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Volatility Regimes in Macroeconomic Time Series: The Case of the Visegrad Group*

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Abstract
We analyze several monthly and quarterly macroeconomic time series for the Czech Republic, Poland, Hungary, and Slovakia. These countries embarked on an economic transition in the early 1990s which ultimately led to their membership in the European Union, with Slovakia joining the euro area in 2009. It is natural to assume that changes of such a magnitude should also influence the major macroeconomic indicators. We explore the characteristics of these series by endogenously identifying their volatility regimes. In the course of our analysis, we show the difficulties in the handling of unit roots as a necessary step preceding volatility modeling. The final set of breaks identified shows very few changes near the beginning of the series, which corresponds to the transition period.

1. Introduction

In the early 1990s, the Central and Eastern European (CEE) countries embarked on a unique transformation process toward Western-type market economies. Even without examining this transition in much detail, it would be difficult not to expect some social and political turmoil to be associated with this kind of economic development. For example, in 1997 alone, Slovakia faced a political crisis, a highly controversial referendum (with constitutional issues), and the European Commission's rejection of its application to join the European Union. Events of such significance and potentially substantial influence were not unusual for the other CEE countries either. Such events naturally leave traces in the economy and influence our perception of economic relationships (see Estrin et al., 2009).

There are several ways we can observe such structural changes in macroeconomic variables: through sudden or gradual shifts in their means,[1] through changes in trend, or through changes in volatility. Our focus here is on changes in volatility, following the remark by Égert et al. (2006b) that: "Often, empirical research seeks to detect structural changes in the mean of the series but pays little attention to the variability."

An increase in the number of volatility regimes of the main macroeconomic series suggests instability in the economy. Together with a decrease in volatility, it

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[1] See Kočenda (2005) and Fidrmuc and Tichit (2009).

might suggest a dampening of business cycles in the economy (Sensier and Dijk, 2004).

More recently, in an earlier version of their paper, Égert et al. (2006a) used the Inclán and Tiao (1994) test (*IT* test) with the Iterated Cumulative Sum of Squares (ICSS) algorithm for detecting volatility changes, and the Wang and Zivot (2000) procedure for detecting mean, trend, and volatility regimes at the same time. They searched for volatility breaks using data ending in 2004 on ten CEE countries (including the countries analyzed in our sample: CZE – Czech Republic, HUN – Hungary, POL – Poland, SVK – Slovakia). The macroeconomic series included industrial production (IP) and production in the construction sector, price series such as the consumer and producer price indices (CPI and PPI, respectively), monetary aggregates (M1, M2 and M3), nominal exchange rates, employment and unemployment, and gross and net nominal wages.[2] Using the *IT* test they detected six breaks for unemployment (CZE: 2, HUN: 1, POL: 0, SVK: 3), four for IP (one for each country), six for CPI (CZE: 2, HUN: 1, POL: 0, SVK: 3), and six for PPI (CZE: 0, HUN: 1, POL: 2, SVK: 3). In Égert et al. (2006b) they did not report the results from the ICSS algorithm using the *IT* test, as they noted that the methodology "presents several weaknesses". Owing to a different sample period and the use of a different methodology, our results are not directly comparable with theirs or with Lyócsa et al. (2010). However, by using an improved version of the *IT* test proposed by Sansó et al. (2004), we found far fewer volatility breaks.[3]

As for the methodological consequences of these findings, ignoring structural breaks might have important implications for the inferences made from macroeconomic modeling (e.g., by the identification of spurious economic relationships); see, for example, Fang et al. (2008) and Baumöhl et al. (2011). Last but not least, break dates might be used in historical event studies for detecting significant social and economic events.

Our methodological approach differs from those used in previous studies in two ways. First, when compared to Égert et al. (2006a), we use the improved *IT* test of Sansó et al. (2004). Second, we account for shifts in the mean and trend of the series by adjusting the mean equations where necessary. The goal of this paper is therefore twofold: (1) to identify possible volatility regimes for selected macroeconomic series of the Czech Republic, Hungary, Poland, and Slovakia, and (2) to determine whether these volatility shocks are concentrated in specific time periods across indicators as well as across countries.

2. Data and Methodology

2.1 Data

Our selection of macroeconomic variables for four CEE countries (the Czech Republic, Hungary, Poland, and Slovakia) was largely motivated by the seminal paper and dataset of Nelson and Plosser (1982), who challenged the belief in the stationarity of macroeconomic time series. Further on, we were motivated by the previous work of Égert et al. (2006a, 2006b).[4] However, we were restricted by the availability

[2] The version of Égert et al. (2006b) was more subtle.

