Eesti Pank
Bank of Estonia

Business Cycle Regimes in CEECs Production: A Threshold Approach

Nektarios Aslanidis

Working Paper Series
1/2006

Business Cycle Regimes in CEECs Production: A Threshold SUR Approach

Nektarios Aslanidis*

Abstract

The aim of this paper is to study economic activity in CEECs and to look at the transmission of economic activity between the euro area and CEECs. Econometric techniques appropriate for a threshold seemingly unrelated regressions specification are developed to take account of factors that are common to all CEECs. This methodology also allows for asymmetries in the activity of the CEECs governed by the overall euro area activity. The results show slow growth for most CEECs when the euro area economy decelerates, but high growth when the euro area economy grows.

JEL Code: C50, E32

Keywords: threshold SUR, asymmetry, business cycles

Author's e-mail address: n.aslanidis@econ.soc.uoc.gr

---

*University of Crete and University of Monash, Department of Economics. This research was conducted during the five-month period when I was visiting Eesti Pank, and the hospitality of the research department during my stay is gratefully acknowledged. Comments from seminar participants at Eesti Pank, Stockholm School of Economics, University of Sydney and Monash University are greatly appreciated. am also grateful to Robert Bartels, David G Mayes, Martti Randveer and Timo Teräsvirta for useful suggestions and comments. Any remaining errors are exclusively mine.

Contents

1. Introduction

The aim of this paper is to study the business cycle in Central and Eastern European countries (CEECs) and new EU member states, and to look at the transmission of business cycle regimes between the euro area and the CEECs. Intuitively, we would expect the business cycle in CEECs to be strongly affected by the euro area cycle since they are smaller both geographically and economically compared to the euro area. Studying the transmission and synchronization of business cycles between countries is of particular interest because according to the optimal currency area (OCA) theory business-cycle synchronization is important for participation in a monetary union[1].

A natural approach to modelling economic variables appears to involve defining different states of the world or regimes, and allowing for the possibility that the dynamic behaviour of economic variables depends on the regime in place at any given point in time. Roughly speaking, two main classes of statistical models have been proposed, which formalize the idea of the existence of different regimes. The first class is the Markov-switching models originally employed in the business cycle context by Hamilton (1989), and these assume that the regime cannot be observed, but is governed by an underlying stochastic process. This implies that one can never be certain that a particular regime is in place at a particular point in time, but can only assign probabilities for the occurrence of the different regimes.

The second approach considers explicitly modelling the regime as a continuous function of an observable variable as in threshold autoregressive (TAR) models, initially proposed by Tong and Lim (1980) and subsequently developed in Tsay (1989, 1998) and Tong (1990)[2]. Consequently, the regimes that have occurred in the past and present are known with certainty (though they have to be found using statistical techniques). Therefore, in the present context TAR models have an advantage over Markov-switching models because this way we mainly focus on the exploration of the nature of the underlying regimes. Modelling the business cycle in CEECs within the threshold context can be motivated by the fact that the transition mechanism could be controlled by the euro area cycle. Therefore, it would be of interest to see if recession and expansions in the euro area activity may have distinct effects on the business cycle in CEECs.

The main contribution this study makes is that it takes account of factors that are common to all CEECs, such as area-wide factors as a result of tran-

[1] For a review of recent literature on the synchronization of business cycles between the euro area and CEECs, see e.g. Fidrmuc and Korhonen (2004).

[2] It is worth pointing out that Teräsvirta and Anderson (1992) and Granger and Teräsvirta (1993) promote the STR model as a smooth transition generalization of the TAR.

sition economies and recent EU membership, and employs estimation procedures that simultaneously estimate the parameters of the models. More specifically, econometric techniques appropriate for a threshold seemingly unrelated regressions (SUR) specification are developed. A relatively simple algorithm is proposed to obtain a maximum likelihood estimation of the complete model. A bootstrap method to assess the statistical significance of the threshold effect is also described. The methods are similar to those developed by Hansen (1996, 1999). Under the null hypothesis, there is no threshold, so the model reduces to a conventional linear SUR.

The results support the hypothesis that the euro area cycle implies interesting asymmetries for the business cycle in CEECs. Particularly, most CEECs grow slowly when the euro area economy decelerates but appear to experience high growth rates when the euro area economy starts expanding.

