JEL Classification: E42, F31, F36 Keywords: CEEC, exchange rate volatility, regime switching GARCH, Markov switching model, transition economies

# Volatility Regimes in Central and Eastern European Countries' Exchange Rates<sup>\*</sup>

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#### Abstract

We investigate changes between volatility regimes in five Central and Eastern European countries to analyze whether these changes are consistent with changes in the official exchange rate arrangements. The analysis merges two approaches, the GARCH model (Bollerslev, 1986) and the Markov switching model (Hamilton, 1989). We discover switches between high- and low-volatility regimes consistent with policy settings for Hungary, Poland, and, to a lesser extent, the Czech Republic, whereas Romania and Slovakia do not show a clear picture. Furthermore, we check the robustness of the model regarding the choice of the error distribution and find that heavy-tailed conditional distributions substantially improve the results.

#### 1. Introduction

Central and Eastern European countries (CEEC) have experienced remarkable changes in the settings of their exchange rate arrangements. They are often regarded as examples for the hollowing out of intermediate exchange rate regimes (for a general discussion of the "hollowing of the middle" hypothesis, see inter alia Fischer, 2001). Most countries started with more or less pronounced intermediate exchange rate regimes and then chose different ways of adjusting them during their transition. The credibility of these arrangements was crucial to their success (for the need for a credible exchange rate system, see, for instance, De Grauwe and Grimaldi, 2002). Similar problems with exchange rate regime credibility<sup>1</sup> are known from the history of the exchange rate mechanism (ERM) of the European monetary system (EMS) between 1979 and 1999. The CEEC form a much more heterogeneous group than the former participants in the ERM regarding their exchange rate policy, because the ERM was supposed to be symmetric and the legal conditions were identical for all members. The CEEC, in contrast, chose very different exchange rate policies from the beginning and were not affected by any legal restrictions, as they opted unilaterally for their policy settings.

Thus, the contribution of this paper to the empirical literature on CEEC exchange rates is twofold:

First, we investigate structural breaks in exchange rate volatility over a sample which covers almost the whole process of transition for a set of five new member states of EU: the Czech Republic, Hungary, Poland, Romania, and Slovakia.<sup>2</sup> They

<sup>\*</sup> For helpful suggestions the author would like to thank Olaf Hübler, Robinson Kruse, and Lukas Menkhoff and anonymous referees.

<sup>&</sup>lt;sup>1</sup> The credibility of the exchange rate system cannot of course be separated from the credibility of monetary policy.

 $<sup>^{2}</sup>$  We also did the calculations for Slovenia. As there is a break in the data which seems to be due to sampling, the results are not consistent with the other series. The results are therefore not presented here.

will join the European Monetary Union (EMU) in the future.<sup>3</sup> We do not consider other new central European member or candidate countries because they have opted for very fixed exchange rate regimes without major changes.<sup>4</sup>

Second, we apply modern econometric methods by using a Markov switching GARCH model with *t*-distributed errors, which has not been applied yet to a broad set of CEEC. It allows distinguishing daily volatility clusters from permanent shifts and provides additional benefit compared to the use of a plain Markov switching model. Furthermore we show that heavy-tailed error distributions such as the student *t*-distribution or the generalized error distribution lead to more stable results in terms of regime persistence than the commonly applied normal distribution.

The structure of the paper is as follows. Section 1 has provided the motivation for the use of regime switching models for analysis of the credibility of exchange rate arrangements in CEEC. Section 2 reviews the literature while section 3 highlights the economic background of the CEEC. Section 4 introduces the Markov switching GARCH model, section 5 presents the data and estimation results, and section 6 summarizes the main results.

#### 2. Literature Survey

For the CEEC we can observe an increasing degree of exchange rate flexibility between 1994 and 2004, too.<sup>5</sup> Increased flexibility of the exchange rate, however, may not necessarily lead to higher volatility. Krugman (1991) argues that widening the fluctuation band will make it more credible, because it gets less likely that the fluctuation margins will be reached, and consequently volatility decreases. In contrast, Flood and Rose (1999) conclude that fixed exchange rate regimes are in general less volatile than floats. This result is confirmed by Hughes Hallett and Anthony (1997) and Frömmel and Menkhoff (2001) for the European Monetary System. Stannic (2007) corroborates this result for the Visegrád countries and Slovenia, but also stresses the importance of trade openness. Frömmel and Menkhoff (2003) additionally identify changes in monetary policy settings as a determinant of volatility switches for exchange rates of major industrial countries.

Empirical results from Berger et al. (2000) indicate that not only does the type of exchange rate regime affect volatility, but even the "wrong" choice of a peg (that is, the choice of peg by a country for which a flexible exchange rate would be more appropriate) induces higher exchange rate volatility than a peg which is in line with the macroeconomic conditions. Volatility can be seen as a measure of credibility of an exchange rate arrangement and serves as "a symbolic and visible measure of the gov-

<sup>&</sup>lt;sup>3</sup> Slovakia recently joined the Exchange Rate Mechanism 2 (ERM2) of the European monetary system, and in 2009 joined EMU. As all new member countries are obliged to join EMU as soon as possible, other countries will follow. For entry scenarios, see, inter alia, De Grauwe and Schnabl (2005).

<sup>&</sup>lt;sup>4</sup> Bulgaria, Estonia, and Lithuania have had currency boards since the early 1990s. Latvia has pegged its exchange rate to the special drawing right and since 2005 to the euro.

<sup>&</sup>lt;sup>5</sup> This movement towards more flexible exchange rate arrangements stopped in recent years after several of the CEEC joined the exchange rate mechanism (ERM2) of the European Monetary System and pegged their exchange rate to the euro within a band of ±15 percent. This is the case in particular for Slovakia and Slovenia, which had officially announced managed floats prior to their entry to ERM2. Slovenia and Slovakia joined EMU in 2007 and 2009, respectively.

ernment's success in macroeconomic management" (Duttagupta et al., 2004). Fidrmuc and Horváth (2008) apply various GARCH-type models to five new member states of the EU and find an inverse relation between credibility of the exchange rate regime and exchange rate volatility.

