Business Cycle Regimes in CEECs Production: A Threshold SURE Approach

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Abstract

We use a threshold seemingly unrelated regressions specification to assess whether the Central and East European countries (CEECs) are synchronized in their business cycles to the Euro-area. This specification is useful in two ways: First, it takes into account the common institutional factors and the similarities across CEECs in their process of economic transition. Second, it captures business cycle asymmetries by allowing for the presence of two distinct regimes for the CEECs. As the CEECs are strongly affected by the Euro-area these regimes may be associated with Euro-area expansions and contractions. We discuss representation, estimation by maximum likelihood and inference. The methodology is illustrated by using monthly industrial production in 8 CEECs. The results show that apart from Lithuania the rest of the CEECs experience "normal" growth when the Euro-area contracts and "high" growth when the Euro-area expands. Given that the CEECs are "catching up" with the Euro-area this result shows that most CEECs seem synchronized to the Euro-area cycle.

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1. Introduction

The optimal currency area (OCA) theory (Mundell, 1961) argues that the cost of using a common currency is potentially high for economies that are sufficiently different. This is an important issue for the Central and East European countries (CEECs) that recently joined the European Union. If the CEECs are not economically integrated with the Euro-area, and in particular are not synchronized in their business cycles to the Euro-area, a common currency would result in conflicts across countries about the preferred monetary policy, and therefore, an early enlargement of the European Monetary Union (EMU) would be too costly. The goal of this paper is to assess whether the CEECs are synchronised in their business cycles to the Euro-area and thus to provide some insights on the degree of success we might expect of their joining the EMU.

In recent years there has emerged a burgeoning empirical literature on business cycle synchronization between the CEECs and the Euro-area[1]. There is a wide range of approaches to measure synchronization. For instance, Boone and Maurel (1998) compute correlation coefficients between the cyclical components of industrial production and unemployment rates for the CEECs vs the Euro-area and Germany. They find a relatively high degree of cycle synchronization for several CEECs with Germany, though lower with the whole EU. Artis, Marcellino and Proietti (2004) use concordance measures and find that business cycle synchronization with the Euro-area is low with the exception of Poland, Slovenia and Hungary. Darvas and Szapáry (2004) use various measures of synchronization (e.g., correlation, volatility and persistence of business cycles) and based on the behaviour of a wide range of expenditure and sectoral components of GDP, also

[1] A comprehensive survey is given by the meta-analysis in Fidrmuc and Korhonen (2006).

find higher degrees of synchronization for Poland, Slovenia and Hungary. On the other hand, Eickmeier and Breitung (2006) use structural dynamic factor analysis; they find that there is considerable heterogeneity across the CEECs with Poland, Slovenia, Hungary and Estonia being the most suitable EMU candidates.

Another bulk of literature, Frenkel et al. (1999), Frenkel and Nickel (2002) Fidrmuc and Korhonen (2003) has used the Blanchard-Quah technique to identify common demand and supply shocks in the CEECs and the Euro-area. For instance, Frenkel et al. (1999) look at several CEECs during the early years of the transition into a market economy and point out that there are significant differences between individual CEECs and Germany or France. Using a longer time series, Frenkel and Nickel (2002) find that the more advanced CEECs are fairly synchronized to the smaller states of the EU.

This paper contributes to the existing literature in two main ways. First, we propose a different approach to measure synchronization of business cycles between the CEECs and the Euro-area. Our empirical strategy to identify synchronization takes into account the common institutional factors and the similarities across CEECs in their process of economic transition. So far little attention has been given to common factors in the literature.[2] More precisely, we put forward a threshold seemingly unrelated regressions (TSURE) model that can capture common factors across the CEECs.

This paper also makes a contribution to the econometric literature on non-linear threshold autoregressive (TAR) models. In effect, the TSURE specification can be seen as an extension of the TAR model, initially proposed by Tong (1978) and Tong and Lim

[2] With Kočenda (2001) and Kutan and Yigit (2004) constitute a few exceptions.

(1980) and subsequently developed in Tsay (1989) and Tong (1990)[3]. In the present context, the TSURE model can capture business cycle asymmetries by allowing for the presence of two distinct regimes for the CEECs. As the CEECs economies are strongly affected by the Euro-area these regimes may be associated with Euro-area expansions and contractions. We propose a simple algorithm to obtain maximum likelihood estimators for the complete TSURE model. Such algorithm is based on a combination of grid search procedures and Iterated Feasible Generalized Least Squares (IFGLS) methods. In addition, a linearity test is proposed to assess the statistical significance of the threshold effect.

The rest of the paper is organized as follows. Section 2 presents the TSURE specification as well as a discussion of maximum likelihood estimation and testing for the threshold effect. We also discuss inference in this section. Section 3 discusses the data and presents the results. Finally, Section 4 briefly concludes.

2. Methodology

2.1 Model

Consider first the linear seemingly unrelated regressions (SURE) model for CEECs

$$y_{1t} = x'_{1t}\beta_1 + u_{1t}$$

$$\begin{matrix} . \\ . \\ . \end{matrix} \qquad (1)$$

[3] It is worth mentioning that Teräsvirta and Anderson (1992) and Granger and Teräsvirta (1993) promote a related family of models, the smooth transition regression models (STR), as a smooth transition generalization of the TAR.

