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Foreign Exchange Market Volatility in EU Accession Countries in the Run-Up to Euro Adoption: Weathering Uncharted Waters

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Foreign Exchange Market Volatility in EU Accession Countries in the Run-Up to Euro Adoption: Weathering Uncharted Waters

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Abstract

The paper analyzes foreign exchange market volatility in four Central European EU accession countries in 2001–2003. By using a Markov regime-switching model, it identifies two regimes representing high- and low-volatility periods. The estimation results show not only that volatilities are different between the two regimes but also that some of the cross-correlations differ. Notably, cross-correlations increase substantially for two pairs of currencies (the Hungarian forint–Polish zloty and the Czech koruna–Slovak koruna) in the high-volatility period. The paper concludes by discussing the policy implications of these findings.

JEL Classification Numbers: C10, G10

Keywords: Markov regime-switching model, foreign exchange market volatility, EU accession countries

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I. INTRODUCTION

As European Union (EU) membership in 2004 became increasingly certain and macroeconomic stabilization took hold firmly in accession countries, expectations about euro adoption changed substantially bringing about rapid nominal convergence in the lead EU accession countries (but not in the accession countries overall) while stimulating convergence trades. Nominal convergence has, however, been anything but straightforward so far in financial markets. Expectations about the time of euro adoption have changed frequently (see, for example, Csermely, 2004), not least because of changing macroeconomic fundamentals and the unexpected turns of macroeconomic polices. As a result, market volatility has increased and spillovers among certain countries appear to have also become more frequent and stronger.

While market participants and policymakers have increasingly realized this phenomenon (see, for example, Reuters 2003 and 2003b; MTI, 2003; and TASR, 2003), the nature of these changes has not been analyzed in a formal way. In particular, no quantitative analysis is yet available to answer the question whether increased volatility and spillovers in certain countries and periods are due to an underlying structural change or are an inherent characteristic of these markets that has recently become more visible as market and policy shocks have become more frequent.

The paper aims to shed light on this question by carrying out a statistical analysis of foreign exchange spot markets in four Central European accession countries (CEACs): the Czech and Slovak Republics, Hungary, and Poland. The sample period covers May 2001 to September 2003, when no major exchange rate regime change took place in the countries under investigation.[2] We exclude the Baltic accession countries, because they continued to pursue highly fixed exchange rate regimes during this period.

The paper focuses on identifying periods in foreign exchange markets with different characteristics. The empirical analysis is based on Markov regime-switching models. This methodology allows us to identify separate joint normal distributions for the exchange rates of these countries for periods in which the parameters of these distributions are significantly different. Identifying and better understanding the nature of high-volatility periods and estimating the increases in volatility (standard deviation) and spillovers to other countries (correlations among markets in different countries) will enable policymakers to formulate better policies, including those on prudential regulations, for high-volatility periods.

[2] Choosing the sample period this way, we had to exclude some periods of particular interest in this regard in the 1990s, such as the attack on the Czech koruna in 1997. Though it would be interesting to analyze this period separately, we do not undertake this task here because we wish to concentrate on the run-up to the euro adoption.

II. Methodology

When analyzing economic time series, the data-generating process can often be described by shifting regimes characterized by different parameters. Regime-switching models enable us to separate these periods statistically and estimate the probability of an observation belonging to a given regime. The methodological difficulty is that, unlike in the case of a foreign exchange policy regime change which is declared by a central bank, regime changes in financial markets cannot be observed directly, because the regime change itself is treated statistically as a stochastic process. Consequently, we have to estimate the conditional parameters of the distributions in the different regimes, as well as those of the regime change process simultaneously.

Regime-switching models were first applied to macroeconomic analyses (see, e.g., Hamilton, 1989 and 1990), but by now they have become popular tools for risk analysis and asset pricing. Soledad Martinez Peria (1999) applied regime-switching models to analyze speculative attacks against EMS currencies. Darvas (2001) worked with SWARCH models (the combination of ARCH and regime switching models) to assess the credibility of the Hungarian exchange rate policy. Hardy (2001) applied a regime-switching price model for the calculation of both Value-at-Risk (VaR) and Expected Shortfall estimates, as well as for option pricing. She found that the majority of financial time series can be sufficiently described with two regimes. Billio and Pelizzon (2000) also applied such a model to estimate VaR. They found that the regime-switching model provided better VaR-estimations than the EWMA or GARCH (1,1) based models. Dueker and Neely (2001) applied regime switching models with conditional *t*-distributions to generate currency trading signals.

