0.06]	8.76^{++} [0.03]	1.30^{+} [0.72]	27.42 [0.000]	4.20^{+} [0.24]	7.98^{++} [0.04]	---

Notes:
L^*: AR(1)-ARCH(1,1)-t log likelihood value
L^{**}: AR(1)-SWARCH(2,1)-L log likelihood value
L^{***}: AR(1)-SWARCH(3,1)-t log likelihood value
LR1: Likelihood Ratio test. Null hypothesis is no regime switch
LR2: Likelihood Ratio test. Null hypothesis is a two-state SWARCH model against the three-state model
LB(6): Ljung–Box test for standardized residuals with six lags, which is distributed χ_6^2.
LBS(6): Ljung–Box test for squared standardized residuals with six lags, which is distributed χ_6^2.
* Significant at the 5% level.
$^+$ Acceptance of the Null hypothesis at the 5% significance level.
$^{++}$ Acceptance of the Null hypothesis at the 1% significance level.
The number in the brackets reports what the p-value for the likelihood ratio tests.

Table 4: Identification of "unusually high volatility" episodes around major crises events

	Asian crisis 23/10/97	Russian crisis 17/08/98	Braz. Crisis 14/01/99	Turkish Crisis 11/00-02/01	Dot-com bubble 13/03/2000	US Terror. Attack 11/09/2001
Czech	---	19/06/98 (28)	1/01/99 (18)	---	---	---
Estonia	24/10/97 (22)	27/03/98 (40)	1/01/99 (10)	---	---	14/09/01 (9)
Hungary	31/10/97 (7)	31/07/98 (21)	25/12/98 (14)	24/11/00 (3)	---	---
Latvia	---	27/03/98 (39)	---	---	---	---
Lithuania	07/11/97 (5)	19/06/98 (31)	---	---	---	14/09/01 (6)
Poland	---	24/07/98 (15)	---	---	---	---
Romania	17/10/97 (14)	10/07/98 (22)	---	05/01/01 (2)	---	---
Slovakia	---	---	---	---	---	---
Slovenia*	---	---	---	---	---	---

Notes: Each date refers to the week that each CEE market started being in the "unusually high volatility" state (state 3) around the time some major financial crises occurred. The number in parenthesis corresponds to the weeks each market was in the "unusually high volatility" state during each crisis. The dash (---) means the market was not in the third state during the given crisis. * means that the estimation of the SWARCH (3,1) specification was not possible for the Slovenian market.