There are, however, few works which investigate structural breaks in the exchange rate volatility of Central and Eastern European transition economies. Kočenda (1998) compares GARCH estimates for the Czech koruna before and after the exchange rate band was widened in 1996 and finds significantly differing volatility patterns. Kóbor and Székely (2004) apply a simple Markov switching model to the exchange rates of the so-called Visegrád Group (the Czech Republic, Hungary, Poland, and Slovakia) between 2001 and 2003 and find frequent regime switches. Their sample period, however, does not include any change of the officially announced exchange rate system. Kočenda (2005) argues that a lack of coincidence between policy changes and structural breaks in exchange rate behavior may hint at policy settings which are not consistent with the opinion of market participants and therefore low credibility of the system. This is in line with the observation that if the costs of changing an exchange rate regime are high, a country may uphold an exchange rate regime even though it is not the optimal choice or even sustainable in the long run (Eichengreen and Masson, 1998; Juhn and Mauro, 2002).

Besides the credibility problem of intermediate exchange rate regimes, there is another, econometric reason to investigate structural breaks in exchange rate volatility: The GARCH model has turned out to be the workhorse in estimating conditional volatility. It is widely used<sup>6</sup> and provides accurate forecasts (Andersen and Bollersley, 1998). However, problems in estimating GARCH models may arise if the underlying volatility process is subject to structural breaks, especially shifts in the overall level of volatility. Klaassen (2002) argues that the empirical finding that the sum of estimated GARCH coefficients is close to or even exceeds one, implying an (almost) non--stationary volatility process in single-regime GARCH models, is due to neglecting regime changes, that is, the model is misspecified. In this case the persistence of volatility shocks is systematically overestimated (Lamoureux and Lastrapes, 1990; Timmermann, 2000; Caporale et al., 2003). A common way to deal with such structural breaks is to introduce dummy variables for subperiods reflecting the change in volatility level. In most cases, however, it is not possible to determine the date of the shift sufficiently accurately, or the date itself is subject to the analysis and cannot be determined exogenously. Therefore, we apply a Markov switching GARCH model (MS-GARCH) for modeling the structural break endogenously.

We apply a Markov Switching GARCH model (MS-GARCH) for modeling the structural break endogenously. This model merges the classical GARCH model (Bollerslev 1986) with the Markov switching model (Hamilton 1989). While there have been various applications of plain Markov switching models to exchange rates following the seminal paper by Engel and Hamilton (1990)<sup>7</sup>, the Markov Switching GARCH (MS-GARCH) model has been independently introduced by Cai (1994) and

<sup>&</sup>lt;sup>6</sup> For a survey see, inter alia, Bollerslev, Engle, and Nelson (1994).

<sup>&</sup>lt;sup>7</sup> Applications include inter alia Engel (1994), Dewachter (1997), Frömmel et al. (2005), Kanas (2006), De Grauwe and Vansteenkiste (2007) among others.

Czech Republic		Hungary		Poland		
03/03/1993– –29/02/1996	<i>Basket peg</i> : 65% DEM, 35% USD, Band: ±0.5%	02/08/1993– –15/05/1994	Adjustable peg: (irregular devaluations): 50% USD, 50% DEM, Band: ±0.3-±2.25%	14/10/1991- 05/03/199	Crawling peg: 45% USD, 35% DEM, 50% FRF, 5% CHF, Band: ±0.6 %	
		16/05/1994– –15/03/1995	ECU 70%, USD 30 %	06/03/1995- 	Band: ±2 %	
01/03/1996– –26/05/1997	Band: ±7.5%	16/03/1995– –31/12/1996	Crawling peg: Band: ±2.25%	16/05/1995- 24/02/1998	Band: ±7%	
27/05/1997– –present	Managed float	01/01/1997– –31/12/1998	70% DEM, 30% USD	25/02/1998- 31/12/1998	Band: ±10%	
		01/01/1999– –31/12/1999	70% EUR, 30% USD	01/01/1999- 	- 45% USD, 55% EUR	
		01/01/2000– -30/04/2001	100% EUR	25/03/1999- 	Band: ±15%	
		01/05/2001– –30/09/2001	Band $\pm 15\%$	12/04/2000- -presenT	Free float	
		01/10/2001– –25/02/2008	Horizontal peg: 100% EUR, Band: ±15%			
		26/02/2008– –present	Free float			
Romania				Slovak Republic		
01/01/1994-present Managed float			14/07/1994–31/1	Basket peg:           14/07/1994–31/12/1995         60% DEM, 40% USD,           Band: ±1.5%         80% DEM, 40% USD,		
			01/01/1996-30/0	)7/1996	Band: ±3%	
			31/07/1996-31/1	31/07/1996–31/12/1996		
			01/01/1997_30/0	01/01/1997–30/09/1998		
			01/10/1998–24/1	1/2005	Managed float	
			25/11/200 31/12/200 01/01/200	5 8 9	<i>Peg:</i> 100% EUR, ±15% (ERM2) <i>EMU</i>	

#### Table 1 Official Exchange Rate Regimes since 1994

Source: Kočenda (2005) extended by the author based on national sources.

Hamilton and Susmel (1994). It has only recently been applied to exchange rates (see inter alia Klaassen 2005, Brunetti et al. 2008, Wilfling 2009).

## 3. Exchange Rates of Central and Eastern European Countries

Post-communist countries often started the process of transition by opting for a stabilization strategy in terms of a fixed exchange rate. *Table 1* shows the evolution of (official) exchange rate regimes, which have often been subject to changes.<sup>8</sup> These changes have involved changes to currency weights in basket pegs or to the devaluation rate (Hungary: January 1, 1997, January 1, 2000, May 1, 2001; Poland: January 1,

<sup>8</sup> Some authors, however, argue that there are significant discrepancies between official and de facto exchange rates (Levy-Yeyati and Sturzenegger, 2005; in particular for CEEC Frömmel and Schobert, 2006).

1999), changes to the bandwidth (Czech Republic: March 1, 1996; Hungary: May 1, 2001; Poland: May 16, 1995, February 25, 1998; Slovakia: January 1, 1997) or complete changes of regime, i.e., the introduction of a managed or free float (Czech Republic: May 27, 1998; Poland: April 12, 2000; Slovakia: October 1, 1998). The question of which of the changes are relevant is mainly an empirical one.