[3] See Section 2.3 for further discussion of the choice of break identification procedure.

of data for CEE countries in the OECD and Eurostat databases (for the sample periods and a data description, see the *Appendix*). We analyzed 25 indicators – a mix of quarterly and monthly data – which may be separated into following categories:

Economic output and activity variables

- Gross domestic product at current prices (GDP_CP) and its components final consumption expenditure (FC_CP), gross capital formation (GCF_CP), exports of goods and services (EX_CP), and imports of goods and services (IM_CP), as well as real gross domestic product (GDP_R) and industrial production (IP), and we decided to include government debt (GD) in this category as well.

Price indicators

- The deflator (DEF), the consumer price index (CPI), the harmonized price index (HCPI), the harmonized price index without the food and energy components (HCPIa), and the producer price index (PPI).

Labor market indicators

- The unemployment rate (UR) and unit labor costs (ULC).

Financial indicators

- Money aggregates M1 (M1) and M3 (M3), stock market prices (SM), long-term interest rates (LTIR), short-term interest rates (STIR), real interest rates (RIR), nominal exchange rates against USD (EX_USD), nominal exchange rates against EUR (EX_EUR), and real exchange rates with both USD and EUR as numeraire currencies (RER_USD, RER_EUR).

We analyzed both the level and changes of the series. To analyze the levels of the series, we first calculated the logarithm of the nominal values for all the variables except the unemployment rate, long-term interest rates, short-term interest rates, and real interest rates. Changes were calculated as logarithmic differences, again with the exception of the aforementioned variables, where we used percentage changes. Some of the indicators were not available for all countries; therefore, 192 series entered our analysis. The data covers the period from January 1990 to March 2011, but most of the series start as late as 1995–1996. Considering this, our study searches for volatility regimes in the period of accession of the CEE countries to the European Union. It is therefore difficult to make immediate comparisons with the previous study of Égert et al. (2006a, 2006b).

2.2 Unit Root Tests

Our unit root testing strategy was as follows.[5] First, we computed the MZ^{α} and MZ^{t} unit root tests of Ng and Perron (2001) with two specifications: the first with a constant and the second with a constant and trend. We regarded the series as stationary if one of the tests rejected the null hypothesis of a unit root at a significance level of 5% (with only three exceptions, both tests gave the same conclusions). If not, we proceeded with the Lee and Strazicich (2003, 2004) LM test, with one break in the mean and trend of the series.

[4] The previous version of this paper consisted of 12 indicators and 4 countries and the analysis was performed on the level and changes of the series, thus we started with 96 time series. However, based on a reviewer`s recommendations, we decided to expand the dataset.

2.2.1 Standard Unit Root Tests

For the Ng and Perron (2001) tests, we set the highest lag order according to Schwert's (1989) "rule of thumb", which might be regarded as being rather conservative, $k_{max} = int(12(T/100)^{1/4}$. In our case, Schwert's rule chose a maximum of up to 14 lags (with a minimum of 10 lags for shorter quarterly data series), for which the test statistics were calculated. When working with monthly data, 14 lags seemed to be enough, while for the quarterly data, the lag order was probably too strict. However, setting the highest lag order is a generally recommended procedure by Ng and Perron (1995, see Section 2.1) and using Schwert's rule is a frequent choice in empirical research (Perron and Qu, 2007): "(the highest lag order) is usually set to $k_{max} = int(12(T/100)^{1/4}$ but other values are possible."

The final choice of the number of autoregressive components in both test statistics was made according to the Modified Akaike Information Criteria (MAIC), following Ng and Perron (2001), although other approaches were possible as well (see Wu, 2010). For the estimation of the long-run variance, we used the autoregressive spectral density estimate based on the GLS detrended data. The test statistics were compared with the critical values as in Ng and Perron (2001).

2.2.2 Unit Root Tests with Structural Breaks

It is well known that unit root tests have low power. A notoriously low power arises for autoregressive processes with ρ close to (but less than) unity. This is the case in many macroeconomic series. Perron (1989) showed that the traditional (DF) test lacks the ability to reject the unit root if the true data-generating process (DGP) is stationary around a deterministic trend with a structural break in trend. Such considerations might be of interest if one is using economic data from emerging markets, where the economic transformation might manifest itself as a structural break in the macroeconomic series. From the empirical perspective, if one does not reject the presence of the unit root using conventional tests, it might be the case that the series contains a structural change and the regressions used in unit root testing are incorrectly specified.