$$y_{Mt} = x'_{Mt}\beta_M + u_{Mt}$$

more compactly

$$y_m = X_m\beta_m + u_m, \qquad i = 1,\ldots,M$$

where y_m is a $T\times 1$ vector and measures economic activity (e.g., industrial production) in country m and X_m is a $T\times k_m$ matrix of explanatory variables in country *m*. Essentially, autoregressive lags are included to sufficiently reduce the errors to white noise. In principle, X_m can be extended to also include exogenous variables. The vector β_m is the $k_m\times 1$ vector of coefficients and u_m is a $T\times 1$ error vector in country *m*. The usual error structure for the classical linear regression formulation for $i = 1,\ldots,M$ is

$$E[u_m] = 0, \; E[u_m u'_m] = \sigma_m^2 I_T$$

The above set of equations can be stacked and represented as the system

$$y = X\beta + u$$

where y is $TM\times 1$, X is $TM\times K$, β is $K\times 1$, u is $TM\times 1$, $K = \sum_{m=1}^{M} k_m$, and $E[u] = 0$. If the errors across equations are contemporaneously correlated then

$$E[uu'] = \begin{bmatrix} \sigma_1^2 I_T \;\; \sigma_{12} I_T \;\; \ldots \;\; \sigma_{1M} I_T \\ \sigma_{21} I_T \;\; \sigma_2^2 I_T \;\; \ldots \;\; \sigma_{2M} I_T \\ . \\ \sigma_{M1} I_T \;\; \sigma_{M2} I_T \ldots \sigma_M^2 I_T \end{bmatrix} = \Sigma \otimes I_T$$

In the present context, the effect of common institutional factors and the similarities across CEECs in their process of economic transition may be picked up by Σ. If Σ is known, parameter estimates can be obtained by using the Generalized Least Squares (*GLS*) estimator $\hat{\beta}_{GLS} = \left[X'(\Sigma^{-1} \otimes I_T)X\right]^{-1} X'(\Sigma^{-1} \otimes I_T)y$. In practice, however, Σ is rarely known and for this case Feasible Generalized Least Squares (FGLS) estimators have been proposed. The equation-by-equation Ordinary Least Squares (OLS) residuals can be used to consistently estimate Σ. Both these estimators are due to Zellner (1962, 1963). Iterating on this FGLS procedure (IFGLS) produces maximum likelihood (ML) estimates with equivalence conditions given in Oberhofer and Kmenta (1974).

It is also of interest to test whether Σ is a diagonal matrix, that is, whether there are the gains in efficiency from the FGLS estimation. The likelihood ratio statistic is given by

$$\lambda_{LR}= T\left[\sum_{m=1}^{M} \ln \hat{\sigma}_m^2 - \ln |\hat{\Sigma}|\right] \overset{a}{\sim} \chi^2_{M(M-1)/2}$$

where $\hat{\sigma}_m^2$ is obtained from equation-by-equation Least Squares (LS) regressions and $\hat{\Sigma}$ is the maximum likelihood estimate of Σ.

As an extension of model (1), the two-regime threshold seemingly unrelated regressions (TSURE) model is given by

$$\begin{aligned} y_{1t} &= (x'_{1t}\beta_1)d_{1t}(\gamma) + (x'_{1t}\theta_1)d_{2t}(\gamma) + u_{1t} \\ &\;\,. \\ &\;\,. \\ &\;\,. \\ y_{Mt} &= (x'_{Mt}\beta_M)d_{1t}(\gamma) + (x'_{Mt}\theta_M)d_{2t}(\gamma) + u_{Mt} \end{aligned} \qquad (2)$$

where

$$d_{1t}(\gamma) = 1(s_t \le \gamma)$$
$$d_{2t}(\gamma) = 1(s_t > \gamma)$$

where $1(.)$ denotes the indicator function, γ is the threshold parameter and s_t is the (common) threshold variable (e.g., Euro-area production). For exposition the stacked model is given by

$$y = X\beta d_1(\gamma) + X\theta d_2(\gamma) + u$$

As in the linear context, the errors are contemporaneously correlated through a covariance matrix Σ.

The TSURE model can capture business cycle asymmetries by allowing for the presence of different regimes for the CEECs. These regimes may be associated with Euro-area expansions and contractions. For specifically, if $\gamma \approx 0$ then when $s_t \leq \gamma$ (associated with contractions in the Euro-area production) we are in Regime 1 and the SURE model for the CEECs is $y = X\beta + u$. On the other hand, when $s_t > \gamma$ (associated with expansions in the Euro-area production) we are in Regime 2 and the SURE model for the CEECs is $y = X\theta + u$.

Notice that in principle the threshold variable could be different across equations (e.g., lag of industrial production in each country). However, as existing research shows the CEECs are strongly affected by the Euro-area since they are collectively smaller both geographically and economically[4]. Thus, in the present context it is more intuitive to focus on asymmetries in the CEECs production initiated by the Euro-area.

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[4] See, for instance, the studies mentioned in introduction on business cycle synchronization.

2.2 Estimation

The parameters of interest are the vectors β and θ, the matrix Σ and the threshold γ. Estimation of model (2) is carried out by ML under the assumption that the errors are normal $u \sim N(0, \Sigma \otimes I_T)$. The Gaussian likelihood is

$$\ln L(\beta, \theta, \Sigma, \gamma) = -\frac{T}{2} \ln |\Sigma| - \frac{1}{2} \sum_{t=1}^{T} u'_t \Sigma^{-1} u_t$$

The *MLE* $(\hat{\beta}, \hat{\theta}, \hat{\Sigma}, \hat{\gamma})$ maximizes $\ln L(\beta, \theta, \Sigma, \gamma)$.

Notice that it is computationally convenient to first concentrate out (β, θ, Σ). That is, holding γ fixed the IFGLS estimator computes the constrained ML estimator for (β, θ, Σ). This yields the concentrated likelihood function

$$\ln L(\hat{\beta}, \hat{\theta}, \hat{\Sigma}, \gamma) = -\frac{T}{2} \ln |\hat{\Sigma}(\gamma)| - \frac{Tm}{2} \tag{3}$$

Thus, the ML estimator $\hat{\gamma}$ minimizes $\ln |\hat{\Sigma}(\gamma)|$ subject to the constraint ensuring that

$$\pi_0 \leq P(s_t \leq \gamma) \leq 1 - \pi_0$$

where $\pi_0 > 0$ is a trimming parameter. For the empirical application, π_0 is set to 0.1[5].

The criterion function (3) is not continuous, so conventional gradient hill-climbing algorithms are not suitable for its maximization. This problem can be solved by direct grid search over γ and requires approximately T IFGLS SURE regressions.