If we assume that financial factor changes follow an *m*-dimensional normal distribution with expected values μ_i and covariance matrices Ω_i conditional on the regimes, the density function of series y_t is given by

$$f(y_t | s_t = i) = \frac{1}{(2\pi)^{m/2} \det(\Omega_i)^{1/2}} \exp\left\{ -\frac{1}{2} (y_t - \mu_i)' \Omega_i^{-1} (y_t - \mu_i) \right\},$$

where s_t denotes the state or regime in period t . In the simplest way the switching of the regime s_t can be expressed as Markov-chain: let s_t be a random variable, which takes its values from the set of integer numbers of $\{1,2,\ldots,N\}$, assuming an N-state Markov-chain. The probability of $s_t = j$ is assumed to depend only on the previous observation:

$$P\{s_t = j | s_{t-1} = i, s_{t-2} = k, \ldots\} = P\{s_t = j | s_{t-1} = i\} = P_{ij}$$

In the case of N=2 regimes the transition probabilities are:

$$P(s_t = 1 | s_{t-1} = 1) = P_{11}$$
$$P(s_t = 2 | s_{t-1} = 1) = P_{12} = 1 - P_{11}$$
$$P(s_t = 1 | s_{t-1} = 2) = P_{21} = 1 - P_{22}$$
$$P(s_t = 2 | s_{t-1} = 2) = P_{22}$$

Hamilton (1994) shows that in the case of N=2 the $P(s_t=j)$ state probabilities can be expressed from the transition probabilities in the following form:

$$P(s_t = 1) = \frac{1 - P_{22}}{2 - P_{11} - P_{22}}$$

For further details see Hamilton (1994). The technical details of estimating this model are given in Appendix I. In our analyses we assume that the foreign exchange rate changes ($y_t = S_t / S_{t-1} - 1$) are not autocorrelated, and the conditional volatilities are time-independent.

III. Empirical Results

The analysis covers four CEACs—the Czech Republic, Hungary, Poland, and the Slovak Republic—in the period May 2001-September 2003.[3] As our preliminary analysis found the foreign exchange spot market in Slovenia almost completely independent from the other four CEACs, we limited our analysis to these four countries.

In analyzing these currencies, we used a 4-dimensional 2-state regime-switching model. As described above, we assumed the daily rate changes to follow a mixture of multivariate normal distributions; i.e., to be conditionally normally distributed. To test for stability, we also estimated the model for separate calendar years. The estimation results are presented in Tables 1 and 2 and Tables A1 to A4 in Appendix II. The autocorrelation test results shown in Table A5 (in Appendix II) generally support the assumption that daily exchange rate changes in these countries were not autocorrelated in the sample period.

The estimated regimes can be best interpreted as *high-* and *low-volatility periods* (Regimes 1 and 2). Although we found that all the moments were significantly different in the two regimes, it is the volatility which showed the most dramatic difference. The Czech, Polish and Slovak currencies had roughly twice as high volatilities in the high-volatility regime as in the low-volatility one. The Hungarian forint, on the other hand, showed an even more

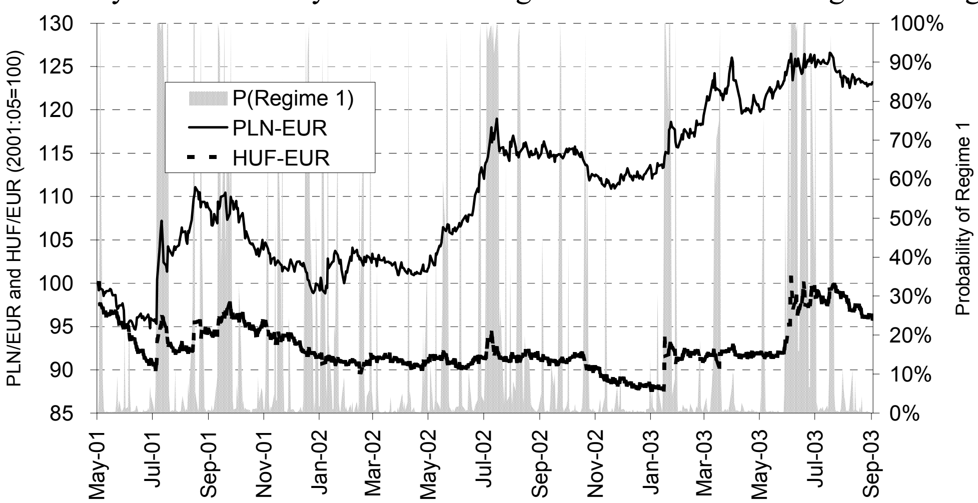
[3] The data set used in this analysis is available upon request from the authors.

dramatic increase in volatility, mainly explained by the speculative attack and the currency band shift in 2003.[4]

Our most important finding is not only that the volatilities were not constant over time, but they changed simultaneously across the four countries. That is, some of these currencies are closely related to each other, especially in the high volatility periods. Although these currencies did not necessarily and consistently moved into the same direction in the high-volatility periods, we could detect a consistent and simultaneous increase in their volatilities (Figures 1 and 2, and Table 1).

Generally, the high-volatility regime is characterized by a relatively sudden home currency depreciation (or appreciation of the euro), while in the low-volatility periods the home currencies tended to slowly appreciate.[5] Moreover, the cross-correlations of two currency-pairs—the Polish Zloty and the Hungarian Forint, and the Czech Koruna and Slovak Koruna—exhibited significant increases in the high-volatility regime (Table 1 and Figure 3).