Figure 1. Stock price indices

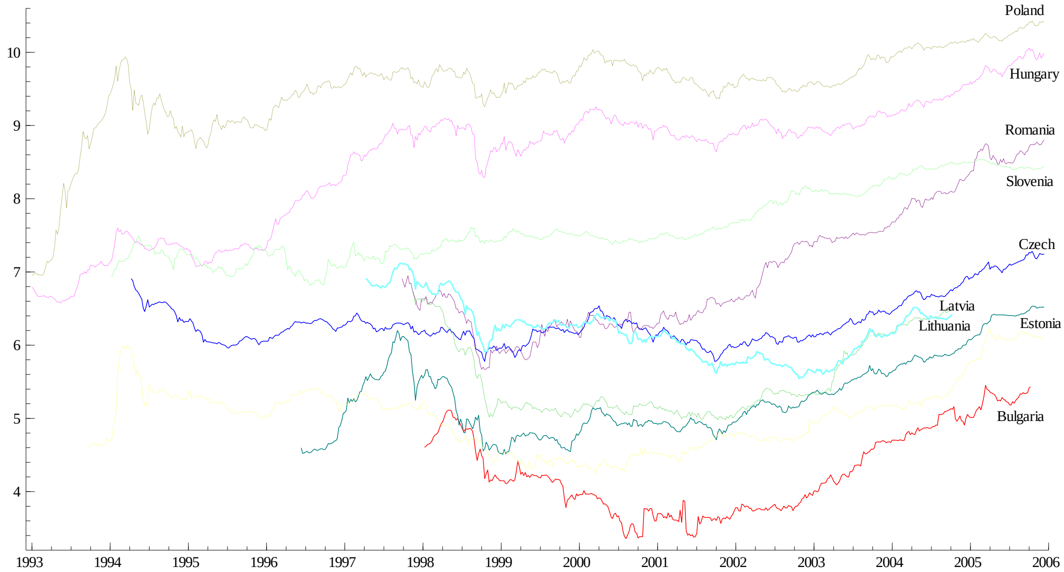

Figure 2. Smoothed probabilities for Czech Republic

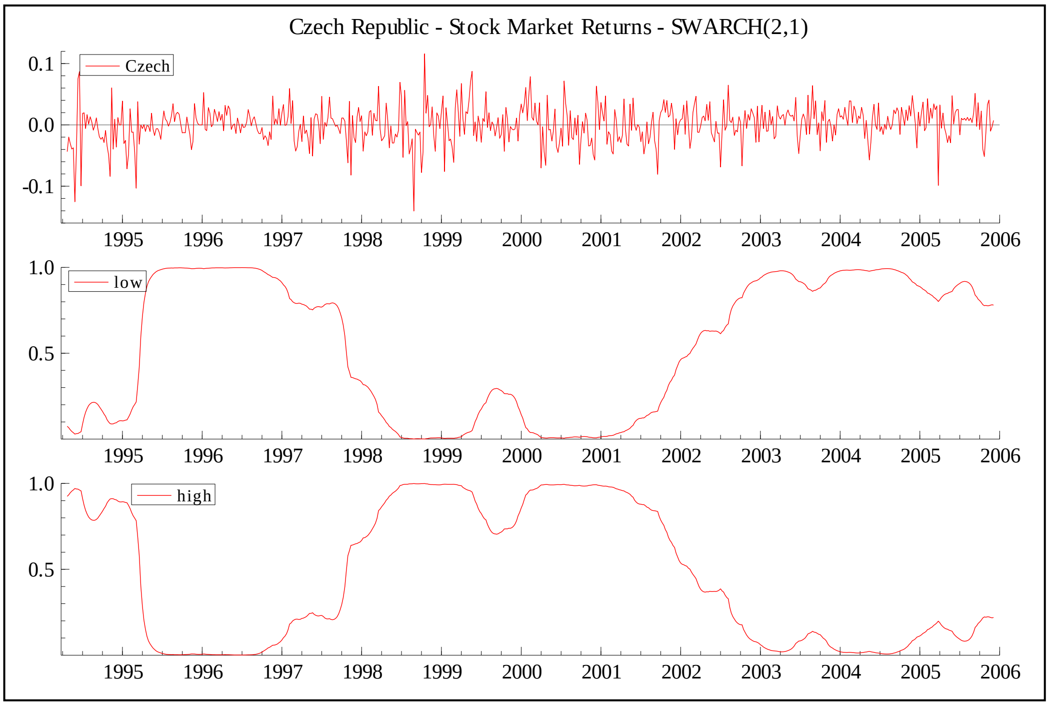

