ACADEMY OF ECONOMIC STUDIES
DOCTORAL SCHOOL OF FINANCE AND BANKING

COMMON VOLATILITY TRENDS AMONG CENTRAL AND EASTERN EUROPEAN CURRENCIES

- DISSERTATION PAPER -

MSc Student: ODANGIU ANDREEA RALUCA
Coordinator: Professor MOISĂ ALTĂR

Bucharest, July 2007

ABSTRACT

For the 12 new member states of the European Union, adopting the euro as the national currency some time in the next few years is not optional, as it was for the first 15 member states of the EU; it is a definite requirement which they eventually have to meet. This raises numerous questions regarding whether the economies in these countries are strong enough and sufficiently prepared for such an important step. While most of the papers on the subject deal with business cycle convergence, we focus on the common volatility trends among Central and Eastern European (CEE) currencies. We compare the long-run as well as short run volatility components and measure the intensity of volatility spillovers for each component. We also examine the evolution of conditional correlations, estimated from a multivariate GARCH model. Consistent with existing literature, our results suggest stronger linkages between the five currencies under analysis, although less strong than had previously been found for major European currencies. From the optimum currency area perspective, this would be a positive conclusion, but at the same time we believe it raises more problems for the policy makers of each country, as they have to increasingly take into account the actions of the other countries when making their own decisions. This calls for coordinated courses of action, which would be a very good exercise in preparation for euro adoption and a single, unified monetary policy.

CONTENTS

I. INTRODUCTION………………………………………………………………………… 4
II. LITERATURE REVIEW……………………………………………………………… 6
III. METHODOLOGY…………………………………………………………………… 10
1. The Component GARCH model……………………………………………….. 10
2. The Spillover Index…………………………………………………………….. 14
3. Multivariate models – the orthogonal GARCH model…………………………… 16
IV. EMPIRICAL DATA AND RESULTS………………………………………………….. 20
1. The data…………………………………………………………………………… 20
2. Preliminary analysis………………………………………………………………. 22
3. The Component GARCH model……………………………………………….. 23
4. The Spillover Index…………………………………………………………….. 28
5. The orthogonal GARCH model…………………………………………………31
V. CONCLUDING REMARKS……………………………………………………...35
Bibliography…………………………………………………………………………… 37
Appendix figures……………………………………………………………………...39
Appendix tables……………………………………………………………………….46

I. INTRODUCTION

It cannot be overstated how important exchange rates are for the economy, at any level that one might consider, be it micro- or macroeconomic. Furthermore, asset return volatility also plays a significant role in finance theory and practice. These are the reasons why exchange rate volatility has intensely preoccupied researchers, and an impressive number of papers have been written on the subject, from many different perspectives.

Focusing on the macroeconomic point of view, exchange rates have become more and more important especially in the context of increasing globalization and financial integration. The Asian crisis of '97 is probably the most cited example in this respect. The likelihood of such events happening again might be considered very small; nevertheless, it is probably a good idea to keep such phenomena in mind, to know how exchange rates work, and especially how they influence each other.

On the 1st May 2004, 10 new countries joined the European Union. On the 1st January 2007, another two, Romania and Bulgaria. For these 12 new member states, adopting the euro as the national currency some time in the next few years is not optional, as it was for the first 15 member states of the EU; it is a definite requirement which they eventually have to meet. This raises a great deal of questions regarding whether the economies in these countries are strong enough and sufficiently prepared for such an important step. Do business cycles have similar patterns in these countries? How are different types of shocks transmitted among them? How would giving up the national currencies impact on monetary policies?

But apart from these undoubtedly important questions, there are a lot of other issues regarding exchange rates per se. Before adopting the euro, every country has to be part of the Exchange Rate Mechanism, also known as ERM II, for at least two years. Specifically, the Maastricht Treaty requires, as a convergence criteria for any member country who wants to become part of the European Monetary Union, "the observance of the normal fluctuation margins provided for by the exchange-rate mechanism of the European Monetary System, without severe tensions, for at least two years, without devaluing against the currency of any other Member State". In the application of Treaty provisions, the ECB states that "the issue of the absence of "severe tensions" is generally addressed by: (i) examining the degree of deviation of exchange rates from the ERM II central rates against the euro; (ii) using indicators such as exchange rate volatility vis-à-vis the euro and its trend, as well as short-term interest rate differentials vis-à-vis the euro area and their development; and (iii) considering the role played by foreign exchange interventions"[1].

Under these circumstances, it appears essential for Central Banks to know very well the exchange rate volatility patterns of their country's own currency, but also the ones of the other currencies in the region, in order to have better expectations of how the exchange rate is going to be affected. Being part of the European Union essentially means increased mobility of persons, goods and capital, so markets are likely to become even more integrated; in order to avoid pressures due to very frequent foreign exchange interventions, Central Banks and other policy makers need to understand these aspects, in order to continuously adapt their policies and procedures to changing market behavior.

On the other hand, similar patterns of exchange rate volatility would suggest that the economies in question have achieved a sufficient degree of convergence in their economic and financial structures for a common monetary policy to be sustainable. If such similarities cannot be identified, then those countries probably would not form an optimum currency area[2].

The present paper examines the exchange rates of five of the twelve new member states of the EU, namely the Czech Republic, Hungary, Poland, Romania and Slovakia, over the sample period May 2001 – April 2007[3].

While these countries share some similarities, such as constant appreciation trends in their currencies' exchange rates during the past months, they also face specific issues. Poland is the only one of the twelve new member states that has not yet proposed a definite deadline for euro adoption, while Slovakia has already joined ERM II as of 28 November 2005. However, due to constant appreciation pressures on the koruna, the Slovak Central Bank has had to intervene frequently on the foreign exchange market, and eventually gain approval from the European Central Bank to lift the central parity rate by 8.5% as of 19 March 2007. The RON also faces similar appreciation pressures, which is one of the reasons why the National Bank of Romania has cut its monetary policy rate four times already since the beginning of 2007. Hungary was forced to postpone its plan to adopt the euro in 2010 after running up the European Union's widest budget deficit in 2006.

---

[1] For more details, see ECB's Convergence Report of May 2006 regarding Slovenia and Lithuania.

[2] The optimum currency area theory, as initiated by Mundell (1961), actually refers to regions/countries which already have a common currency, so the three requirements stated by Mundell do not include any references to exchange rates. However, when talking about countries which do not already have a common currency, adding the requirement of similar exchange rate patterns seems like a reasonable assumption.

[3] More details regarding the choice of countries and sample period, together with a full description of the data used, can be found in Section IV of this paper.

In light of all these different issues, we believe it is interesting to examine just how much do these five currencies really have in common. The aims of the present paper are as follows:

1. To identify a unitary model for the five exchange rate volatilities and to identify similar patterns among them;
2. To isolate the different sources of exchange rate volatility and to compute a measure for how much the currencies influence each other;
3. To examine how the correlations between these five currencies have evolved over the time period under analysis.

Our main contribution, apart from estimating the CGARCH and OGARCH models for this particular group of currencies over the specified sample period, relies especially on the measures of volatility spillovers which we compute, following the approach of Diebold and Yilmaz (2007), for the permanent component of volatility as well as for the transitory component. Such an analysis has never been performed before in previous papers, at least to this author's knowledge.

The rest of the paper is organized as follows: Section II presents a selection of relevant literature on the issues at hand. Section III introduces the concepts and models used in the empirical analysis. Section IV describes the data, the actual implementation of the models and discusses the results, while Section V concludes.

II. LITERATURE REVIEW

An impressive number of papers have been written concerning asset return volatility in general, and exchange rate volatility in particular, so it is very difficult to present a comprehensive summary of approaches and conclusions reached. However, this section presents the studies believed to be most relevant for the specific issues analyzed in the present paper.

Engle and Bollerslev first presented the ARCH and GARCH models in the early '80s. Although these models have enjoyed great success, being able to capture several features of financial returns series (such as volatility clustering, for instance) and proving themselves very useful in forecasting volatility of these series (especially over short time horizons), they do have certain limitations which leave room for improvement. Consequently, for the past two decades numerous attempts have been made to create new types of GARCH models that would avoid the shortcomings of the original specification. Teräsvirta (2006) presents a review of several univariate GARCH models, from the initial GARCH of Bollerslev to GJR-GARCH (the asymmetric model of Glosten, Jagannathan and Runkle), exponential GARCH (of Engle and Ng), nonlinear GARCH (smooth transition GARCH and threshold GARCH), time-varying GARCH and Markov-switching ARCH/GARCH (introduced to eliminate the restriction of constant parameters over time), integrated and fractionally integrated GARCH (to account for the slow decay in autocorrelation functions of many squared returns), and GARCH-in-mean models. The paper also discusses the ability of both the GARCH(1,1) and the EGARCH models to capture the so-called 'stylized facts' of financial time series (high kurtosis, slow decay of the absolute values or squares of the returns) and ways of comparing the appropriateness of different GARCH specifications.

Also on the subject of the ability of different volatility measures to capture the high kurtosis observed in asset returns (especially at higher frequencies), Andersen et al. (2000) conclude that exchange rate returns become almost Gaussian only when standardized by realized volatility. By daily realized volatility they understand the sum of the 30-minute continuously compounded returns over one day. Neither GARCH(1,1) volatility, nor forecasts of realized volatility cannot fully account for the excess kurtosis. They illustrate their findings with the help of the USD/JPY and USD/DEM exchange rates.

Andersen et al. (2005) is an extensive review of different volatility measures, at univariate as well as multivariate, presented from a very practical risk management perspective. First they consider portfolio level analysis, computing Value at Risk (VaR) measures using volatility from historical simulations, exponential smoothing and the GARCH(1,1) model. Then, moving on to multiple-asset level analysis, they model covariance matrices via exponential smoothing and multivariate GARCH. On this last issue, the focus turns to dimensionality reduction by using the Flex-GARCH model (suggested by Ledoit, Santa-Clara and Wolf) or the Dynamic Conditional Correlation model (suggested by Engle). In the same spirit as Andersen et al. (2000), they also introduce the notions of realized variances and realized covariances, and explore risk measures for high-frequency data. In the last part of the article they discuss modeling entire conditional return distributions using analytic simulation methods.

Engle and Lee (1993) is the article which first presents the Component GARCH model. Based on the finding of a unit root in the volatility process, which indicates that there is a stochastic trend as well as a transitory component in stock return volatility, they propose a decomposition of conditional variance into a long-run and a short-run component. After establishing the statistical properties and the stationarity conditions for the new model, they illustrate it empirically using the S&P Index for the period 1941 – 1991 and the NIKKEI Index for the period 1971 – 1991. The new model appears to outperform the GARCH(1,1) model (as suggested by Likelihood Ratio tests), enriching the dynamic specification of the conditional variance. They also augment the new model with a GJR-like term meant to capture asymmetries in the response of volatility to shocks, which proves to be significant only in the case of the transitory component of volatility.

The CGARCH model is the starting point of several relatively recent papers. Maheu (2005) examines whether the CGARCH model is able to capture long-range dependence observed in time series volatility, as measured by the sample autocorrelation function. Using several equity and exchange rate returns, he finds that the rate of decay implied by the CGARCH model is generally more appropriate than the exponential decay implied by the GARCH(1,1), and very comparable to the FIGARCH(1,d,1) model. Byrne and Davis (2003) use the volatility estimates from the CGARCH model in a panel of the G7 countries to study the impact of exchange rate uncertainty on the level of investment, concluding that it is the transitory and not the permanent component of volatility which has a negative impact on investments. They also find that the volatility estimate obtained from the component model is more appropriate than the one from the GARCH(1,1) model. Guo and Neely (2006) investigate the risk-return profile of 19 international stock markets, using the CGARCH volatility as the measure for risk. They find that statistical tests strongly support the more elaborate CGARCH model, which also provides more support than the standard GARCH model for a positive risk-return relation. Furthermore, the long-run volatility component appears to significantly determine the international conditional equity premium while the short-run component does not. Another important use for the CGARCH model is found by Christoffersen et al. (2006) for the valuation of European options. Their version of the Engle and Lee model substantially outperforms a benchmark single-component volatility model because of its ability to generate a better volatility term structure. This enables them to jointly model both long-maturity and short-maturity options. Finally, Bauwens and Storti (2007) propose a generalization of the CGARCH model to account for time-varying, state-dependent persistence in the volatility dynamics. Applying the new model to the prediction of VaR and Expected Shortfall for a time series of daily returns on the S&P 500, they show that the predictive performance favorably compares with that of the standard GARCH models.

Closer to our area of interest is the paper by Pramor and Tamirisa (2006), who use the USD exchange rates of five currencies (CZK, HUF, PLN, SIT and SKK) to find common volatility trends among them and the EUR/USD exchange rate. In line with the findings of Byrne and Davis (2003) for more mature markets, they show that the long-run volatility component outweighs the transitory component, suggesting that exchange rate volatility is mainly driven by shocks to economic fundamentals rather than shifts in market sentiment. They also estimate the significance spillovers of volatility into means, long-run components and transitory components, finding that they have declined over time (2001 – 2005 compared to 1997 – 2001).

Quite to the contrary, Kóbor and Székely (2004) find that between 2001 and 2003 exchange rate volatilities have increased, and that spillovers among certain countries appear to have become more frequent and stronger. They conclude this on the basis of Markov regime-switching models, using joint normal distributions for four euro exchange rates (CZK, HUF, PLN and SKK). The models also present clear evidence that correlations among countries are higher during high volatility periods.

Borghijs and Kuijs (2004) use a Structural VAR approach in the spirit of Clarida and Gali (1994) to examine the usefulness of flexible exchange rates as shock absorbers in the economies of the Czech Republic, Hungary, Poland, the Slovak Republic and Slovenia. They find that (with the possible exception of Poland) the exchange rate appears to have served as much or more as an unhelpful propagator of monetary shocks than as a useful absorber of demand shocks, concluding that the costs of losing exchange rate flexibility in these countries are limited, if even positive.

Moving on to the multivariate part of our paper, the two relevant studies for the Orthogonal GARCH model are Klaassen (1999) and Alexander (2000). The first article illustrates the model by using eight USD exchange rates of developed countries and examining their conditional correlations over a substantial sample period (1974 – 1997). The second article uses price series for crude oil futures contracts of different maturities. In both cases, the model appears to successfully capture the correlation patterns of the underlying assets. Further details about the OGARCH model are presented in Section III.

Finally, although it is not the direct subject of the present paper, another article of potential interest is the one by Dungey et al. (2004), which presents an extensive review of methodologies for the empirical modeling of contagion, under normal market conditions and during crises.

III. METHODOLOGY

1. The CGARCH model

The first part of our analysis relies on the Component GARCH model introduced by Engle and Lee (1993). This model extends the classical GARCH(1,1) model of Bollerslev by decomposing volatility, which is measured by the conditional variance of asset returns, into a permanent or long-run trend and a transitory or short run component. The transitory component is mean-reverting towards the trend component. The rationale behind such an approach is the finding (in several studies cited by Engle and Lee in their paper) of a unit root in the volatility process, which indicates that there is a stochastic trend as well as a transitory component in asset return volatility.

Let y_t be the return on an asset with expected return μ_t. Define h_t as the conditional variance of y_t: $h_t \equiv Var(y_t \mid I_{t-1}) = E[(y_t-\mu_t)^2 \mid I_{t-1}]$, where I_{t-1} is the information set containing all the information available at time t-1. The GARCH(1,1) process can be written as:

(1) $$y_t = \mu_t + \varepsilon_t \qquad \varepsilon_t \mid I_{t-1} \sim N(0, h_t)$$

(2) $$h_t = \omega + \alpha \varepsilon^2{}_{t-1} + \beta h_{t-1}$$

The conditional multi-step forecast of variance based on I_{t-1} is $h_{t+k} \equiv Var(y_{t+k} \mid I_{t-1})$. Provided that y_t is a covariance stationary process (i.e. $(\alpha+\beta) < 1$), the multi-step forecast of the conditional variance in the GARCH(1,1) model is:

$$h_{t+k} = \omega[1-(\alpha+\beta)^k]/(1-\alpha-\beta) = \omega/(1-\alpha-\beta) \quad \text{as } k \to \infty$$

which converges to the unconditional variance $\sigma^2 \equiv Var(y_t)$. So the GARCH(1,1) can also be written as:

(3) $$h_t = (1-\alpha-\beta)\sigma^2 + \alpha\varepsilon^2{}_{t-1} + \beta h_{t-1} = \sigma^2 + \alpha(\varepsilon^2{}_{t-1} - \sigma^2) + \beta(h_{t-1} - \sigma^2)$$

From this representation, extending the model to allow the possibility that volatility is not constant in the long run, is very straightforward. Letting $\mathbf{q_t}$ be the *permanent component* (trend) of the conditional variance, the component model for the conditional variance is defined as:

(4) $$h_t = q_t + \alpha(\varepsilon^2{}_{t-1} - q_{t-1}) + \beta(h_{t-1} - q_{t-1})$$

(5) $$q_t = \omega + \rho q_{t-1} + \phi(\varepsilon^2{}_{t-1} - h_{t-1})$$

It is easy to see that (4) is just (3) with the constant long-term volatility, σ^2, being replaced by the time-varying trend, q_t, and its past value. The equation for q_t also includes an autoregressive root, ρ. To incorporate the empirical finding of integration for return volatility, one can also define q_t as an integrated process (i.e. $\rho = 1$) plus a constant drift. The difference between the conditional variance and its trend, **(h_t – q_t)**, is the *transitory component* of the conditional variance.