Gallant (1975) showed that the non-linear FGLS estimator obtained for the seemingly unrelated non-linear regressions is consistent and asymptotically normal even in the absence of normality of the error distribution. The threshold SURE in (2) falls in the class of models considered by Gallant, and therefore, it can be argued that the grid-IFGLS

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[5] Andrews (1993) argues that values of π_0 in the range of 0.05-0.15 are good choices.

estimator of $\zeta = (\beta', \theta')$ is expected to be consistent and classical asymptotic hypothesis testing could be used. Furthermore, if in addition the errors are multivariate normal, Gallant (1987) showed that iterating the non-linear FGLS estimator between Σ and the slope parameters converges to the (tail equivalent) ML estimation[6]. Similarly, at the present context we argue that the grid-IFGLS estimation of TSURE as an iterated technique could yield full-information ML estimators.

2.3 Testing for threshold SURE

When estimating the threshold SURE specification an important question is whether the threshold effect is statistically significant. The relevant null hypothesis of no threshold effect (or linearity) is $H_0\!: \beta = \theta$. In single equation threshold AR (TAR) models, Hansen (1996) shows that this test does not have a conventional asymptotic distribution and the statistic is defined as the maximum (or average or exponential) of a set of F statistics which are calculated for comparison between the linear model and the threshold model for each possible value of the threshold. The p-value of this test can be calculated using the asymptotic results of Hansen (1996) or a bootstrap as suggested by Hansen (1999) in finite samples.

Hansen and Seo (2002) propose a similar no threshold (or linearity) test in the context of threshold vector error correction models (TVECM), which they argue its asymptotic distribution is a multivariate extension of Hansen (1996, 1999). Also, Clements and Galvão (2004) employ this test to assess the predictability of US interest rates using the

[6] See Chapters 3,5 and 6 in Gallant (1987).

term structure in TVECM. We describe an extension of this test for TSURE (2) in what follows. More specifically, the supremum likelihood ratio test of $H_0: \beta = \theta$ in (2) is

$$SupLR = \sup_{\gamma_L \le \gamma \le \gamma_U} LR(\gamma) = T\left[\ln|\hat{\Sigma}_R| - \ln|\hat{\Sigma}_{UR}(\gamma)|\right] \quad (4)$$

where $\ln|\hat{\Sigma}_R|$ is the log of the determinant of the variance-covariance matrix of the errors obtained under the null whereas $\ln|\hat{\Sigma}_{UR}(\gamma)|$ is the corresponding matrix obtained under the alternative. Under the null, there is no threshold, so the model reduces to the linear SURE. For this test, the search region $[\gamma_L, \gamma_U]$ is set so that γ_L is the $\pi_0 = 0.1$ percentile of the transition variable and γ_U is the $1 - \pi_0 = 0.9$ percentile. As the function $LR(\gamma)$ is non-differentiable in γ, the maximization of (4) is obtained through a grid- IFGLS evaluation over $[\gamma_L, \gamma_U]$[7].

Given that asymptotic critical values of the sampling distribution of the *SupLR* statistics cannot be tabulated since in general the distribution depends upon moments of the sample, a bootstrap algorithm is proposed and performed in the following manner. Treat the threshold variable s_t as given, holding its values fixed in repeated samples. Draw with replacement a sample of size T from the empirical distribution of the estimated errors estimated under the null hypothesis and use these errors to create a bootstrap sample under H_0. Using the bootstrap sample, estimate the model under the null (1) and alternative (2) and calculate the bootstrap value of the likelihood ratio statistic *SupLR*. Repeat this procedure a large number of times and calculate the

[7] Notice that the value of γ which maximizes (4) is different from the ML estimator $\hat{\gamma}$ presented in Section 2.2.

percentage of draws for which the simulated statistic exceeds the actual. This would be the bootstrap approximation to the asymptotic *p*-value of the test.

2.4 Inference

There have been a number of important developments in the asymptotic theory for inference in TAR models (e.g., Chan, 1993, Hansen, 2000, among others). Chan (1993) and Hansen (2000) showed that the LS estimator of the threshold γ is super-consistent, and that its asymptotic distribution is highly non-standard. The super-consistency property is due to the fact that the underlying process is discontinuous in the neighbourhood of the threshold, discontinuity which is present in these models via the indicator function. Similarly in the TSURE model the IFGLS estimator of γ is also expected to be super-consistent and the analysis could proceed as in Hansen (2000) (Theorem 2). Hansen (2000) proposes a simple procedure for forming confidence intervals for γ based on the 'no-rejection region' of the likelihood ratio statistic for tests on γ. Here, we followed his recommendation and used the asymptotic critical values he provides. It should be noted, however, that in the TSURE model it is expected that there would be efficiency gains in estimation not only for the coefficient estimates but also for the threshold estimate. In other words, compared to the TAR model, in the TSURE model the confidence interval for the threshold is expected to be narrower. Showing this is beyond the scope of this paper, though it would be an interesting point to explore in future research.

3. Empirical analysis

3.1 The data

The analysis is based on industrial production index (total industry) series. Although its deficiencies, at month frequencies this series is probably more accurately measured than any other indicator of economic activity in transition economies. Specifically, we use the seasonally adjusted values of the logarithmic indices of industrial production IP_t for Hungary (HU), Slovenia (SI), Poland (PL), the Czech Republic (CZ), Slovakia (SK), Lithuania (LT), Latvia (LV) and Estonia (EE). The sample is monthly from 1999:2 through 2004:11. Admittedly, the sample is short, partly due to the availability of the Euro-area industrial production and partly due to the exclusion of the early years of the transition process so that the results are not affected by the main structural changes during the first phase of the transition process.

The original series are made approximately stationary by one-month differencing $\Delta IP_t = \ln(IP_t) - \ln(IP_{t-1})$; Figure 1 shows the series for all CEECs as used in the estimated models.