2. Methodology

2.1. Model

Consider first the linear SUR model:

$$\begin{aligned} y_{1t} &= x'_{1t}\beta'_1 + u_{1t} \\ &\vdots \\ y_{Mt} &= x'_{Mt}\beta'_M + u_{Mt}, \end{aligned} \tag{1}$$

more compactly:

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

where y_m is a $T \times 1$ vector and measures economic activity (e.g., industrial production) in country *m*, X_m is a $T \times k_m$ matrix of explanatory variables in country *m*, β_m is the $k_m \times 1$ vector of coefficients and u_m is a $T \times 1$ error vector in country *m*[3]. The usual error structure for the classical linear regression formulation for $i = 1, ..., M$ is:

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

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

$$y = X\beta + u \ ,$$

[3]Essentially, autoregressive lags are included to sufficiently reduce the errors to white noise. In principle, X_m can be extended to also include independent variables.

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:

$$\mathbf{E}[\mathbf{uu}'] = \begin{bmatrix} \sigma_1^2 I_T & \sigma_{12} I_T & \dots & \sigma_{1M} I_T \\ \sigma_{21}^2 I_T & \sigma_2^2 I_T & \dots & \sigma_{2M} I_T \\ \dots & & & \\ \sigma_{M1}^2 I_T & \sigma_{M2} I_T & \dots & \sigma_M^2 I_T \end{bmatrix}$$

If Σ is known, parameter estimates can be obtained by using the generalized least squares (*GLS*) estimator:

$$\hat{\beta}_{GLS} = [X'(\Sigma^{-1} \otimes I_T) X]^{-1} X'(\Sigma^{-1} \otimes I_T) y.$$

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 residuals can be used to consistently estimate Σ. Both these estimators are due to Zellner (1962, 1963). Iterating on this FGLS procedure produces maximum likelihood (*ML*) estimates with equivalence conditions given in Oberhofer and Kmenta (1974).

It may also be of interest to test whether Σ is a diagonal matrix. The likelihood ratio statistic would be:

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

where $\hat{\sigma}_m^2$ is obtained from equation-by-equation least squares regressions and $\hat{\Sigma}$ is the maximum likelihood estimate of Σ.

As an extension of model (1), the 2-regime threshold seemingly unrelated regressions (SUR) model is given by:

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

where:

$$\begin{aligned} d_{1t}(\gamma, d) &= 1(s_t \leq \gamma) \\ d_{2t}(\gamma, d) &= 1(s_t > \gamma) \end{aligned}$$

and $1(.)$ denotes the indicator function, γ is the threshold parameter and s_t is the (common) threshold variable (e.g., a measure of economic activity in the euro area). Notice that in principle the threshold variable could be different across equations (e.g., measures of economic activity in each country). However, in the present context, to study the transmission of business cycle regimes between the euro area and CEECs it is more reasonable to focus on cycle asymmetries implied by the (common) euro area cycle.

For exposition the stacked model is given as:

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

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

Threshold model (2) has two regimes defined by the euro area cycle. In the analysis of business cycles in CEECs this specification can describe a situation where expansion and recessions in the euro area may have distinct effects on the business cycle in CEECs.

2.2. Estimation

The parameters of interest are β, θ, Σ and γ. The estimation of model (2) is carried out using maximum likelihood under the assumption that the errors are normal $u \sim N(0, \Sigma \otimes I_T)$. The Gaussian likelihood is:

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

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* computes the constrained *ML* estimator for (β, θ, Σ). This yields the concentrated likelihood function:

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

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 distribution of s_t, it is set $\pi_0 = 0.1$.

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 a direct grid search over γ and requires approximately *T IFGLS* SUR regressions.