Analyzing the forecast profile of the component model allows us to get a better insight into the implications of the decomposition. In the trend equation, the error term ($\varepsilon^2_t - h_t$) has zero expected value by the definition of the conditional variance. The multi-step forecast of q_t based upon I_{t-1} is thus:

$$q_{t+k} = [(1-\rho^k)/(1-\rho)]\omega + \rho^k q_t$$

From (4), the forecast for the transitory component of the conditional variance is:

$$h_{t+k} - q_{t+k} = (\alpha + \beta)^k (h_t - q_t)$$

If $(\alpha+\beta) < 1$, then $(h_t - q_t)$ is a zero mean stationary AR(1) process. The forecast of $(h_{t+k} - q_{t+k})$ will eventually converge to zero as the forecasting horizon increases:

$h_{t+k} - q_{t+k} = 0$ as $k \rightarrow \infty$

Therefore there will be no difference between the conditional variance and its trend in the long run. This is why q_t is called the permanent component of the conditional variance in this model. If $\rho > (\alpha+\beta)$, the transitory component will decay faster than the trend so that the latter will dominate the forecast of the conditional variance as the forecasting horizon extends. The conditional variance will eventually (as $k \rightarrow \infty$) converge to a constant since the trend itself is stationary:

$$h_{t+k} = q_{t+k} = \omega/(1-\rho)$$

Actually the data generating process for the conditional variance defined in this component model is represented by a GARCH(2,2) process[4]. By substituting (5) into (4) and using (5) once more the model can be written as to:

(6) $$h_t = (1-\alpha-\beta)\omega + (\alpha+\phi)\varepsilon^2{}_{t-1} + [-\phi(\alpha+\beta)-\alpha\rho]\varepsilon^2{}_{t-2} + (\rho+\beta-\phi)h_{t-1} + [\phi(\alpha+\beta)-\beta\rho]h_{t-2}$$

As a special case, the component model reduces to the GARCH(1,1) model if α = β = 0 or ρ = Φ = 0 in (6) above. So the GARCH(1,1) only describes a single dynamic component of the conditional variance. By decomposition, the component model enriches the dynamic specification.

Furthermore, the relationship between CGARCH and GARCH(2,2) provides a convenient way to establish the stationarity condition of the conditional variance defined in the component model. Bollerslev proves that the GARCH process is covariance stationary if and only if the sum of the GARCH dynamic coefficients is less than one. Similarly, for the component model, this stationarity condition implies that $(\alpha+\beta)(1-\rho) + \rho < 1$, which requires $\rho<1$ and $(\alpha+\beta) < 1$. Hence the conditional variance is stationary if both the permanent and the transitory components are covariance stationary.

Non-negativity of the conditional variance in the component model is also a very significant aspect, and it is ensured if the following inequality constraints are satisfied:

$1 > \rho > (\alpha+\beta)$, $\beta > \Phi > 0$, $\alpha > 0$, $\beta > 0$, $\Phi > 0$, $\omega > 0$

Another important issue concerns the significance of the parameters in the model.

(7) $$\partial q_t / \partial \varepsilon^2{}_{t-1} = \phi$$

(8) $$\partial (h_t - q_t) / \partial \varepsilon^2{}_{t-1} = \alpha$$

So Φ and α represent the shock effects on the permanent component and the transitory component of the conditional variance, respectively. The effect of the last-period shock on the multi-step forecasts of the component are:

$$\partial q_{t+k} / \partial \varepsilon^2{}_{t-1} = \rho^k \partial q_t / \partial \varepsilon^2{}_{t-1} = \rho^k \phi$$

$$\partial (h_{t+k} - q_{t+k}) / \partial \varepsilon^2{}_{t-1} = (\alpha+\beta)^k \partial (h_t - q_t) / \partial \varepsilon^2{}_{t-1} = (\alpha+\beta)^k \alpha$$

[4] For a more detailed discussion about the relationship between the component model and the GARCH model see Engle and Lee (1993).

Connecting this to the constraints mentioned before, if 1 > ρ > (α+β), the shock effect on the component will both die out over time. If ρ = 1 > (α+β), the shock effect on the transitory component will die out, but the shock effect on the permanent component will, however, be persistent.

The Component Model with Asymmetric Structure to Shocks

Volatility has been shown to respond to price movements asymmetrically; 'bad' news, meaning negative shocks, tend to increase expectations about future market volatility more than 'good news' (positive shocks). This asymmetric volatility pattern was first studied for equity prices, and it is often called the 'leverage effect'. According to Engle and Lee (1993), this phenomenon was first studied by Black and Christie in the late '70s; they attribute it to the failure of firms to adjust their debt/equity ratio. A drop in the firm's stock price decreases its market value and increases its debt/equity ratio, which thus increases the risk of the investors. Therefore, negative shocks to the price will increase volatility expectations more than positive shocks.

On the foreign exchange market, this asymmetry is not so thoroughly researched as it is for equities (at least to this author's knowledge). There is no sound theoretical explanation for such a phenomenon in the case of currencies, but some empirical evidence proves that it does exist in some cases (Pramor and Tamirisa (2006)). This is why we have decided to test for the presence of such asymmetric structure and include it in the CGARCH model where relevant.

The complete form of the variance equations (including an asymmetry term) is the following:

(9) $$h_t = q_t + \alpha({\varepsilon^2}_{t-1} - q_{t-1}) + \beta(h_{t-1} - q_{t-1}) + \gamma({\varepsilon^2}_{t-1} - q_{t-1})D_{t-1}$$

(10) $$q_t = \omega + \rho q_{t-1} + \phi({\varepsilon^2}_{t-1} - h_{t-1})$$

where D_t is a slope dummy variable that takes the value $D_t = 1$ for $\varepsilon_t < 0$ and $D_t = 0$ otherwise. If this model were estimated for stock returns, the presence of a leverage effect would imply a significant *positive* γ, so that h_t would be larger if $D_t = 1$ (i.e. for negative shocks)

In the case of currencies, this restriction does not apply – asymmetry can exist both ways. The phenomenon can be described as follows: if γ is positive, then a drop in the currency price (which means an appreciation of the currency in question, since quotes are usually expressed an number of domestic currency units per one unit of foreign currency) implies greater volatility; if γ is negative, volatility is actually lower when the currency price falls.

2. The Spillover Index

After computing the conditional variances for each currency and each sample period with the help of the CGARCH setup, one naturally wonders whether they affect each other, and if so, by how much?

The notion of volatility ‘spillover’ has been around for a long time, especially since the frequently cited paper of Engle, Ito and Lin (1990). One way to test for the existence of volatility spillovers is to estimate a GARCH model and add the volatility of another asset (in our case, currency) in one of the model equations. For instance, in the CGARCH setup described above, there are three possible spillovers that can be tested:

1. spillovers into means – by adding the variance or volatility of a currency in its own mean equation or in another currency’s mean equation;
2. spillovers into permanent volatility – by adding the variance of a currency in another currency’s permanent variance equation;
3. spillovers into the transitory component of volatility – by adding the variance of a currency in another currency’s transitory variance equation.

This is the approach taken by Pramor and Tamirisa (2006); while it may yield some interesting results, revealing which currency’s volatility influences which others, it does not quantify these spillovers in any way, and there is no measure of how strong these relationships among currencies are. Furthermore, some of the relationships found could even be suspected of being spurious, unless there are also several other indicators that point to the same conclusion.

For these reasons, we decide not to pursue this line of estimations, but rather to follow the approach of Diebold and Yilmaz (2007). Starting from a simple vector autoregressive (VAR) model, and using variance decomposition, they compute a very simple and intuitive, yet rigorous measure of return and volatility spillovers across markets.

The typical representation of a covariance stationary first-order two-variable VAR is:

(11) $$x_t = \Phi x_{t-1} + \varepsilon_t$$

where $x_t = (x_{1,t}, x_{2,t})^T$ and Φ is a 2x2 parameter matrix.

In our context, x_t is the vector of exchange rate variances (either permanent or transitory) obtained from the component GARCH model.

By covariance stationarity, the moving average representation exists and can be written as:

(12) $$x_t = A(L)u_t$$

where $A(L) = \Theta(L)Q^{-1}$, $\Theta(L) = (1-\Phi L)^{-1}$, $u_t = Q_t\varepsilon_t$, $E(u_t u_t^T) = I$, and Q_t^{-1} is the unique lower-triangular Cholesky factor of the covariance matrix of ε_t.

Under these circumstances, the optimal 1-step-ahead forecast is: $x_{t+1,t} = \Phi x_t$

and the corresponding 1-step-ahead error vector:

(13) $$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix}$$

which has the covariance matrix:

(14) $$E(e_{t+1,t} e_{t+1,t}{}^T) = A_0 A_0{}^T$$

So the total variance of the 1-step-ahead error in forecasting is $a_{0,11}{}^2+a_{0,12}{}^2$ for x_{1t} and $a_{0,21}{}^2+a_{0,22}{}^2$ for x_{2t}. But volatility decomposition allows us to see how much (in percentage terms) of these total variances are due to a variable own variance and how much to the variance of the other variable(s).

Diebold and Yilmaz define *own variance shares* as the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_i, and *cross variance shares*, or *spillovers*, to be the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_j, $i \neq j$. The **Spillover Index** is thus defined as the ratio between the sum of all cross variance shares and the total forecast error variation, which is $a_{0,11}{}^2+a_{0,12}{}^2+ a_{0,21}{}^2+a_{0,22}{}^2 = trace(A_0A_0{}^T)$.

Thus for a general p^{th}-order N-variable VAR, the Spillover Index is:

(15) $$S = \frac{\sum_{i,j=1,i\neq j}^{N} a_{0,ij}^2}{trace(A_0 A_0^T)}$$

And for the p^{th}-order N-variable VAR using H-step-ahead forecasts, the Spillover Index is:

(16) $$S = \frac{\sum_{h=0}^{H-1} \sum_{i,j=1,i\neq j}^{N} a_{0,ij}^2}{\sum_{h=0}^{H-1} trace(A_0 A_0^T)}$$

This index gives us a very computationally effective and easily interpretable measure of how volatilities interact with one another, which we can use in absolute terms or in comparisons across markets and/or time periods.

3. Multivariate models – the Orthogonal GARCH model

Let us denote by Y a Txk matrix consisting of T observations on k asset or risk factor returns. Using principal component analysis (PCA) we can obtain up to k uncorrelated stationary variables, called the principal components[5] of Y. Each component is a simple linear combination of the original returns as in (17) below. At the same time we can compute how much of the total variation in the initial system of risk factors is explained by each principal component, and the components are ordered according to the amount of variation they explain.

The first step in principal component analysis is to normalize the data in a Txk matrix X that represents the same variables as Y, but whose columns are standardized to have mean zero and variance one. Thus, denoting the i^{th} risk factor or asset return in the system by y_i, the normalized variables are $x_i = (y_i - \mu_i)/\sigma_i$, where μ_i and σ_i are the mean and standard deviation of y_i, $i = 1,\ldots, k$. Furthermore, let W be the matrix of eigenvectors of the correlation matrix of X (X'X), and Λ be the associated diagonal matrix of eigenvalues (ordered according to decreasing magnitude of eigenvalue). The principal components of Y are given by the Txk matrix:

(17) $$P = XW$$

Consequently a linear transformation of the original risk factor or asset returns has been made in such a way that the transformed risk factors are orthogonal, that is, they have zero correlation.

The fore mentioned ordering of Λ (and W) ensures that these new risk factors are ordered by the amount of the variation they explain. Hence only the first few, the most important factors may be chosen to represent the whole system as follows: since W is orthogonal, (17) is equivalent to

(18) $$X = PW^T$$

[5] It is interesting to note that although the principal components produced are *non-correlated*, they are only *independent* if the asset returns (and hence the principal components) are *normally* distributed. In practice fat-tailed asset returns are not normally distributed and hence principal components are *dependent*.

that is

(19) $$x_i = w_{i1} p_1 + w_{i2} p_2 + ... + w_{ik} p_k$$

so the matrix W is called the matrix of 'factor weights'.

In terms of the original variables Y, the representation (19) is equivalent to

(20) $$y_i = \mu_i + \omega^*_{i1} p_1 + \omega^*_{i2} p_2 + ... + \omega^*_{ik}\ p_k + \varepsilon_i$$

where $\omega^*_{ij} = w_{ij}\sigma_i$, and the error term picks up the approximation from using only the first m of the k principal components. These m principal components are the most important risk factors of the system, as they usually explain over 95% of the total variation; the rest of the variation is ascribed to 'noise' in the error term.

The number, m, of principal components needed depends upon the degree of correlation between the original assets – the more correlated they are, the fewer the number of principal components required for a given accuracy as measured by variance of the residuals.

It is clear from representation (20) how, when covariance or scenario calculations are based only on the 'key' principal components, the effect may be easily translated back to the original system through a simple linear transformation. The principal component variances can be quickly transformed into a covariance matrix of the original system (Y) using the factor weights as follows: taking variances of (20) we obtain

(21) $$V\{y_t\} = AV\{p_t\}A^T + V\{\varepsilon_t\}$$

where $A=(\omega^*_{ij})$ is the kxm matrix of normalized factor weights, $V\{p_t\}$ is the diagonal matrix of variances of principal components and $V\{\varepsilon_t\}$ is the covariance matrix of the errors.

The most important advantage of this type of orthogonal transformation is the computational efficiency, as only m variances of the key principal components need to be estimated, instead of k(k+1)/2 variances and covariances of the original system[6].

Furthermore, this methodology also ensures that the obtained covariance matrix is always positive semi-definite, and even strictly positive definite if m = k (for a more detailed discussion see Alexander (2000)).

[6] For instance, in the most common example of a yield curve with, say, 10 maturities, only the variances of the first 3 principal components need to be computed, instead of the 55 variances and covariances of the yields of the 10 different maturities. In the case of yield curves, these first 3 principal components represent the 'level', 'slope' and 'curvature' of the curve.

$V\{p_t\}$ can be estimated using exponentially weighted moving averages or one of the models from the GARCH family. If the latter is used, the model is usually called 'orthogonal GARCH'. This type of model was introduced by Klaassen (1999) and Alexander (2000); it is in fact a generalization of the factor GARCH model introduced by Engle, Ng and Rothschild (1990) to a multi-factor model with orthogonal factors.

Other options for computing covariance matrices are:

1. exponentially weighted moving averages (EWMA) of the squares and cross products of returns;
2. multivariate GARCH models.

However, both of these alternatives present serious limitations. The main advantage of the EWMA approach (made popular by RiskMetrics[7]) is also its own worst enemy: it uses only one smoothing constant for all the data, which mares risk measures very easy to compute. This is necessary in order for the covariance matrix to be positive semi-definite. But it implies that the reaction of volatility to market events and the persistence of volatility are the same in all the assets or risk factors that are represented in the covariance matrix.

GARCH models have been proven to be superior to the EWMA approach, because of their mathematical coherency and the fact that GARCH volatility and correlation term structure forecasts converge to the long term average level. Consequently, large covariance matrices that are based on GARCH models would have clear advantages over those generated by EWMA. However, it is extremely difficult to estimate a multivariate GARCH model for more than two or three assets, because of the very large number of parameters involved. The likelihood function becomes very flat, and so convergence problems are common in the optimization routine. Several solutions have been proposed, but the number of parameters is still too large for higher-variate systems (such as in the cases of VECH and BEKK models) or the assumptions one needs to make are too strict (such as the case of Bollerslev's CCC-GARCH model, which assumes constant conditional correlations between the asset returns in the system).

The orthogonal GARCH model combines the advantages of GARCH and principal components modeling. It allows kxk covariance matrices to be estimated from just m univariate GARCH models, without any dimensional restrictions on k. This is indeed very

[7] The EWMA approach was the key ingredient for the first methodology that RiskMetrics proposed, back in 1994, and for the following updates. Due to its merits, it was very popular for more than a decade. However, in October 2006 RiskMetrics published a new risk methodology, based on a long memory ARCH process approach (for more details see www.riskmetrics.com)

useful, because the main problems encountered with other types of multivariate GARCH models are thus avoided.

Although m, the number of principal components necessary to estimate the model, can be much less than k[8], the number of variables in the system (especially if one wishes to exclude extraneous 'noise' from the system), Klaassen (1999) proves that incorporating the maximum number of factors into the model (i.e. m = k) is significantly optimal. Among the advantages of such an approach we can enumerate:

1. it eliminates the problem of the choice of k, which so far has been based on several ad hoc criteria, such as the Kaiser-Guttman rule[9];
2. it avoids the danger of losing important information about the initial system by ignoring the last components, which may sometimes contain more than just 'noise';
3. to estimate usual factor GARCH models[10], one commonly takes a two-step estimation method, which involves correction of the second step standard errors for first-step estimation inaccuracy; this is difficult to do in practice and thus often ignored, leading to biased inference. The orthogonal GARCH method does not present this potentially serious problem, since there is no estimation involved in reverting from the second moment of the principal components to the one of the initial system;
4. as already mentioned, if k = m the obtained covariance matrix is guaranteed to be strictly positive definite.

After estimating the variances of the principal components, conditional on the information set I_{t-1} (i.e. all the information available up to, and including the moment t-1), by standard univariate GARCH(1,1), we complete the covariance matrix of the principal components by assuming that the off-diagonal elements are zero. Principal components are only unconditionally uncorrelated, so the GARCH covariance matrix of principal components is not necessarily diagonal; however, the assumption of zero conditional correlations has to be made, otherwise it misses the whole point of the model, which is to generate large GARCH covariance matrices from GARCH volatilities alone. The degree of accuracy that is lost by making this assumption can be investigated by a thorough calibration of the model,

[8] As mentioned before, the higher the correlation between the system variables, the lower the number of principal components needed for an accurate approximation of the initial system. In the particular case of the exchange rates studied in the empirical part of this paper, because the correlation coefficients were not very high, k=m=5 (see Section IV.5 for more details).

[9] This rule states that one should select only those principal components that have a larger variance than the average variance of the initial variables in the system. The problem with this rule is that in many cases it selects only very few components, thus losing a great wealth of information that could be present in other components.

[10] For a detailed comparison between this particular orthogonal GARCH model and the other factor GARCH models see Klaassen (1999).

comparing the variances and covariances produced with those from other models, such as EWMA or (for small systems) multivariate GARCH (for an example of such calibration see Alexander (2001)); but since this assumption is common in literature (Klaassen (1999), Alexander (2000)) we will not insist on it further.
Summing up, the steps involved in estimating this model are as follows (notations are the same as above unless stated otherwise):

Step 1: Computing the principal components of the normalized initial system:

$$P = XW$$

Step 2: Estimating the conditional variance of the principal components by standard univariate GARCH(1,1) models:

$$E_{t-1}\{p_{jt}\} = \mu_j$$

$$V_{t-1}\{p_{jt}\} = \omega_j + \alpha_j * (p_{jt-1} - E_{t-2}\{p_{jt-1}\})^2 + \beta_j * V_{t-2}\{p_{jt-1}\}$$

$$Cov_{t-1}\{p_{jt}, p_{lt}\} = 0$$

for every principal component j, l = 1,…,k ($j \neq l$).
Step 3: Transform the conditional moment of the principal components into the ones for the original series:

$$E_{t-1}\{y_t\} = AE_{t-1}\{p_t\}$$

$$V_{t-1}\{y_t\} = AV_{t-1}\{p_t\}A^T$$

This last formula is very similar to (21) above; in this case $V\{\varepsilon_t\} = 0$, since m = k (there is no residual information left out by reducing the number of principal components).