Perron (1989) proposed a test with a structural change on an exogenously determined date. A more popular approach is the Zivot and Andrews (1992) test, allowing for an endogenously determined break in the mean (the crash model), the trend (the changing growth model), or both. The Zivot and Andrews (1992) test has a null hypothesis of a unit root without a break against the "break stationary" alternative. However, if the true process is a unit root with a structural break, then the test might lead to over-rejection of the unit root hypothesis and, thus, to spurious

[5] There is no unified approach to testing for the (non)stationarity of time series. Analyzing papers published in 17 journals (155 papers) covering the period 2000–2010 (as of September 17, 2010) we found out that in 64.9% of cases the ADF or DF test was used, in 9% the DF-GLS test was used, in 12.3% the Phillips and Perron test was used, in 3.3% the Ng and Perron (2001) test was used, and in 7.1% the KPSS test was used. Tests that take structural breaks into account were used only rarely. More interestingly, in 66.5% of cases the researchers used only one test, and in 27.7% of cases they used two tests. When the overall results were inconclusive, the researchers usually continued the analysis with a warning note or simply chose one of the alternatives. As one of the reviewers pointed out, new tests are under-represented. However, this brief review outlined the general testing strategies in empirical research. For more details, see Lyócsa et al. (2010).

results. We decided to use the test proposed by Lee and Strazicich (2003, 2004). Their test implies that by rejecting the null hypothesis of non-stationarity, the series is stationary with breaks, regardless of whether the structural break(s) occurs under the null of a unit root.[6] If we denote the analyzed series as $\boldsymbol{y}$ and the matrix of exogenous variables (such as a deterministic trend, as well as mean and trend shifts) as $\boldsymbol{Z}$, we first run the regression

$$\Delta y_t = \tilde{\boldsymbol{\delta}} \Delta \mathbf{Z}_t \tag{1}$$

to obtain the estimates $\tilde{\boldsymbol{\delta}}$. Then a new series is defined by

$$\tilde{s}_t = y_t - \left(y_1 - \mathbf{Z}_1 \tilde{\boldsymbol{\delta}}\right) - \mathbf{Z}_t \tilde{\boldsymbol{\delta}} \tag{2}$$

This series is used in an LM test, based on fitting the regression

$$\Delta y_t = \Delta \mathbf{Z}_t \boldsymbol{\delta}' + \varphi \tilde{s}_{t-1} + \sum_{j=1}^{k} \gamma_j \Delta \tilde{s}_{t-j} + u_t \tag{3}$$

The test for stationarity is based on the t-statistic for $\varphi = 0$. The number of augmented terms k is chosen according to Ng and Perron (1995) by first selecting the maximum lag order according to Schwert's rule (1989) and then reducing the number of lags until the coefficient on the last lag remains significant. The break dates were chosen by a grid search minimizing the t-statistic of $\varphi = 0$ in Equation (3). Instead of using asymptotic critical values, we follow Lee and Strazicich (2004) and obtain (sample size and break date specific) critical values by conducting a Monte Carlo simulation with 5,000 replications.[7]

2.3 Mean Equations

The modified *IT* test by Sansó et al. (2004) requires that the data under consideration do not contain a unit root and are without autocorrelation. Therefore, if the evidence from the unit root tests suggests that the series is stationary or stationary with breaks, we proceed by modeling the mean equations. The goal is to obtain residuals without autocorrelation, the squares of which form the volatility series, which is tested using the modified *IT* test. Our most general form of the mean equation is an ARMAX model:

$$\begin{gathered} y_t = \beta_1 + \beta_2 t + \beta_3 DU_t + \beta_4 DT_{b,t} + z_t \\ \left(1 - \sum_{i=1}^{p} \varphi_i L^i\right) z_t = \left(1 + \sum_{j=1}^{q} \theta_j L^j\right) \varepsilon_t \end{gathered} \tag{4}$$

where $\varepsilon_t \sim N(0,\sigma^2)$ and z_t is the stationary ARMA component. This general form breaks down to three cases: a) if the series was found to be stationary with a constant, then $DU_t = DT_{b,t} = 0$ and we remove the trend component t from the equation; b) if the series was found to be stationary with a deterministic trend, then we include the trend component and set $DU_t = DT_{b,t} = 0$; and c) if the series was found to be

[6] For a short review of other tests see Lyócsa et al. (2011).

[7] Our *R*-code for the test statistic (including Monte Carlo simulations and the grid search) is available upon request. The original GAUSS code from J. Lee is available at http://www.cba.ua.edu/~jlee/gauss.

stationary with structural breaks in the mean and trend, then we again include the trend and set $DT_{b,t} = t - T_{bt}$ for $t > T_{bt}$ and $DT_{b,t} = 0$ otherwise, with T_{bt} denoting the break date for the trend shift and $DU_t = 1$ for $t > T_{bl}$ and $DU_t = 0$ otherwise, with T_{bl} denoting the break date for the mean shift.[8] For all data with less than 150 observations, the MA terms in Equation (4) were omitted, as maximum likelihood estimation in smaller samples might be questionable.