2.3. Testing for threshold SUR

When estimating the threshold SUR specification an important question is whether the threshold effect is statistically significant. The relevant null hypothesis of linearity is $H_0 : \beta = \theta$. This sections reviews the testing methodology suggested by Hansen (1996, 1999). As is well known, this testing problem is tainted by the difficulty that threshold γ is not identified under H_0. This is typically called the "Davies" Problem (see Davies, 1977, 1987) and has been investigated by Andrews and Ploberger (1994) and Hansen (1996) among others. The threshold SUR model (2) falls in the class of models considered by Hansen, who suggested a bootstrap to simulate the asymptotic distribution of the likelihood ratio test. Specifically, the likelihood ratio test of H_0 is:

$$SupLR = \sup_{\gamma L \leq \gamma \leq \gamma U} LR(\gamma) = T \left[\ln |\hat{\Sigma}_R| - \ln |\hat{\Sigma}_{UR}(\gamma)| \right], \tag{4}$$

where $\ln |\hat{\Sigma}_R|$ is obtained under the null, whereas $\ln |\hat{\Sigma}_{UR}(\gamma)|$ is obtained under the alternative. Under the null, there is no threshold, so the model reduces to the conventional linear SUR specification. 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 evaluation over $[\gamma_L, \gamma_U]$ [4].

Given that asymptotic critical values of the sampling distribution of $SupLR$ statistics cannot be tabulated since in general the distribution depends upon moments of the sample, a bootstrap algorithm is 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 percentage of draws for which

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

the simulated statistic exceeds the actual. This is the bootstrap approximation to the asymptotic *p*-value of the test.

3. Nonlinear modelling of industrial production in CEECs

3.1. Data

The analysis is based on the industrial production index (total industry) series. This series shows more cyclical variation than GDP, which contains some sluggish components. I have specifically used seasonally adjusted values of the logarithmic indices of industrial production IP_t for Hungary (HU), Slovenia (SI), Poland (PL), Czech Republic (CZ), Slovakia (SK), Lithuania (LT), Latvia (LV) and Estonia (EE). The sample is monthly from 1999:2 through 2004:11. The original series are made approximately stationary by one-month differencing $\Delta IP_t = \ln(IP_t) - \ln(IP_{t-1})$; Appendix 1 shows the series for all CEECs as used in the estimated models.

Industrial production in the euro area is considered to act as the threshold variable s_t, and in particular as the following choice for this variable:

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

for some $d \leq 12$. This long difference for the threshold variable is useful as a business cycle indicator for the euro area. The series is graphed in Appendix 2. The principal period of decline for this variable is mid-2000 until the end of 2001, which is effectively the recession of 2001.

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

When using threshold models there is no economic theory to determine the coefficient vectors β and θ that govern the dynamics of the two regimes, so that the choice of the coefficients that switch between the regimes has to be based on the data. For example, model (2) allows all coefficients to switch between these two regimes. In the present application, because of the small sample size it may make sense to impose greater parsimony on the model by allowing some coefficients to switch between regimes. For example, I restrict my consideration to models that allow the constants or the constants as well as the coefficients on the first-order autoregressive terms across the equations to switch between regimes.

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

3.2. Discussion of the estimated models

This section presents the estimated models. To address the issue of whether the euro area cycle implies asymmetries for the CEECs business cycle, a linear SUR specification is estimated first. The next step of the analysis is to test the null hypothesis of linear against threshold SUR. 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 estimated steady state mean could provide information regarding the long-run properties of the series. The following regressions are estimated:

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

the steady state mean of each series:

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

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

The estimates of the linear SUR model are given in Appendix 5, while the correlation matrix of its errors, in Appendix 6. According to the *R-sq* values, this specification explains between 32% (e.g., Slovakia, Lithuania) and almost 60% (e.g., Slovenia) of the total variation of the industrial production growth rate. It is seen that the estimated steady state means imply that all CEECs have experienced positive growth during 1999–2004. The growth rates are higher for Estonia and Hungary while Slovenia grows slowly. Further, Appendix 6 shows that there are strong positive relationships between the errors of the models that should be accounted for — for example, between Estonia and Latvia (0.57), Poland and Latvia (0.54), Poland and Czech Republic (0.50), Poland and Hungary (0.34) and Czech Republic and Slovenia (0.45) among others. This finding is consistent with the SUR test reported in Appendix 5, which indicates that the gain in efficiency from the system estimation is highly significant with a *p*-value of 6.26×10^{-26}.

Appendix 7 presents the threshold SUR model that allows only constants across the equations to switch between regimes, while Appendix 8 reports the correlation matrix of the errors. Appendix 7 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 the 2.5% level, indicating threshold behaviour on the constants of the processes. The estimated specification indicates $\hat{d}$ and gives a threshold of 0.00397, and Appendix 3 shows the scatter plot of the log-likelihood versus possible transition values. The selection is clear. What is more interesting, however, is that there are two regimes implied by this specification for CEECs economies. The first regime, which applies to 34% of the sample (Reg. 1), is when $\Delta_{12} IP^{EURO}_{t-6} \leq 0.00397$ and can be associated with negative growth or very slow positive growth in the euro area. This regime implies slow growth in CEECs and is called the "slow growth regime". Indeed, it reflects the low steady state means implied by the processes as shown in Appendix 7. One exception is Lithuania, which experiences high growth rates under this regime.