IV. EMPIRICAL DATA AND RESULTS

1. The data

The empirical part of this paper deals with the daily nominal exchange rates of five Central and Eastern European (CEE) currencies against the euro, namely the Czech koruna (CZK), the Hungarian forint (HUF), the Polish zloty (PLN), the Romanian new leu (RON)[11] and the Slovak koruna (SKK). The data is obtained from Eurostat (for SKK) and from the web site of each Central Bank respectively (for CZK, HUF, PLN and RON). Each exchange rate is quoted as number of national currency units per euro, so that an increase in the exchange rate represents a depreciation of the national currency. For holidays, the quote used is the one from the last available working day before that holiday.

Another country of potential interest, from the same geographic area as the others, is Slovenia. The Slovenian tolar (SIT) is sometimes included in studies together with the currencies mentioned above, but we have decided to exclude it from the present analysis because Slovenia has entered ERM II with effect from 28 June 2004 and has also adopted the euro as the national currency as of 1 January 2007. Participation in the ERM II mechanism has meant very low volatility for the tolar, and some studies find that even before 2004 the foreign exchange market in Slovenia was almost completely independent from the other countries analyzed (Kóbor and Székely (2004)), which makes SIT unsuitable for the present analysis.

The sampling period covers 4 May 2001 to 5 April 2007. This time period has been chosen so that CEE countries would have an exchange regime flexible enough to render the analysis meaningful (Borghijs and Kuijs (2004)), and at the same time no major exchange rate regime change would take place in the countries under investigation (Kóbor and Székely (2004)). This way we can concentrate better on the most recent history of these currencies and make more plausible inferences about the run-up to the euro adoption in these countries as well.

A note must be made regarding exchange rate regime changes during the chosen sampling period. 4 May 2001 represents the date of the last change in the width of the HUF intervention band (from ±2.25% to ±15%). For the CZK, PLN and SKK exchange rate flexibility had been introduced a long time before that (in 1997, 2000 and 1998, respectively). The only exception to this rule is the RON, which had a managed exchange rate until December 2004. Because starting the analysis in December 2004 would have imposed a great limitation on the available data and potentially eliminated important information, we decided to start the sampling period in 2001, but also to divide it into two sub-periods, namely May 2001 – November 2004 and December 2004 – April 2007, and perform most of the analyses on both the full period and the sub-periods (to examine any changes that might have taken place and as a robustness check).

[11] In the case of RON, all data before 1 July 2005 (which was expressed in ROL) has been divided by 10,000 to make it comparable with the current value of the Romanian currency.

2. Preliminary analysis

We begin by performing some basic analysis of the data. A graphic representation of the five series of raw data is given in Figure A1. All series in levels display a unit root, as evident from the Augmented Dickey-Fuller test[12] results presented in Table A1. The null hypothesis of a unit root cannot be rejected even at the 10% level of significance, except for the HUF (but even in this case it cannot be rejected at the 5% level). Hence the series are transformed into log-differences and we obtain the continuously compounded exchange rate returns:

$$y_t = \ln(S_t) - \ln(S_{t-1})$$

where S_t is the spot rate. These are the series we will be working with henceforth, as these are definitely stationary (the null of a unit root is clearly rejected).

A graphic representation of the new series is given in Figure A2, and several descriptive statistics are presented in Table A2. The series are clearly not normally distributed, and as most financial time series they present 'fat tails' (a leptokurtic distribution, with high kurtosis).

We also perform a Ljung-Box test to check the presence of autoregressive conditional heteroskedasticity in the series of squared returns. The test has the following form:

$$Q^* = T(T+2)\sum_{k=1}^{m}\frac{y_k^2}{T-k}$$

and is asymptotically distributed as a $\chi^2(m)$ under the null hypothesis that all m autocorrelation coefficients are zero (Brooks (2002)).

The test was computed using Rats 6.01. We use m = 15, as do Engle and Lee (1993). The results (presented in Table A3) clearly indicate the presence of ARCH effects in all data series and for all sample periods[13], as the null hypothesis of no serial correlation in y_t^2 is strongly rejected. Consequently, we continue with the estimation of the Component GARCH model.

[12] The test are performed initially with both a constant and a deterministic trend in the equation, but the trend is eliminated in some cases from the level equations because it is not statistically significant. In the case of the first difference equations, neither the trend, nor the constant are significant (except for the RON).

[13] The only exception is SKK for the late sample period (2004 – 2007), but we still believe that the CGARCH model is appropriate, because there is clear evidence of ARCH effects in both of the other two sample periods.

3. The Component GARCH model

The form of the model we actually estimate is the following:

(22) $$y_t = \mu_t + \varepsilon_t$$

(23) $$h_t = q_t + \alpha({\varepsilon^2}_{t-1} - q_{t-1}) + \beta(h_{t-1} - q_{t-1}) + \gamma({\varepsilon^2}_{t-1} - q_{t-1})D_{t-1}$$

(24) $$q_t = \varpi + \rho(q_{t-1} - \varpi) + \phi({\varepsilon^2}_{t-1} - h_{t-1})$$

The only difference from the model described before (in equations (1), (8) and (9)) is that equation (24) more clearly shows how q_t is mean reverting to a long time average of volatility, ϖ, which is actually the unconditional level of each series' variance.

We also augment the mean equation (22) with a number of AR terms in the cases where they appear to be significant. While Pramor and Tamirisa (2006) argue that there is no need for more than one AR term, we find that in some cases higher-order AR terms are also significant.

In order to check for the presence of asymmetry to shocks, we use the sign test developed by Engle and Ng (as described in Brooks (2002)). If we define S^-_{t-1} as an indicator dummy that takes the value 1 if $\hat{u}_{t-1} < 0$ and zero otherwise ($\hat{u}_t$ being the series of standardized residuals from a GARCH model), the test for sign bias is based on the significance or otherwise of Φ_1 in the following regression:

$$\hat{u}_t^2 = \phi_0 + \phi_1 S^-_{t-1} + \upsilon_t$$

where υ_t is an iid error term. if positive and negative shocks to $\hat{u}_{t-1}$ impact differently upon the conditional variance, then Φ_1 will be statistically significant.

It is also possible that the magnitude of the shock will affect whether the response of volatility to shocks is symmetric or not. Defining $S^+_{t-1} = 1 - S^-_{t-1}$, Engle and Ng propose a joint test for sign and size bias based on the regression:

$$\hat{u}_t^2 = \phi_0 + \phi_1 S^-_{t-1} + \phi_2 S^-_{t-1}\hat{u}_{t-1} + \phi_3 S^+_{t-1}\hat{u}_{t-1} + \upsilon_t$$

Φ_1 is interpreted in the same way as before, while the significance of Φ_2 or Φ_3 would suggest the presence of size bias. Table A4 presents the results of these two regressions, together with a joint test statistic calculated (for the second regression) as T^*R^2, which asymptotically follows a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects ($\Phi_1 = \Phi_2 = \Phi_3 = 0$).

As a general rule, we only include the asymmetric term in equation (23) of the component GARCH model if the Engle-Ng test validates its significance.

Both the Engle-Ng tests and the CGARCH models are implemented using the Rats econometric software[14]. The CGARCH models are estimated using the quasi-maximum likelihood method, and computing Bollerslev-Wooldridge robust standard errors, in order to account for the possibility that the residuals are not conditionally normally distributed (as suggested in Brooks (2002)). The full results of the component model are presented in Tables A5 through A9 and summarized in Table 1 below. Graphical representations of the conditional variance components for each currency and sample period are presented in Figure A3.

Table 1. CGARCH Estimates

Sample period: 2001 – 2007

		CZK	HUF	PLN	RON	SKK
Trend intercept	ω	0.00001238***	0.00001955***	0.00003181***	0.00011813***	0.00026282***
Trend AR Term	ρ	0.9914***	0.9889***	0.9771***	0.9982***	0.9999***
Forecast Error	φ	0.0338***	0.0088	0.0344***	0.1146***	0.0265**
ARCH Term	α	0.1242***	0.2693***	0.1420***	0.1275***	0.3385***
GARCH Term	β	0.5312***	0.7058***	0.4361***	-0.1992	0.4261***
Asymm. Term	γ	-	-0.2919***	-0.0778**	-	-0.3535***

Sample period: 2001 – 2004

		CZK	HUF	PLN	RON	SKK
Trend intercept	ω	0.00001635***	0.00002016***	0.00003733***	0.00009251	0.00000490
Trend AR Term	ρ	0.9899***	0.9626***	0.9775***	0.9991***	1.0000***
Forecast Error	φ	0.0478	0.0061	0.0460***	0.0483**	0.0261***
ARCH Term	α	0.1418***	0.2991***	0.2154***	0.0285	0.0940***
GARCH Term	β	0.4873***	0.5827***	0.3105***	0.9283***	0.7298***
Asymm. Term	γ	-	-0.2985***	-0.1254**	-	-

Sample period: 2004 – 2007

		CZK	HUF	PLN	RON	SKK
Trend intercept	ω	0.00000747***	0.00002801	0.00001701***	0.00002088***	0.00001484***
Trend AR Term	ρ	0.9908***	0.9958***	0.9967***	0.9467***	0.9800***
Forecast Error	φ	0.0149	0.0474***	0.0153***	0.0420	0.0171
ARCH Term	α	0.0855**	0.1481***	0.0428***	0.1300**	0.0461**
GARCH Term	β	0.5705**	0.7961***	0.7406***	0.7282***	0.7999***
Asymm. Term	γ	-	-0.1136***	-0.0206***	0.1633***	-

Source: Author's estimates
*, ** and *** andicate significance at the 10%, 5% and 1% levels, respectively

[14] The reason why Rats is preferred is because it allows the two variance components to be stored into two separate series variables that can be printed at the end of the optimisation routine. The EViews software is able to estimate the model parameters, but in the end it only provides the total variance (h_t). The Rats code used to estimate the CGARCH model has been written by the author, starting from the examples given in Brooks (2002).

The signs and relative magnitudes of coefficients confirm that the CGARCH model is well specified and is an appropriate framework for analyzing volatility patterns in the five CEE countries. The only exception is the RON over the whole sample period (2001 – 2007), where we obtain a negative value for the β coefficient (in the short-run component of volatility). Following the suggestion in Alexander (2001), that the largest outliers in the series can be excluded from the sample, so that they do not create convergence and/or stability problems for the GARCH model, we exclude the three largest outliers in the RON return series. This solves the problem only partially, as β becomes smaller (in absolute terms), but remains negative. We also implement dummy variables, which take the value 1 when an outlier is present and zero otherwise. This approach comes from the literature on contagion between markets, more precisely from Favero and Giavazzi (2002) (as described in Dungey et al. (2004)). Adding the dummy variables to either the mean equation or to one of the variance equations does change the sign of β, making it positive, but at the expense of making q_t, the long-term variance, negative for a certain period of time, which is also a violation of the CGARCH restrictions. Moreover, the use of dummy variables seems somewhat artificial, so we decide to go back to the initial approach.

A negative (and insignificant) β suggests that in the case of RON volatility is mainly of a long-run nature. When considering the nature of exchange rate regimes in Romania during the sample period in question here (2001 – 2007), this is not a very surprising conclusion. As mentioned before, until December 2004 (so for about two thirds of the sample period) Romania had a managed float, with frequent Central Bank interventions on the foreign exchange market. This way, the currency was constantly devalued. Furthermore, there were very strict regulations concerning foreign capital mobility, so foreign investors had only limited influence on the Romanian exchange market. These are the reasons which lead us to believe that the most important sources of shocks for the RON were the Central Bank interventions, which were obviously aimed to have long-term effects, while other shocks to the foreign exchange market were far less important.

This conclusion is also supported by the results of the CGARCH model for the two sub-sample periods: over 2001 – 2004, the long-run variance also seems to outweigh short-run variance, and shocks to the former are more important than shocks to the latter ($\Phi > \alpha$), while over 2004 – 2007 the long-run variance becomes more stable and shocks are mostly of a short-run nature (after adopting a free float regime and the liberalization of the capital account).

For the other currencies, the CGARCH model does not present any surprises. Coefficients are generally highly significant (at the 1% level), with very few exceptions that do not invalidate the models. Shocks to variances are mostly of a short-run nature ($\Phi < \alpha$) and volatility persistence, as measured by ρ, is higher for the long-run component than for the short-run component ($\alpha+\beta$). Except for the RON, the estimations for the whole sample period and the two sub-periods appear consistent, with the coefficient values for the 2001 – 2007 models being like an 'average' of the values for the other two models.

As a further validation that the CGARCH models are correctly specified, we perform the Ljung-Box test again, this time on the series of standardized residuals from each of the CGARCH models. The results, presented in Table A10, show a tremendous improvement in the values of the Q* statistics over the ones for the squared returns, so the component model successfully captures the typical pattern of serial correlation. Furthermore, analyzing some descriptive statistics for the standardized returns shows that the CGARCH model is able to capture some (although not all) of the excess kurtosis present in the return series.

As a final check, we also compare the values of the maximized log-likelihood function for each of the 15 CGARCH models estimated with the corresponding GARCH(1,1) specifications. All the values of the LLF from the CGARCH setup are substantially larger than the GARCH(1,1) ones, so a Likelihood Ratio test would clearly reject the hypothesis that the two models are not significantly different from each other.

Certain similarities between volatilities can be seen even at this early stage, along the same lines as in Kóbor and Székely (2004) and Pramor and Tamirisa (2006). The asymmetric effects are generally not significant for CZK, SKK and RON. However, we include the asymmetric term in the conditional variance equation of the RON for the late period, although the sign test rejects its significance, because the CGARCH specification seems to have better statistical properties when this term is included, and the coefficient appears highly significant. Furthermore, the size bias test indicates that the size of positive shocks influences volatility more than the size of negative shocks. The positive value of the asymmetry term coefficient indicates that in the case of RON, negative returns (i.e. currency appreciations) have a higher impact on volatility than positive returns.

On the other hand, asymmetric effects are also highly significant for HUF and PLN (for all sample periods). In this case the coefficients are consistently negative, which indicates that negative returns actually decrease variances, and that exchange rate volatility is higher during times of currency depreciation.

The autoregressive parameters in the trend equations, ρ, is very close to one for all currencies and all time periods (the smallest being 0.9467 for RON 2004 – 2007), so the series are very close to being integrated. This is a very common feature for the CGARCH setup, and according to Engle and Lee (1993) it may indicate the presence of a unit root. This finding does not invalidate estimation results, but requires caution when using parameter estimates for forecasting purposes, so that negative estimates of variance are not obtained.

The shock effects on the transitory component of volatilities (the α coefficients, as shown in equation (8)), are much larger than the shock effects on the permanent component (the φ coefficients, as shown in equation (7)). The estimation results show that α's are generally around three to six times larger than φ's. However, as found in all the papers that use the CGARCH specification, the shocks to short-run volatility are very short-lived, even if they are stronger. This is reflected by their very short half-lives, which generally range between less than a day (in the case of SKK over the full sample period) to almost 5 days. Also, it is interesting to notice that these half-lives appear to have slightly increased over time, being longer in the late period than in the early period.

When comparing the means and standard deviations of the short-run components to those of the long-run components, we find that they are generally smaller (Table A11). In some instances (HUF and PLN in the early period, CZK, RON and SKK in the late period) the standard deviation of the transitory component exceeds that of the permanent component, reflecting periods of temporary turbulence in these markets. Relative to its lower mean level, the short-run component is in all cases more volatile than the trend component, as expected. Similar patterns have been observed by Byrne and Davis (2003) in currencies of industrial currencies, and by Pramor and Tamirisa (2006) for a group of CEE countries.

Tables A12, A13 and A14 present the unconditional correlations of returns, long-run components and short-run components of volatility, respectively. A first observation is that generally correlations are higher in the late period than in the early period – the only exception being PLN-RON – probably due to increased financial integration and greater capital mobility. Furthermore, while the five currencies appear to respond to temporary market shocks in similar ways (as suggested by positive correlations between transitory volatilities), they respond differently to more permanent shocks. One possible explanation could be that the long-run volatility component responds more to country-specific factors, such as macroeconomic fundamentals, causing different long-term trends.

We now turn to the analysis of volatility spillovers among the five currencies considered.

4. The Spillover Indices

After decomposing the conditional variances into their long-run and short-run components, we begin to ask ourselves how do the currencies influence each other and how can we express these influences quantitatively, in order to compare and make inferences in a unitary framework.

A suitable answer is provided by the approach of Diebold and Yilmaz (2007), as described in Section III of this paper. We begin by estimating six Vector Autoregressive (VAR) models, using the two volatility components from each of the three sample periods. All 30 volatility series are examined using the Augmented Dickey-Fuller test, which confirms the absence of unit roots (hence the series are stationary and can be used in VAR models[15]). The appropriate number of lags is determined using the information criteria (Table A15); when the different criteria are contradictory, we base our decision on AIC (Akaike Information Criteria). We also perform a check on the AR roots, and the results indicate that all six VAR specifications are stable (Figure A4).

The results of volatility decomposition are presented in Tables 2, 3 and 4 below. We use 20-step-ahead forecast error variance and a Cholesky ordering as shown in the table headers (we keep the same ordering and number of forecast periods for all six decompositions in order to maintain the results comparable). The reasons behind these decisions are as follows: volatility has been found to be highly persistent (especially the trend component), so a large enough number of forecast steps is necessary; furthermore, according to Brooks (2002), the differences between the different Cholesky orderings become smaller as the number of forecast periods increases.

[15] The only exception is the permanent component of volatility in the case of SKK. However, we continue with the series as such, following the suggestion of Brooks (2002); he argues, refering also to opinions of other researchers, that diferencing such series in order to induce stationarity implies losing potentially important information regarding the series dynamics, especially since the other series in the VAR do not have to be differentiated.