2.4 Volatility Regimes

We used the κ_1 and κ_2 statistic introduced by Sansó et al. (2004) and the *ICSS* algorithm for detecting multiple breaks (for details of the algorithm see Inclán and Tiao, 1994). The main advantage of this procedure is that the breaks are detected endogenously from the data. Following Inclán and Tiao (1994), let ε_t be a series of residuals with zero mean and variance σ^2, where $t = 1, 2, \ldots, T$ and T is the number of observations. Denote the cumulative sum of the squares $C_0 = 0$ and $C_k = \sum_{t=1}^{k} \varepsilon_t^2$ for $k = 1, 2, \ldots, T$. Then the *IT* test statistic is $|D_k|\sqrt{T/2}$, where:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}, \quad k = 1, 2, \ldots, T \tag{5}$$

Sansó et al. (2004) showed that the *IT* test might have substantial size distortions (see Table 3 in Sansó et al., 2004, with just over 80% rejections of no volatility regimes for *iid* data from a lognormal distribution where no variance regimes were actually present. The sample size was $T = 100$). We therefore prefer the modified *IT* test. Sansó et al. (2004) proposed two statistics. The first one corrects for the violation of the normality assumption for ε_t and is calculated as

$$\kappa_1 = \sup_k \left| T^{-1/2} B_k \right| \tag{6}$$

where

$$B_k = \frac{C_k - \frac{k}{T} C_T}{\sqrt{\hat{\eta}_4 - \hat{\sigma}^4}} \tag{7}$$

and $\hat{\eta}_4 = T^{-1} \sum_{t=1}^{T} \varepsilon_t^4$, $\hat{\sigma}^2 = T^{-1} C_T$ for $k \in \{1, 2, \ldots, T\}$.

The second one (κ_2) also takes into account conditional heteroskedasticity, which is common in financial data. Where the analyzed series exhibited conditional heteroskedasticity (as indicated by the Ljung-Box test of squared residuals from the mean equations), we used the κ_2 statistics given by

$$\kappa_2 = \sup_k \left| T^{-1/2} G_k \right| \tag{8}$$

where

$$G_k = \hat{\omega}_4^{-1/2} \left(C_k - \frac{k}{T} C_T \right) \tag{9}$$

[8] When choosing the appropriate model, we relied on the results of the stationarity tests, and where multiple options were possible we chose the more parsimonious model.

Table 1 Results from Unit-Root Testing Procedure

	Levels				Changes			
	CZE	HUN	POL	SVK	CZE	HUN	POL	SVK
	Economic output and activity variables							
GDP_CP	N	N	N	S^B	S^μ	S^B	S^B	S^B
FC_CP	S^B	S^τ	N	S^B	S^B	S^B	S^B	S^B
GCF_CP	S^B	S^B	N	S^B	S^B	S^B	S^μ	S^B
EX_CP	S^B	S^B	N	N	S^τ	S^μ	S^τ	S^τ
IM_CP	N	N	S^B	S^B	S^B	S^τ	S^B	S^τ
GDP_R	N	S^τ	S^B	N	S^μ	S^B	S^B	S^μ
IP	S^B	S^B	S^B	S^B	S^B	S^B	S^B	S^τ
GD	S^B	S^B	N	N	S^B	S^μ	S^μ	S^μ
	Price indicators							
DEF	N	S^B	S^B	S^B	S^τ	S^τ	S^μ	S^τ
CPI	N	N	N	N	S^B	S^B	S^B	S^B
HCPI	N	N	N	N	S^B	S^B	S^B	S^μ
HCPIa	S^τ	S^B	N	N	S^μ	S^B	S^B	S^B
PPI	N	N	N	S^B	S^τ	S^μ	S^B	S^B
	Labor market indicators							
UP	N	N	N	N	S^μ	S^μ	S^μ	S^μ
ULC	N	N	N	N	S^B	S^μ	S^μ	S^B
	Financial indicators							
*M*1	N	N	N	NA	S^B	S^μ	S^B	NA
*M*3	N	N	N	NA	S^B	S^μ	S^τ	NA
SM	N	N	N	N	S^B	S^μ	S^μ	S^μ
LTIR	N	N	S^B	N	S^μ	S^μ	S^μ	S^μ
EX_USD	N	N	N	N	S^μ	S^μ	S^μ	S^μ
EX_EUR	N	S^τ	S^μ	N	S^B	S^μ	S^μ	S^μ
RER_USD	N	N	N	N	S^B	S^B	S^B	S^μ
RER_EUR	N	N	N	S^τ	S^B	S^μ	S^μ	S^μ
STIR	N	NA	N	S^B	S^B	NA	S^μ	S^μ
RIR	S^μ	NA	S^B	S^B	S^μ	NA	S^μ	S^μ

Notes: NA – data not available, N – we were not able to reject the null hypothesis of non-stationarity of the series , S^μ – the series was regarded as stationary with a constant, S^τ – the series was regarded as stationary with a constant and trend, S^B – the series was regarded as stationary with structural breaks in mean and trend.