The Euro-area industrial production is considered to act as the threshold variable s_t and particularly the following choice for this variable

$$s_t = \Delta_{12} IP_t^{EURO} = \ln(IP_t^{EURO}) - \ln(IP_{t-12}^{EURO}) \text{ with } s_{t-d} = \Delta_{12} IP_{t-d}^{EURO}$$

for some $d \leq 12$. This long difference for the threshold variable proves useful as a business cycle indicator for the Euro-area. The series is graphed in Figure 2. As seen, the principal period of decline for this variable is from mid-2000 until the end of 2001, which effectively captures the German recession of 2001 with its macroeconomic context.

Note that typically d is unknown so it must be estimated. The estimation algorithm described in Section 2.2 allows d to be estimated along with the other parameters. Essentially, The estimation problem of equation (3) can be augmented to include a search over d, so instead of T IFGLS regressions a two-dimensional grid search is performed which requires approximately $12T$ IFGLS regressions.

The data source for most of the series is the *IMF International Financial Statistics*, apart from the Estonian series,which is obtained from the *Statistical Office of Estonia* while the Latvian one comes from the *Central Bank of Latvia*.

3.2 Discussion of the estimated models

This section presents the estimated models. We start by estimating a linear SURE specification. The next step is to test the null hypothesis of linear against threshold SURE using the linearity test described in Section 2.3. The estimated correlation matrix of the errors for both specifications is also reported. All reported results in this paper have been obtained using the package RATS.

It is usually difficult to interpret the individual coefficients of the autoregressive models, but the implied growth rate could provide information regarding the properties of the series. The following regressions are estimated by linear and threhsold SURE

$$E(y_{it}/I_{it-1}) = \beta_{i0} + \beta_{i1} y_{it-1} + \ldots + \beta_{ik_i} y_{it-k_i} \quad i = 1,\ldots,M$$

the implied growth rate for each series is given by

$$\mu_i = \frac{\beta_{i0}}{1 - \beta_{i1} - \ldots - \beta_{ik_i}}$$

where $E(y_{it}) = \mu_i$, $\forall\ t$.

The estimates of the linear SURE model are given in Table 1 and the correlation matrix of errors obtained from the equations in Table 2. According to the *R-sq* values, this specification explains between 31% (e.g., Poland, Lithuania) and almost 60% (e.g., Slovenia) in the total variation of the industrial production growth rate. The implied (annualized) growth rates show that CEECs experience strong growth during 1999-2004, though it varies across countries. For example, Estonia grows very fast together with Hungary and Lithuania, while Slovenia grows slow. Turning to Table 2 the results show that, apart from Lithuania, there seem to be strong relationships between the errors of the other countries. For example, the estimated correlation between the errors obtained from the Estonian model and the errors obtained from the Latvian model is 0.602, is 0.599 for Polish and Latvian equations, 0.561 for the Polish and Czech Republic equations, 0.380 for the Polish and Hungarian equations, 0.462 for the Czech Republic and Slovenian equations. These correlations may be explained by the common institutional factors and the similarities across CEECs in their process of economic transition. This result is in line with Kočenda (2001) and Kutan and Yigit (2004) who showed that common economic policies tend to increase real and nominal convergence in these countries. Statistically, this finding confirms the SURE test reported in Table 1, which indicates that the gain in efficiency from the system estimation is highly significant with a *p*-value of 3.86×10^{-31}.

Table 3 presents the estimated threshold SURE model. Notice that, in principle, all coefficients could be allowed to switch between the regimes. In the present context, however, because of the small sample size it may make sense to impose greater parsimony on the model by allowing only the constants and the coefficients on some lags to switch. For instance, the first lags effects seem highly significant in the linear model, and therefore, we restrict our consideration on testing for threshold effects on those lags. Table 3 also reports results for the linearity test given by (4). The *p*-value was calculated using a bootstrap experiment with 2,000 simulation replications. It is found that the test is significant at 1.6% level indicating asymmetric behaviour in the system. Furthermore, the estimated specification indicates $\hat{d} = 6$ and gives a threshold value of 0.0040 with a 95% confidence interval of [.0032, .0050]. This narrow confidence interval shows that estimation is quite precise. This can also be seen in Figure 3, which plots the log-likelihood versus the transition variable, $\Delta_{12} IP_{t-6}^{EURO}$. As seen, the selection is clear.

What is more interesting about this model, however, is that there seem to be two distinct regimes for the CEECs. The first regime, which applies to 35% of the sample (Regime 1), is when $\Delta_{12} IP_{t-6}^{EURO} \leq 0.0040$ and may be associated with contractions in the Euro-area production. From the implied (annualized) growth rates, it is seen that in this regime most CEECs experience positive growth. One exception is Lithuania, which experiences very strong growth in this regime. In this light, Regime 1 may be called the "normal" growth regime for most CEECs.

On the other hand, a second regime (Regime 2) is identified when $\Delta_{12} IP_{t-6}^{EURO} > 0.0040$, which may be associated with expansions in the Euro-area. Interestingly in Regime 2, the implied (annualized) growth rates show that in most CEECs accelerates, and therefore, we may call this regime the "high" growth regime. Again Lithuania constitutes an exception as it experiences slow growth. Differences in regime-dependent growth rates across the regimes can be large for some countries. For instance, Latvia grows at a rate of 13% in the high growth regime, but 1.9% in the normal growth regime. Poland grows at a rate of 11.5% in the high growth regime, whereas 3.1%

in the normal growth regime. For the Czech Republic and Slovakia the differences are quite large as well. Given that CEECs are "catching up" with the Euro-area this result shows that most CEECs business cycle seem synchronized to the Euro-area cycle. Once again, the results in Table 4 indicate strong relationships between errors obtained from the equations pointing to common significant factors in the CEECs.