Table 2. Volatility Spillovers for the Sample Period May 2001 – April 2007

Permanent volatility		FROM					
		HUF	SKK	RON	CZK	PLN	Contribution from others
	HUF	97.03	0.34	0.11	0.69	1.83	2.97
	SKK	2.80	96.63	0.06	0.08	0.44	3.37
TO	RON	0.09	0.99	97.93	0.02	0.98	2.07
	CZK	0.17	0.82	1.30	97.59	0.12	2.41
	PLN	15.76	0.20	2.36	0.11	81.57	18.43
Contribution to others		18.82	2.35	3.83	0.89	3.36	29.25
Contribution including own		115.85	98.98	101.76	98.48	84.93	500.00
Spillover Index							**5.85%**

Transitory volatility		FROM					
		HUF	SKK	RON	CZK	PLN	Contribution from others
	HUF	98.38	0.34	0.07	0.50	0.71	1.62
	SKK	3.32	95.08	0.65	0.64	0.31	4.92
TO	RON	0.57	0.29	96.42	0.48	2.24	3.58
	CZK	0.64	3.23	0.47	95.32	0.34	4.68
	PLN	11.30	3.43	1.02	0.40	83.84	16.16
Contribution to others		15.82	7.29	2.22	2.02	3.60	30.95
Contribution including own		114.21	102.37	98.64	97.34	87.44	500.00
Spillover Index							**6.19%**

Source: Author's estimates

Table 3. Volatility Spillovers for the Sample Period May 2001 – November 2004

Permanent volatility		FROM					
		HUF	SKK	RON	CZK	PLN	Contribution from others
	HUF	98.99	0.39	0.05	0.22	0.36	1.01
	SKK	2.00	92.59	0.91	2.35	2.15	7.41
TO	RON	0.65	0.50	94.54	2.50	1.82	5.46
	CZK	0.39	0.30	1.83	96.79	0.69	3.21
	PLN	14.87	6.81	4.32	0.95	73.04	26.96
Contribution to others		17.91	8.00	7.11	6.02	5.02	44.05
Contribution including own		116.90	100.59	101.64	102.81	78.06	500.00
Spillover Index							**8.81%**

Transitory volatility		FROM					
		HUF	SKK	RON	CZK	PLN	Contribution from others
	HUF	97.16	0.98	0.28	0.80	0.78	2.84
	SKK	4.10	91.85	1.02	1.59	1.44	8.15
TO	RON	0.18	0.49	92.60	0.91	5.82	7.40
	CZK	0.27	1.04	0.32	98.04	0.33	1.96
	PLN	9.60	5.99	1.94	0.28	82.19	17.81
Contribution to others		14.15	8.51	3.56	3.58	8.36	38.15
Contribution including own		111.31	100.36	96.16	101.62	90.55	500.00
Spillover Index							**7.63%**

Source: Author's estimates

Table 4. Volatility Spillovers for the Sample Period December 2004 – April 2007

Permanent volatility		FROM					
		HUF	SKK	RON	CZK	PLN	Contribution from others
	HUF	97.83	0.07	0.05	1.86	0.19	2.17
	SKK	21.10	73.71	0.36	4.77	0.07	26.29
TO	RON	2.33	0.30	93.31	4.00	0.06	6.69
	CZK	0.33	21.79	5.93	70.02	1.94	29.98
	PLN	11.22	0.82	0.24	11.26	76.46	23.54
Contribution to others		34.97	22.98	6.57	21.89	2.25	88.67
Contribution including own		132.80	96.68	99.89	91.91	78.72	500.00
Spillover Index							**17.73%**

Transitory volatility		FROM					
		HUF	SKK	RON	CZK	PLN	Contribution from others
	HUF	97.00	1.58	0.60	0.53	0.28	3.00
	SKK	3.53	88.81	1.67	2.20	3.79	11.19
TO	RON	0.28	0.17	96.72	0.42	2.41	3.28
	CZK	0.85	8.93	0.15	83.41	6.66	16.59
	PLN	29.24	1.17	0.18	3.51	65.90	34.10
Contribution to others		33.91	11.86	2.59	6.66	13.14	68.15
Contribution including own		130.91	100.67	99.31	90.06	79.04	500.00
Spillover Index							**13.63%**

Source: Author's estimates

The (i,j)-th value in any of the above tables is the estimated contribution TO the variance of the 20-day-ahead exchange rate volatility forecast error of country i coming FROM innovations to the exchange rate volatility of country j.

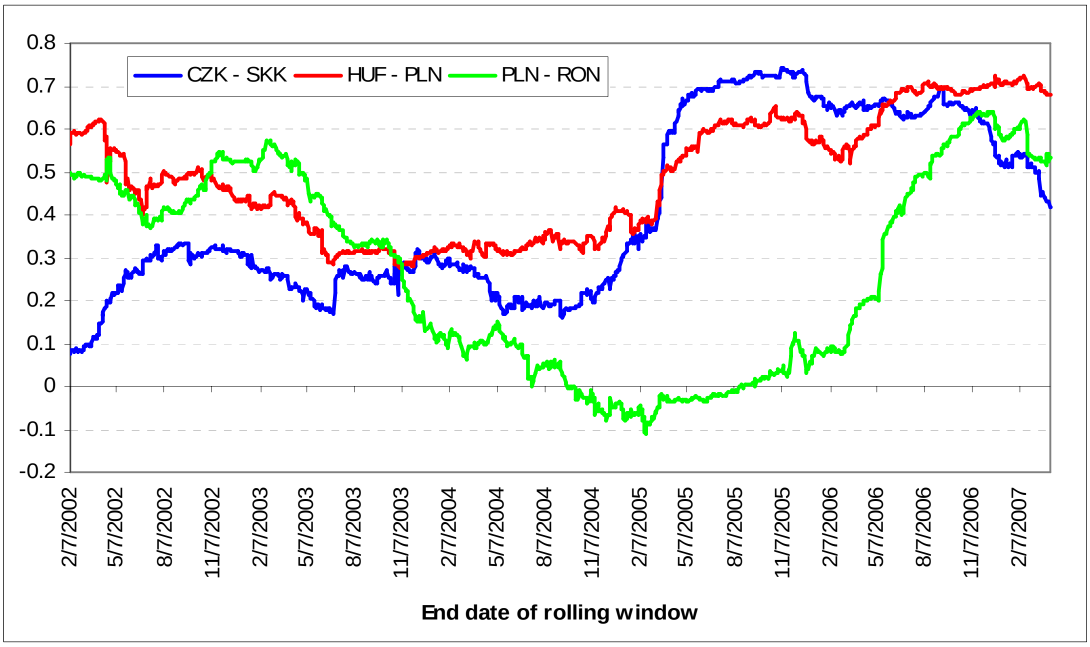
The results clearly indicate that volatility spillovers have increased over time, in line with the findings of Kóbor and Székely (2004) but contrary to Pramor and Tamirisa (2006). While during the May 2001 – November 2004 sample period, approximately 9% of forecast error variance comes from spillovers for the permanent component of volatility, the percentage doubles over the December 2004 – April 2007 sample period. Spillovers into permanent volatility appear stronger than into the transitory component over two of the three sample periods, possibly suggesting increased economic convergence of the five countries in question. From the optimum currency area perspective, this would be a positive conclusion, but at the same time we believe it raises more problems for the policy makers of each country, as they have to increasingly take into account the actions of the other countries when making their own decisions. This calls for coordinated courses of action, which would be a very good exercise in preparation for euro adoption and a single, unified monetary policy.

Considering each currency individually, we can see from the tables that the HUF has consistently been the most important source of volatility in the region, while the PLN has been the most important shock absorber. Pramor and Tamirisa (2006) and Borghijs and Kuijs (2004) reach similar conclusions; the latter study finds that in Poland, the exchange rate plays a more significant role as a buffer for demand, supply and monetary shocks than the exchange rates of other CEE countries[16].

5. The orthogonal GARCH model

This part of the paper examines the evolution of cross-currency correlations during the sample period. This is done by implementing the orthogonal GARCH model described in Section III. The orthogonal GARCH model is chosen in order to avoid the problems related to other types of multivariate GARCH models, such as a very large number of parameters to estimate or too strong assumptions that are not supported by the data. For instance, it is evident from Figure 1 that the correlations are not constant over time and that they have different dynamics, so the CCC model would probably not be appropriate.

Figure 1. Evolution of 3 Selected Unconditional Correlations Using a 200-day Moving Window



Source: Author's own calculations

[16] See Section II for more details on the paper by Borghijs and Kuijs (2004).

We follow the approach of Klaassen (1999) and we take into consideration the same number of principal components as series in the initial system. Thus in our case (keeping the same notations as before) m = k = 5.

We construct the principal components after the methodology described in Alexander (2000 and 2001) and Bufton and Chaudri (2005). The eigenvectors and eigenvalues of the correlation matrix C of the normalized exchange rate returns are presented in Table A16. Each of the five components has a name that indicates the dominating currencies in it. The first component is influenced by each exchange rate almost equally. It is interesting to examine the proportion of the total variance explained by each component. Of course the most influential component is the first one, but it only explains just over 40%. This is to be expected, because the correlations between the original series are not very high to begin with. Had they been higher, the first component would have explained more of the total variance. For example, for the eight currencies studied by Klaassen (1999) – which all belong to more developed economies, namely six EU members plus Canada and Japan – the first component explains 77% of the total variance.

Along the same lines, in our case the fifth component accounts for almost 10%, which is quite high for a last component[17]. This is one of the main reasons why we decided to follow Klaassen's approach and consider all five components. Obviously, had we decided to leave out the fifth component (or even the fourth, which is clearly dominated by SKK), a lot of potentially important information would have been ignored.

In the second stage of this setup, standard univariate GARCH models are estimated for each of the five principal components. Klaassen suggests the use of AR(1)-GARCH(1,1) models, but in our case we have tested for the presence of the AR(1) term in the mean equations and the estimated coefficients are not significant in any of the five models, so we proceeded without them. The results, presented in Table A17, are as expected, strongly reflecting the presence of conditional heteroskedasticity. According to the orthogonal GARCH model, this is the source of time-variation in the conditional variances as well as correlations of the individual exchange rates. All coefficients in the conditional variance equations are significant even at the 1% level (except for the intercept term in the equation of PC4, which is close to being significant at the 10% level).

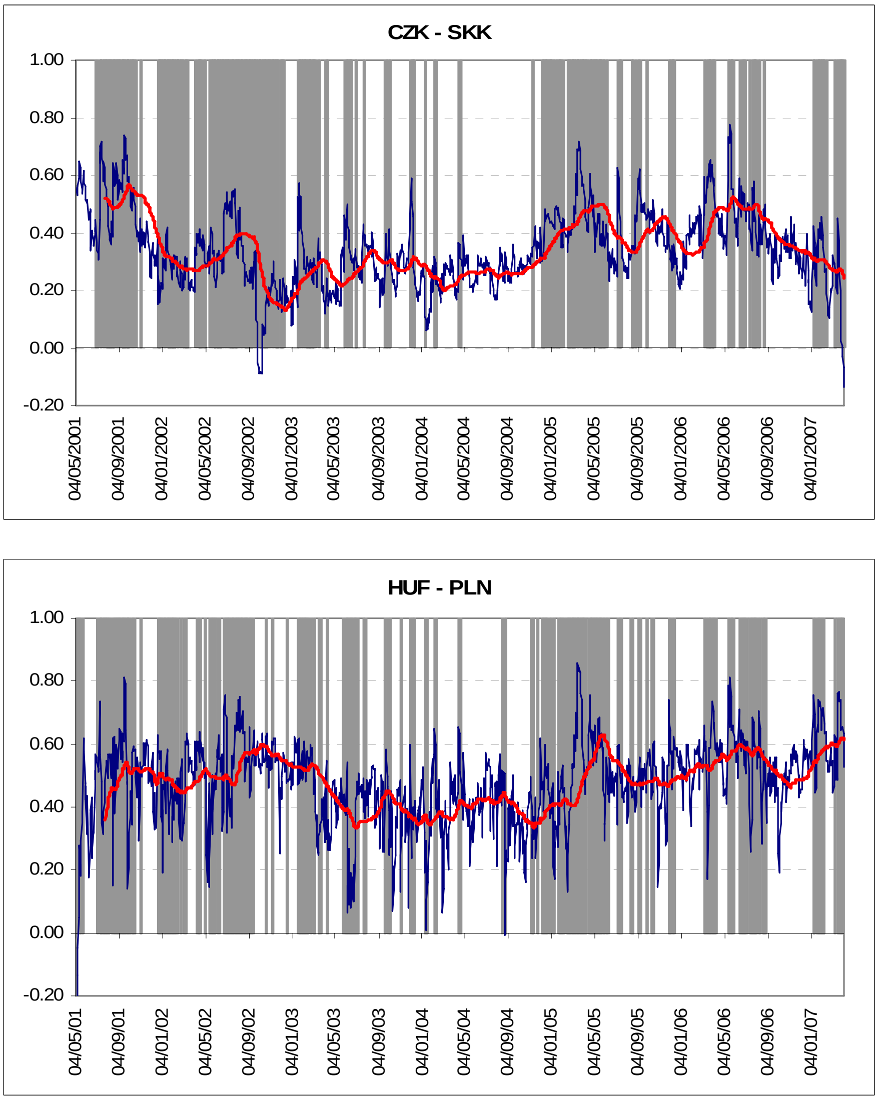
[17] Klaassen's last (eighth) component explains only 0.27% of the total system variance .

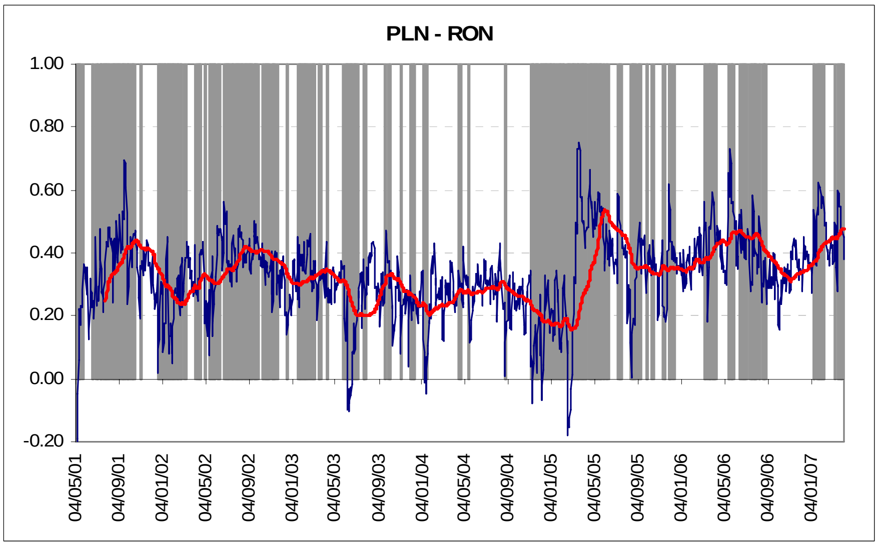
In the final part of the orthogonal GARCH model, we construct the diagonal matrices of the principal components' conditional variances for each moment t (t = 1,…,T) and multiply each of them with the weighting matrix and its transpose. In order to obtain the correlation matrix, we use the individual values in the variance-covariance matrix:

$$\rho_{ij} = \frac{\sigma_{ij}}{\sigma_i \sigma_j}$$

The most significant correlations, as found by the orthogonal GARCH model, are presented in the following three graphs. The shaded areas represent a 'naïve' measure of high volatility: they show the time periods when either of the two currencies presented in that particular graph had a volatility higher than the average volatility for the whole sample period (2001 – 2007).

Figure 2. Evolution of 3 Selected Conditional Correlations, Together With 60-day Moving Averages





Source: Author's estimates

Even with such a simple measure of high volatility, it is clear from these graphs that conditional correlations exhibit larger swings during times of market turbulences than during 'quiet' times. Thus higher volatility is generally associated with higher correlation coefficients among the CEE currencies (up to 0.8 for the currency pairs illustrated above), which is in line with the findings of Kóbor and Székely (2004). Sometimes they are also associated with sudden falls in correlation coefficients. However, it is also evident that under any circumstances correlations are highly volatile, which presents problems especially at a risk management level; for macroeconomic analyses, policy makers are usually concerned with a longer-term trend of correlations.

Figure A5 shows the graphic representations of all ten currency pairs conditional correlations. Apart from short-term highs or lows, which we believe to be driven by temporary market shocks, examination of the longer-term trends of correlations (such as the moving averages included in the graphs) reveals that correlations have generally increased over the sample period in question (May 2001 – April 2007), or at least remained at broadly similar levels. The only exception is the correlation between CZK and SKK, especially in the later part of the sample, since the SKK has entered ERM II. These conclusions thus confirm the previous findings of this paper, indicating increased cross-linkages among regional currency markets and a higher degree of commonality in the long-term currency trends.

V. CONCLUDING REMARKS

In light of the recent European Union enlargements of 2004 and 2007, new issues arise regarding the adoption of the European common currency by the new member states. Many papers have focused on the degree of business cycle convergence[18]; however, we believe that exchange rate volatility is also a very important aspect, especially when entering ERM II, prior to actual changeover.

Under these circumstances, it appears essential for Central Banks to know very well the exchange rate volatility patterns of their country's own currency, but also the ones of the other currencies in the region, in order to have better expectations of how the exchange rate is going to be affected.

The aims of the present paper have been the following:

1. To identify a unitary model for the five exchange rate volatilities and to identify similar patterns among them;
2. To isolate the different sources of exchange rate volatility and to compute a measure for how much the currencies influence each other;
3. To examine how the correlations between these five currencies have evolved over the time period under analysis.

We have used the Component GARCH model introduced by Engle and Lee (1993), which enriches the dynamic specification of the conditional variance compared to the GARCH(1,1) model by decomposing variance into a permanent component (a long-term volatility trend) and a transitory (short-term) component. We have also augmented the model with an asymmetry term where relevant, in order to capture asymmetric responses of volatility to shocks. The model successfully captures the pattern of conditional heteroskedasticity found in squared exchange rate returns and appears to perform better than the GARCH(1,1) model, providing higher values for the log-likelihood function.

Our results are in line with similar analyses, for both industrial countries (Byrne and Davis (2003)) and CEE countries (Pramor and Tamirisa (2006)). Shocks to variances are mostly of a short-run nature and volatility persistence is higher for the long-run component than for the short-run component. Furthermore, while the five currencies appear to respond to temporary market shocks in similar ways (as suggested by positive correlations between transitory volatilities), they respond differently to more permanent shocks. One possible explanation

[18] For an extensive review of relevant literature see Fidrmuc and Korhonen (2004)

could be that the long-run volatility component responds more to country-specific factors, such as macroeconomic fundamentals.