As *Table 1* shows, the Visegrád Group had very rigid systems in 1994. Subsequently, these fixed exchange rate regimes became more flexible (Sachs, 1996) and, after widening their bands, the Czech Republic (1997), Poland (2000), and Slovakia (1998) declared managed or freely floating exchange rates. Hungary kept the forint fixed versus the euro, but substantially widened its band to  $\pm 15\%$ , thus mirroring the exchange rate regime envisaged in the Exchange Rate Mechanism 2 (ERM2). The strategies of these countries combine the benefits of pegging to an anchor currency at the beginning, which reduced inflation and stimulated growth (Szapáry and Jakab, 1998), with the ability to cope better with volatile capital movements later (Corker et al., 2000). In contrast, Romania opted from the beginning for managed floats and has officially never changed its official exchange rate system.<sup>9</sup>

The evolution of exchange rate regimes in the CEEC is in line with the bipolar view (Fischer, 2001), which has emerged as some kind of mainstream opinion of exchange rate policy. The basic idea of the bipolar view is that adjustable pegs may be very costly and unsustainable, given that capital mobility is high. Therefore, they will be replaced in the long run by either hard pegs, such as currency boards and currency unions, or flexible exchange rates.

The empirical literature, however, shows that "what countries say they are doing may not be what they are doing" (Ishii and Habermeyer, 2002:344). It is widely accepted that monetary authorities suffer from a so-called fear of floating (Reinhart and Rogoff, 2004).

#### 4. The Markov Switching GARCH Model

The Markov switching GARCH (MS-GARCH) model was independently introduced by Cai (1994) and Hamilton and Susmel (1994).

For the *mean process* we rely on a simple random walk, since the analysis focuses solely on the variance dynamics of the exchange rate. That is, for the log of the exchange rate  $e_t$  the exchange rate return  $r_t = e_t - e_{t-1}$  is given by (conditional on the state variable  $s_t$ , which can take the value 1 or 2)

$$r_t = \begin{cases} \mu_1 + \varepsilon_t, s_t = 1\\ \mu_2 + \varepsilon_t, s_t = 2 \end{cases}$$
(1)

with conditional means  $\mu_i$ ,  $i \in \{1,2\}$  and an error term  $\varepsilon_t$ , which will be discussed in more detail later.

The *state process*  $s_t$  follows a time-discrete Markov process with two possible states.<sup>10</sup> The dynamics of this process are given by the transition matrix *P* and the probability distribution at t = 1:

<sup>&</sup>lt;sup>9</sup> Romania, however, introduced some administrative measures after a sharp depreciation of the leu in the first half of 1997, and since then it has actually used a series of crawling arrangements.

$$\boldsymbol{P} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}$$
(2)

Thus,  $p_{ii}$  is the probability of switching from state *i* to state *j*. If the regimes are stable one would expect  $p_{11}$  and  $p_{22}$  to be high, clearly above 0.5.  $\pi_1$  denotes the steady state probabilities of the Markov process (Hamilton, 1994), i.e. the unconditional probabilities of either regime as the starting values for the process in t = 0.  $\boldsymbol{\Phi}_t$  is the vector of available information at time t, i.e. the set of all realisations of the returns process up to time *t* and the vector  $\boldsymbol{\vartheta}$  of parameters,  $\mathbf{\Phi}_{t} = \{r_{t}, r_{t-1}, ..., r_{1}; \boldsymbol{\vartheta}\}$ (see Hamilton 1994:237).

Starting with the initial probabilities several series of probabilities can be calculated recursively:

The *filter probabilities*  $P(s_t=i|\boldsymbol{\Phi}_t)$  are the probabilities of being in state *i*, taking into account all the information up to time t that is based on the information set  $\Phi_t$  (see Kim and Nelson, 1999:63):

$$P(s_{t} = 1 | \boldsymbol{\Phi}_{t}) = \frac{f_{1}(r_{t}) \cdot P(s_{t} = 1 | \boldsymbol{\Phi}_{t-1})}{f_{1}(r_{t}) \cdot P(s_{t} = 1 | \boldsymbol{\Phi}_{t-1}) + f_{2}(r_{t}) \cdot P(s_{t} = 2 | \boldsymbol{\Phi}_{t-1})}$$

$$P(s_{t} = 2 | \boldsymbol{\Phi}_{t-1}) = 1 - P(s_{t} = 1 | \boldsymbol{\Phi}_{t})$$
(3)

and

$$P(s_t = 2 \mid \boldsymbol{\Phi}_t) = 1 - P(s_t = 1 \mid \boldsymbol{\Phi}_t)$$

where  $f_i(r_i) = f(r_i|s_i = i), i \in \{1,2\}$  are the densities of the return distribution, conditional on the state variable  $s_t$ .

The *ex-ante probabilities*  $P(s_{t+1} = i | \boldsymbol{\Phi}_t)$ , are the probabilities of being in regime *i* in the next period, based on today's information  $\boldsymbol{\Phi}_t$  (see Kim and Nelson, 1999:63):

$$P(s_{t+1} = 1 \mid \boldsymbol{\Phi}_t) = \sum_{i=1}^{2} P(s_t = i \mid \boldsymbol{\Phi}_t) \cdot p_{i1}$$
(4)

and

 $P(s_{t+1} = 2 | \boldsymbol{\Phi}_t) = 1 - P(s_{t+1} = 1 | \boldsymbol{\Phi}_t)$ 

Both series of probabilities are estimated recursively when calculating the likelihood function of the model. In contrast, the smoothed probabilities  $P(s_t = i | \boldsymbol{\Phi}_T)$ , based upon all information on its entire dataset, require an additional filter procedure. For our calculations we use the filter by Kim (1994).<sup>12</sup>

The major differences between different regime switching GARCH models follow the specification of the variance process, i.e., the conditional variance  $\sigma_t^2 =$ = Var( $\varepsilon_t | s_t$ ). It is a good starting point to consider the conditional variance along the lines of Bollerslev's (1986) original GARCH model and to consider the regime dependent equation for the conditional variance:

<sup>&</sup>lt;sup>10</sup> The model can be easily generalized to k states, and the mean process can be modified as well. This will not, however, lead to substantial changes in the model, so we rely on the simple model as described in the main text.

<sup>&</sup>lt;sup>11</sup> These include the transition probabilities, the GARCH parameters for both regimes, the conditional means and the distribution parameters.