Figure 1. History of Polish Zloty/Euro and Hungarian Forint/Euro Foreign Exchange Rates

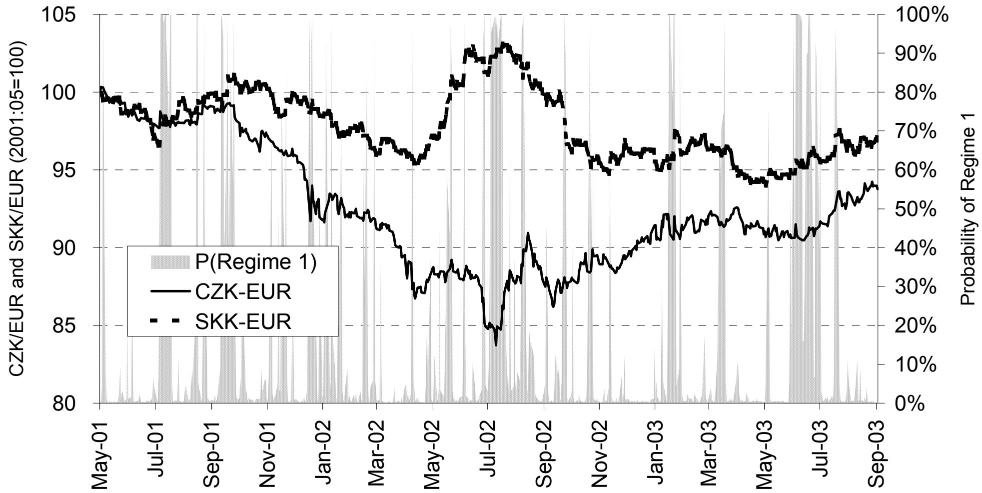


Source: Bloomberg

[4] We do not regard the band shift as a regime change because the central rate was changed by only 2.3 percent and the other main characteristics of the exchange rate regime remained unchanged.

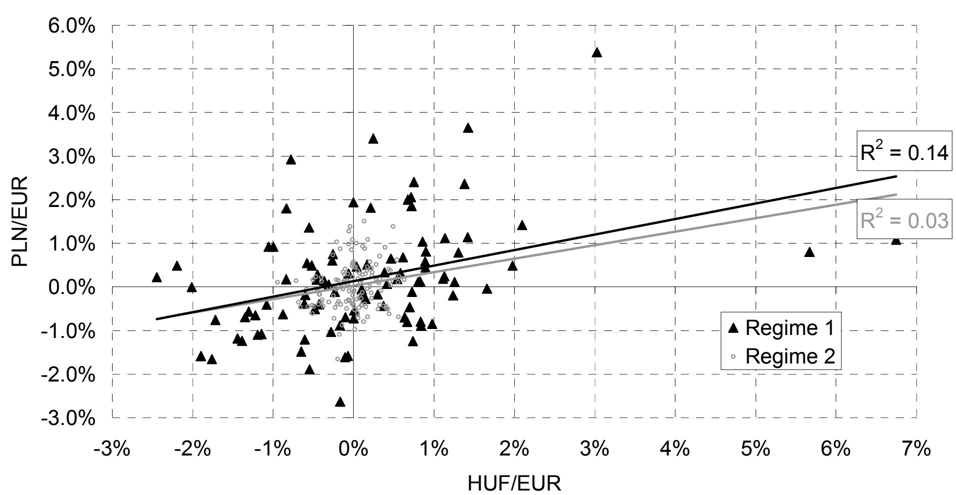
[5] However, as estimates of the conditional daily average exchange rate changes show, for certain-sub-periods characterized by strong trends, the regimes may not have been different in this regard.

Figure 2. History of Czech Koruna/Euro and Slovakian Koruna/Euro Rates



Source: Bloomberg

Figure 3. Daily Polish Zloty/Euro and Hungarian Forint/Euro Foreign Exchange Rate Changes 2001–2003



Source: Authors' own calculations.