To illustrate the usefulness of the TSURE model, we estimated single-equation TAR models for each CEEC separately with the Euro-area production as a transition variable. In other words, we did not take into account the correlation matrix of errors. The results for the implied (annualized) growth rates are reported in Table 5.[8] Interestingly, only for Latvia and Lithuania the models obtained from the TAR are close to those obtained from the TSURE specification. Notice that for Hungary, Slovenia and Czech Republic the regime-dependent growth rates show no synchronization to the Euro-area at all. On the other hand, Poland, Slovakia and Estonia seem to be synchronized, though the estimated threshold is too high for Poland and too low for the other two counties to imply regimes of expansion versus contraction in the Euro-area. Intuitively and taking into consideration the results of the literature we would expect the more advanced CEECs such as Hungary, Slovenia and the Czech Republic to have achieved reasonably high synchronization. Statistically, notice that the IFGLS and LS estimators are consistent, and therefore, we would expect them asymptotically to deliver similar results. However, when it comes to applications with small samples because the IFGLS is efficient and the LS is not, the results obtained from the former are more reliable than those obtained from the latter. Therefore, this finding shows the usefulness of the TSURE model.

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[8] To save space, only implied growth rates are reported. However, the full results are available from the author upon request.

The TSURE model in (2) assumes that the threshold γ is equal across the CEECs. In practice, this assumption may be too restrictive, and therefore, it would be of interest to know whether the threshold for one country differs from that for another. Estimating the equations separately as in TAR model one cannot formally test this hypothesis. The TSURE model, however, can provide the framework to formally test this restriction. More specifically, the relevant null hypothesis of identical thresholds across countries (or threshold homogeneity) is $H_0{:}\gamma_{HU}=\ldots=\gamma_{EE}=\gamma$ against the alternative that for one country the threshold is different. For that purpose, a 'LR-like' test statistic can be built as follows

$$LR_i^{\hom o} = T\left[\ln|\hat{\Sigma}_{\hom o}| - \ln|\hat{\Sigma}_{hetero}|_i\right] \tag{6}$$

where $\ln|\hat{\Sigma}_{\hom o}|$ is the log of the determinant of the variance-covariance matrix of the errors obtained under the null (TSURE model with threshold homogeneity) whereas $\ln|\hat{\Sigma}_{hetero}|_i$ is the log of the determinant of the variance-covariance matrix of the errors obtained under the alternative (TSURE model with threshold heterogeneity for country *i*). This test can be performed for each country separately and the null would be rejected if the statistic is too "large". Gallant (1975) suggested standard asymptotic inference to test parameter restrictions across equations in seemingly unrelated non-linear regressions. One might be skeptical that standard asymptotic inference will yield good finite sample approximations in practice, particularly in small samples. Therefore, we consider a bootstrap experiment to obtain the *p*-value of the statistic using 2,000 simulation replications. The results are reported in Table 6. It can be seen that the test is significant at 5% level only for Estonia (p-value is 0.037), which rejects the null hypothesis of threshold homogeneity for this country.

In light of this result, we re-estimate the TSURE model in (2) allowing the Estonian equation to have different threshold from the rest of the CEECs. To estimate this specification a two-dimensional grid search is performed over (γ, γ_{EE}), which requires approximately T^2 IFGLS regressions. The estimates are given in Table 7. As seen, although the threshold for Estonia is found to be higher at 0.0223, the results are qualitatively similar to those in Table 3. The threshold for the rest of the CEECs is estimated as before at 0.004. Once again, there seem to be two distinct regimes for the CEECs. The normal growth regime (Regime 1: associated with contractions in the Euro-area production) in which most CEECs experience positive growth, and the high growth regime (Regime 2: associated with expansions in the Euro-area production) in which growth in most CEECs accelerates. Once again, Lithuania constitutes a notable exception and seems that it is not synchronized to the Euro-area business cycle.

4. Concluding remarks

The goal of this paper is to assess whether the CEECs are synchronised in their business cycles to the Euro-area and thus to provide some insights on the degree of success we might expect of their joining the EMU. Compared to the literature we propose a different approach to measure synchronization of business cycles between the CEECs and the Euro-area. We estimate a threshold seemingly unrelated regressions (TSURE) specification, which proves useful in two ways: First, it takes into account the common institutional factors and the similarities across CEECs in their process of economic transition. Second, it captures business cycle asymmetries by allowing for the presence of two distinct regimes for the CEECs. As the CEECs are strongly affected by the Euro-area these regimes may be associated with Euro-area expansions and contactions. The main finding of the paper is that apart from Lithuania the rest of the CEECs experience normal growth when the Euro-area contracts and high growth when the Euro-area expands. Given that the CEECs are "catching up" with the Euro-area this result shows that most CEECs seem fairly synchronized to the Euro-area cycle.

The achieved degree of synchronization implies that some new EU member states would probably not suffer from asymmetric shocks in the Euro-area. Naturally, the new EU members must ensure that their economic policies are sustainable and in line with the requirements of the EMU.

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Table 1: Linear SURE estimates for industrial production growth in CEECs

	HU	SI	PL	CZ	SK	LT	LV	EE
Con	.014 (.004)	.007 (.003)	.008 (.004)	.012 (.003)	.009 (.002)	.016 (.007)	.008 (.003)	.014 (.004)
ΔIP_{t-1}	-.732 (.088)	-.701 (.071)	-.483 (.091)	-.724 (.089)	-.659 (.099)	-.622 (.096)	-.594 (.080)	-.483 (.075)
ΔIP_{t-2}	-.456 (.086)	-.516 (.072)	-.182 (.100)	-.298 (.088)	-.342 (.100)	-.458 (.101)	-.282 (.081)	-.326 (.076)
ΔIP_{t-3}			-.056 (.085)			-.183 (.098)		
ΔIP_{t-4}						-.251 (.090)		
Implied growth	.0787	.0383	.0579	.0686	.0550	.0740	.0522	.0949
R-sq	.5199	.5818	.3112	.5016	.3204	.3117	.4292	.4195
LL	1712.77							
SUR chi-sq (p-value)	3.86×10^{-31}							

Notes: Estimation period 1999:5-2004:11; values in parentheses are standard errors; *Implied growth* is unconditional (annualised) mean of series; *LL* is value of log likelihood function; *SUR* tests gains in efficiency from *GLS* estimation; *R-sq* is usual coefficient of determination.