<sup>&</sup>lt;sup>12</sup> For a detailed derivation of the filter see Kim and Nelson (1999), chapter 4.3.1.

$$\sigma_t^2 = \omega_{s_t} + \alpha_{s_t} \varepsilon_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2$$
(5)

The coefficients  $\omega_{s_t}$ ,  $\alpha_{s_t}$  and  $\beta_{s_t}$  correspond to the respective coefficients in the one-regime GARCH model, but may differ depending on the present state.

In equation (6) the term  $\varepsilon_{t-1}^2$  can be easily calculated as:

$$\mathcal{E}_{t-1}^{2} = (r_{t-1} - E[r_{t-1} | \boldsymbol{\Phi}_{t-2}])^{2}$$

$$= \left( r_{t-1} - \left[ P(s_{t-1} = 1 | \boldsymbol{\Phi}_{t-2}) \cdot \mu_{1} + \overbrace{P(s_{t-1} = 2 | \boldsymbol{\Phi}_{t-2})}^{=1-P(s_{t-1} = 1 | \boldsymbol{\Phi}_{t-2})} \cdot \mu_{2} \right] \right)^{2}$$
(6)

where  $\boldsymbol{\Phi}_t$  is again the set of information available at time t.

In contrast to  $\varepsilon_{t-1}^2$  the term  $\sigma_{t-1}^2$  in equation (5) requires additional consider-ations. When calculating  $\sigma_{t-1}^2$  problems arise due to its path dependence (Cai, 1994; Hamilton and Susmel, 1994; Gray, 1996; Klaassen, 2002). The present conditional variance  $\sigma_t^2$  depends not only on  $\sigma_{t-1}^2$  and  $\varepsilon_{t-1}^2$ , but also through  $\sigma_{t-1}^2$  on  $\sigma_{t-2}^2$  and  $\varepsilon_{t-2}^2$ and so forth. As  $\sigma_1^2$  to  $\sigma_t^2$  are also influenced by the respective value of  $s_t$ , today's conditional variance  $\sigma_t^2$  depends on the whole path of the state process  $s_1,..,s_t$  and the number of possible paths grows exponentially in t. Even on shorter series it is not convenient to integrate all the paths.

This problem will not occur if the term  $\beta_{s_t} \sigma_{t-1}^2$  is abandoned, i.e., where the model reflects a pure ARCH model, or if just the last few days are taken into consideration (Cai, 1994; Hamilton and Susmel, 1994).

Another, more appealing approach proposed by Grav (1996) is to follow the Markov switching model as a mixture of distributions and use in equation (5) the expected volatility based upon the ex-ante probabilities  $P(s_{t-2}|\boldsymbol{\Phi}_{t-2})$ , rather than the actual volatility. This leads to:

$$\sigma_{t-1}^{2} = E[r_{t-1}^{2} | \boldsymbol{\Phi}_{t-2}] - (E[r_{t-1} | \boldsymbol{\Phi}_{t-2}])^{2}$$
  
=  $P(s_{t-1} = 1 | \boldsymbol{\Phi}_{t-2}) \cdot (\mu_{1}^{2} + \sigma_{1,t-1}^{2}) + P(s_{t-1} = 2 | \boldsymbol{\Phi}_{t-2}) \cdot (\mu_{2}^{2} + \sigma_{2,t-1}^{2}) - (7)$   
 $- \{P(s_{t-1} = 1 | \boldsymbol{\Phi}_{t-2}) \cdot \mu_{1} + P(s_{t-1} = 2 | \boldsymbol{\Phi}_{t-2}) \cdot \mu_{2}\}^{2}$ 

Furthermore, Klaassen (2002) suggests replacing the ex-ante probability in equation (7) by the filter probability to use as much information as possible for the estimation. In this case equation (7) evolves to:

$$\sigma_{t-1}^{2} = P(s_{t-1} = 1 | \boldsymbol{\Phi}_{t-1}) \cdot (\mu_{1}^{2} + \sigma_{1,t-1}^{2}) + P(s_{t-1} = 2 | \boldsymbol{\Phi}_{t-1}) \cdot (\mu_{2}^{2} + \sigma_{2,t-1}^{2}) - \left\{ P(s_{t-1} = 1 | \boldsymbol{\Phi}_{t-1}) \cdot \mu_{1} + P(s_{t-1} = 2 | \boldsymbol{\Phi}_{t-1}) \cdot \mu_{2} \right\}^{2}$$
(8)

As Klaassen (2002) states, the choice of specification (7) or (8) only marginally affects the results. Therefore, we rely on Gray's specification.

We model the conditional *distribution of the error term* as a *t*-distribution,<sup>13</sup> which is quite popular in the traditional single-regime GARCH literature (see, for instance, Bollersley, Chou, and Kroner, 1992), but has been less widely used in the regime switching GARCH context so far (Klaassen, 2002). The fatter tails of the *t*-disribution (in comparison to the normal distribution) significantly improve the ability of the model to distinguish the different regimes (Klaassen, 2002). For example, in the low-volatility regime a single large innovation does not cause the model to switch to the high-volatility regime and the estimated regimes become much more stable. Hence, the distribution of the returns takes the following form:

$$f(r_t) = \begin{cases} f_1(r_t) = t_{\nu_1,\mu_1,\sigma_{1,t}^2}(r_t), \text{ if } s_t = 1\\ f_2(r_t) = t_{\nu_2,\mu_2,\sigma_{2,t}^2}(r_t), \text{ if } s_t = 2 \end{cases}$$
(9)  
$$P(s_t = j | s_{t-1} = i) = p_{ij}, \text{ for } i, j \in \{1,2\}$$

where  $t_{\nu_i, \mu_1, \sigma_{1,t}^2}(r_t)$  is the probability density function of the decentralized *t*-distribution with degrees of freedom  $\nu_i$ , mean  $\mu_i$  and variance  $\sigma_{i,t}^2$  for the regimes  $i \in \{1,2\}$ .