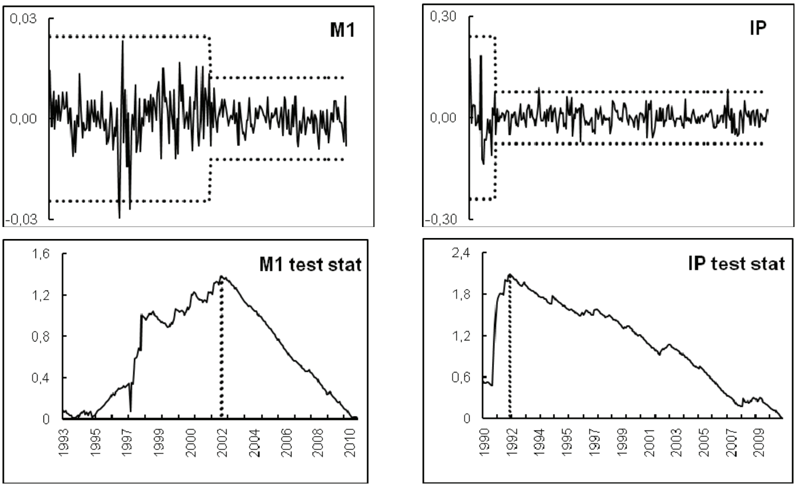
Sansó et al. (2004) give two possible ways to estimate $\hat{\omega}_4$ consistently. We used the nonparametric estimation procedure. The critical values for each statistic were obtained from a response surface provided by Sansó et al. (2004) because of their better performance in small samples.[9]

3. Empirical Findings

Of the 192 series, we regard 129 as stationary (see *Table 1*). However, we should add that without taking into account structural breaks in the unit root testing procedure, we would end up with only 61 series. Level series of macroeconomic variables are frequently regarded as non-stationary. This testing procedure clearly

[9] Our *R*-code, which calculates all alternatives, is available upon request.

Figure 1 Changes of M1 and Industrial Production with Corresponding Kappa Test Statistics



helped to signal stationarity, most significantly for the level of the series, with 78.8% of all positive results being stationary with breaks in mean and trend (compared to a still considerable 43.8% for the changes).

For the series of changes of CPI (Hungary) and the level series of GDP_R (Hungary) and IP (Czech Republic), we were unable to find a suitable ARMAX model with p and q of up to 10. We therefore omitted these three series from the subsequent analysis. Therefore, 126 series out of the 192 underwent the volatility regime tests.

Although, the results are not directly comparable, one of the most extensive studies was conducted by Sensier and Dijk (2004), who found that 78.5% of 214 monthly US macroeconomic series from January 1959 to December 1999 had unconditional volatility changes. Using the *IT* test, Égert et al. (2006a) found volatility regimes in 88.0% of series for the same countries as ours and in 92.0% using the Wang and Zivot (2000) methodology.[10] As we employ different methods (they used the supW test) and time periods, our results for CEE countries stand in sharp contrast. As reported in *Tables 2* and *3*, volatility regime changes were detected in 30 of the 126 series (in 23.8% of cases), with 36 breaks altogether. It seems that if one does not take into account structural breaks in the mean and trend of the series, and non-normality and conditional heteroskedasticity of the series, the results for the macroeconomic series in CEE countries might overestimate the true number of volatility regimes. *Figure 1* presents an illustrative example of two time series for Czech Republic with the volatility regimes and the corresponding kappa statistics.

Hence, contrary to the previous research, our findings suggest that volatility regimes occur rarely in macroeconomic indicators (and thus in the underlying economic data-generating processes).

[10] Égert et al. (2006b) found at least one volatility regime for each of the following series: PPI, CPI, nominal exchange rate, industrial production, and unemployment rate. We refer to the estimation of structural breaks in the mean, trend, and volatility. The methodology used in this study differs also in that it estimates the volatility regimes separately.