Following the approach of Diebold and Yilmaz (2007), we have constructed a measure of volatility spillovers, called Spillover Index, for each volatility component from the CGARCH model. We find evidence that volatility spillovers have increased over time, in line with the findings of Kóbor and Székely (2004) but contrary to Pramor and Tamirisa (2006). Spillovers into permanent volatility generally appear stronger than into the transitory component.

Finally, we use the orthogonal GARCH model of Klaassen (1999) and Alexander (2000) to compute conditional correlations of exchange rate returns. We find that daily conditional correlations are highly volatile, and that coefficient values are higher during times of market turbulences. Examination of the longer-term trends of correlations reveals that they have generally increased over the sample period in question or at least remained at broadly similar levels. The only exception is the correlation between CZK and SKK, especially in the later part of the sample, since the SKK has entered ERM II.

One of the limitations of several GARCH models is that they assume constant coefficients over long periods of time, during which different market events may take place that cannot be fully captured by the simplest forms of GARCH models. Although the CGARCH model is better than the GARCH(1,1), it would be interesting to examine volatilities estimated from even more complex models, such as smooth transition GARCH or Markov-switching GARCH. Furthermore, the evidence of different exchange rate behavior during high and low volatility periods suggests that future research could also include a study of contagion phenomena per se among the CEE currencies, especially during turbulent market times, using one of the approaches presented in Dungey et al. (2004).

To sum up, our results suggest increased economic convergence of the five countries in question. From the optimum currency area perspective, this would be a positive conclusion, but at the same time we believe it raises more problems for the policy makers of each country, as they have to increasingly take into account the actions of the other countries when making their own decisions. This calls for more coordinated courses of action, which would be a very good exercise in preparation for euro adoption and a single, unified monetary policy.

Being part of the European Union essentially means increased mobility of persons, goods and capital, so markets are likely to become even more integrated; in order to avoid pressures due very frequent foreign exchange interventions, Central Banks and other policy makers need to understand these aspects these aspects, in order to continuously adapt their policies and procedures to changing market behavior.

BIBLIOGRAPHY

Alexander, C. (2000), "Orthogonal Methods for Generating Large Positive Semi-Definite Covariance Matrices", Discussion Papers in Finance 2000-06, ICMA Centre, The University of Reading

Alexander, C. (2001), "Market Models. A Guide to Financial Analysis", John Wiley & Sons Ltd.

Andersen, T.G., Bollerslev, T., Christoffersen, P.F. and Diebold, F.X. (2005), "Practical Volatility and Correlation Modelling for Financial Market Risk Management", NBER Working Paper 11069

Andersen, T.G., Bollerslev, T., Diebold, F.X. and Labys, P. (2000), "Exchange Rate Returns Standardized by Realized Volatility are (Nearly) Gaussian", NBER Working Paper 7488

Bauwens, L. and Storti, G. (2007), "A Component Garch Model With Time Varying Weights", CORE Discussion Paper 2007/19

Borghijs, A. and Kuijs, L. (2004), "Exchange Rates in Central Europe: A Blessing or a Curse?", IMF Working Paper 04/2

Brooks, C. (2002), "Introductory Econometrics for Finance", Cambridge University Press

Bufton, G. and Chaudhri, S. (2005), "Independent Component Analysis", Quantitative Research, Royal Bank of Scotland

Byrne, J.P. and Davis, P.E. (2003), "Panel Estimation Of The Impact Of Exchange Rate Uncertainty On Investment In The Major Industrial Countries", NIESR Working Paper

Christoffersen, P.F., Jacobs, K. and Wang, Y. (2006), "Option Valuation with Long-run and Short-run Volatility Components", Working Paper, McGill University

Diebold, F.X. and Yilmaz, K. (2007), "Measuring Financial Asset Return and Volatility Spillovers, With Application to Global Equity Markets", Manuscript, Department of Economics, University of Pennsylvania

Dungey, M., Fry, R. Gonzales-Hermosillo, B. and Martin, V. (2004), "Empirical Modeling of Contagion: A Review of Methodologies", IMF Working Paper 04/78

Égert, B. and Morales-Zumaquero, A. (2005), "Exchange Rate Regimes, Foreign Exchange Volatility and Export Performance in Central and Eastern Europe: Just Another Blur Project?", BOFIT Discussion Papers 8/2005

Engle, R.F. and Lee, G.G.J. (1993), "A Permanent and Transitory Component Model of Stock Return Volatility", Discussion Paper 92-44R, University of California, San Diego

Fidrmuc, J. and Korhonen, I. (2004), "A meta-analysis of business cycle correlation between the euro area and CEECs: What do we know – and who cares?", BOFIT Discussion Papers 2004 No. 20

Guo, H. and Neely, C. (2006), "Investigating the Intertemporal Risk-Return Relation in International Stock Markets with the Component GARCH Model", Working Paper 2006-006A, Federal Reserve Bank of St. Louis

Klaassen, F. (1999), "Have Exchange Rates Become More Closely Tied? Evidence from a New Multivariate GARCH Model", Discussion Paper 10/1999, CentER and Department of Econometrics, Tilburg University

Kóbor, Á. and Székely, I.P. (2004), "Foreign Exchange Market Volatility in EU Accession Countries in the Run-Up to Euro Adoption: Weathering Uncharted Waters", IMF Working Paper 04/16

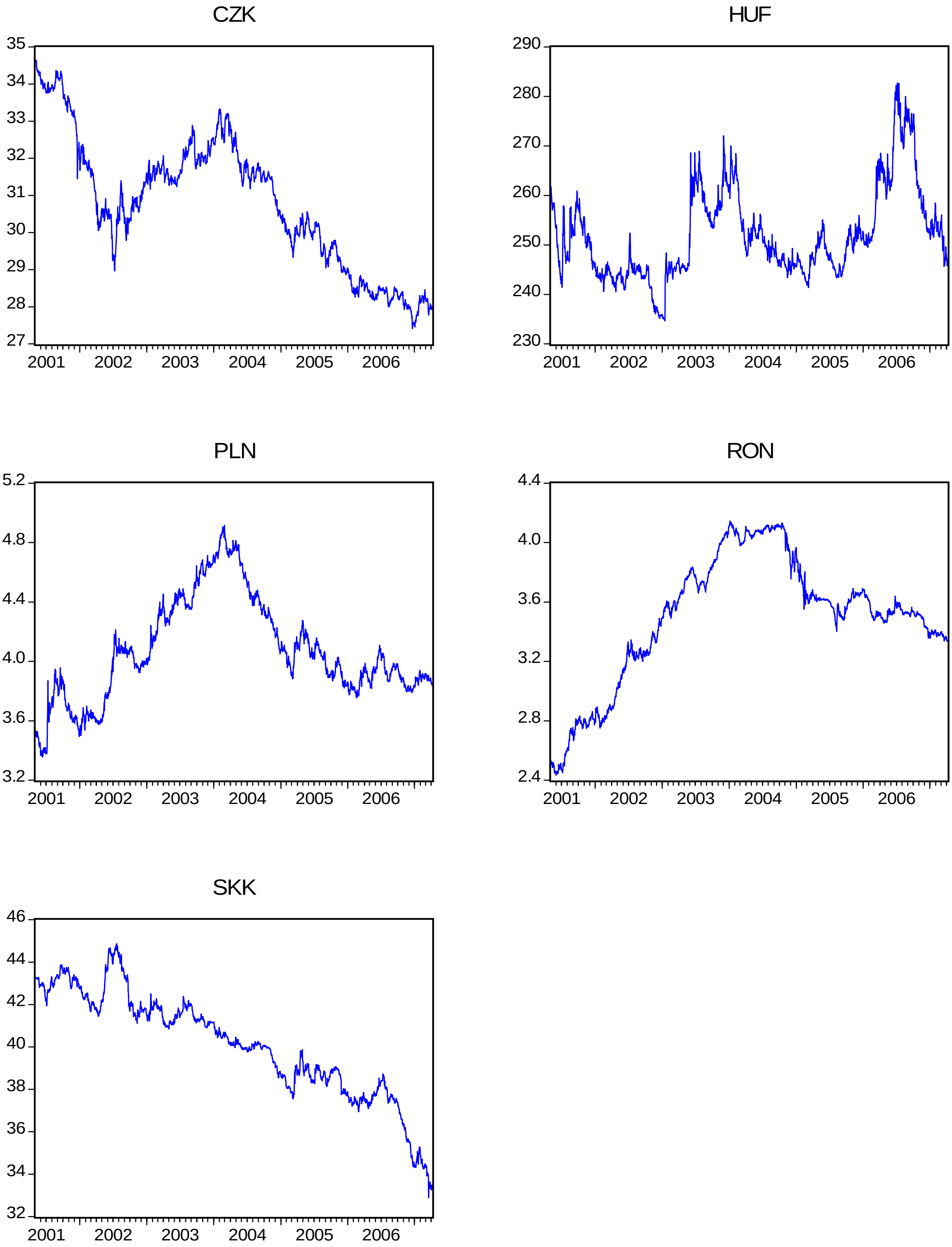
Maheu, J. (2005), "Can GARCH Models Capture Long-Range Dependence?", Studies in Nonlinear Dynamics & Econometrics, Volume 9, Issue 4, Article 1

Pramor, M. and Tamirisa, N.T. (2006), "Common Volatility Trends in the Central and Eastern European Currencies and the Euro", IMF Working Paper 06/206

Teräsvirta, T. (2006), "An Introduction to Univariate GARCH Models", SSE/EFI Working Papers in Economics and Finance, No. 646, Stockholm School of Economics

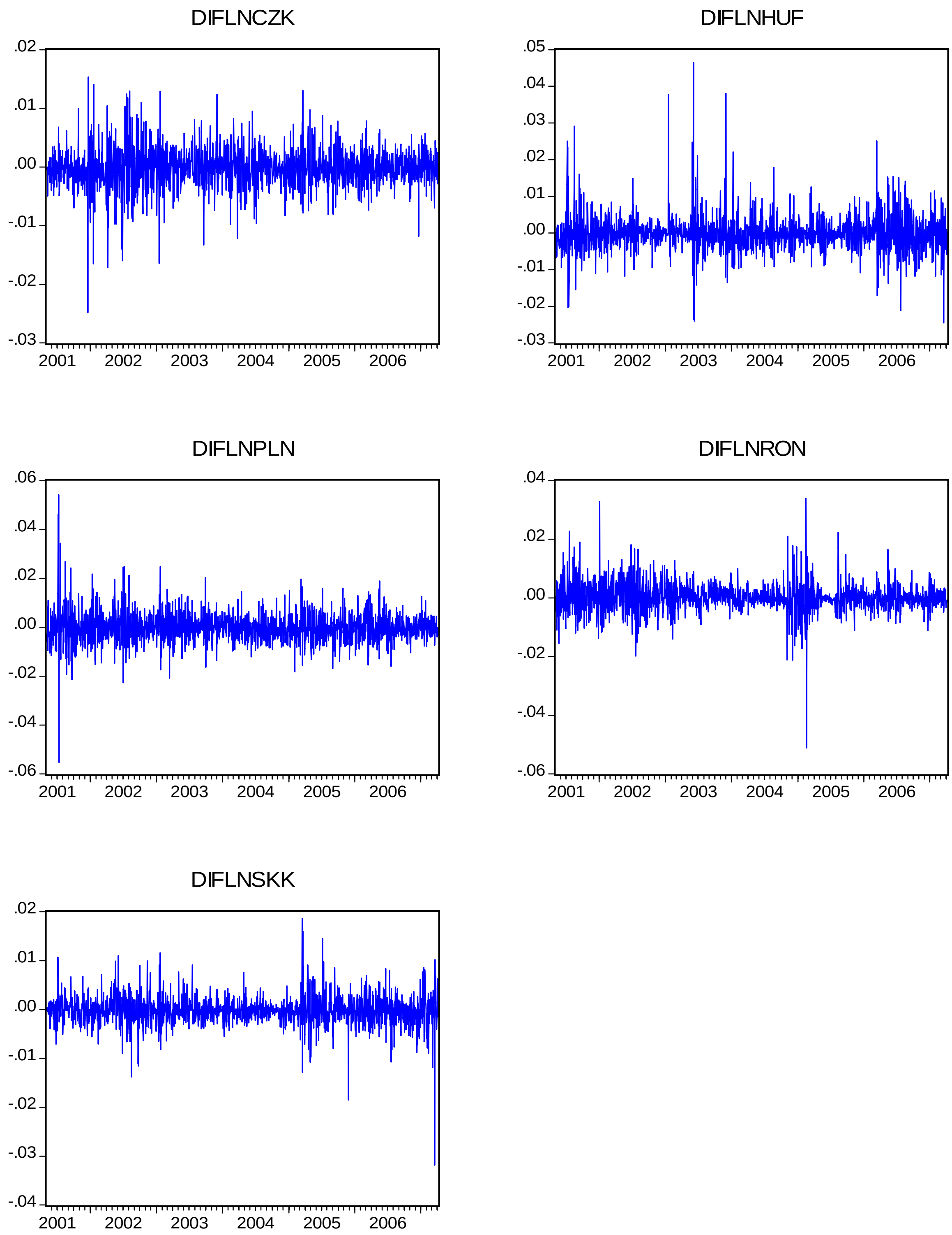
*** European Central Bank, Convergence Report May 2006

Figure A1. Daily Euro Nominal Exchange Rates, May 2001 – April 2007



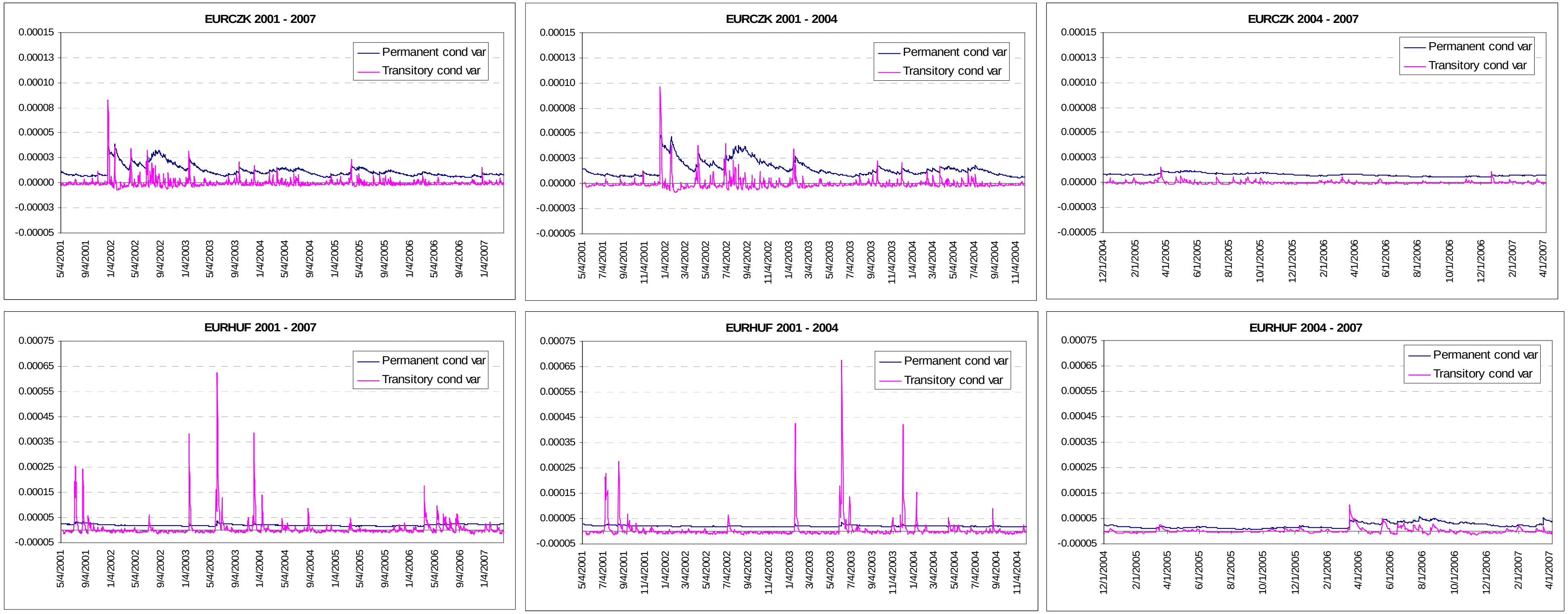
Source: Author's calculations

Figure A2. Daily Euro Nominal Exchange Rate Returns, May 2001 – April 2007



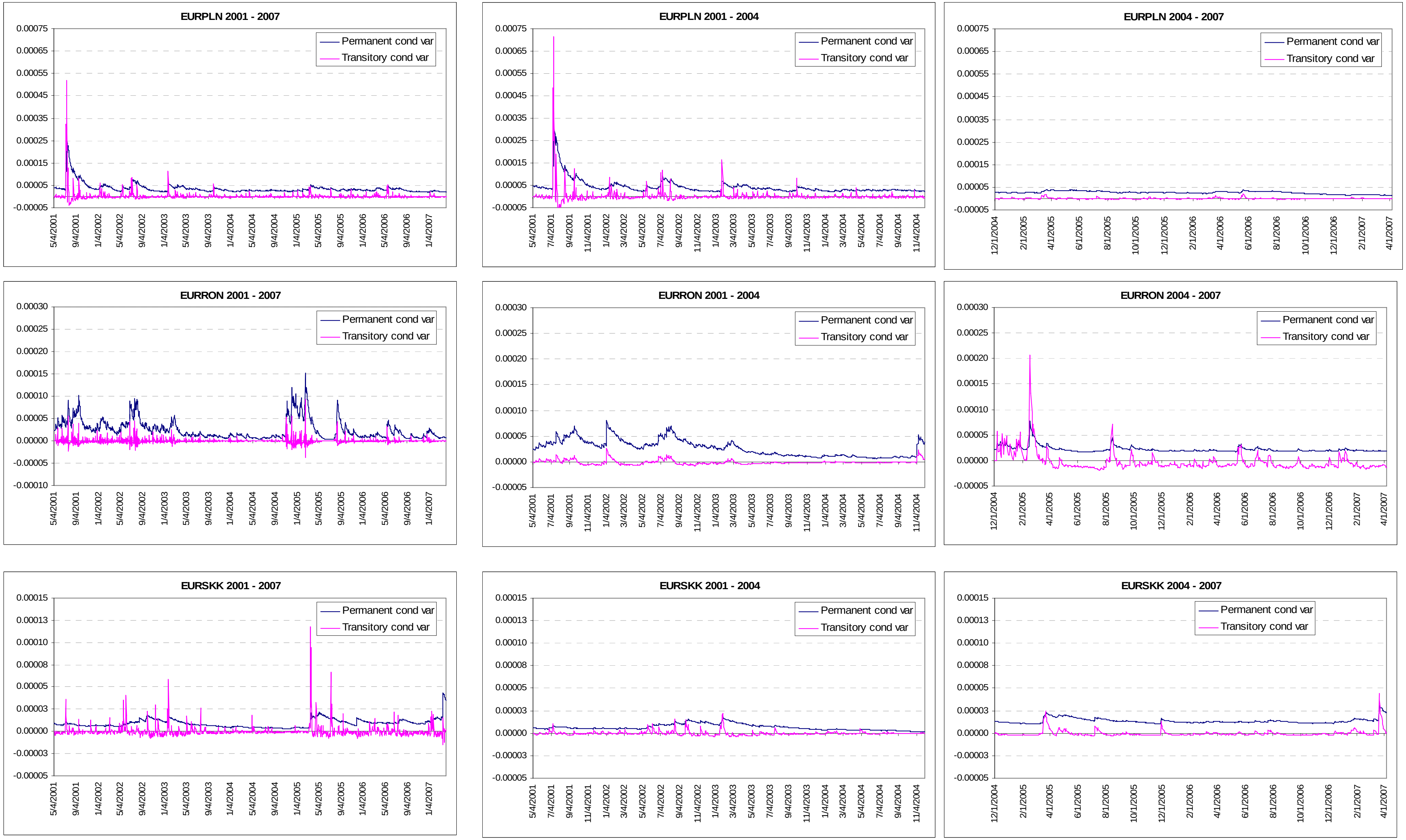
Source: Author's calculations

Figure A3. Permanent and Transitory Components of Conditional Variance from the CGARCH Model