Figure 3: Smoothed probabilities for Estonia

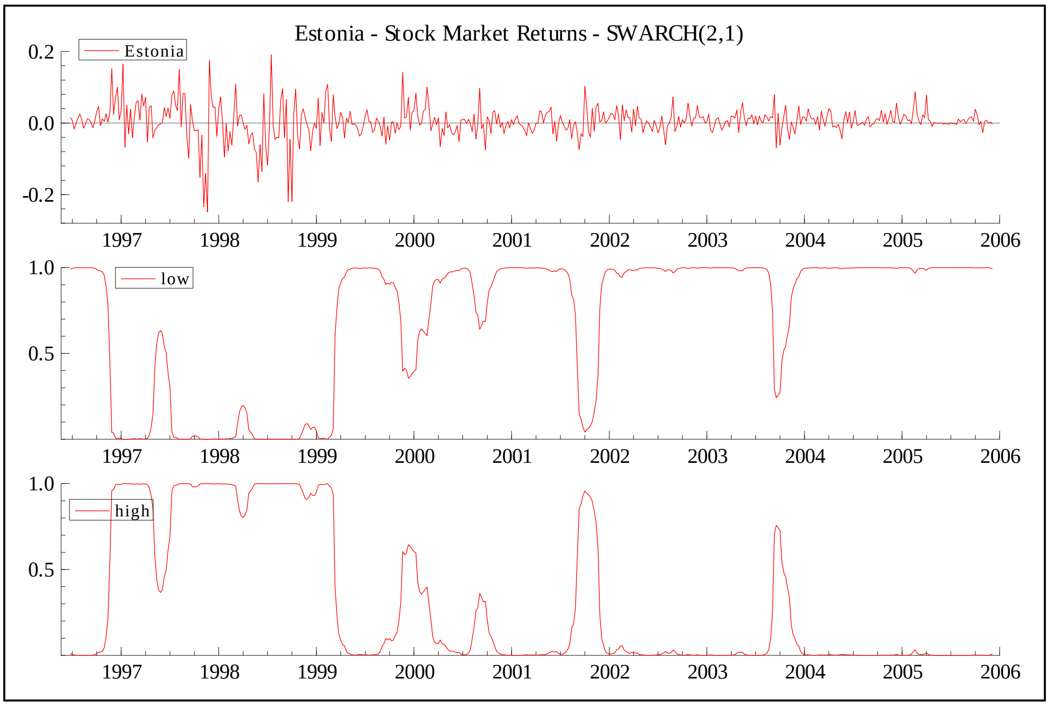

Figure 4. Smoothed probabilities for Latvia

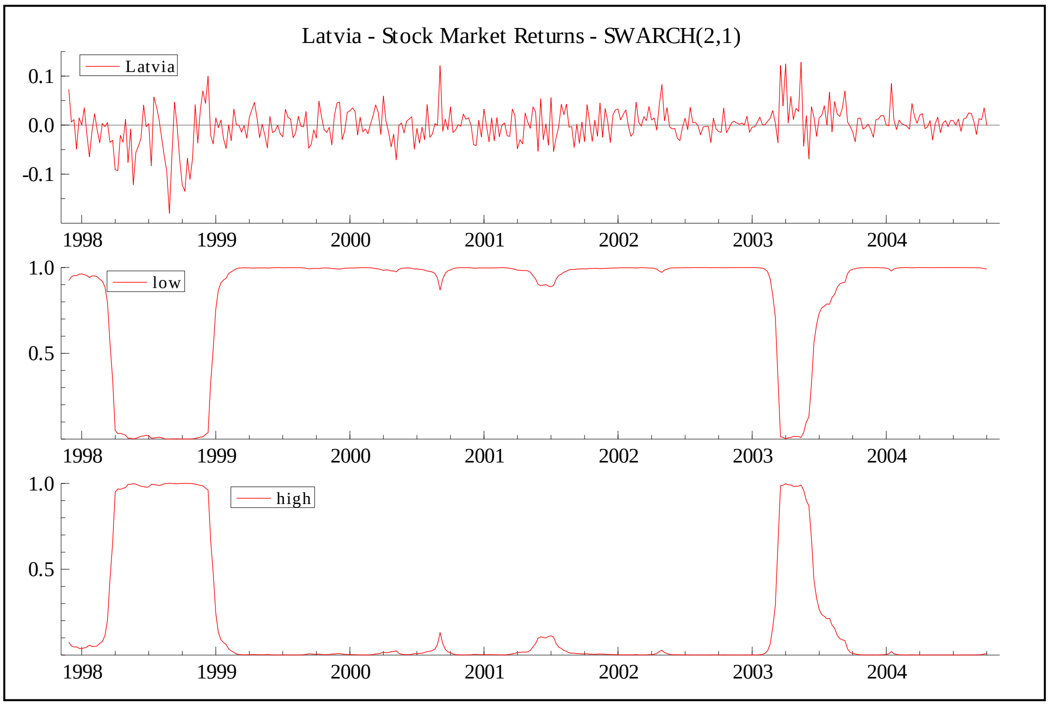