The use of a Markov switching model may not be obvious if only one regime change is found. However, even in the case of exactly one permanent break point the Markov switching model is not misspecified, as this is included as a special case.<sup>14</sup>

The constrained maximum likelihood function is calculated and maximized using GAUSS (edition 3.5). The transition probabilities  $p_{11}$  and  $p_{22}$  are constrained to the interval [0.001, 0.999]. Indeed, in section 4 some of the estimated transition probabilities are close to 0.999. This is not necessary, however, as the model will not break down in the presence of an absorbing state, but it seems to make some sense. Even if there is only one change from a volatile to a more tranquil period, a shift back would be likely if the sample was longer. Hamilton explicitly proposes this as the more appealing alternative to modeling the Markov switching model with an absorbing state: "Alternatively [to using a Markov chain with an absorbing state 2], we could have  $p_{21}$  quite close to zero, with the implication that in a sample of given size *T* we would likely see only a single shift, though that at some point in the future we should see a return to regime 1." (Hamilton, 1993:235).

#### 5. Data and Estimation Results

We use daily data for five CEEC – the Czech Republic, Hungary, Poland, Romania, and Slovakia – from January 1, 1994 to March 31, 2004. As the euro is the main anchor currency for these countries (see *Table 1*), we focus on the volatility of exchange rates versus the euro (and the Deutsche mark prior to 1999). The data is provided by the relevant national central banks and Thomson Financial DataStream. The use of daily data refers to exchange rate volatility as a high-frequency concept.<sup>15</sup>

 $<sup>^{13}</sup>$  An alternative to the use of the *t*-distribution could be the generalized error distribution (GED), which we also checked. The results are quite similar to those from the *t*-distribution. However, as the *t*-distribution is more commonly used in the context of (Markov switching) GARCH models, and converges faster, we rely on this one. We will take up this issue again in section 4 and provide some results for comparison.

<sup>&</sup>lt;sup>14</sup> Hamilton (1993:235) states: "Some might object that a change in regime could be represented as a *permanent* change [...], rather than the cycling and back and forth between states 1 and 2 that seems to be implicit in (1.2) [i.e., the Markov chain in Hamilton (1993)]. However the specification (1.2) allows the possibility of a permanent change as a special case if  $p_{21}$ =0."

	CZK	HUF	PLZ	ROL	SKK
μ	-0.011**	0.013***	0.022***	0.073***	-0.009*
	(0.005)	(0.002)	(0.008)	(0.011)	(0.004)
ω	0.002***	0.000	0.007***	0.015***	0.004***
	(0.001)	(0.000)	(0.002)	(0.004)	(0.001)
α	0.085***	0.304***	0.136***	0.097***	0.109***
	(0.013)	(0.041)	(0.018)	(0.014)	(0.018)
β	0.907***	0.828***	0.857***	0.882***	0.858***
	(0.012)	(0.012)	(0.016)	(0.014)	(0.019)
α+β	0.992	1.132	0.993	0.979	0.967
volatility	0.250	∞	1.000	0.714	0.121
V	4.608	2.877	4.735	4.501	4.080
L	-810.212	-190.993	-1907.470	-2623.959	-228.931
AIC	0.629	0.151	1.475	2.028	0.180
SIC	0.640	0.162	1.486	2.039	0.192
ARCH	0.119	0.004	0.181	1.203	0.192
LM	0.822	0.210	0.395	2.086*	2.516*
DW	2.077	1.993	2.092	1.766	1.640
SSR	462.341	504.269	1004.033	1764.552	280.947

Table 2 Results of GARCH Estimation for EU Accession Countries

Notes: Asterisks refer to the level of significance, \*\*\*: 1 per cent, \*\*: 5 per cent, \*: 10 percent; asymptotic standard errors in parentheses.

L: LogLikelihood; AIC, SIC: Akaike and Schwarz information criteria; ARCH: test for ARCH heteroskedasticity of standardized residuals; LM: Breusch-Godfrey serial correlation LM test; DW: Durbin Watson; SSR: sum of squared residuals.

Volatility is the unconditional variance:  $\omega/(1-\alpha-\beta)$ .

Single regime GARCH model:  $r_t = \mu + \varepsilon_t; \varepsilon_t \sim t_{\nu,\mu,\sigma_t^2}(r_t); \sigma_t^2 = \omega + \alpha \cdot \varepsilon_{t-1}^2 + \beta \cdot \sigma_{t-1}^2$ 

*Table 2* provides estimation results for a single regime GARCH model, whereas *Table 3* shows the corresponding results for the Markov switching GARCH model. It is obvious that for the single regime GARCH model some problems arise regarding the persistence of the variance process. For all exchange rates the sum  $\alpha + \beta$ is very close to one. A value of not much less than one implies that the conditional volatility converges to a steady state, but at a very low rate, i.e., the persistence of a volatility shock is extremely high. For the Hungarian forint  $\alpha + \beta$  even significantly exceeds 1, which means that a volatility shock does not converge to the steady state at all, but volatility shocks are persistent, implying a non-stationary variance-process.

In contrast, for the MS-GARCH model this issue is substantially improved. For all rates and regimes the sum  $\alpha+\beta$  is far away from one, indicating that the variance process returns much faster to the steady-state volatility than for the singleregime GARCH model. Generally, the volatility persistence is higher in the highvolatility regime 2 than in the low-volatility regime 1. This means the higher volatility in regime 2 is partly driven by a higher volatility persistence compared to regime 1. This observation is in line with recent empirical studies (Chaudhuri and Klaassen, 2001; Klaassen, 2002), which allow – in contrast to earlier studies (Cai, 1994; Hamil-

<sup>&</sup>lt;sup>15</sup> "Volatility is a 'high-frequency concept' referring to movements in the exchange rate over comparatively short periods of time. Misalignment, on the other hand, refers to the capacity of an exchange rate to depart from its fundamental equilibrium value over a protracted period of time." (Artis and Taylor, 1988:188).