Table 2 Volatility Breaks Detected (level data)

Series	Czech Rep.	Poland	Hungary	Slovakia
Economic output and activity variables				
GCF_CP	2006Q4$^{\kappa 1}$			
FC_CP			2000Q4$^{\kappa 1}$	
GD	2009Q1$^{\kappa 1}$			
IP		1993M07$^{\kappa 1}$		1992M03$^{\kappa 2}$
Price indicators				
DEF		2004Q1$^{\kappa 1}$		
Financial indicators				
RIR		2001M08$^{\kappa 2}$		2004M01$^{\kappa 1}$

Note: Superscripts $\kappa 1$ and $\kappa 2$ denote the type of test applied to the given series according to the presence of ARCH effects.

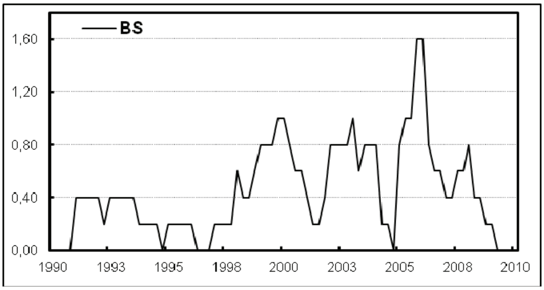
Table 3 Detected Volatility Breaks (changes)

Series	Czech Rep.	Poland	Hungary	Slovakia
Economic output and activity variables				
IM_CP			2000Q2$^{\kappa 1}$	
IP	1992M01$^{\kappa 2}$		1993M08;2008M09$^{\kappa 1}$	
Price indicators				
DEF		1999Q4$^{\kappa 2}$		
CPI		1994M09;2003M02$^{\kappa 2}$		
HCPI		1998M01$^{\kappa 2}$		
HCPIA		2001M02;2004M03;2004M07$^{\kappa 1}$		
PPI		2003M03$^{\kappa 2}$	2006M05$^{\kappa 2}$	
Labor market indicators				
UP	2006M10$^{\kappa 1}$		2006M12 $^{\kappa 1}$	
Financial indicators				
M1	2002M11$^{\kappa 2}$			
SM		1996M01$^{\kappa 2}$	1999M02$^{\kappa 1}$	
EX_USD	2008M02$^{\kappa 2}$	1999M01;2008M02$^{\kappa 2}$	2000M04$^{\kappa 2}$	
EX_EUR			2006M02$^{\kappa 2}$	
RER_USD		2006M03$^{\kappa 2}$	2000M03;2006M03$^{\kappa 2}$	2002M11$^{\kappa 2}$
RER_EUR			2006M01$^{\kappa 2}$	

Note: Superscripts $\kappa 1$ and $\kappa 2$ denote the type of test applied to the given series according to the presence of ARCH effects.

One would expect volatility breaks to have occurred more frequently at the beginning of the transformation process, when systematic policy changes influenced the macroeconomic environment. Another period that seemed to be rich in volatility breaks is the mid-2000s, with accession to the EU as well as strong growth in CEE economies in the first five years of the decade (moderate for Hungary only) and the global crisis at the end.

Figure 2 Calculated Moving Averages for Breaks Detected in CEE Countries



Notes: Let DPL_t be a dichotomous variable such that $DPL_t = 1$ if a volatility break has occurred in the series in quarter t, and $DPL_t = 0$ otherwise. Then, the series in the figure above is represented as follows: $BS_t = (DPL_{t+2} + DPL_{t+1} + DPL_t + DPL_{t-1} + DPL_{t-2})/5$.

Most breaks were recorded for the financial indicators (41.7% of the total), followed by the price and economic activity indicators (27.8% and 25.0%, respectively), while only around 5.6% of all breaks were found for the labor market. However, with only two indicators, the labor market was probably under-represented. From *Tables 2* and *3*, it is obvious that Poland (41.7%) and Hungary (33.3%) contained most of the volatility breaks, with Czech Republic (16.6%) and Slovakia (8.3%) trailing some distance behind.

Our conclusion is that for Czech Republic and Slovakia, which underwent drastic transitions, there were surprisingly very few volatility regimes detected. Therefore, macroeconomic changes during the transition period and the EU accession period or tendencies toward EMU do not necessarily induce a switch in volatility regimes.

If a social or economical event induces an increase in volatility, it can manifest itself in the macroeconomic series with a delay or even a lead, depending on the series under consideration. For this purpose, we decided to calculate the moving average series of the number of breaks for the group of CEE countries. As we combine quarterly and monthly data, we sorted the breaks in monthly series into the corresponding quarters. We used a five-quarter window for calculating the moving averages of the number of breaks. We consider this to be probably large enough to capture the various breaks which can be associated with important social and economical events. The results are shown in *Figure 2*.