Figure 5. Smoothed probabilities for Lithuania

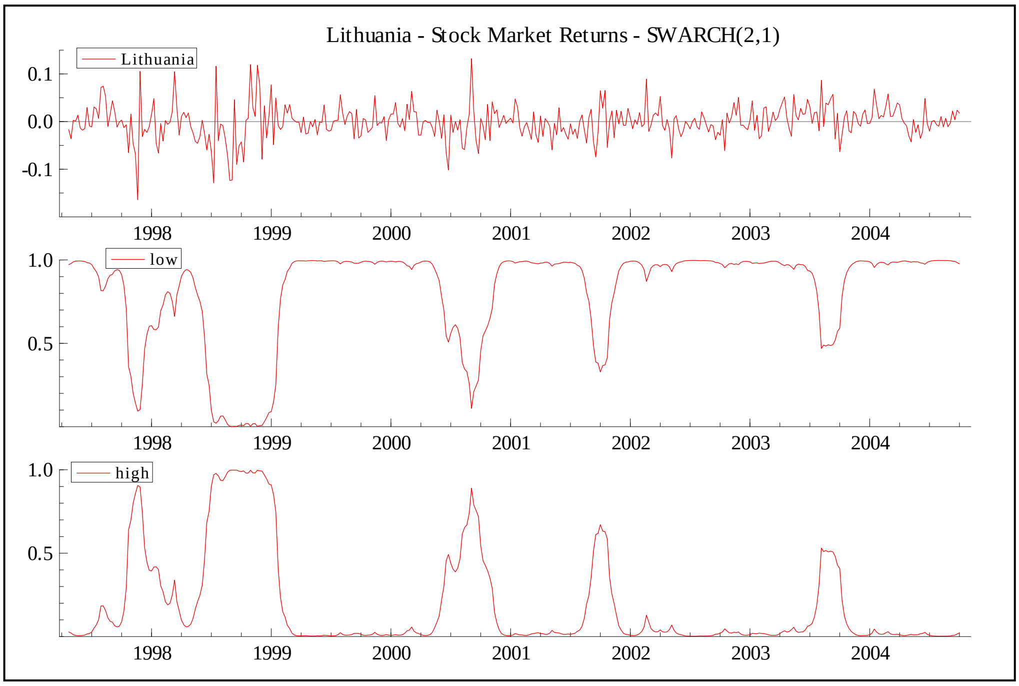

Figure 6. Smoothed probabilities for Hungary