MS GARCH								
	CZK	HUF	PLZ	ROL	SKK			
Regime 1 (low volatility regime)								
μ <sub>1</sub>	-0.013** (0.006)	0.012*** (0.002)	0.046*** (0.010)	0.058*** (0.011)	-0.015*** (0.005)			
$\omega_1$	0.011*** (0.003)	0.001 <sup>a</sup> ()	0.016** (0.007)	0.003 (0.002)	0.007 (0.005)			
α <sub>1</sub>	0.122*** (0.029)	0.407*** (0.148)	0.106*** (0.033)	0.013 (0.010)	0.120 (0.051)			
β <sub>1</sub>	0.698*** (0.063)	0.409*** (0.067)	0.785*** (0.060)	0.948*** (0.013)	0.670*** (0.153)			
α <sub>1</sub> +β <sub>1</sub>	0.820	0.816	0.891	0.961	0.790			
volatility	0.063	0.005	0.144	0.075	0.033			
<i>V</i> <sub>1</sub>	4.548	2.976	3.908	3.901	3.973			
	Regime 2 (high volatility regime)							
μ <sub>2</sub>	-0.004	0.017**	-0.016	0.213***	0.005			
	(0.014)	(0.006)	(0.013)	(0.051)	(0.010)			
$\omega_2$	0.037**	0.047***	0.028**	0.587***	0.030***			
	0.010)	0.074)	0.011)	0.076)	0.014)			
α <sub>2</sub>	(0.035)	(0.074)	(0.031)	(0.074)	(0.037)			
β2	0.893*** (0.055)	0.712*** (0.058)	0.809*** (0.047)	0.106 (0.054)	0.670*** (0.113)			
$\alpha_2 + \beta_2$	0.952	0.921	0.958	0.375	0.754			
volatility	0.754	0.596	0.646	0.938	0.165			
V <sub>2</sub>	5.694	2.673	5.788	7.206	4.699			
P <sub>11</sub>	0.998	0.997	0.999	0.998	0.992			
P <sub>22</sub>	0.995	0.998	0.999	0.984	0.991			
L	-788.210	-147.156	-1876.726	-2588.102	-211.810			
AIC	0.617	0.123	1.457	2.005	0.173			
SIC	0.624	0.129	1.463	2.012	0.179			
ARCH	0.010	0.001	0.011	0.001	0.001			
LM	0.833	0.960	2.161*	1.821	1.801			
DW	2.077	1.994	2.095	1.783	1.644			
SSR	462.230	504.024	1003.416	1753.93	280.570			

#### Table 3 Results of MS-GARCH Estimation for EU Accession Countries

Notes: Asterisks refer to the level of significance, \*\*\*: 1 per cent, \*\*: 5 per cent, \*: 10 percent; asymptotic standard errors in parentheses.

L: LogLikelihood; AIC, SIC: Akaike and Schwarz information criteria; ARCH: test for ARCH heteroskedasticity of standardized residuals; LM: Breusch-Godfrey serial correlation LM test;DW: Durbin Watson; SSR: sum of squared residuals.

Volatility is the unconditional variance per regime:  $\omega/(1-\alpha-\beta)$  [for the MS-GARCH-model separate calculation for each of the regimes].

<sup>a</sup> Coefficient estimates reach boundary.

ton and Susmel, 1994) – independent GARCH coefficients in both regimes. Only for the Romanian leu is the persistence in the low-volatility regime higher. The sum  $\alpha + \beta$ differs remarkably between the regimes. The difference is highest for the Romanian leu (0.375 in regime 1, 0.961 in regime 2). As an interim summary, our results support the view of Klaassen (2002), who argues that the high persistence of volatility shocks in single-regime GARCH models is due to neglecting regime changes, that is, the single-regime GARCH model is misspecified, whereas in our analysis the comparatively low values of  $\alpha + \beta$  do not point at additional undetected structural breaks.

Moreover, the choice of the *t*-distribution for the error terms is justified by the fact that all estimated degrees of freedom, for the single-regime GARCH as well as for the MS-GARCH model, are comparatively small. For the MS-GARCH model they are between  $v_2$ =2.673 for the Hungarian forint and  $v_1$ = 7.206 for the Romanian leu. These values imply a distribution with finite variance (as all degrees of freedom exceed 2) but much higher kurtosis compared with the normal distribution.<sup>16</sup>

While we do not provide a formal test between the alternatives, conventional information criteria in *Table 1* and 2 indicate that the regime switching model captures the characteristics of the volatility process better.<sup>17</sup> Furthermore, residuals tests show no sign of misspecification.

Another important feature of the estimation is the high persistence of the regimes: the transition probabilities  $p_{11}$  and  $p_{22}$  are close to 1 and never smaller than 0.984. This high regime persistence, which is also visible in *Figure 1* showing the smoothed probabilities  $P(s_l|\Phi_T)$ , is due to the choice of the *t*-distribution as the conditional distribution for the error term (see section 3 and also Klaassen, 2002).

We also did the calculations for alternative distributions of the error term. The model assuming normally distributed errors performs worst and leads to less stable regimes and less pronounced overall results. This serves as evidence for the usefulness of a heavy-tailed conditional distribution for distinguishing volatility regimes. In contrast, the generalized error distribution provides results that are quite similar to those achieved from the model with the *t*-distribution, leading to the impression that the results are comparatively stable to the particular type of conditional error distribution, as long as it is a heavy-tailed one. A visual comparison of the evolution of the smoothed probabilities is given in *Figure 2*. It is obvious that the methods, to some extent even the one making use of the normal distribution, hint at the same direction.<sup>18</sup>

*Figure 1* shows the probability of being in the high-volatility regime. The results indicate different characteristics of the countries. Hungary and Poland show the most clear-cut results, i.e., regime changes coincide with changes in the exchange rate system. In the case of *Poland* the volatility was initially low when the zloty was

<sup>&</sup>lt;sup>16</sup> The *t*-distribution can be approximated with the normal distribution for much higher degrees of freedom (Greene, 2000:68). Usually, the normal distribution is supposed to be a good approximation for  $\nu > 30$ . For some currencies we retrieve infinite kurtosis ( $\nu \le 4$ ) in the low volatility regime. The observation is in line with the general observation that the rigidity of an exchange rate regime strongly corresponds with the distributional properties of returns. Similarly, Hughes Hallett and Anthony (1997) and Frömmel and Menkhoff (2001) show that the introduction of the European Monetary System in 1979 has led to return distributions with lower volatility, but higher kurtosis.

<sup>&</sup>lt;sup>17</sup> Recent results such as in Psaradakis et al. (2009) provide evidence that model selection via standard information criteria turns out to be reliable in the case of regime switching models. Psaradakis et al. (2009) explicitly refer to the decision problem between Markov Switching and linear models. They come to the conclusion that standard information criteria are particularly useful "when the sample size and the parameter changes are not too small" (p. 393), which is clearly the case in our analysis.