Table 1. Regime-Switching Model Estimation Results

Currencies	Regimes	2001-2003	2001	2002	2003
Conditional Daily Volatility Estimations (%)					
CZK/EUR	Regime 1	0.63	0.65	0.59	0.47
	Regime 2	0.35	0.20	0.40	0.34
HUF/EUR	Regime 1	1.24	0.98	0.44	1.80
	Regime 2	0.31	0.39	0.31	0.30
PLN/EUR	Regime 1	1.19	1.52	0.90	0.93
	Regime 2	0.56	0.58	0.46	0.54
SKK/EUR	Regime 1	0.48	0.34	0.23	0.49
	Regime 2	0.23	0.25	0.34	0.22
Conditional Daily Average Return Estimation (%)					
CZK/EUR	Regime 1	0.05	-0.02	-0.04	0.03
	Regime 2	-0.02	-0.05	0.01	0.01
HUF/EUR	Regime 1	0.12	0.10	0.00	0.32
	Regime 2	-0.03	-0.09	-0.02	-0.01
PLN/EUR	Regime 1	0.19	0.26	0.14	0.11
	Regime 2	0.00	-0.08	0.01	0.04
SKK/EUR	Regime 1	0.09	0.04	-0.04	0.13
	Regime 2	-0.03	-0.02	0.00	-0.02
Selected Conditional Daily Correlations					
HUF/EUR vs. PLN/EUR	Regime 1	0.37	0.52	0.29	0.41
	Regime 2	0.27	0.34	0.26	0.16
CZK/EUR vs. SKK/EUR	Regime 1	0.42	0.66	0.48	0.58
	Regime 2	0.26	0.16	0.23	0.30

Source: Authors' own calculations.

State probability estimates provide information about the historical frequency of each regime, while the transition probabilities reflect regime persistence. The estimated probability of having a high-volatility day during the whole sample period was 18.4 percent (Table 2). The transition probabilities in the same table show that the probability of staying in the low-volatility regime was rather high, 90.7 percent. Put differently, the probability of switching to the high-volatility regime was 9.3 percent, while the probability of staying in the high-volatility regime, at 58.6 percent, was lower than for the low-volatility regime.

Table 2. State Probability and Transition Probability Estimations

	2001-2003	2001	2002	2003
P (Regime 1)	18.4%	23.2%	31.2%	20.1%
P (Regime 1 | Regime 1)	58.6%	69.6%	95.7%	73.1%
P (Regime 2 | Regime 2)	90.7%	90.9%	97.5%	93.2%

Source: Authors' own calculations.

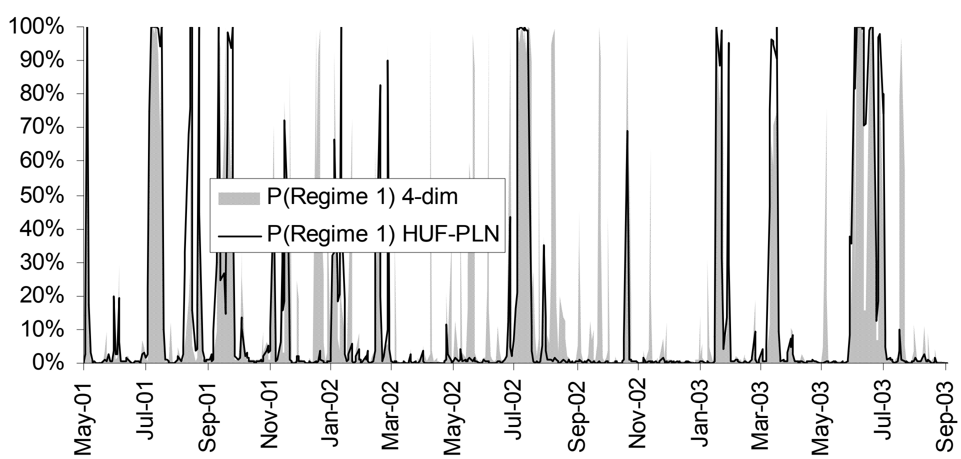
To test for parameter stability, we estimated the model for three sub-periods. Comparing these results (Table 1 and Tables A2 to A4), we find that estimates for 2002 seem to be different from those for the whole period, showing smaller volatility differences: only the Polish zloty had twice as high volatility in the high-volatility regime as in the low-volatility one. Different currencies behaved somewhat differently in the sub-periods. The Polish zloty had markedly larger changes in the conditional volatilities in 2001 (1.52 percent versus 0.58 percent daily volatilities) than in the whole sample period, while the Hungarian Forint showed a similar behavior in 2003 (1.80 percent versus 0.30 percent daily volatilities). Similar differences can be observed in conditional cross-correlations, state probabilities and transition probabilities.

Nonetheless, our main finding that volatilities are significantly different in the two regimes and that certain cross-correlations increase significantly in the high-volatility period remains valid in each of the sub-periods. The changes in the parameters however suggest that there are certain factors that may change some of the parameters of the model over time.

As Forbes and Rigobon (2001) point out, there may be a spurious increase in measured cross-correlations across markets in high volatility periods. While the essence of this critique may apply to this case as well, the fact that the cross-correlations increase only for the two pairs of currencies mentioned above suggest that the increase found here may be more than just a spurious increase. Given that the assumptions on the absence of exogenous global shocks and simultaneity do not hold in general we cannot, unfortunately, use the correction factor suggested by Forbes and Rigobon.