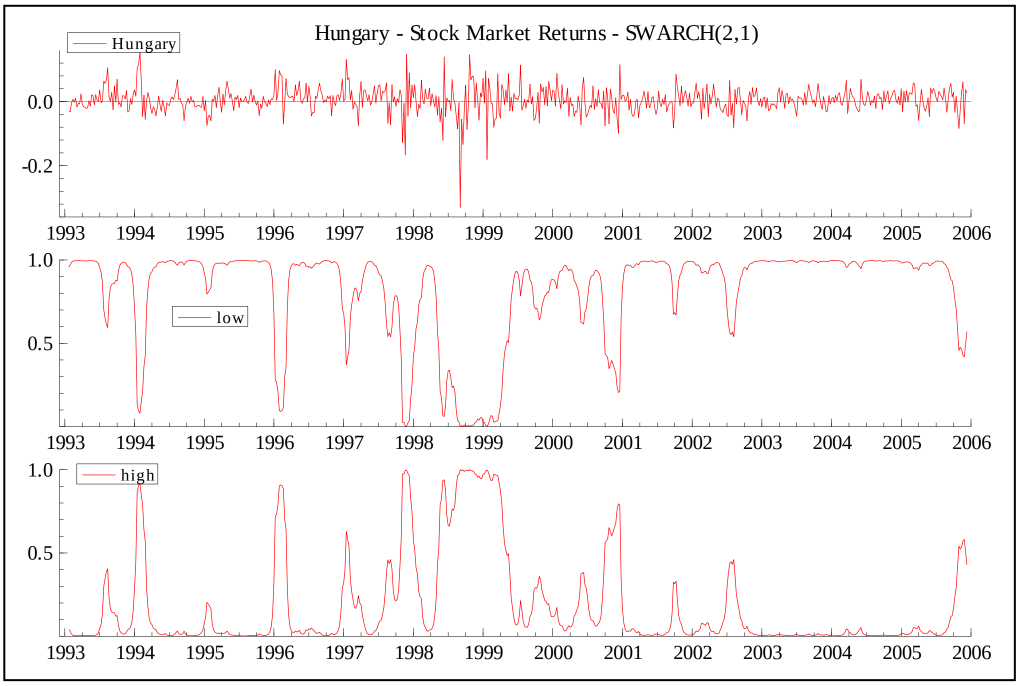

Figure 7. Smoothed probabilities for Poland

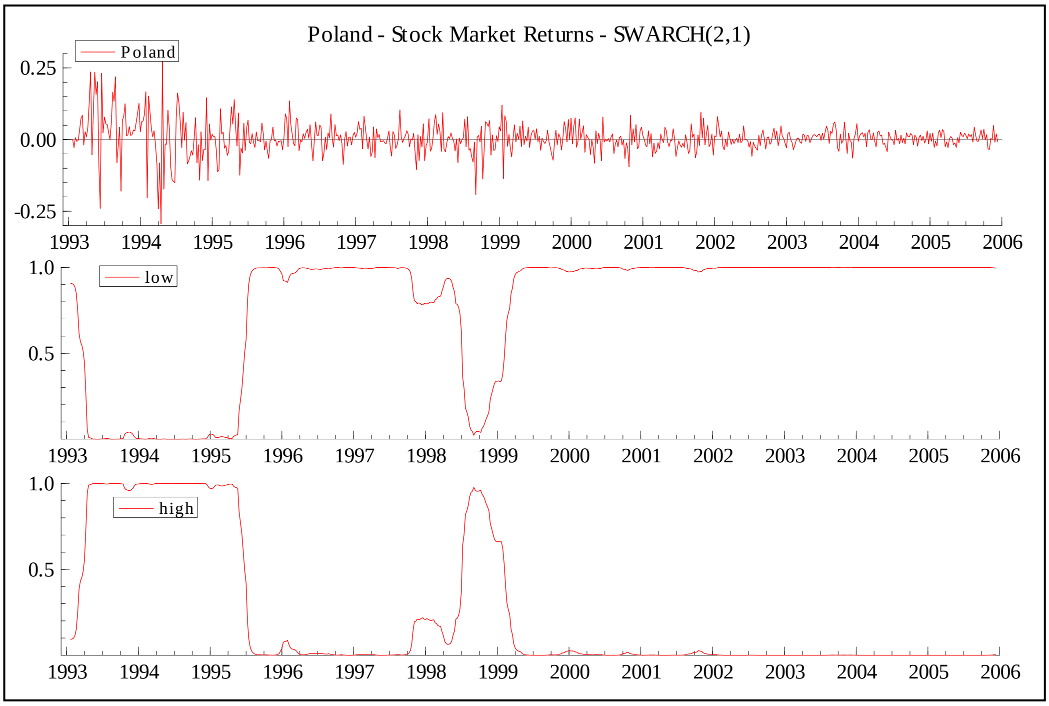

Figure 8. Smoothed probabilities for Romania