On the other hand, there is a second regime (Reg. 2) identified when $\Delta_{12} IP^{EURO}_{t-6} > 0.00397$ and can be associated with rapid growth in the euro area. As seen, in this regime the steady state means get larger implying that growth in CEECs accelerates with the exception of Lithuania, which experiences slow growth. This regime is called the "high growth regime". Differences in growth rates across the regimes are noticeable for Latvia and Poland. For example, the Latvian economy grows at a monthly rate of 0.99% in the high growth regime whereas at 0.16% in the slow growth regime. The Polish economy grows at 0.95% in the high growth regime, but only 0.24% in the slow growth regime. On the other hand, for the Estonian economy, growth differences across the regimes are not particularly remarkable. Once again, the results in Appendix 8 indicate strong positive relationships between the errors of the models.

Next, Appendix 9 gives the results for the threshold SUR model, which allows constants as well as the coefficients on the first lags[5] across the equations to switch between regimes. As can be seen, the results essentially do not change, with the regimes identified as before — slow growth for the CEECs when the euro area shrinks and high growth associated with periods when the euro area grows. It also seems the threshold effect on the constants gives reasonable mileage, though perhaps the threshold effect on the first lags seems

[5] In principle, the coefficients on all lags could be allowed to switch between the regimes. However, because of the small sample size it may make sense to impose greater parsimony on the model by allowing only the coefficients on the first lags to switch.

to offer little. As to the correlation matrix of the errors in Appendix 10 the picture is the same as before.

The above findings imply that most of the CEECs show significant synchronization of business cycles with the euro area. This finding is broadly consistent with the growing literature on the synchronization of business cycles between the euro area and CEECs (Fidrmuc and Korhonen, 2004). However, the main contribution of the present study is that it takes account of area-wide factors that affect those economies and employs estimation procedures that simultaneously estimate the parameters of the models. The literature so far has ignored factors that are common to all CEECs, which run a higher risk of producing inconsistent and biased parameter estimates.

4. Conclusions

This paper studies the business cycle in CEECs and looks at the transmission of business cycles between the euro area and CEECs. Econometric techniques appropriate for a threshold seemingly unrelated regressions specification are developed to account for factors that are common to all CEECs and for asymmetries in the CEECs cycles governed by the overall euro area cycle. The results support the hypothesis that the euro area cycle implies asymmetries for the CEECs. In particular, economic growth in most CEECs is slow when the euro area economy decelerates but appear to experience high growth rates when the euro area economy starts expanding.

References

Andrews, D. W. K. and W. Ploberger., 1994. Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica*, Vol. 62, 1383–1414.

Davies, R. B., 1977. Hypothesis testing when a nuisance parameter is present only under the alternative. *Biometrika*, Vol. 64, 247–254.

Davies, R. B., 1987. Hypothesis testing when a nuisance parameter is present only under the alternative. *Biometrika*, Vol. 74, 33–43.

Fidrmuc, J. and I. Korhonen., 2004. A meta-analysis of the business cycle correlation between the euro-area and CEECs: What do we know-and who cares?. *BOFIT-Institute for Economies in Transition Working Paper*, No. 20.

Granger, C. W. J. and T. Teräsvirta., 1993. *Modelling nonlinear economic relationships*. Oxford: Oxford University Press.

Hansen, B.E., 1996. Inference when a nuisance parameter is not identified under the null hypothesis. *Econometrica*, Vol. 64, 413–430.

Hansen, B.E., 1999. Testing for linearity. *Journal of Economic Surveys*, Vol. 13, 551–576.

Oberhofer, W. and J. Kmenta., 1974. A general procedure for obtaining maximum likelihood estimates in generalized regression models. *Econometrica*, Vol. 43, 579–590.

Teräsvirta, T. and H. M. Anderson., 1992), Characterizing nonlinearities in business cycles using smooth transition autoregressive models. *Journal of Applied Econometrics*, Vol. 7, S119–S136.