Table 2: Correlations of errors from linear SURE model

	HU	SI	PL	CZ	SK	LT	LV	EE
HU	1	.308	.380	.252	.225	.226	.330	.374
SI		1	.399	.462	.166	-.117	.207	.585
PL			1	.561	.252	-.062	.599	.420
CZ				1	.110	-.008	.385	.389
SK					1	.275	.323	.459
LT						1	.257	.229
LV							1	.602
EE								1

Table 3: Threshold SURE estimates for industrial production growth in CEECs

	HU		SI		PL		CZ		SK	
	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1
Con	**.016**	**.014**	**.009**	**.006**	**.015**	**.004**	**.018**	**.008**	**.015**	**.006**
	(.007)	**(.005)**	**(.006)**	**(.004)**	**(.006)**	**(.004)**	**(.005)**	**(.004)**	**(.004)**	**(.003)**
ΔIP_{t-1}	**-.677**	**-.762**	**-.723**	**-.654**	**-.363**	**-.497**	**-.621**	**-.754**	**-.822**	**-.466**
	(.151)	**(.095)**	**(.113)**	**(.079)**	**(.180)**	**(.098)**	**(.171)**	**(.093)**	**(.120)**	**(.129)**
ΔIP_{t-2}	-.467	-.467	-.498	-.498	-.175	-.175	-.292	-.292	-.447	-.447
	(.084)	(.084)	(.069)	(.069)	(.100)	(.100)	(.089)	(.089)	(.092)	(.092)
ΔIP_{t-3}					-.072	-.072				
					(.084)	(.084)				
Implied growth	.0873	.0740	.0500	.0312	.1150	.0307	.1106	.0474	.0804	.0407
R-sq	.5218		.5755		.3222		.5191		.4157	
Linearity SupLR (p-value)	.016									
Transition Variable	$\Delta_{12} IP^{EURO}_{t-6}$				Regime 2, when $\Delta_{12} IP^{EURO}_{t-6} > .0040$					
Threshold	.0040 [.0032, .0050]				Regime 1, when $\Delta_{12} IP^{EURO}_{t-6} \leq .0040$					
LL	1731.81									

Notes: Estimation period 1999:5-2004:11; Regime 1 ("normal" growth regime) applies to 35% of sample and Regime 2 ("high" growth regime) applies to 65% of sample; values in parentheses are standard errors; values in brackets next to threshold form its 95% confidence interval; *Implied growth* is (local) regime-dependent unconditional annualised mean of series; *Linearity* tests for the null of no threshold effect by using bootstrapped *SupLR* statistic; *LL* is value of log likelihood function; *R-sq* is usual coefficient of determination.

Table 3: (continued)

	LT		LV		EE	
	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1
Con	**.008**	**.025**	**.019**	**.003**	**.016**	**.014**
	(.011)	**(.008)**	**(.005)**	**(.004)**	**(.007)**	**(.005)**
ΔIP_{t-1}	**-.089**	**-.817**	**-.464**	**-.673**	**-.276**	**-.574**
	(.156)	**(.105)**	**(.137)**	**(.085)**	**(.109)**	**(.088)**
ΔIP_{t-2}	-.527	-.527	-.327	-.327	-.347	-.347
	(.094)	(.094)	(.077)	(.077)	(.074)	(.074)
ΔIP_{t-3}	-.318	-.318				
	(.093)	(.093)				
ΔIP_{t-4}	-.345	-.345				
	(.083)	(.083)				
Implied growth	.0407	.0984	.1297	.0194	.1175	.0896
R-sq	.3917		.4890		.4308	
Linearity SupLR (p-value)	*.016*		*Regime 2, when* $\Delta_{12}IP^{EURO}_{t-6} > .0040$			
			Regime 1, when $\Delta_{12}IP^{EURO}_{t-6} \leq .0040$			
Transition Variable	$\Delta_{12}IP^{EURO}_{t-6}$					
Threshold	.0040 [.0032, .0050]					
LL	1731.81					

Notes: See the notes to Table 3.

Table 4: Correlations of errors from threshold SURE model

	HU	SI	PL	CZ	SK	LT	LV	EE
HU	1	.311	.388	.249	.179	.263	.311	.372
SI		1	.414	.466	.127	-.234	.193	.620
PL			1	.553	.105	-.047	.589	.439
CZ				1	.033	-.005	.317	.374
SK					1	.229	.196	.440
LT						1	.254	.029
LV							1	.584
EE								1

Table 5: Threshold SURE versus threshold AR implied growth rates for industrial production growth in CEECs

	HU		SI		PL		CZ		SK		LT		LV		EE	
	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1
Threshold SURE	.0873	.0740	.0500	.0312	.1150	.0307	.1106	.0474	.0804	.0407	.0407	.0984	.1297	.0194	.1175	.0896
Transition variable	$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$	
Threshold	.0040		.0040		.0040		.0040		.0040		.0040		.0040		.0040	
Threshold AR	.0706	.1612	.0284	.0556	.0628	-.0048	.0715	.0783	.1752	.0432	.0427	.0986	.1201	.0217	.2234	.0828
Transition Variable	$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$		$\Delta_{12} IP^{EURO}_{t-6}$	
Threshold	.0521		.0481		.0521		.0275		-.0120		.0050		.0040		-.0120	

Notes: *Implied growth* rate is (local) regime-dependent unconditional annualised mean of series.

Table 6: Threshold homogeneity test in TSURE model

	HU	SI	PL	CZ	SK	LT	LV	EE
p-values	0.123	0.067	0.114	0.142	0.177	0.297	0.159	0.037

Notes: Tests for the null of identical thresholds across countries (or threshold homogeneity) against the alternative that for one country the threshold is different by using a bootstrapped 'LR-like' statistic.