Breaks occurred with a slightly higher frequency between 1998 and 2007. These breaks can be attributed mostly to Hungary and Poland. Nevertheless, it is surprising to see that breaks were not particularly frequent at the beginning of our series. This could mean that economic transitions are not necessarily accompanied by volatile macroeconomic fluctuations. However, one needs to be cautious, as we use series with different period lengths, which are often trimmed from the beginning of the series. We thus consider our results to be only informative with regard to the accession of CEE countries to the EU.

4. Conclusion

The results presented in the previous section allow us to discuss the problems that motivated our analysis. The first one was concerned with the identification of volatility regimes in the macroeconomic series of selected CEE countries.

The identification procedure used has itself raised several important methodological issues. Most importantly, the analysis of volatility is usually conducted under the assumption of stationarity within the individual regimes. The question of unit root testing prior to the use of cumulative sum of squares tests seems to be of the utmost importance. First, we used the Ng and Perron (2001) tests and then the Lee and Strazicich (2003, 2004) test, which allowed us to take into account structural breaks in the mean and trend of the series. This proved to be an important decision, as 68 out of the 192 time series were regarded as stationary with structural breaks and 61 as stationary without structural breaks.

The calculation of volatility breaks was conducted using the κ_1 and κ_2 tests of Sansó et al. (2004). The choice of this procedure instead of the more commonly used *IT* test was motivated by the robustness of κ_1 and κ_2 to non-normality and heteroskedasticity of the underlying series. As these two problems are very common in macroeconomic time series, we again tended toward the more conservative alternative. If no ARCH effects were present, we used and reported the breaks of the κ_1 test; otherwise we used κ_2. However, this decision ultimately led to a smaller number of volatility breaks being reported than in the case of the *IT* test. The number of series exhibiting volatility switching was only a quarter of the number reported in other studies.

Our results might seem counterintuitive, as all of the countries analyzed underwent transformation processes from the very beginning of the 1990s onwards.[11] One explanation might be that changes in the real economy manifest themselves in macroeconomic indicators in the form of sudden changes in means and trends. These were controlled for in our analysis. A second explanation might be that our series did not cover enough observations at the beginning of the 1990s. This is the most plausible explanation. For example, industrial production and consumer price indices were among the longest series and in both cases we found breaks at the beginning of the 1990s (see *Tables 2* and *3*). A third explanation might be that the transformation was rather smooth. Considering recent events, it seems that in the short term, a global crisis can have a more severe impact on the fluctuation of macroeconomic variables than a transformation that lasts for more than a decade.

The breaks themselves were somewhat surprising, as our initial expectations suggested the presence of breaks in the early observations of the series, which encompassed the major transition periods. However, the breaks were identified mostly at much later dates. The explanation of the lack of early breaks is also less straightforward owing to the nature of the estimation procedure for volatility break detection. As both the κ_1 and κ_2 test statistics are based on the ICSS algorithm of Inclán and Tiao (1994), they partition the series into smaller parts between breaks. Especially at the beginning of the series, the partitions might be too small to justify an early break given the power of the test. Thus, the results may also reflect the limitations of the testing procedure. Additionally, we identified only six breaks for the Czech Re-

[11] We thank one of the reviewers for emphasizing this fact.

public and three for Slovakia, which suggests either that even profound changes in an economy might not be detectable using this approach or that transition (and perhaps more importantly, accession to the EU) does not induce changes in a volatility regime.

APPENDIX

Data Description (part 1/2)