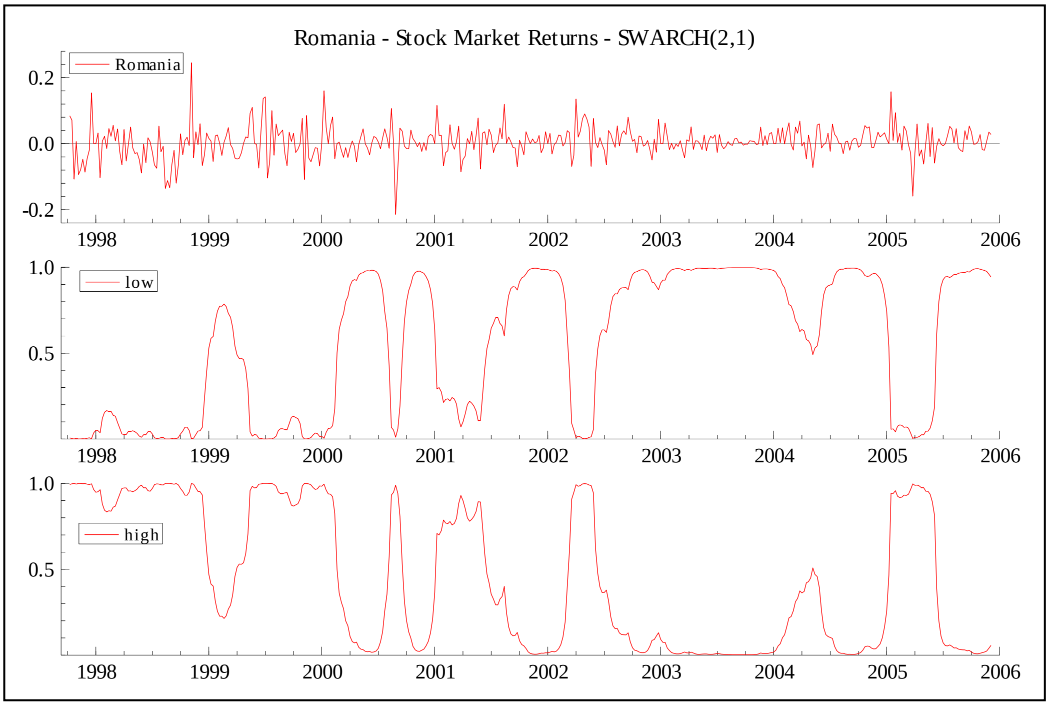

Figure 9. Smoothed probabilities for Slovakia

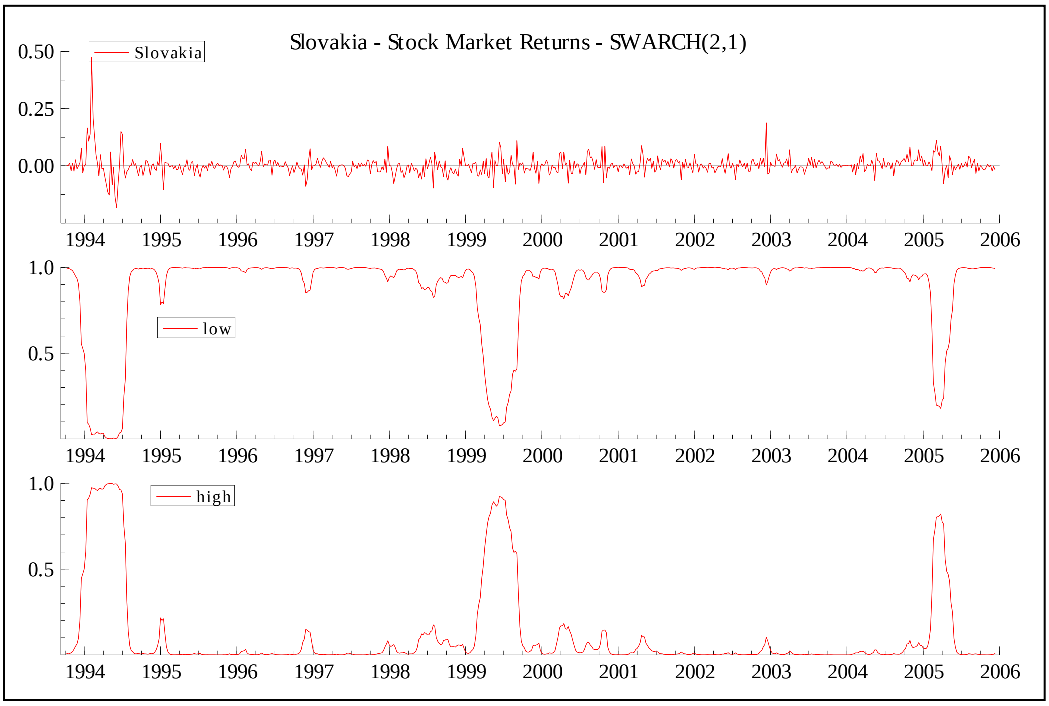

Figure 10. Smoothed probabilities for Slovenia