Tong, H., 1990. *Nonlinear time series. A dynamic system approach*. Oxford: Oxford University Press.

Tong, H. and K. S. Lim., 1980. Threshold autoregressions, limit cycles and data. *Journal of the Royal Statistical Society*, Vol. 42, 242–292.

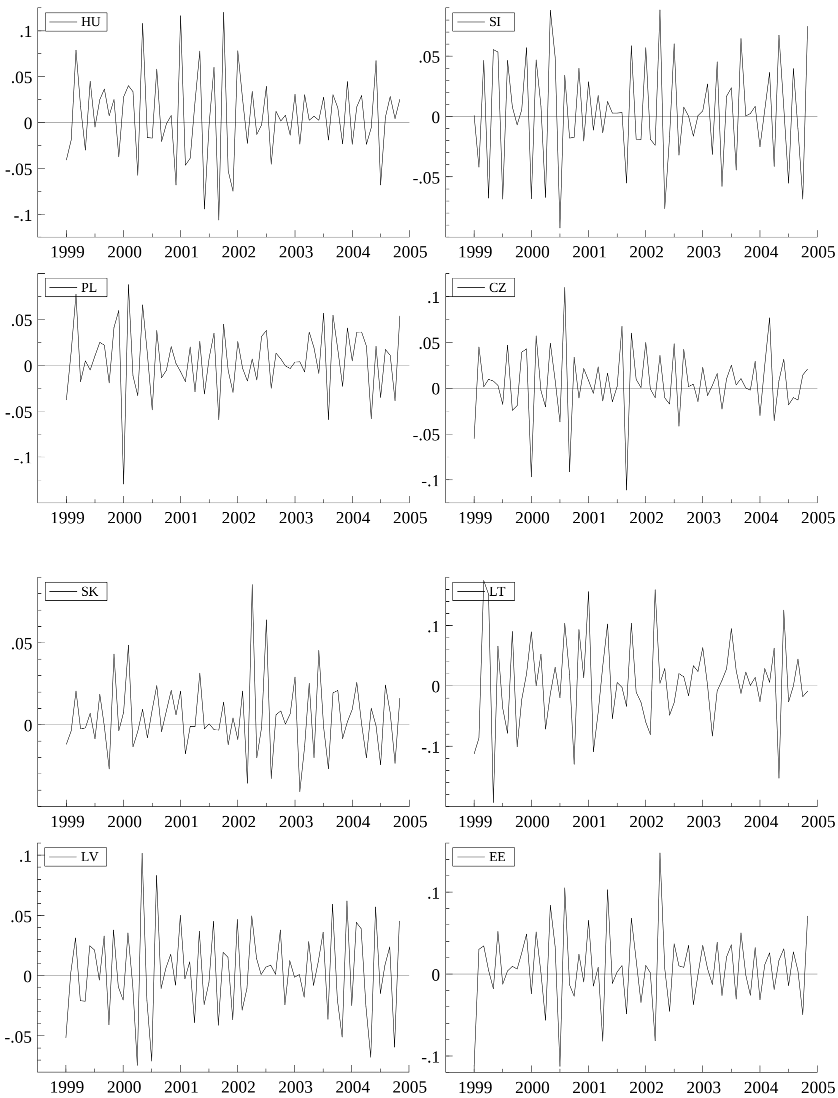
Tsay, R., 1989. Testing and modelling threshold autoregressive processes. *Journal of the American Statistical Association*, Vol. 84, 231–240.

Tsay, R., 1998. Testing and modelling multivariate threshold models. *Journal of the American Statistical Association*, Vol. 93, 1188–1202.

Zellner, A., 1962. An efficient method of estimating seemingly unrelated regression and tests for aggregation bias. *Journal of the American Statistical Association*, Vol. 57, 348–368.