<sup>&</sup>lt;sup>18</sup> We also tried a simple switching ARCH model of order one. The results are mixed. For some of the currencies the results are almost the same, but for some they get extremely noisy. It seems that the simpler structure of the ARCH model is not able to capture the complex dynamics of the volatility process sufficiently well. The results are not presented here, but are available on request.



Figure 1 Filter- and Smoothed Probabilities for EU Accession Countries

*Notes:* The bold lines are the smoothed probabilities  $P(s_t = 1|\Phi_t)$  of being in the high volatility regime, the dotted lines reflect the filter probabilities  $P(s_t = 1|\Phi_t)$  of being in the high volatility regime 1. The vertical lines represent changes in the exchange rate system of the respective country.

pegged to a broad basket of anchor currencies, with a fluctuation range of  $\pm 1$  percent at the beginning. Remarkably the extension of the range to  $\pm 7$  percent in 1995 did not lead to a substantial change in the volatility characteristics, although the filter probability (the dotted line) shows some more peaks after the change between 1995 and 1998. The results indicate that the most important change in the exchange rate regime in terms of volatility was the broadening of the range to  $\pm 10$  percent on February 25, 1998, which leads to a permanent transition to the high-volatility regime. At the same time, Poland changed its monetary policy strategy to inflation targeting, as suggested by Eichengreen (1999:C9). In contrast, the changes in Poland's basket of anchor currencies on January 1, 1999, had only a limited effect on the exchange rate volatility. The smoothed probability of the high-volatility regime increased to a value very close to one, and there are hardly any declines in the filter probability.



Figure 2 Smoothed Probabilities for Alternative Error Distributions

*Notes:* Given are the smoothed probabilities  $P(s_t = 1 | \Phi_T)$  of being in the high volatility regime, the bold line is the model with the *t*-distribution, the dotted line is the model with generalized error distribution and the thin grey line is the model with normal distribution.

The same applies to the period of Poland's independently floating exchange rate from 2000 on. Poland may be seen as the most successful country in our sample introducing greater exchange rate flexibility during a period of capital inflows (Eichengreen, 1999).

The estimation provides similarly clear results for *Hungary*. The initial volatility of the forint versus the Deutsche mark was comparatively high, although Hungary followed a very strict exchange rate peg with fluctuation margins of  $\pm 2.25$  percent only. This result, however, is puzzling at first sight only. Until January 2000, Hungary had pegged the forint to a basket of the ECU (since 1997 the Deutsche mark) and US dollar and then switched to a pure euro peg, thus significantly lowering the volatility against the Deutsche mark/euro. Therefore, there was a sharp decline in volatility (versus the euro) in early 2000. The situation changed again when Hungary sub-

stantially widened the fluctuation band from  $\pm 2.25$  to  $\pm 15$  percent in May 2001, accompanied by the introduction of an inflation targeting strategy instead of pure exchange rate targeting. In contrast, the transition from the crawling peg to a horizontal one a few months later had no effect on volatility. Summing up, both Poland and Hungary so far show a remarkable coincidence between changes in exchange rate volatility and changes in exchange rate and monetary policy.

Although the Czech Republic and Slovakia show a similar evolution in the official exchange rate regime as Hungary and Poland, the relationship between the volatility regimes and the exchange rate arrangement is – particularly for Slovakia – less pronounced. While the Czech koruna stayed in the low-volatility regime until the fluctuation margins were widened to  $\pm 7.5$  percent in March 1996, the probability of the high-volatility regime increased steadily from then on and was around 0.6 when the Czech Republic abandoned the peg and introduced a managed float in May 1997. The Czech Republic's exit from its peg took place amid a severe exchange rate crisis (for details see Begg, 1998, and Böhm and Ždárský, 2005). The Czech National Bank then decided not to spend its foreign exchange reserves and was forced to leave the peg in response to an increase in the current account deficit and massive capital outflows. Our results support the impression of a "not peaceful exit" (Asici and Wyplosz, 2003) from the peg and confirm the general picture of increased volatility after disorderly exits as drawn in Duttagupta et al. (2004). After the crisis and the abandoning of the peg the koruna's volatility swung back to the low-volatility regime in 1999 and again experienced some turmoil in 2002, which may be due to some lack of fiscal discipline at this time (Kočenda and Valachy, 2007).

The figure looks similar for Slovakia, starting with quite volatile exchange rates which calmed down after the turbulent first years. Dealing with substantial current account deficits and excessive budgetary spending by the government, Slovakia widened the band to  $\pm 7$  percent in January 1997. This was accompanied by a sudden transition to the high-volatility regime. During 1998, however, Slovakia's foreign exchange reserves dropped and the market started expecting a change in Slovakia's exchange rate arrangement. After a period of attempts to defend the peg, accompanied by high interest rates, the National Bank of Slovakia had to respond by replacing the basket peg by a managed float in October 1998. The effect on the volatility regime is not clear: the exchange rate changed frequently and irregularly between the high and the low-volatility state.<sup>19</sup> Compared to Hungary, Poland, and even the Czech Republic, the volatility of the Slovak koruna therefore shows the least distinguished and clear-cut evolution. Obviously there is little coincidence between monetary and exchange rate policy and the exchange rate behavior. This is in line with Kočenda (2005), who states that the decision was "only taken in response to the structural break that had already happened".

*Romania* is a special case in our sample, as it never changed its official exchange rate system. The regime probabilities reflect this well, showing no clear pattern in exchange rate volatility, which oscillates between the two regimes and does

<sup>&</sup>lt;sup>19</sup> Kočenda and Valachy (2006) report several parliamentary and presidential elections as well as political instability, which may account for the increases in probability of being in the high-volatility regime (Kočenda and Valachy, 2006:742).

not show any clear picture. However, there are some periods of increased probability of the high-volatility regime.

The sharp increase in late 1996 and the whole of 1997 coincides with the beginning of the liberalization of the Romanian foreign exchange market and administered prices, leading to an increase in yearly CPI inflation from less than 40 to more than 150 percent and a significant devaluation of the Romanian leu. The next and even more pronounced period of turmoil in the foreign exchange market starts at the end of 1998 and lasts for about one year. Problems in signing a stand-by agreement with the IMF, the correction of a potential overvaluation of the leu as well as some effect of the Russian crisis may be seen as the main reasons for this turmoil (Romanian National Bank, 1999).