Table 7: Threshold SURE estimates for industrial production growth in CEECs allowing for threshold heterogeneity for EE

	HU		SI		PL		CZ		SK		LT		LV		EE	
	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1	Reg 2	Reg 1
Con	**.018**	**.013**	**.011**	**.004**	**.017**	**.004**	**.019**	**.008**	**.017**	**.006**	**.009**	**.025**	**.021**	**.003**	**.018**	**.005**
	(.006)	**(.005)**	**(.005)**	**(.004)**	**(.006)**	**(.004)**	**(.005)**	**(.004)**	**(.004)**	**(.003)**	**(.011)**	**(.008)**	**(.004)**	**(.004)**	**(.005)**	**(.005)**
ΔIP_{t-1}	**-.527**	**-.796**	**-.690**	**-.605**	**-.386**	**-.516**	**-.645**	**-.750**	**-.853**	**-.476**	**-.108**	**-.807**	**-.478**	**-.646**	**-.345**	**-.558**
	(.183)	**(.093)**	**(.110)**	**(.076)**	**(.180)**	**(.098)**	**(.175)**	**(.094)**	**(.115)**	**(.123)**	**(.170)**	**(.103)**	**(.133)**	**(.083)**	**(.091)**	**(.088)**
ΔIP_{t-2}	-.472	-.472	-.470	-.470	-.212	-.212	-.304	-.304	-.484	-.484	-.521	-.521	-.338	-.338	-.348	-.348
	(.084)	(.084)	(.068)	(.068)	(.100)	(.100)	(.088)	(.088)	(.089)	(.089)	(.099)	(.094)	(.077)	(.077)	(.073)	(.073)
ΔIP_{t-3}					-.088	-.088					-.327	-.327				
					(.084)	(.084)					(.093)	(.093)				
ΔIP_{t-4}											-.352	-.352				
											(.083)	(.083)				
Implied growth	.1064	.0690	.0631	.0245	.1245	.0290	.1152	.0472	.0875	.0371	.0459	.1011	.1393	.0165	.1308	.0298
R-sq	.5282		.5586		.3280		.5202		.4184		.3941		.4913		.3907	
Transition Variable	$\Delta_{12} IP_{t-6}^{EURO}$		$\Delta_{12} IP_{t-6}^{EURO}$		$\Delta_{12} IP_{t-6}^{EURO}$		$\Delta_{12} IP_{t-6}^{EURO}$		$\Delta_{12} IP_{t-6}^{EURO}$		$\Delta_{12} IP_{t-6}^{EURO}$		$\Delta_{12} IP_{t-6}^{EURO}$		$\Delta_{12} IP_{t-6}^{EURO}$	
Threshold	.0040		.0040		.0040		.0040		.0040		.0040		.0040		.0223	
LL	1735.54															

Notes: Estimation period 1999:5-2004:11; Regime 1 is "normal" growth regime and Regime 2 is "high" growth regime; values in parentheses are standard errors; *Implied growth* is (local) regime-dependent unconditional annualised mean of series; *LL* is value of log likelihood function; *R-sq* is usual coefficient of determination.