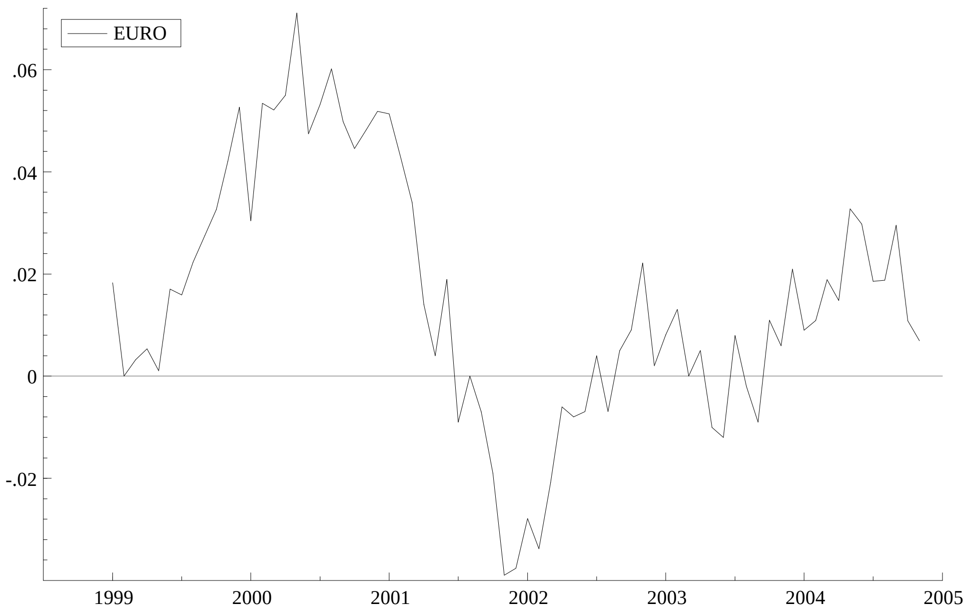
Zellner, A., 1963. Estimators for seemingly unrelated regression equations: some exact finite sample results. *Journal of the American Statistical Association*, Vol. 58, 977–992.

Appendix 1. One-month difference of the logarithm of seasonally adjusted industrial production

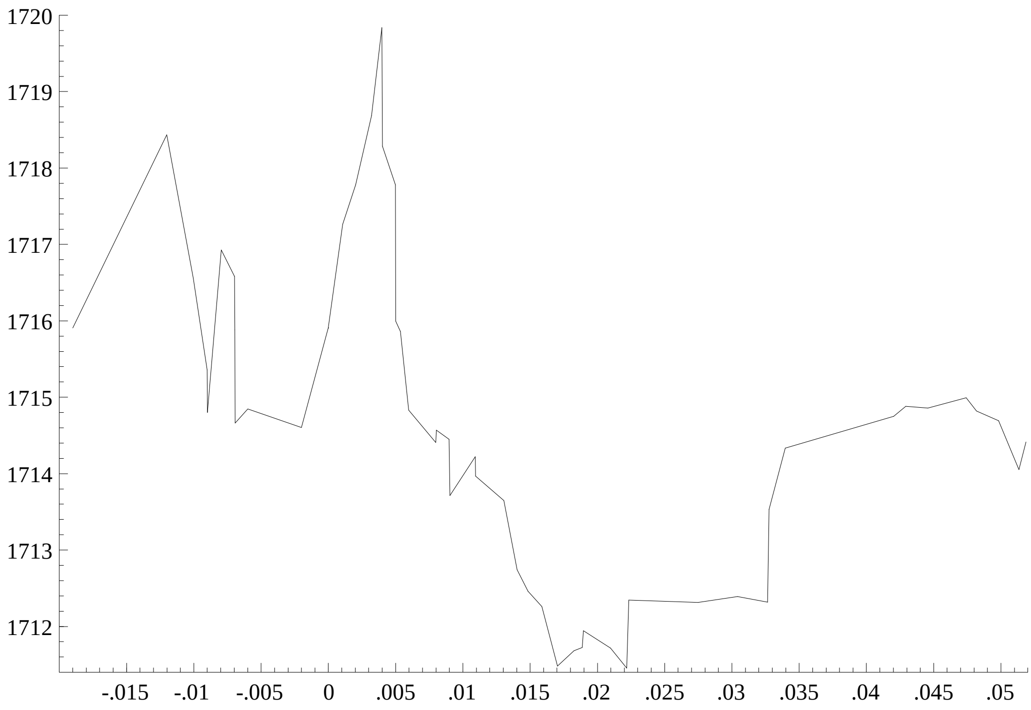


Note: Hungary (HU), Poland (PL), Slovakia (SK), Latvia (LV), Slovenia (SI), Czech Republic (CZ), Lithuania (LT) and Estonia (EE)