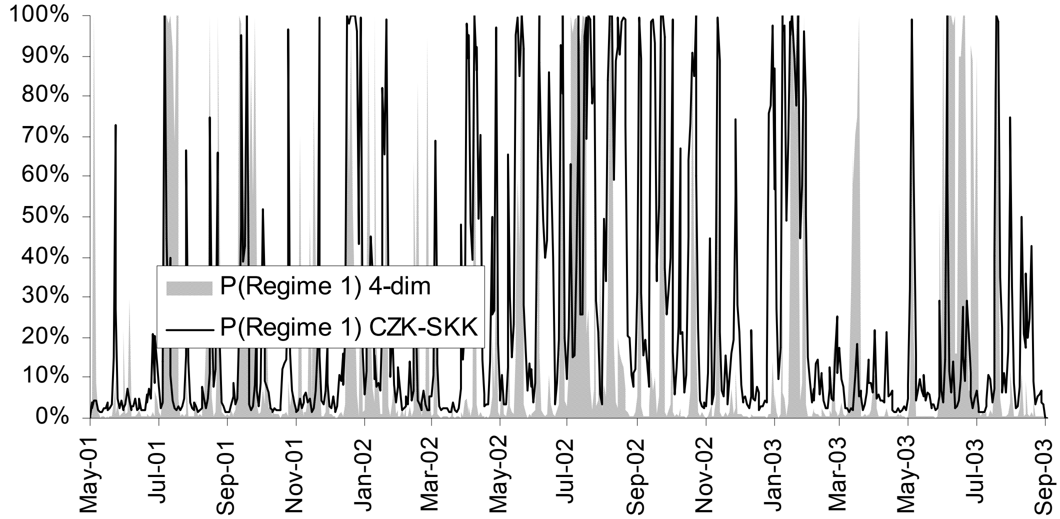
As we identified two pairs of currencies that appear to be closely linked, we re-estimated the model using 2-dimensional 2-state regime-switching models for the two pairs mentioned above (Tables A6 and A7 in Appendix II). Figures 4 and 5 show the probabilities of the high-volatility period for the two pairs using these estimates against the probabilities estimated from the original 4-dimensional model.

Figure 4. Hungary and Poland: Probability of High-Volatility Regime: Four- and Two-Dimensional Estimations



Source: Authors' own calculations.

Figure 5. Czech and Slovak Republics: Probability of High-Volatility Regime: Four- and Two-Dimensional Estimations



Source: Authors' own calculations.

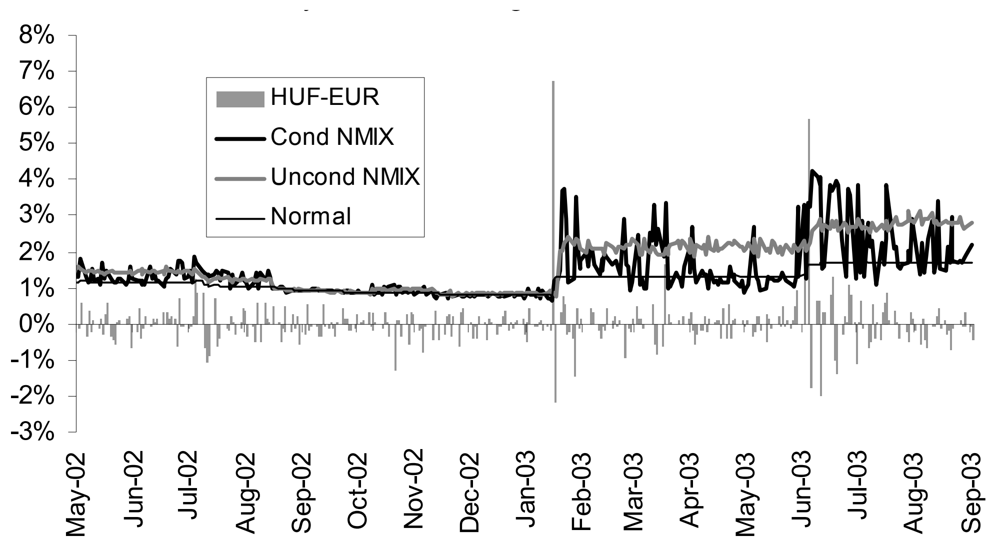
Though the model used here is not particularly designed to predict regime switch or future exchange rate changes, we tested the out of sample predictive performance of the model. The model was re-estimated for rolling 1-year sample periods. Using the model estimates, a 99-percent VaR estimate is given for the daily exchange rate change for the first out-of sample day. We followed three approaches in the VaR predictions, assuming:

- a joint normal distribution for the four currencies analyzed here;
- a mixture of joint normal distributions, applying the parameter estimations of the regime switching model. In this case the VaR-prediction depends on the distribution parameters and the general state probabilities $P(s=i)$, but it is independent from the state probability estimation $P(s_T=i)$ for the last observation day (*T*).
- a conditional mixture of joint normal distributions: the starting point is our state probability estimation $P(s_T=i)$ for the last observation day (*T*). We give our VaR-prediction based on this and the estimated transition probabilities.[6]

Figure 6 shows these estimates for the Hungarian Forint, while Table 3 presents the results for the Kupiec-p test for the period May 2002 to September 2003. The 4-dimensional mixed normal distribution based model clearly outperforms the single normal distribution based model.