GDP_CP	Gross domestic product at current prices	EUROSTAT – Seasonally adjusted and adjusted data by working days all in national currency, excluding Slovakia, which is a euro fixed series.	ALL: 1995.Q1–2010.Q4
FC_CP	Final consumption expenditure at current prices		
GCF_CP	Gross capital formation at current prices		
EX_CP	Exports of goods and services at current prices		
IM_CP	Imports of goods and services at current prices		
GDP_R	Real gross domestic product	OECD – Quarterly National Accounts. Calculated as index from quarterly growth rates of real GDP, change over previous quarter of seasonally adjusted data.	CZE: 1996.Q1–2010.Q4 HUN: 1995.Q1–2010.Q4 POL: 1995.Q1–2010.Q4 SVK: 1997.Q1–2010.Q4
DEF	Deflator	OECD – Quarterly National Accounts. Seasonally adjusted data.	CZE: 1996.Q1–2010.Q4 HUN: 1995.Q1–2010.Q4 POL: 1995.Q1–2010.Q4 SVK: 1997.Q1–2010.Q4
IP	Industrial production	OECD – Main Economic Indicators database, Index of Industrial Production, Volume changes over time as indices, seasonally adjusted series with 2005 as base year, April 2011 edition.	ALL: 1990.M1–2011.M1
CPI	Consumer price index	OECD – Main Economic Indicators database, all items with 2005 as base year, April 2011 edition.	CZE: 1991.M1–2011.M2 HUN: 1990.M1–2011.M2 POL: 1990.M1–2011.M2 SVK: 1991.M1–2011.M2
HCPI	Harmonized price index	EUROSTAT – all items with 2006 as base year.	ALL: 1996.M1–2011.M2
HCPIa	Harmonized price index adjusted	EUROSTAT – all items excluding energy and seasonal food.	CZE: 1999.M12–2011.M2 HUN: 2000.M12–2011.M2 POL: 1996.M1–2011.M2 SVK: 1996.M1–2011.M2
PPI	Producer price index for industrial activities	OECD – Main Economic Indicators, for CZE since 2007 change in sampling methodology, base year is 2005.	CZE: 1996.M1–2011.M1 HUN: 1998.M1–2011.M1 POL: 1995.M1–2011.M1 SVK: 2003.M1–2011.M1
UP	Unemployment rate	EUROSTAT – Labor Force Survey data, seasonally adjusted data.	CZE: 1998.M1–2011.M2 HUN: 1996.M1–2011.M2 POL: 1997.M1–2011.M2 SVK: 1998.M1–2011.M2
ULC	Unit labor costs	EUROSTAT – Labor cost index with 2000 as base year in nominal value, for industry and services (except public administration and community services; activities of household and extra-territorial organizations).	ALL: 1996.Q1–2008.Q4

Data Description (part 2/2)

M1	M1	OECD – Financial Indicators, Main Economic Indicators, index with 2005 as base year, seasonally adjusted. For M1 (HUN) and M3 (HUN and POL) the series has two methodological breaks, but they did not seem to be significant.	CZE: 1993.M2–2011.M1 HUN: 1993.M6–2011.M2 POL: 1991.M1–2011.M2
M3	M3		CZE: 1992.M1–2011.M1 HUN: 1991.M1–2011.M2 POL: 1991.M1–2011.M2
SM	Stock market	PX directly from www.pse.cz end-of--month daily closing prices. WIG, SAX, BUX from www.stooq.pl.	CZE: 1993.M9–2011.M3 HUN: 1993.M1–2011.M3 POL: 1993.M1–2011.M3 SVK: 1995.M7–2011.M3
LTIR	Long-term interest rates	OECD – Main Economic Indicators, Financial Indicators, 10-year government bond yields as provided by National Central Banks.	CZE: 2000.M4–2011.M2 HUN: 1999.M2–2011.M3 POL: 2001.M1–2011.M3 SVK: 2000.M9–2011.M1
EX_USD	Nominal exchange rates against USD	All data were obtained from publicly available dataset www.oanda.com. Data correspond to average of daily averages for corresponding month.	CZE: 1997.M6–2011.M3 HUN: 1995.M10–2011.M3 POL: 1995.M10–2011.M3 SVK: 1995.M10–2009.M12
EX_EUR	Nominal exchange rates against EUR		CZE: 1999.M1–2011.M3 HUN: 1999.M1–2011.M3 POL: 1999.M1–2011.M3 SVK: 1999.M1–2008.M6
RER_USD	Real exchange rates, USD as numeraire currency	CPI-based real exchange rates, calculated from OECD database, CPIs and nominal exchange rates as defined above.	CZE: 1997.M6–2011.M2 HUN: 1995.M10–2011.M2 POL: 1995.M10–2011.M2 SVK: 1995.M10–2009.M12
RER_EUR	Real exchange rates, EUR as numeraire currency	HCPI-based real exchange rates, calculated from OECD database, nominal exchange rates as defined above. For EUR, EU-17 HCPI is used.	CZE: 1997.M6–2011.M2 HUN: 1999.M1–2011.M2 POL: 1999.M1–2011.M2 SVK: 1999.M1–2008.M6
STIR	Short-term interest rates	OECD – Main Economic Indicators, short-term interest rates, 3-month annualized nominal interest rates. Due to missing values or methodological breaks we excluded one series (HUN) and shortened another (SVK).	CZE: 1993.M6–2011.M2 POL: 1993.M6–2011.M3 SVK: 1999.M6–2011.M3
RIR	Real interest rates	Real interest rates were calculated from STIR and HCPI. Annualized STIRs were transformed to 3-month rates. Ex post RIRs for period t were calculated as difference between $STIR_{t-3}$ and change in HCPI between t and t–3.	CZE: 1996.M4–2011.M2 POL: 1996.M4–2011.M2 SVK: 1999.M6–2011.M2
GD	Government debt	EUROSTAT – Government debt as percent of GDP	ALL: 2000.Q1–2010.Q3

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