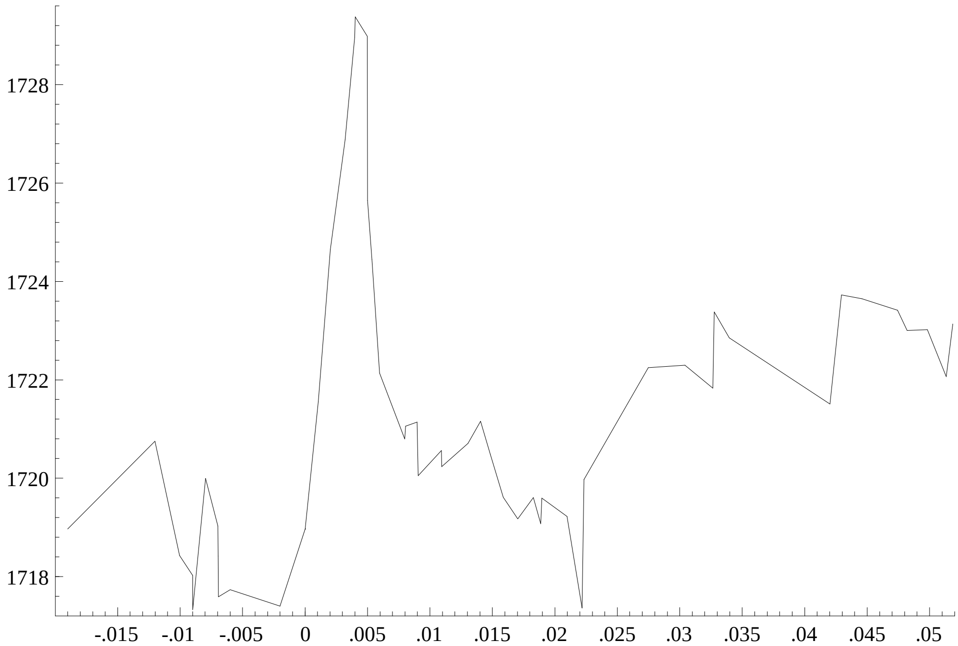
Appendix 2. Twelwe-month difference of the logarithm of seasonally adjusted euro area industrial production



Appendix 3. Log likelihood function from the threshold SUR 1 versus candidate threshold values



Appendix 4. Log likelihood function from the threshold SUR 2 versus candidate threshold values



Appendix 5. Linear SUR Specification

	HU	SI	PL	CZ	SK	LT	LV	EE
Con	0.015	0.007	0.008	0.012	0.009	0.016	0.009	0.016
	(3.740)	(2.306)	(2.369)	(3.885)	(3.880)	(2.260)	(2.690)	(3.975)
ΔIP_{t-1}	-0.748	-0.763	-0.554	-0.785	-0.668	-0.607	-0.652	-0.580
	(-8.166)	(-10.09)	(-5.676)	(-8.458)	(-6.514)	(-6.023)	(-7.681)	(-7.066)
ΔIP_{t-2}	-0.478	-0.577	-0.209	-0.373	-0.349	-0.457	-0.349	-0.406
	(-5.309)	(-7.565)	(-1.920)	(-4.022)	(-3.388)	(-4.324)	(-4.060)	(-4.874)
ΔIP_{t-3}			0.044			-0.233		
			(0.480)			(-2.265)		
ΔIP_{t-4}						-0.259		
						(-2.741)		
Steady state	0.0066	0.0032	0.0047	0.0057	0.0046	0.0062	0.0043	0.0079
R-sq	0.5235	0.5989	0.3882	0.5221	0.3202	0.3275	0.4548	0.4629
LL	1710.96							
SUR								
ch-sq								
p-value	6.26×10^{-26}							

Note: Estimation period 1999:5-2004:11; values in parentheses are t-rations; Steady state is estimated unconditional mean; LL is value of log likelihood function; SUR tests gains in efficiency from GLS estimation

Appendix 6. Correlation Matrix of Residuals from Linear SUR Specification

	HU	SI	PL	CZ	SK	LT	LV	EE
HU	1	0.29	0.34	0.22	0.22	0.24	0.31	0.33
SI		1	0.36	0.45	0.16	-0.09	0.19	0.56
PL			1	0.50	0.23	-0.001	0.54	0.34
CZ				1	0.08	0.01	0.34	0.34
SK					1	0.24	0.31	0.44
LT						1	0.24	0.16
LV							1	0.57
EE								1