[6] When applying the previous methodology, the VaR predictions do not depend on which regime the exchange rates are in. Here, however, the predictions will vary if the exchange rates are more likely to be in regime 1 than in regime 2.

Figure 6. Rolling 99 Percent VaR Estimation of Daily Change in Exchange Rate of Hungarian Forint



Source: Authors' own calculations.

Table 3. Out-of-Sample Predictive Performance (VaR Predictive Errors)

	CZK	HUF	PLN	SKK
Normal	2.6%	1.4%	1.4%	2.9%
Kupiec-p	*1%*	*45%*	*45%*	*0%*
Unconditional Normal Mixture	1.7%	0.9%	1.1%	2.9%
Kupiec-p	*22%*	*79%*	*79%*	*0%*
Conditional Normal Mixture	2.0%	1.1%	0.9%	2.6%
Kupiec-p	*10%*	*79%*	*79%*	*1%*

Source: Authors' own calculations.

Notes: Relative predictive errors (in percentage) of 99-percent VaR estimates for daily exchange rate changes. Values in the row for Kupiec-p show the probabilities, where the proportion for the exception test (see: Kupiec, 1995) is defined as

$$LR = 2\left[\ln\left(\left(\frac{N}{T}\right)^{N}\left(1-\frac{N}{T}\right)^{T-N}\right) - \ln\left(p^{N}(1-p)^{T-N}\right)\right] \sim \chi_1^2 .$$

N= number of losses exceeding VaR-prediction; T=number of observations; p=VaR confidence level

Rolling parameter estimations for May 2, 2002 – Sep 2, 2003 (350 days) with a sample period of one year.

IV. Policy Implications

There are a number of important policy implications of the finding that foreign exchange markets in the CEACs are likely to be subject to sudden shifts from low- to high-volatility regimes.

First, after entering ERM2 and aiming to meet the Maastricht exchange rate stability criterion, CEACs are likely to carry out intramarginal foreign exchange market interventions to keep their currencies within the band defined by the exchange rate stability criterion. As the band for this criterion is likely to be narrow, such interventions could be frequent and, almost by definition, carried out in high-volatility periods. Our results, however, suggest that foreign exchange intervention carried out in a high-volatility period in one CEAC may have strong (and helpful) implications for other CEACs. In these circumstances, the authorities have strong incentives to pursue a coordinated approach to intramarginal foreign exchange market interventions. When designing coordinated interventions, it would be better to take into account the characteristics of the joint distribution of exchange rates for the high-volatility period, rather than relying on an estimate for any given period that may include both high- and low-volatility periods.

Second, to the extent that the permissible range of exchange rate variability will be narrow (for example, 2¼ percent) on the weak side of the central parity for the purpose of the exchange rate stability criterion, CEACs with high variances (relative to the band's width) in the high-volatility regime will have an incentive to keep their exchange rates sufficiently above the central parity if they want to avoid frequent market interventions. Otherwise, with variances as high as 1.2 percentage points in the high-volatility period (for the Hungarian forint and the Polish zloty) and a probability of the high-volatility regime of around 18 percent, the probability of the exchange rate moving outside the permissible range in these countries would be considerable. If the permissible range will be narrow on both sides of the central parity, our results suggest that frequent interventions will be inevitable in these countries.

Third, when calibrating the parameters of stress tests and VaR analyses—which are standard methods used to assess financial system stability and compliance with certain prudential norms—it is of utmost importance to rely on the joint distribution of the exchange rates for the high-volatility periods rather than on a univariate distribution for any period that includes high- as well as low-volatility periods. This applies not only to the variance but also to the covariances, which also increase significantly when the system switches into a high-volatility period.

The increased volatility and cross-correlation detected in this paper reflect the behavior of market participants, in particular their portfolio-allocation decisions. Though our results show some stability of the underlying joint distributions and of the likelihood of switching from one regime to the other, the allocation and hedging strategies of investors can change rapidly and may even turn out to be endogenous to market volatility and central bank policies. Therefore, it would be important to identify the channels and products through which these markets are linked. By understanding these aspects, central banks and supervisory agencies will be in a much better position to continuously adapt their polices and procedures to changing market behavior.

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I. Estimation of Regime-Switching Models

Since the log-likelihood function of the mixture of normal distributions can have several local maxima, the ML-process is very sensitive to the initial parameters applied in the estimations, and the problem of singularity can easily occur (Hamilton, 1994). We applied the Expectation Maximization estimation process which effectively leads to an estimation result maximizing the likelihood function at the highest local maximum point (see for example, Hamilton, 1990).