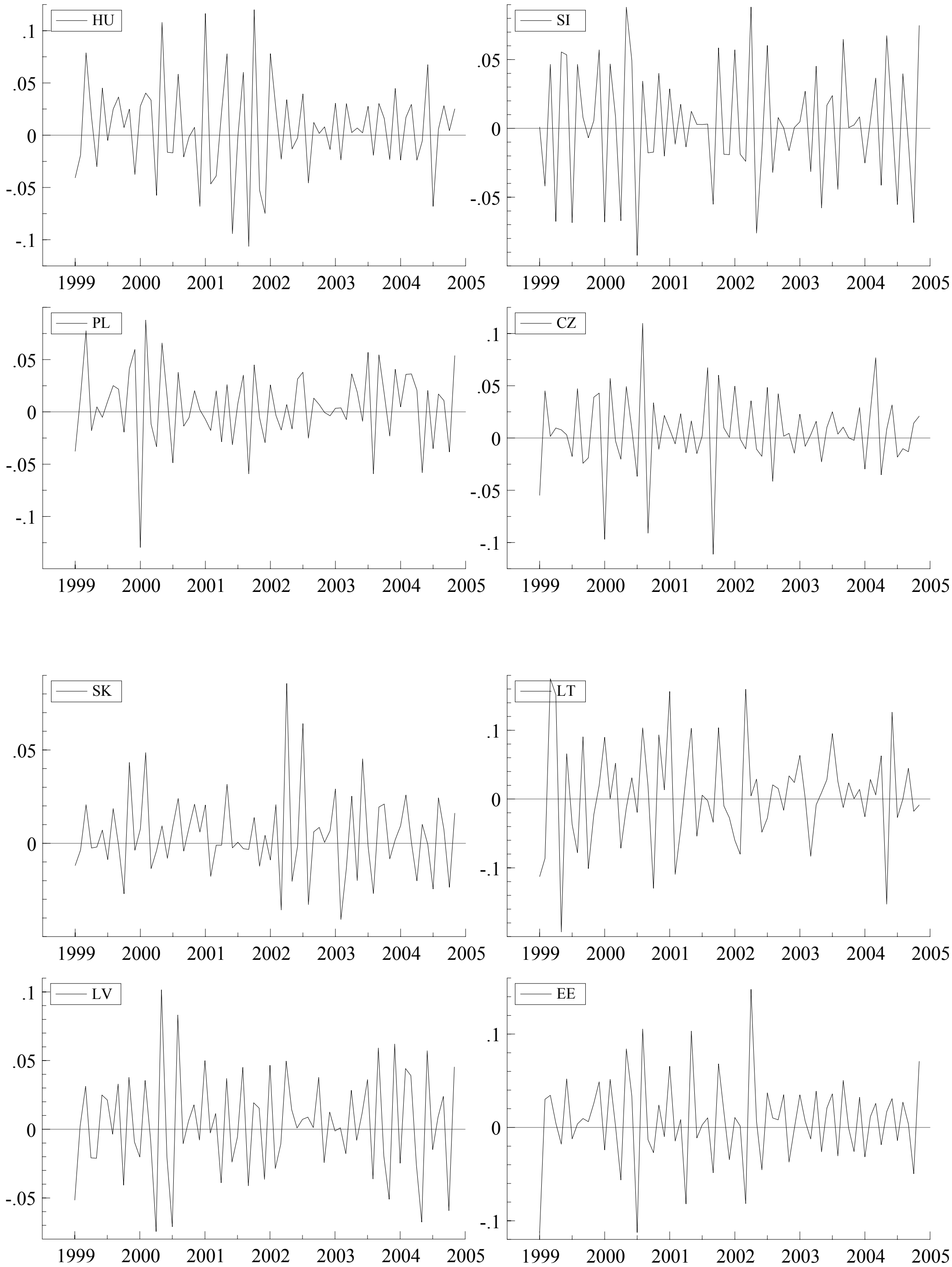

Fig. 1. One-month difference of the logarithm of seasonally adjusted industrial production. Hungary (HU), Poland (PL), Slovakia (SK), Latvia (LV), Slovenia (SI), Czech Republic (CZ), Lithuania (LT) and Estonia (EE).

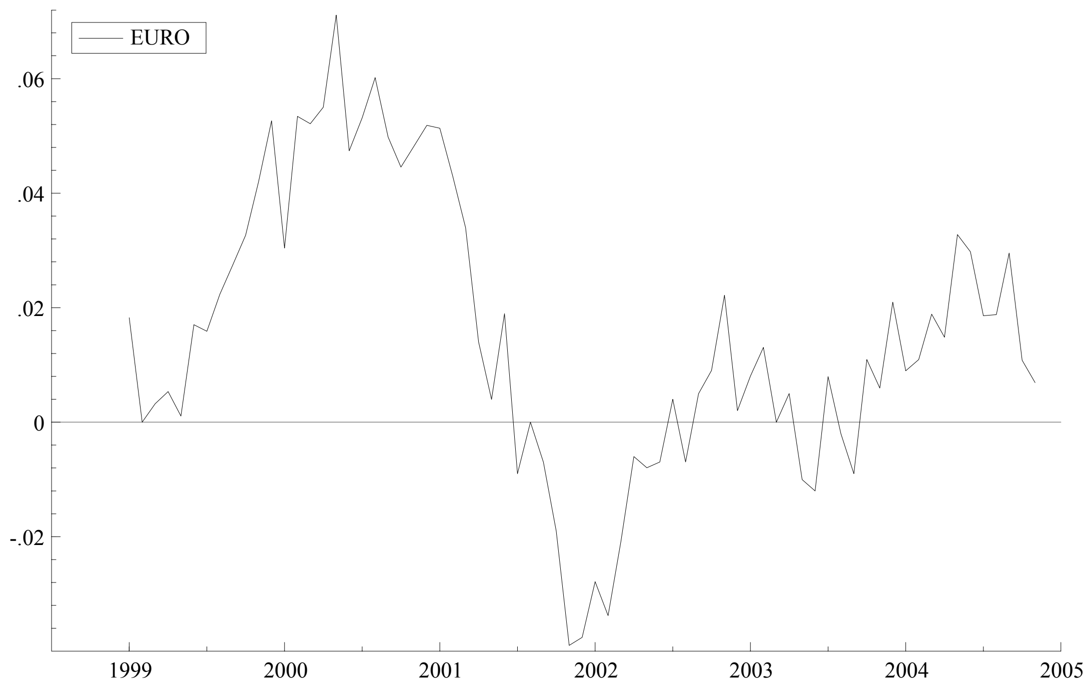

Fig. 2. Twelve-month difference of the logarithm of seasonally adjusted Euro-area industrial production.

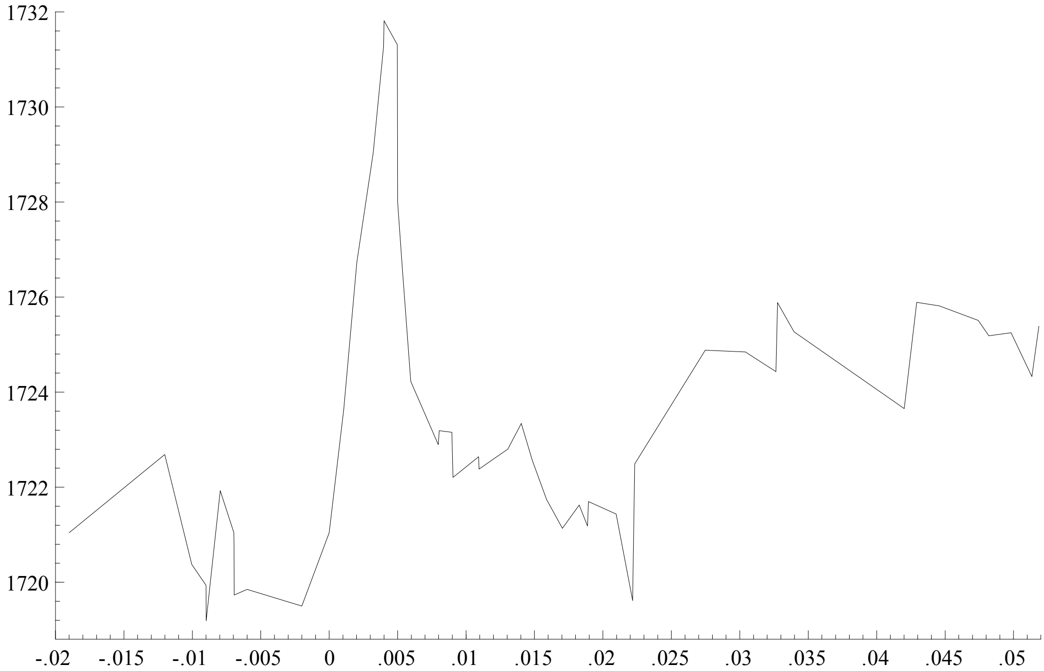

Fig. 3. Log likelihood function from threshold SUR versus candidate threshold value.