Source: Author's estimates

(continued on next page)

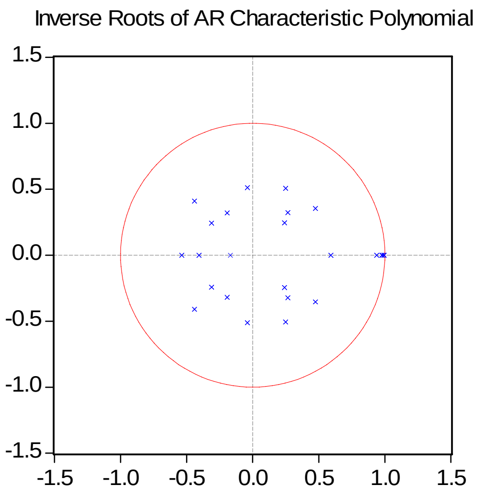


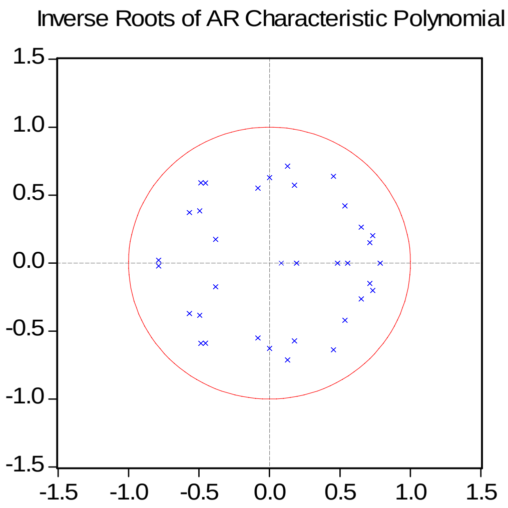
Source: Author's estimates

Figure A4. VAR Stability

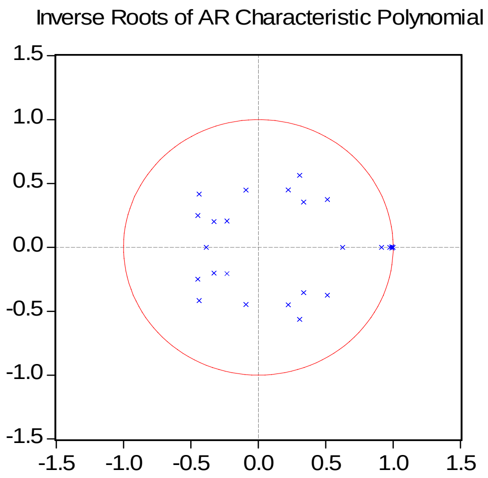
Permanent volatility | Transitory volatility

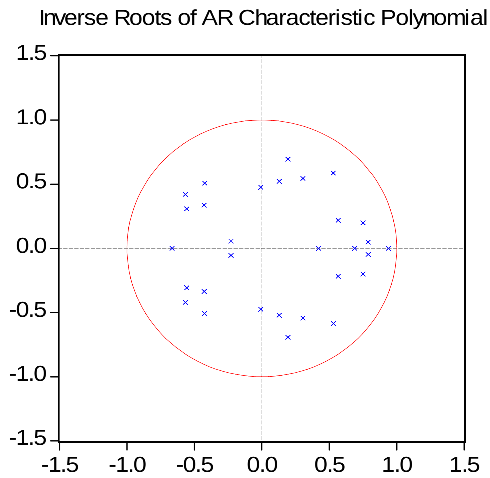
2001 - 2007



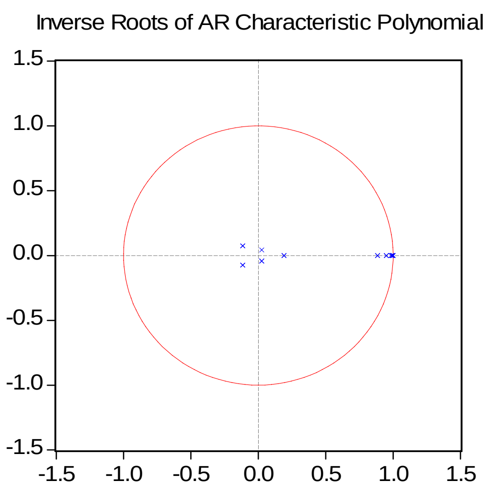


2001 – 2004





2004 – 2007



Source: Author's estimates

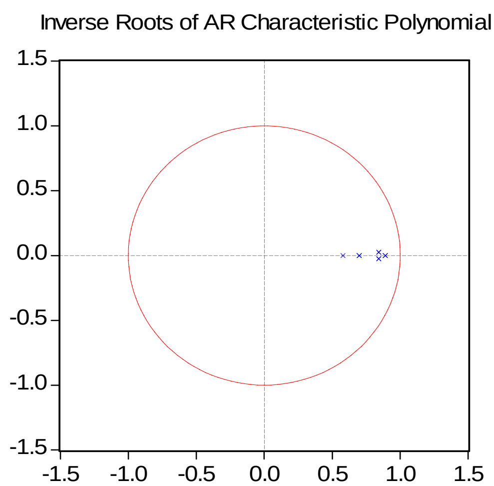
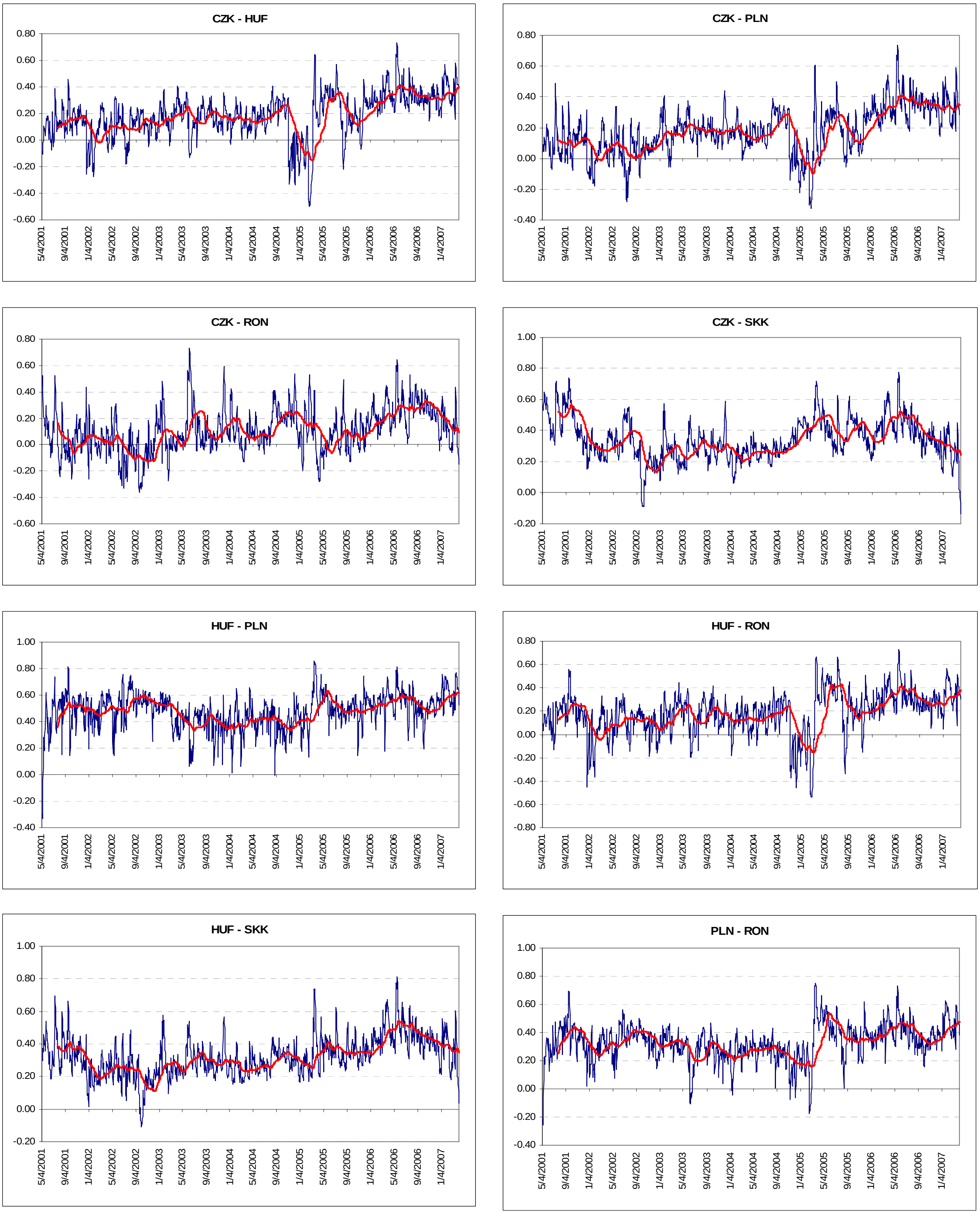
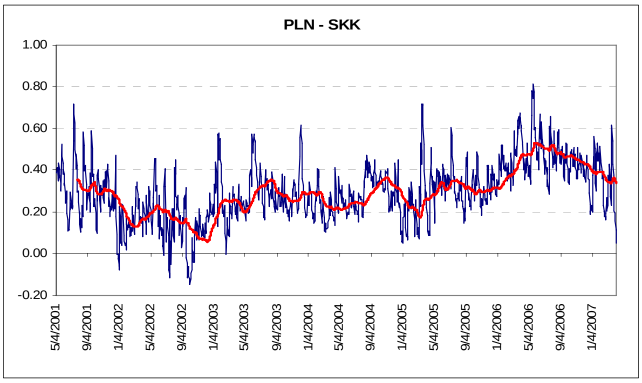
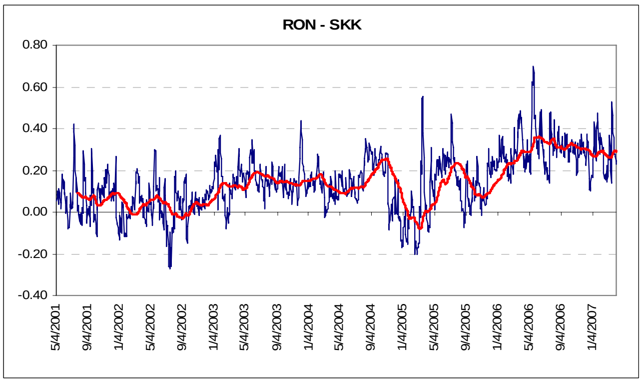


Figure A5. Evolution of All Conditional Correlations Resulting From the Orthogonal GARCH Model, Together With 60-days Moving Averages



(conditional correlations cont'd)





Source: Author's estimates

Table A1. Unit Root Tests

Currency	CZK	HUF	PLN	RON	SKK
Levels					
ADF t-stat	-2.261356	-3.261931	-1.728481	-0.973516	-2.026927
p-value	0.4545	0.0731	0.4166	0.9457	0.5855
First differences					
ADF t-stat	-39.90148	-40.57899	-43.14971	-27.50045	-37.87403
p-value	0.0000	0.0000	0.0001	0.0000	0.0000

Source: Author’s estimates

Table A2. Descriptive Statistics for Log-differences of Exchange Rates (y_t)

Sample period: May 2001 – April 2007

Currency	CZK	HUF	PLN	RON	SKK
Mean	-0.000139	-4.07E-05	5.40E-05	0.000180	-0.000167
Median	0.000000	-8.18E-05	0.000000	-4.92E-05	-0.000219
Maximum	0.015301	0.046408	0.054150	0.033856	0.018500
Minimum	-0.024805	-0.024447	-0.055269	-0.051064	-0.031801
Std. Dev.	0.003422	0.005098	0.006294	0.005106	0.002993
Skewness	-0.328967	1.377172	0.558913	0.056080	-0.466304
Kurtosis	7.395329	14.82252	13.33275	13.89330	15.21314
Jarque-Bera	1270.699	9480.058	6948.982	7634.853	9651.967
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-0.214915	-0.062905	0.083416	0.278152	-0.257680
Sum Sq. Dev.	0.018070	0.040100	0.061134	0.040235	0.013819

Sample period: May 2001 – November 2004

Currency	CZK	HUF	PLN	RON	SKK
Mean	-0.000118	-0.000086	0.000196	0.000452	-0.000106
Median	0.000000	-0.000120	0.000000	0.000000	-0.000120
Maximum	0.015300	0.046410	0.054150	0.032920	0.011560
Minimum	-0.024810	-0.024020	-0.055270	-0.021070	-0.013750
Std. Dev.	0.003765	0.005284	0.006894	0.005018	0.002514
Skewness	-0.461409	1.953605	0.617415	0.442558	0.331568
Kurtosis	7.423758	18.68955	14.34709	6.517078	7.086120
Jarque-Bera	793.8752	10163.02	5064.684	511.3332	666.1671
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-0.110300	-0.080280	0.182420	0.421510	-0.098840
Sum Sq. Dev.	0.013211	0.026026	0.044301	0.023466	0.005891

Sample period: December 2004 – April 2007

	DIFLNCZK	DIFLNHUF	DIFLNPLN	DIFLNRON	DIFLNSKK
Mean	-0.000169	-5.70E-06	-0.000153	-0.000234	-0.000264
Median	-0.000170	-6.00E-05	-1.00E-05	-0.000235	-0.000389
Maximum	0.013020	0.025140	0.019650	0.033860	0.018500
Minimum	-0.011780	-0.024450	-0.018130	-0.051060	-0.031801
Std. Dev.	0.002821	0.004872	0.005246	0.005212	0.003601
Skewness	0.159539	0.083472	0.207266	-0.450547	-0.806145
Kurtosis	4.606669	6.115887	4.312083	23.48965	15.66789
Jarque-Bera	68.42151	248.2839	48.28165	10726.26	4158.410
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-0.103410	-0.003490	-0.093410	-0.143400	-0.161352
Sum Sq. Dev.	0.004861	0.014503	0.016817	0.016597	0.007923

Source: Author’s estimates

Table A3. Ljung-Box Tests for Squared Returns

Correlations of Series DIFLNCZK
Daily(5) Data From 2001:05:04 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 210.3951. Significance Level
0.00000000

Correlations of Series DIFLNCZK1
Daily(5) Data From 2001:05:04 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-0)= 118.5668. Significance Level
0.00000000

Correlations of Series DIFLNCZK2
Daily(5) Data From 2004:12:01 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 41.4951. Significance Level
0.00026867

Correlations of Series DIFLNHUF
Daily(5) Data From 2001:05:04 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 156.9530. Significance Level
0.00000000

Correlations of Series DIFLNHUF1
Daily(5) Data From 2001:05:04 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-0)= 93.8240. Significance Level
0.00000000

Correlations of Series DIFLNHUF2
Daily(5) Data From 2004:12:01 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 102.9077. Significance Level
0.00000000

Correlations of Series DIFLNPLN
Daily(5) Data From 2001:05:04 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 533.4170. Significance Level
0.00000000

Correlations of Series DIFLNPLN1
Daily(5) Data From 2001:05:04 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-0)= 337.6208. Significance Level
0.00000000

Correlations of Series DIFLNPLN2
Daily(5) Data From 2004:12:01 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 30.7554. Significance Level
0.00947085

Correlations of Series DIFLNRON
Daily(5) Data From 2001:05:04 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 332.1083. Significance Level
0.00000000

Correlations of Series DIFLNRON1
Daily(5) Data From 2001:05:04 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-0)= 105.4624. Significance Level
0.00000000

Correlations of Series DIFLNRON2
Daily(5) Data From 2004:12:01 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 178.7027. Significance Level
0.00000000

Correlations of Series DIFLNSKK
Daily(5) Data From 2001:05:04 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 59.6085. Significance Level
0.00000029

Correlations of Series DIFLNSKK1
Daily(5) Data From 2001:05:04 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-0)= 102.3658. Significance Level
0.00000000

Correlations of Series DIFLNSKK2
Daily(5) Data From 2004:12:01 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 17.0371. Significance Level
0.31664972

Source: Author’s estimates

Table A4. Engle-Ng Test Results

CZK 2001 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.011596482	0.072428756	13.96678	0.00000000
2. SMINUS{1}	-0.043717299	0.103851962	-0.42096	0.67384452

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.083321607	0.107480736	10.07922	0.00000000
2. SMINUS{1}	-0.184206218	0.153405372	-1.20078	0.23002092
3. USMINUS{1}	-0.090634052	0.105774384	-0.85686	0.39165446
4. USPLUS{1}	-0.101542512	0.112410580	-0.90332	0.36649837