The major steps of the applied E-M iterative algorithm are:

1. Parameters initialization for the iteration, $\theta^{(0)}$

2. Estimation of state and transition probabilities (E-step):

$$P\left(s_t = 1 \middle| y_T; \theta^{(0)}\right) \quad \forall t$$
$$P\left(s_t = 0 \middle| y_T; \theta^{(0)}\right) \quad \forall t$$
$$P\left(s_t = 1, s_{t-1} = 1 \middle| y_T; \theta^{(0)}\right) \quad \forall t$$
$$P\left(s_t = 1, s_{t-1} = 0 \middle| y_T; \theta^{(0)}\right) \quad \forall t$$
$$P\left(s_t = 0, s_{t-1} = 0 \middle| y_T; \theta^{(0)}\right) \quad \forall t$$
$$P\left(s_t = 0, s_{t-1} = 1 \middle| y_T; \theta^{(0)}\right) \quad \forall t$$

and calculating the $E \log f\left(y_T, s_T \middle| \theta^{(0)}\right)$ with the help of the estimated probabilities. In our application, the unobserved states are estimated by their smoothed probabilities.

1. *M-step*: new parameter estimation converging to the criterion of

$$\theta^{(1)} = \arg\max_{\theta} E\left[\log f\left(y_T, s_T \middle| \theta^{(0)}\right)\right].$$

2. Continuing the iterations until some convergence-criteria is met. The convergence can be defined as the marginal increase of the log-likelihood function, or as the change in the θ parameters. We followed the latter solution, continuing the iteration as long as the change of either of the values of the state and transition probabilities exceeded the 0.01 percent value per iteration.

In our analyses we applied the calculations and estimation steps as described in Diebold *et al.* (1994)[7]

[7] We worked with the C++ application implemented by *Arjan B. Berkelaar* and *Ádám Kóbor* for the Quantitative Strategies, Risk and Analytics Department, The World Bank.

II. Detailed Estimation Results

Table A1. Daily Observations for 2001–2003

Probability Regime 1	18.4
Probability Regime 2	81.6
Probability R1/R1	58.6
Probability R2/R2	90.7

	CZK	HUF	PLN	SKK
Mean Unconditional	**-0.01**	**-0.01**	**0.04**	**-0.01**
Mean 1	0.05	0.12	0.19	0.09
Mean 2	-0.02	-0.03	0.00	-0.03
Variance Unconditional	**0.41**	**0.60**	**0.72**	**0.30**
Variance Regime 1	0.63	1.24	1.19	0.48
Variance Regime 2	0.35	0.31	0.56	0.23

Correlations	CZK	HUF	PLN	SKK
CZK	1.0000	0.1510	0.1832	0.3400
HUF		1.0000	0.3289	0.1870
PLN			1.0000	0.1586
SKK				1.0000

Correlations Regime 1	CZK	HUF	PLN	SKK
CZK	1.0000	0.1269	0.1132	0.4211
HUF		1.0000	0.3730	0.1891
PLN			1.0000	0.1682
SKK				1.0000

Correlations Regime 2	CZK	HUF	PLN	SKK
CZK	1.0000	0.2029	0.2350	0.2624
HUF		1.0000	0.2675	0.1696
PLN			1.0000	0.1278
SKK				1.0000

Source: Authors' own calculations.

Table A2. Daily Observations for 2001

Pr Regime 1	23.2
Pr Regime 2	76.8
Pr R1/R1	69.6
Pr R2/R2	90.9

	CZK	HUF	PLN	SKK
Mean Unc.	**-0.05**	**-0.05**	**0.01**	**-0.01**
Mean 1	-0.02	0.10	0.26	0.04
Mean 2	-0.05	-0.09	-0.08	-0.02
Vol Unc.	**0.37**	**0.58**	**0.90**	**0.28**
Vol 1	0.65	0.98	1.52	0.34
Vol 2	0.20	0.39	0.58	0.25

Correl. (Unc.)	CZK	HUF	PLN	SKK
CZK	1.0000	0.2758	0.2895	0.3982
HUF		1.0000	0.4650	0.3618
PLN			1.0000	0.3051
SKK				1.0000

Correlations 1	CZK	HUF	PLN	SKK
CZK	1.0000	0.2819	0.3136	0.6554
HUF		1.0000	0.5166	0.6076
PLN			1.0000	0.5335
SKK				1.0000

Correlations 2	CZK	HUF	PLN	SKK
CZK	1.0000	0.2686	0.3209	0.1558
HUF		1.0000	0.3373	0.1250
PLN			1.0000	0.0832
SKK				1.0000

Source: Authors' own calculations.