Finally, the volatility breakout during 2000/2001 can be seen as a result of changes in exchange rate management by the Romanian National Bank. Although the official exchange rate regime was the same, there was a change in the de facto intervention policy, with the central bank switching to less frequent interventions (Romanian National Bank, 2002)

However, it must be stated that exchange rate volatility is only one indicator of uncertainty and credibility. Therefore, all results have to be considered precautionary, but seem to be reasonable at the same time.

### 6. Conclusions

In this paper we show first that the application of a standard single-regime GARCH model leads to variance processes which are at least almost non-stationary, whereas the use of a Markov switching GARCH model substantially improves the results. This result has some important impact on CEEC exchange rate research, as neglecting the regime switches found may lead to misleading results. Therefore, this first result mainly contributes to the econometric analysis of volatility processes.

Second, changes in the exchange rate volatility regimes for most CEEC in our sample coincide with major changes in the exchange rate system and monetary policy. This result is most pronounced for Hungary and Poland. The results particularly indicate that an increase in the flexibility of the exchange rate regime leads to an increase in exchange rate volatility. Neither country shows any severe mismatch between policy settings and market expectations. Furthermore, it is possible to identify the most influential policy changes in terms of the volatility against the Deutsche mark/ /euro. These are for Hungary the switch from a basket peg to a pure peg to the euro on January 1, 2000, and the introduction of inflation targeting and the widening of the fluctuation margins to  $\pm 15$  percent on May 1, 2001, and for Poland the widening of the band to  $\pm 7$  percent on February, 1998. For the Czech Republic we find a less precise, but still visible, coincidence of volatility regimes and policy settings. Prior to the introduction of wider fluctuation margins ( $\pm 7.5$  percent) exchange rate volatility was remarkably low. With the Czech exchange rate crisis the probability of the highvolatility regime increased steadily and reached its peak just after the peg was abandoned. From there, during the managed float, shifts start to become irregular. For Slovakia, after an initial slow-down in volatility we detect a sharp rise in the probability of the high-volatility regime during the turmoil in the Slovak foreign exchange market and the Russian crisis between 1996 and 1998 and no clear tendency afterwards. The latter also applies to the volatility of the Ro-manian leu over the whole period.

Third, besides these country-specific results one may draw more general conclusions. The results show the benefits of pegging the exchange rate in terms of reducing exchange rate volatility. The cases of Hungary and Poland in contrast provide some evidence for the success of gradually increasing exchange rate flexibility for exiting a peg (Eichengreen, 1999:C9). This is the case particularly when countries have liberalized financial markets, which means that they need to manage their exposure to international capital accounts and that they are more vulnerable to being forced off their currency pegs. This high vulnerability of intermediate exchange rate systems is also stressed by the results, as two out of the four countries pegging their currency – the Czech Republic and Slovakia – had to leave the peg under market pressure. The reason is that there was a mismatch between the existing exchange rate system and its credibility, resulting from a lack of flexibility in the exchange rate (regime) to react to changes in the economic situation. The credibility of an exchange rate arrangement is crucial to its success and it is always too late to exit smoothly from a peg when markets expect it.

As a conclusion, our results are strongly in favor of gradually widening the bandwidth of currency pegs early, and of crawling pegs instead of horizontal ones, giving a certain degree of flexibility to react to an evolving environment and to a clear commitment to a monetary policy strategy.

# APPENDIX

# Figure A1 Flowchart for the Estimation Procedure

 $P(s_1 = 1 \mid \Phi_0) = \frac{1 - p_{22}}{2 - p_{11} - p_{22}}$  $P(s_1=2|\Phi_0)=1-P(s_1=1|\Phi_0), \vartheta_0 \text{ (starting values)}$ Conditional volatility:  $\sigma_{t,s_t}^2 = \omega_{s_t} + \alpha_{s_t} \varepsilon_{t-1}^2 + \beta_{s_t} \sigma_{t-1}^2$ ,  $s_t=1,2$ Unconditional (regarding the regime) volatility:  $\sigma_t^{\ 2} = P\big(s_t = 1 \mid \Phi_{t-1}\big) \cdot \Big(\mu_1^{\ 2} + \sigma_{1,t}^{\ 2}\Big) + P\big(s_t = 2 \mid \Phi_{t-1}\big) \cdot \Big(\mu_2^{\ 2} + \sigma_{2,t}^{\ 2}\Big)$  $-\left\lceil P(s_t = 1 \mid \Phi_{t-1}) \cdot \mu_1 + P(s_t = 2 \mid \Phi_{t-1}) \cdot \mu_2 \right\rceil^2$ Densities:  $f_1(r_t) = t_{\nu_1,\mu_{1i},\sigma_1,t^2}(r_t), \ f_2(r_t) = t_{\nu_2,\mu_{2i},\sigma_2,t^2}(r_t)$ |t = t + 1Filter probabilities:  $P(s_t = 1 \mid \Phi_t) = \frac{f_1(r_t) \cdot P(s_t = 1 \mid \Phi_{t-1})}{f_1(r_t) \cdot P(s_t = 1 \mid \Phi_{t-1}) + f_2(r_t) \cdot P(s_t = 2 \mid \Phi_{t-1})}$  $P(s_{t} = 2 | \Phi_{t}) = 1 - P(s_{t} = 1 | \Phi_{t})$ Ex-ante probabilities:  $P(s_{t+1} = 1 | \Phi_t) = \sum_{i=1}^{2} P(s_t = i | \Phi_t) \cdot p_{i1},$  $P(s_{t+1} = 2 | \Phi_t) = 1 - P(s_{t+1} = 1 | \Phi_t)$ Error term:  $\varepsilon_t = r_t - [P(s_t = 1 | \Phi_{t-1}) \cdot \mu_1 + P(s_t = 2 | \Phi_{t-1}) \cdot \mu_2]$ 

$$\begin{split} & \textbf{Calculation of the log likelihoodfunction:} \\ & \Lambda = \sum^{T}_{l} log \big\{\! P(s_t = 1 \,|\, \Phi_{t-1}) \cdot \mathbf{f}_1(r_t) + P(s_t = 2 \,|\, \Phi_{t-1}) \cdot \mathbf{f}_2(r_t) \big\} \end{split}$$

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