Chi-Squared(3)= 1.729896 with Significance Level 0.78528005

CZK 2001 – 2004

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.9704124580	0.0950168639	10.21306	0.00000000
2. SMINUS{1}	0.0262534405	0.1376776821	0.19069	0.84881207

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.995025759	0.139418800	7.13696	0.00000000
2. SMINUS{1}	-0.055536046	0.201155984	-0.27608	0.78254492
3. USMINUS{1}	-0.074751174	0.137626542	-0.54315	0.58716094
4. USPLUS{1}	-0.036086277	0.149468348	-0.24143	0.80927474

Chi-Squared(3)= 0.391114 with Significance Level 0.94207192

CZK 2004 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.082613725	0.107674603	10.05449	0.00000000
2. SMINUS{1}	-0.135533199	0.152274884	-0.89006	0.37378777

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.237815291	0.161422191	7.66819	0.00000000
2. SMINUS{1}	-0.380519693	0.231542154	-1.64341	0.10081593
3. USMINUS{1}	-0.116599339	0.164083310	-0.71061	0.47759896
4. USPLUS{1}	-0.207338105	0.160681335	-1.29037	0.19741493

Chi-Squared(3)= 2.967487 with Significance Level 0.39666529

Source: Author's estimates

(continued on next page)

(Table A4 cont'd)

HUF 2001 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.238920607	0.130511756	9.49279	0.00000000
2. SMINUS{1}	-0.351976641	0.180905881	-1.94563	0.05188080

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.228889129	0.172768395	7.11293	0.00000000
2. SMINUS{1}	-0.253552948	0.257484407	-0.98473	0.32491127
3. USMINUS{1}	0.134740720	0.219523258	0.61379	0.53944644
4. USPLUS{1}	0.013030366	0.146945832	0.08867	0.92935207

Chi-Squared(4)= 4.165662 with Significance Level 0.38404989

HUF 2001 – 2004

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.182797206	0.191517887	6.17591	0.00000000
2. SMINUS{1}	-0.260977065	0.267411361	-0.97594	0.32934978

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.143510841	0.241657436	4.73195	0.00000257
2. SMINUS{1}	-0.206225754	0.379237977	-0.54379	0.58671729
3. USMINUS{1}	0.024097762	0.350238362	0.06880	0.94516061
4. USPLUS{1}	0.054183008	0.202898330	0.26705	0.78949401

Chi-Squared(3)= 1.029824 with Significance Level 0.79403595

HUF 2004 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.1549132097	0.1077570002	10.71776	0.00000000
2. USMINUS{1}	0.2904942163	0.1717451493	1.69143	0.09095818

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.228889129	0.172768395	7.11293	0.00000000
2. SMINUS{1}	-0.253552948	0.257484407	-0.98473	0.32491127
3. USMINUS{1}	0.134740720	0.219523258	0.61379	0.53944644
4. USPLUS{1}	0.013030366	0.146945832	0.08867	0.92935207

Chi-Squared(4)= 4.165662 with Significance Level 0.38404989

Source: Author's estimates

(continued on next page)

(Table A4 cont'd)

PLN 2001 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.183783064	0.073526879	16.10000	0.00000000
2. SMINUS{1}	-0.342406305	0.104698547	-3.27040	0.00109769

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.115425433	0.106743672	10.44957	0.00000000
2. SMINUS{1}	-0.212945188	0.159300896	-1.33675	0.18150266
3. USMINUS{1}	0.083487754	0.125406641	0.66574	0.50567956
4. USPLUS{1}	0.088467645	0.100124364	0.88358	0.37706246

Chi-Squared(3)= 11.853174 with Significance Level 0.00790343

PLN 2001 – 2004

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.165924912	0.093816937	12.42766	0.00000000
2. SMINUS{1}	-0.315159647	0.132039140	-2.38687	0.01719236

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.063283272	0.135438937	7.85065	0.00000000
2. SMINUS{1}	-0.112503233	0.203028015	-0.55413	0.57962611
3. USMINUS{1}	0.136141623	0.162448074	0.83806	0.40221215
4. USPLUS{1}	0.132750173	0.126325618	1.05086	0.29359868

Chi-Squared(3)= 7.474407 with Significance Level 0.05821972

PLN 2004 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.183783064	0.073526879	16.10000	0.00000000
2. SMINUS{1}	-0.342406305	0.104698547	-3.27040	0.00109769

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.115425433	0.106743672	10.44957	0.00000000
2. SMINUS{1}	-0.212945188	0.159300896	-1.33675	0.18150266
3. USMINUS{1}	0.083487754	0.125406641	0.66574	0.50567956
4. USPLUS{1}	0.088467645	0.100124364	0.88358	0.37706246

Chi-Squared(3)= 11.853174 with Significance Level 0.00790343

Source: Author's estimates

(continued on next page)

(Table A4 cont'd)

RON 2001 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.9467224673	0.0753296948	12.56772	0.00000000
2. SMINUS{1}	0.1048997899	0.1022737991	1.02568	0.30520547

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.929288508	0.112863440	8.23374	0.00000000
2. SMINUS{1}	0.106490431	0.153944156	0.69175	0.48920061
3. USMINUS{1}	-0.022889012	0.113474775	-0.20171	0.84017003
4. USPLUS{1}	0.021514082	0.103662584	0.20754	0.83561604

Chi-Squared(3)= 1.136575 with Significance Level 0.76825295

RON 2001 – 2004

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.8996031322	0.1175009743	7.65613	0.00000000
2. SMINUS{1}	0.1976295542	0.1570052491	1.25874	0.20843837

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.894634638	0.182276466	4.90812	0.00000109
2. SMINUS{1}	0.081015336	0.241932903	0.33487	0.73780112
3. USMINUS{1}	-0.174369058	0.172405233	-1.01139	0.31209307
4. USPLUS{1}	0.005926275	0.166149707	0.03567	0.97155453

Chi-Squared(3)= 2.610862 with Significance Level 0.45558847

RON 2004 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.9758474695	0.1130921913	8.62878	0.00000000
2. SMINUS{1}	0.0527613438	0.1602002149	0.32935	0.74200777

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.769770091	0.162540875	4.73586	0.00000272
2. SMINUS{1}	0.163340369	0.236870759	0.68958	0.49072576
3. USMINUS{1}	-0.128991565	0.175327953	-0.73572	0.46218920
4. USPLUS{1}	0.272024225	0.154302378	1.76293	0.07841802

Chi-Squared(3)= 3.759459 with Significance Level 0.28863704

Source: Author's estimates

(continued on next page)

(Table A4 cont'd)

SKK 2001 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.8528500545	0.1221448239	6.98229	0.00000000
2. SMINUS{1}	0.3161219585	0.1711935677	1.84658	0.06500011

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.6969277978	0.1686019786	4.13357	0.00003764
2. SMINUS{1}	0.6733907574	0.2349153523	2.86653	0.00420648
3. USMINUS{1}	0.2929471666	0.1620104614	1.80820	0.07077052
4. USPLUS{1}	0.2249905037	0.1678862830	1.34014	0.18039872

Chi-Squared(3)= 8.457619 with Significance Level 0.03744286

SKK 2001 – 2004

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	1.012790359	0.098984333	10.23182	0.00000000
2. SMINUS{1}	-0.021505979	0.139610594	-0.15404	0.87760960

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.8822414368	0.1385320922	6.36850	0.00000000
2. SMINUS{1}	0.2020636464	0.2025308699	0.99769	0.31868856
3. USMINUS{1}	0.1295378322	0.1534349105	0.84425	0.39874605
4. USPLUS{1}	0.1797099402	0.1334549636	1.34660	0.17843947

Chi-Squared(3)= 2.553804 with Significance Level 0.46564587

SKK 2004 – 2007

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.7256165415	0.2293013210	3.16447	0.00163126
2. SMINUS{1}	0.4798040861	0.3201100472	1.49887	0.13442578

Variable	Coeff	Std Error	T-Stat	Signif
1. Constant	0.5370698116	0.3156085120	1.70170	0.08932525
2. SMINUS{1}	0.9196711612	0.4237875643	2.17012	0.03038525
3. USMINUS{1}	0.4025377771	0.2781846915	1.44702	0.14840943
4. USPLUS{1}	0.2870038618	0.3303639481	0.86875	0.38532751

Chi-Squared(3)= 5.089174 with Significance Level 0.16538263

Source: Author's estimates

Table A5. Component GARCH Results For CZK

MAXIMIZE - Estimation by BHHH
Convergence in 23 Iterations. Final criterion was 0.0000005 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2001:05:07 To 2007:04:05
Usable Observations 1544
Function Value 8111.75466048

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	1.2377e-05	2.0174e-06	6.13515	0.00000000
2. VR	0.9914	3.2586e-03	304.25260	0.00000000
3. VF	0.0338	8.5715e-03	3.94533	0.00007969
4. BC	-1.3319e-04	7.7414e-05	-1.72054	0.08533410
5. VA	0.1242	0.0187	6.64368	0.00000000
6. VB	0.5312	0.0793	6.69939	0.00000000

MAXIMIZE - Estimation by BHHH
Convergence in 25 Iterations. Final criterion was 0.0000035 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2001:05:11 To 2004:11:30
Usable Observations 928
Function Value 4794.65760647

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	1.6354e-05	4.3064e-06	3.79775	0.00014602
2. VR	0.9899	5.3116e-03	186.37060	0.00000000
3. VF	0.0478	0.0150	3.18742	0.00143546
4. BC	-1.0283e-04	1.0899e-04	-0.94348	0.34543498
5. VA	0.1418	0.0268	5.28349	0.00000013
6. VB	0.4873	0.0920	5.29885	0.00000012

MAXIMIZE - Estimation by BHHH
Convergence in 26 Iterations. Final criterion was 0.0000081 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2004:12:03 To 2007:04:05
Usable Observations 610
Function Value 3290.66031239

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	7.4658e-06	1.1005e-06	6.78408	0.00000000
2. VR	0.9908	8.6714e-03	114.25906	0.00000000
3. VF	0.0149	0.0116	1.29395	0.19568417
4. BC	-1.6444e-04	1.1404e-04	-1.44195	0.14931776
5. VA	0.0855	0.0411	2.08252	0.03729502
6. VB	0.5705	0.2704	2.10989	0.03486782

Source: Author's estimates

Table A6. Component GARCH Results For HUF

MAXIMIZE - Estimation by BFGS
Convergence in 55 Iterations. Final criterion was 0.0000011 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2001:05:14 To 2007:04:05
Usable Observations 1539
Function Value 7569.92708279

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	1.9550e-05	3.9737e-06	4.91991	0.00000087
2. VR	0.9889	4.9689e-03	199.01349	0.00000000
3. VF	8.7726e-03	7.6236e-03	1.15072	0.24984905
4. BC	-1.1671e-04	1.8078e-08	-6456.12857	0.00000000
5. VA	0.2693	0.0404	6.67402	0.00000000
6. VB	0.7058	0.0344	20.54240	0.00000000
7. VD	-0.2919	0.0429	-6.80066	0.00000000

MAXIMIZE - Estimation by BFGS
Convergence in 24 Iterations. Final criterion was 0.0000000 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2001:05:11 To 2004:11:30
Usable Observations 928
Function Value 4557.13033875

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	2.0160e-05	2.8890e-06	6.97812	0.00000000
2. VR	0.9626	0.0116	82.94631	0.00000000
3. VF	6.1215e-03	6.8778e-03	0.89004	0.37344466
4. BC	-1.7906e-04	9.9185e-05	-1.80530	0.07102749
5. VA	0.2991	3.5399e-03	84.48038	0.00000000
6. VB	0.5827	9.4654e-03	61.55787	0.00000000
7. VD	-0.2985	0.0179	-16.64895	0.00000000

MAXIMIZE - Estimation by BHHH
Convergence in 7 Iterations. Final criterion was 0.0000023 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2004:12:06 To 2007:04:05
Usable Observations 609
Function Value 3002.57740596

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	0.000028008	0.000022729	1.23226	0.21785033
2. VR	0.995768382	0.006354989	156.69081	0.00000000
3. VF	0.047415129	0.015175734	3.12440	0.00178165
4. BC	-0.000107704	0.000158769	-0.67837	0.49753818
5. VA	0.148090657	0.026609031	5.56543	0.00000003
6. VB	0.796128889	0.061307328	12.98587	0.00000000
7. VD	-0.113591784	0.038606434	-2.94230	0.00325782

Source: Author’s estimates

Table A7. Component GARCH Results For PLN

MAXIMIZE - Estimation by BHHH
Convergence in 88 Iterations. Final criterion was 0.0000026 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2001:05:10 To 2007:04:05
Usable Observations 1541
Function Value 7204.74473747

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	3.1811e-05	2.5254e-06	12.59621	0.00000000
2. VR	0.9771	6.9738e-03	140.11302	0.00000000
3. VF	0.0344	9.8190e-03	3.49883	0.00046731
4. BC	-1.1722e-04	1.3703e-04	-0.85542	0.39231917
5. VA	0.1420	0.0161	8.82253	0.00000000
6. VB	0.4361	0.1033	4.22121	0.00002430
7. VD	-0.0778	0.0370	-2.09990	0.03573755

MAXIMIZE - Estimation by BHHH
Convergence in 2 Iterations. Final criterion was 0.0000000 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2001:05:10 To 2004:11:30
Usable Observations 929
Function Value 4294.49497527

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	3.7334e-05	4.9567e-06	7.53215	0.00000000
2. VR	0.9775	7.2627e-03	134.58700	0.00000000
3. VF	0.0460	0.0141	3.26224	0.00110534
4. BC	1.5593e-04	1.8500e-04	0.84285	0.39931045
5. VA	0.2154	0.0258	8.35563	0.00000000
6. VB	0.3105	0.1185	2.61976	0.00879925
7. VD	-0.1254	0.0591	-2.12199	0.03383831

MAXIMIZE - Estimation by BFGS
Convergence in 37 Iterations. Final criterion was 0.0000000 < 0.0000000
Robust Standard Error Calculations
Daily(5) Data From 2004:12:02 To 2007:04:05
Usable Observations 611
Function Value 2916.56613443

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	1.7006e-05	2.6821e-08	634.05310	0.00000000
2. VR	0.9967	7.7609e-05	12843.06283	0.00000000
3. VF	0.0153	6.9976e-06	2185.98960	0.00000000
4. BC	-1.8011e-04	8.6989e-07	-207.04670	0.00000000
5. VA	0.0428	3.4719e-05	1233.14876	0.00000000
6. VB	0.7406	1.3500e-04	5485.81555	0.00000000
7. VD	-0.0206	1.3463e-04	-153.30061	0.00000000

Source: Author’s estimates

Table A8. Component GARCH Results For RON

MAXIMIZE - Estimation by BFGS
Convergence in 48 Iterations. Final criterion was 0.0000000 < 0.0000000
Robust Standard Error Calculations
Daily(5) Data From 2001:05:10 To 2007:04:05
Usable Observations 1541
Function Value 7694.54432389

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	1.1813e-04	4.3767e-06	26.99121	0.00000000
2. VR	0.9982	6.5905e-04	1514.56260	0.00000000
3. VF	0.1146	0.0135	8.46303	0.00000000
4. BC	1.4997e-04	8.6685e-05	1.73008	0.08361522
5. VA	0.1275	4.0266e-03	31.66557	0.00000000
6. VB	-0.1992	0.2401	-0.82964	0.40674131

MAXIMIZE - Estimation by BFGS
Convergence in 32 Iterations. Final criterion was 0.0000044 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2001:05:07 To 2004:11:30
Usable Observations 932
Function Value 4574.73603252

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	0.0000925087	0.0004308624	0.21471	0.82999662
2. VR	0.9990990112	0.0045537466	219.40154	0.00000000
3. VF	0.0482819958	0.0211064065	2.28755	0.02216364
4. BC	0.0005225170	0.0001364674	3.82888	0.00012873
5. VA	0.0285135258	0.0196856082	1.44845	0.14749256
6. VB	0.9283349454	0.0320571417	28.95876	0.00000000

MAXIMIZE - Estimation by BHHH
Convergence in 20 Iterations. Final criterion was 0.0000000 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2004:12:07 To 2007:04:05
Usable Observations 608
Function Value 3124.46909688

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	2.0884e-05	4.7795e-06	4.36948	0.00001245
2. VR	0.9467	0.0525	18.01585	0.00000000
3. VF	0.0420	0.0458	0.91734	0.35896701
4. BC	-2.9466e-04	1.2853e-04	-2.29254	0.02187468
5. VA	0.1300	0.0607	2.14027	0.03233257
6. VB	0.7282	0.0562	12.95652	0.00000000
7. VD	0.1633	0.0515	3.17154	0.00151635

Source: Author’s estimates

Table A9. Component GARCH Results For SKK

MAXIMIZE - Estimation by BFGS
Convergence in 16 Iterations. Final criterion was 0.0000000 < 0.0000000
Robust Standard Error Calculations
Daily(5) Data From 2001:05:07 To 2007:04:05
Usable Observations 1544
Function Value 8345.90913611

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	2.6282e-04	9.8625e-05	2.66485	0.00770229
2. VR	0.9999	3.7010e-05	27017.50802	0.00000000
3. VF	0.0265	0.0115	2.30217	0.02132542
4. BC	-1.5780e-04	6.8926e-09	-22894.11375	0.00000000
5. VA	0.3385	0.0801	4.22508	0.00002389
6. VB	0.4261	0.1165	3.65697	0.00025521
7. VD	-0.3535	0.0887	-3.98364	0.00006787

MAXIMIZE - Estimation by BHHH
Convergence in 17 Iterations. Final criterion was 0.0000084 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2001:05:08 To 2004:11:30
Usable Observations 931
Function Value 5185.41025232

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	0.000004896	0.000006991	0.70038	0.48369167
2. VR	1.0000	0.001813037	551.97401	0.00000000
3. VF	0.0261	0.006341787	4.11705	0.00003838
4. BC	-0.95105e-4	0.000067401	-1.41103	0.15823509
5. VA	0.0940	0.027786723	3.38234	0.00071872
6. VB	0.7298	0.081892091	8.91199	0.00000000

MAXIMIZE - Estimation by BHHH
Convergence in 225 Iterations. Final criterion was 0.0000000 < 0.0000100
Robust Standard Error Calculations
Daily(5) Data From 2004:12:03 To 2007:04:05
Usable Observations 610
Function Value 3145.65840663