Table A3. Daily Observations for 2002

Pr Regime 1	31.2
Pr Regime 2	68.8
Pr R1/R1	95.7
Pr R2/R2	97.5

	CZK	HUF	PLN	SKK
Mean Unc.	**0.00**	**-0.01**	**0.05**	**-0.01**
Mean 1	-0.04	0.00	0.14	-0.04
Mean 2	0.01	-0.02	0.01	0.00
Vol Unc.	**0.47**	**0.35**	**0.63**	**0.31**
Vol 1	0.59	0.44	0.90	0.23
Vol 2	0.40	0.31	0.46	0.34

Correl. (Unc.)	CZK	HUF	PLN	SKK
CZK	1.0000	0.0919	0.1247	0.2832
HUF		1.0000	0.2750	0.1026
PLN			1.0000	0.0939
SKK				1.0000

Correlations 1	CZK	HUF	PLN	SKK
CZK	1.0000	-0.0054	0.0378	0.4786
HUF		1.0000	0.2906	0.1119
PLN			1.0000	-0.1157
SKK				1.0000

Correlations 2	CZK	HUF	PLN	SKK
CZK	1.0000	0.1866	0.2501	0.2251
HUF		1.0000	0.2641	0.1014
PLN			1.0000	0.2603
SKK				1.0000

Source: Authors’ own calculations.

Table A4. Daily Observations for 2003

Pr Regime 1	20.1
Pr Regime 2	79.9
Pr R1/R1	73.1
Pr R2/R2	93.2

	CZK	HUF	PLN	SKK
Mean Unc.	**0.02**	**0.05**	**0.05**	**0.01**
Mean 1	0.03	0.32	0.11	0.13
Mean 2	0.01	-0.01	0.04	-0.02
Vol Unc.	**0.37**	**0.86**	**0.63**	**0.30**
Vol 1	0.47	1.80	0.93	0.49
Vol 2	0.34	0.30	0.54	0.22

Correl. (Unc.)	CZK	HUF	PLN	SKK
CZK	1.0000	0.1492	0.1667	0.4030
HUF		1.0000	0.2954	0.1604
PLN			1.0000	0.0811
SKK				1.0000

Correlations 1	CZK	HUF	PLN	SKK
CZK	1.0000	0.1785	0.0394	0.5756
HUF		1.0000	0.4096	0.1641
PLN			1.0000	0.0875
SKK				1.0000

Correlations 2	CZK	HUF	PLN	SKK
CZK	1.0000	0.1959	0.2449	0.3002
HUF		1.0000	0.1566	0.0721
PLN			1.0000	0.0712
SKK				1.0000

Source: Authors' own calculations.

Table A5. Estimated Autocorrelation Coefficients Daily Observations

	CZK-EUR	HUF-EUR	PLN-EUR	SKK-EUR
2001-2003	-0.05	-0.07	-0.03	0.06
95% Box-Jenkins	*±0.08*	*±0.08*	*±0.08*	*±0.08*
2001	-0.04	0.14	0.15	-0.01
95% Box-Jenkins	*±0.15*	*±0.15*	*±0.15*	*±0.15*
2002	-0.02	-0.11	**-0.21**	**0.16**
95% Box-Jenkins	*±0.12*	*±0.12*	*±0.12*	*±0.12*
2003	-0.15	**-0.18**	-0.15	-0.03
95% Box-Jenkins	*±0.15*	*±0.15*	*±0.15*	*±0.15*

Source: Authors' own calculations.
Note: Bolded estimates are outside the 95-percent Box-Jenkins significance interval.

Table A6. Estimation Results Based on Four-dimensional and Two-Dimensional Models: Daily Observations, 2001–2003

Currencies	Regimes	4-dimensional	HUF-PLN	CZK-SKK
Conditional Daily Volatility Estimations (%)				
HUF/EUR	Regime 1	1.24	1.42	N/A
	Regime 2	0.31	0.32	
PLN/EUR	Regime 1	1.19	1.36	
	Regime 2	0.56	0.55	
CZK/EUR	Regime 1	0.63	N/A	0.67
	Regime 2	0.35		0.27
SKK/EUR	Regime 1	0.48		0.47
	Regime 2	0.23		0.20
Conditional Daily Average Return Estimation (%)				
HUF/EUR	Regime 1	0.12	0.18	N/A
	Regime 2	-0.03	-0.03	
PLN/EUR	Regime 1	0.19	0.27	
	Regime 2	0.00	0.00	
CZK/EUR	Regime 1	0.05	N/A	0.07
	Regime 2	-0.02		-0.04
SKK/EUR	Regime 1	0.09		0.07
	Regime 2	-0.03		-0.03
Selected Conditional Daily Correlations				
HUF/EUR vs. PLN/EUR	Regime 1	0.37	0.36	N/A
	Regime 2	0.27	0.28	
CZK/EUR vs. SKK/EUR	Regime 1	0.42	N/A	0.70
	Regime 2	0.26		0.25

Source: Authors' own calculations.

Table A7. State Probability and Transition Probability Estimates

	4-dimensional	HUF-PLN	CZK-SKK
P (Regime 1)	18.4%	13.3%	26.1%
P (Regime 1 | Regime 1)	58.6%	72.5%	65.2%
P (Regime 2 | Regime 2)	90.7%	95.8%	87.7%

Source: Authors' own calculations.