Variable	Coeff	Std Error	T-Stat	Signif
1. VC	1.4838e-05	1.5648e-06	9.48221	0.00000000
2. VR	0.9800	0.0229	42.73430	0.00000000
3. VF	0.0171	0.0189	0.90186	0.36713265
4. BC	-3.2481e-04	1.6477e-04	-1.97133	0.04868632
5. VA	0.0461	0.0232	1.99213	0.04635654
6. VB	0.7999	0.1581	5.06062	0.00000042

Source: Author's estimates

Table A10. Ljung-Box Tests for the Squared Standardized Residuals from the CGARCH Models

CZK
Daily(5) Data From 2001:05:04 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 12.5879. Significance Level 0.63409711

Daily(5) Data From 2001:05:10 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-4)= 11.4790. Significance Level 0.40404791

Daily(5) Data From 2004:12:02 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-1)= 14.5579. Significance Level 0.40902556

HUF
Daily(5) Data From 2001:05:11 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-5)= 8.0893. Significance Level 0.62011559

Daily(5) Data From 2001:05:10 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-4)= 9.3266. Significance Level 0.59177795

Daily(5) Data From 2004:12:03 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-2)= 8.8514. Significance Level 0.78407295

PLN
Daily(5) Data From 2001:05:09 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-3)= 8.2748. Significance Level 0.76330213

Daily(5) Data From 2001:05:09 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-3)= 9.9407. Significance Level 0.62116691

Daily(5) Data From 2004:12:01 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 9.7740. Significance Level 0.83371079

RON
Daily(5) Data From 2001:05:09 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-3)= 19.1325. Significance Level 0.08538029

Daily(5) Data From 2001:05:04 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-0)= 15.1534. Significance Level 0.44042307

Daily(5) Data From 2004:12:06 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-3)= 13.2942. Significance Level 0.34802138

SKK
Daily(5) Data From 2001:05:04 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-0)= 10.0056. Significance Level 0.81938978

Daily(5) Data From 2001:05:07 To 2004:11:30
Ljung-Box Q-Statistics
Q(15-1)= 9.8053. Significance Level 0.77627279

Daily(5) Data From 2004:12:02 To 2007:04:05
Ljung-Box Q-Statistics
Q(15-1)= 6.6743. Significance Level 0.94654046

Source: Author’s estimates

Table A11. Comparison of Long-Run and Short-Run Variance Components

Sample period: May 2001 – April 2007

	Mean Of LR Comp./Mean Of SR Comp.	St. Dev. Of LR Comp./St. Dev. Of SR Comp.	(St. Dev./Mean) Of LR Comp./(St. Dev./Mean) Of SR Comp.
CZK	-189.4787	1.2578	-0.0066
HUF	3.3152	0.1011	0.0305
PLN	36.3140	1.0536	0.0290
RON	-130.7402	3.3029	-0.0253
SKK	165.4842	0.7095	0.0043

Sample period: May 2001 – November 2004

	Mean Of LR Comp./Mean Of SR Comp.	St. Dev. Of LR Comp./St. Dev. Of SR Comp.	(St. Dev./Mean) Of LR Comp./(St. Dev./Mean) Of SR Comp.
CZK	-79.5165	1.2260	-0.0154
HUF	3.6207	0.0488	0.0135
PLN	27.9725	0.8884	0.0318
RON	-35.2796	3.7168	-0.1054
SKK	-53.1863	1.4028	-0.0264

Sample period: December 2004 – April 2007

	Mean Of LR Comp./Mean Of SR Comp.	St. Dev. Of LR Comp./St. Dev. Of SR Comp.	(St. Dev./Mean) Of LR Comp./(St. Dev./Mean) Of SR Comp.
CZK	277.9593	0.9235	0.0033
HUF	15.8592	1.0579	0.0667
PLN	241.2005	2.0237	0.0084
RON	-9.4880	0.3148	-0.0332
SKK	-85.4146	0.7443	-0.0087

Source: Author’s estimates

Table A12. Unconditional Correlations of y_t

Sample period: May 2001 – April 2007

	CZK	HUF	PLN	RON	SKK
CZK	1.000000	0.168499	0.167506	0.107909	0.362435
HUF	0.168499	1.000000	0.482782	0.154498	0.336801
PLN	0.167506	0.482782	1.000000	0.323007	0.310782
RON	0.107909	0.154498	0.323007	1.000000	0.129658
SKK	0.362435	0.336801	0.310782	0.129658	1.000000

Sample period: May 2001 – November 2004

	CZK	HUF	PLN	RON	SKK
CZK	1.000000	0.079048	0.070293	0.097676	0.233516
HUF	0.079048	1.000000	0.413704	0.111398	0.241269
PLN	0.070293	0.413704	1.000000	0.398340	0.210405
RON	0.097676	0.111398	0.398340	1.000000	0.116133
SKK	0.233516	0.241269	0.210405	0.116133	1.000000

Sample period: December 2004 – April 2007

	CZK	HUF	PLN	RON	SKK
CZK	1.000000	0.362231	0.427720	0.130940	0.589921
HUF	0.362231	1.000000	0.624563	0.224203	0.465731
PLN	0.427720	0.624563	1.000000	0.184667	0.485222
RON	0.130940	0.224203	0.184667	1.000000	0.143980
SKK	0.589921	0.465731	0.485222	0.143980	1.000000

Source: Author's estimates

Table A13. Unconditional Correlations of Permanent Component of Volatility

2001 – 2007	CZK	HUF	PLN	RON	SKK
CZK	1.000000	-0.329457	0.075657	0.186766	0.112862
HUF	-0.329457	1.000000	0.425788	-0.039345	-0.034423
PLN	0.075657	0.425788	1.000000	0.366271	0.014948
RON	0.186766	-0.039345	0.366271	1.000000	-0.144366
SKK	0.112862	-0.034423	0.014948	-0.144366	1.000000

2001 – 2004	CZK	HUF	PLN	RON	SKK
CZK	1.000000	-0.324719	-0.022691	0.451603	0.348242
HUF	-0.324719	1.000000	0.468804	0.058656	-0.059283
PLN	-0.022691	0.468804	1.000000	0.487463	0.142589
RON	0.451603	0.058656	0.487463	1.000000	0.352522
SKK	0.348242	-0.059283	0.142589	0.352522	1.000000

2004 – 2007	CZK	HUF	PLN	RON	SKK
CZK	1.000000	-0.578382	0.602073	0.151167	0.481182
HUF	-0.578382	1.000000	-0.081575	-0.219992	0.029967
PLN	0.602073	-0.081575	1.000000	0.124698	0.192053
RON	0.151167	-0.219992	0.124698	1.000000	-0.146691
SKK	0.481182	0.029967	0.192053	-0.146691	1.000000

Source: Author's estimates

Table A14. Unconditional Correlations of Transitory Component of Volatility

2001 – 2007	CZK	HUF	PLN	RON	SKK
CZK	1.000000	0.082451	0.062248	0.006522	0.193709
HUF	0.082451	1.000000	0.348334	0.006946	0.153118
PLN	0.062248	0.348334	1.000000	0.062488	0.173707
RON	0.006522	0.006946	0.062488	1.000000	0.010132
SKK	0.193709	0.153118	0.173707	0.010132	1.000000

2001 – 2004	CZK	HUF	PLN	RON	SKK
CZK	1.000000	0.082367	0.035674	0.034171	0.113013
HUF	0.082367	1.000000	0.314313	0.017151	0.197218
PLN	0.035674	0.314313	1.000000	0.122807	0.201075
RON	0.034171	0.017151	0.122807	1.000000	0.034260
SKK	0.113013	0.197218	0.201075	0.034260	1.000000

2004 – 2007	CZK	HUF	PLN	RON	SKK
CZK	1.000000	0.101129	0.370156	0.023344	0.408747
HUF	0.101129	1.000000	0.561446	0.015689	0.148741
PLN	0.370156	0.561446	1.000000	0.112373	0.299779
RON	0.023344	0.015689	0.112373	1.000000	-0.079994
SKK	0.408747	0.148741	0.299779	-0.079994	1.000000

Source: Author's estimates

Table A15. VAR Lag Order Selection Criteria

Permanent Component of Volatility

Endogenous variables: VARP_CZK VARP_HUF VARP_PLN VARP_RON VARP_SKK
Exogenous variables: C
Sample: 5/04/2001 4/05/2007
Included observations: 1537

Lag	LogL	LR	FPE	AIC	SC	HQ
0	79094.24	NA	1.39e-51	-102.9138	-102.8964	-102.9073
1	91047.15	23812.50	2.52e-58	-118.4348	-118.3306*	-118.3960
2	91122.73	150.0719	2.36e-58	-118.5006	-118.3096	-118.4296*
3	91164.68	83.02818	2.31e-58	-118.5227	-118.2449	-118.4193
4	91196.31	62.40097	2.29e-58	-118.5313	-118.1667	-118.3956
5	91225.56	57.49762	2.28e-58*	-118.5368*	-118.0854	-118.3689
6	91248.55	45.04933	2.28e-58	-118.5342	-117.9959	-118.3339
7	91273.58	48.90102*	2.28e-58	-118.5343	-117.9092	-118.3017

Endogenous variables: VARP_CZK VARP_HUF VARP_PLN VARP_RON VARP_SKK
Exogenous variables:
Sample: 5/04/2001 11/30/2004
Included observations: 925

Lag	LogL	LR	FPE	AIC	SC	HQ
1	55419.33	NA	6.63e-59	-119.7715	-119.6410*	-119.7217*
2	55462.48	85.36464	6.37e-59	-119.8108	-119.5497	-119.7112
3	55509.68	92.87256	6.08e-59	-119.8588	-119.4672	-119.7094
4	55551.26	81.35955	5.86e-59	-119.8946	-119.3725	-119.6954
5	55581.46	58.77982	5.80e-59*	-119.9059*	-119.2532	-119.6569
6	55600.39	36.62230	5.87e-59	-119.8927	-119.1095	-119.5939
7	55624.26	45.93749*	5.89e-59	-119.8903	-118.9765	-119.5417

Endogenous variables: VARP_CZK VARP_HUF VARP_PLN VARP_RON VARP_SKK
Exogenous variables:
Sample: 12/01/2004 4/05/2007
Included observations: 604

Lag	LogL	LR	FPE	AIC	SC	HQ
1	37691.26	NA	4.69e-61	-124.7227	-124.5405*	-124.6518*
2	37721.42	59.31724	4.61e-61*	-124.7398*	-124.3753	-124.5979
3	37743.18	42.44435*	4.66e-61	-124.7291	-124.1823	-124.5163
4	37756.92	26.55642	4.84e-61	-124.6918	-123.9627	-124.4080
5	37773.65	32.08379	4.97e-61	-124.6644	-123.7531	-124.3097
6	37788.57	28.35340	5.14e-61	-124.6310	-123.5374	-124.2054
7	37801.05	23.50768	5.36e-61	-124.5896	-123.3137	-124.0930

(continued on next page)

Transitory Component of Volatility

Endogenous variables: VART_CZK VART_HUF VART_PLN VART_RON VART_SKK
Exogenous variables:
Sample: 5/04/2001 4/05/2007
Included observations: 1537

Lag	LogL	LR	FPE	AIC	SC	HQ
1	78892.77	NA	1.85e-51	-102.6256	-102.5388*	-102.5933
2	78935.13	84.17757	1.81e-51	-102.6482	-102.4746	-102.5836
3	78997.37	123.2571	1.73e-51	-102.6966	-102.4362	-102.5997*
4	79023.32	51.22065	1.72e-51	-102.6979	-102.3506	-102.5687
5	79075.05	101.7779	1.66e-51	-102.7327	-102.2986	-102.5711
6	79106.31	61.30726	1.65e-51	-102.7408	-102.2199	-102.5470
7	79146.35	78.25215*	1.62e-51*	-102.7604*	-102.1527	-102.5343

Endogenous variables: VART_CZK VART_HUF VART_PLN VART_RON VART_SKK
Exogenous variables:
Sample: 5/04/2001 11/30/2004
Included observations: 925

Lag	LogL	LR	FPE	AIC	SC	HQ
1	48826.28	NA	1.03e-52	-105.5163	-105.3857*	-105.4665*
2	48867.71	81.96049	9.93e-53	-105.5518	-105.2907	-105.4522
3	48906.97	77.25368	9.63e-53	-105.5826	-105.1910	-105.4332
4	48930.28	45.61018	9.67e-53	-105.5790	-105.0568	-105.3798
5	48961.21	60.17982	9.54e-53	-105.5918	-104.9391	-105.3428
6	48995.18	65.75136	9.36e-53*	-105.6112*	-104.8280	-105.3124
7	49017.97	43.83988*	9.41e-53	-105.6064	-104.6927	-105.2578

Endogenous variables: VART_CZK VART_HUF VART_PLN VART_RON VART_SKK
Exogenous variables:
Sample: 12/01/2004 4/05/2007
Included observations: 604

Lag	LogL	LR	FPE	AIC	SC	HQ
1	34184.52	NA	5.18e-56*	-113.1110*	-112.9287*	-113.0401*
2	34204.08	38.45715	5.27e-56	-113.0930	-112.7284	-112.9511
3	34218.07	27.28504	5.47e-56	-113.0565	-112.5097	-112.8437
4	34232.75	28.38879	5.66e-56	-113.0223	-112.2933	-112.7386
5	34257.82	48.07910*	5.66e-56	-113.0226	-112.1113	-112.6679
6	34266.27	16.05366	5.98e-56	-112.9678	-111.8742	-112.5422
7	34278.58	23.19409	6.24e-56	-112.9258	-111.6499	-112.4292

Source: Author’s estimates

Table A16. Principal Component Analysis

	All	CZK-RON	RON-HUF	SKK-CZK	HUF-PLN
CZK	0.362436	0.632798	0.421815	-0.538715	0.008031
HUF	0.499222	-0.135617	-0.540310	-0.237258	0.619806
PLN	0.527719	-0.341590	-0.178585	-0.196936	-0.730857
RON	0.331231	-0.542559	0.704352	0.141254	0.282579
SKK	0.480849	0.412457	-0.046183	0.771205	-0.042098
Eigenvalue	2.052538975	1.017339871	0.856254592	0.587905771	0.485960791
Expl. Variance	41.05%	20.35%	17.13%	11.76%	9.72%
Cumulated	41.05%	61.40%	78.52%	90.28%	100.00%

Source: Author's estimates

Table A17. Estimation results of the GARCH(1,1) models for the principal components

Dependent Variable: PC1
Method: ML - ARCH
Sample: 5/04/2001 4/05/2007
Included observations: 1545
Convergence achieved after 13 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.022126	0.022247	-0.994557	0.3200
Variance Equation				
C	0.120778	0.033005	3.659385	0.0003
RESID(-1)^2	0.141271	0.039212	3.602765	0.0003
GARCH(-1)	0.739553	0.060806	12.16243	0.0000

R-squared	-0.000490	Mean dependent var	3.88E-07
Adjusted R-squared	-0.002438	S.D. dependent var	1.000001
S.E. of regression	1.001219	Akaike info criterion	2.740234
Sum squared resid	1544.760	Schwarz criterion	2.754067
Log likelihood	-2112.831	Durbin-Watson stat	2.010994

Source: Author’s estimates

(continued on next two pages)

Dependent Variable: PC2
Method: ML - ARCH
Sample: 5/04/2001 4/05/2007
Included observations: 1545
Convergence achieved after 15 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.012332	0.022001	0.560529	0.5751
Variance Equation				
C	0.018724	0.007822	2.393870	0.0167
RESID(-1)^2	0.066344	0.016806	3.947626	0.0001
GARCH(-1)	0.915587	0.019908	45.99078	0.0000

R-squared	-0.000152	Mean dependent var	5.83E-07
Adjusted R-squared	-0.002099	S.D. dependent var	1.000000
S.E. of regression	1.001049	Akaike info criterion	2.713384
Sum squared resid	1544.235	Schwarz criterion	2.727216
Log likelihood	-2092.089	Durbin-Watson stat	2.034812

Dependent Variable: PC3
Method: ML - ARCH
Sample: 5/04/2001 4/05/2007
Included observations: 1545
Convergence achieved after 27 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.006714	0.022090	0.303923	0.7612
Variance Equation				
C	0.064347	0.021579	2.981889	0.0029
RESID(-1)^2	0.160548	0.037301	4.304076	0.0000
GARCH(-1)	0.779134	0.045766	17.02430	0.0000

R-squared	-0.000045	Mean dependent var	9.71E-07
Adjusted R-squared	-0.001992	S.D. dependent var	0.999999
S.E. of regression	1.000994	Akaike info criterion	2.655152
Sum squared resid	1544.065	Schwarz criterion	2.668984
Log likelihood	-2047.105	Durbin-Watson stat	2.030754

Dependent Variable: PC4
Method: ML - ARCH
Sample: 5/04/2001 4/05/2007
Included observations: 1545
Convergence achieved after 19 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.007600	0.022513	0.337564	0.7357
	Variance Equation			
C	0.017480	0.010843	1.612098	0.1069
RESID(-1)^2	0.031962	0.010666	2.996726	0.0027
GARCH(-1)	0.952518	0.017079	55.77155	0.0000
R-squared	-0.000058	Mean dependent var		1.94E-07
Adjusted R-squared	-0.002005	S.D. dependent var		1.000000
S.E. of regression	1.001002	Akaike info criterion		2.783134
Sum squared resid	1544.091	Schwarz criterion		2.796966
Log likelihood	-2145.971	Durbin-Watson stat		2.072314

Dependent Variable: PC5
Method: ML - ARCH
Sample: 5/04/2001 4/05/2007
Included observations: 1545
Convergence achieved after 17 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.006167	0.022528	0.273760	0.7843
	Variance Equation			
C	0.155779	0.051351	3.033616	0.0024
RESID(-1)^2	0.158405	0.033975	4.662454	0.0000
GARCH(-1)	0.682667	0.073050	9.345240	0.0000
R-squared	-0.000038	Mean dependent var		1.55E-06
Adjusted R-squared	-0.001985	S.D. dependent var		1.000000
S.E. of regression	1.000992	Akaike info criterion		2.725678
Sum squared resid	1544.059	Schwarz criterion		2.739510
Log likelihood	-2101.586	Durbin-Watson stat		1.947798