Appendix 7. Threshold SUR Specification 1

	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	**0.018**	**0.013**	**0.010**	**0.006**	**0.017**	**0.004**	**0.019**	**0.009**	**0.015**	**0.007**	**0.006**	**0.022**	**0.020**	**0.003**	**0.016**	**0.015**
	(2.668)	**(2.784)**	**(1.800)**	**(1.561)**	**(2.904)**	**(1.057)**	**(3.618)**	**(2.434)**	**(3.806)**	**(2.513)**	**(0.549)**	**(2.504)**	**(3.827)**	**(0.923)**	**(2.458)**	**(3.220)**
ΔIP_{t-1}	-0.748	-0.748	-0.765	-0.765	-0.558	-0.558	-0.792	-0.792	-0.690	-0.690	-0.628	-0.628	-0.660	-0.660	-0.579	-0.579
	(-8.144)	(-8.144)	(-10.09)	(-10.09)	(-5.715)	(-5.715)	(-8.600)	(-8.600)	(-6.913)	(-6.913)	(-6.276)	(-6.276)	(-8.219)	(-8.219)	(-7.146)	(-7.146)
ΔIP_{t-2}	-0.480	-0.480	-0.579	-0.579	-0.224	-0.224	-0.384	-0.384	-0.401	-0.401	-0.485	-0.485	-0.405	-0.405	-0.413	-0.413
	(-5.329)	(-5.329)	(-7.635)	(-7.635)	(-2.040)	(-2.040)	(-4.174)	(-4.174)	(-3.983)	(-3.983)	(-4.648)	(-4.648)	(-4.895)	(-4.895)	(-5.032)	(-5.032)
ΔIP_{t-3}					0.048	0.048					-0.270	-0.270				
					(0.516)	(0.516)					(-2.641)	(-2.641)				
ΔIP_{t-4}											-0.276	-0.276				
											(-2.967)	(-2.967)				
Steady state	0.0079	0.0059	0.0043	0.0026	0.0095	0.0024	0.0088	0.0042	0.0072	0.0033	0.0024	0.0081	0.0099	0.0016	0.0082	0.0077
R-sq	0.5258		0.6013		0.4195		0.5404		0.3509		0.3428		0.5152		0.4635	
LL	1719.83															
Linearity bootstrap p-value	0.025															
Transition Variable	$\Delta_{12}IP^{EURO}_{t-6}$						Reg 2 when $\Delta_{12}IP^{EURO}_{t-6} > 0.00397$									
							Reg 1 when $\Delta_{12}IP^{EURO}_{t-6} \leq 0.00397$									
Threshold	0.00397 (-0.01201, 0.00498)															

Note: Estimation period 1999:5-2004:11; First regime labeled Reg 1 ("slow growth regime") applies to 34% of sample and second regime labeled Reg 2 ("high growth regime") applies to 66% of sample; values in parentheses are t-rations; Steady state is estimated unconditional (local) mean; linearity tests whether threshold effect on constants is significant; values in parenthesis next to threshold form the 95% confidence interval; LL is value of log likelihood function

Appendix 8. Correlation Matrix of Residuals from Linear SUR Specification 1

	HU	SI	PL	CZ	SK	LT	LV	EE
HU	1	0.28	0.33	0.21	0.20	0.22	0.29	0.33
SI		1	0.31	0.43	0.10	-0.11	0.12	0.54
PL			1	0.48	0.19	-0.04	0.51	0.33
CZ				1	0.03	0.01	0.28	0.33
SK					1	0.30	0.27	0.44
LT						1	0.30	0.21
LV							1	0.57
EE								1

Appendix 9. Threshold SUR Specification 2

	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	**0.016**	**0.014**	**0.009**	**0.006**	**0.015**	**0.004**	**0.018**	**0.009**	**0.015**	**0.006**	**0.008**	**0.025**	**0.020**	**0.003**	**0.017**	**0.016**
	(2.415)	**(2.896)**	**(1.686)**	**(1.545)**	**(2.757)**	**(1.036)**	**(3.479)**	**(2.321)**	**(4.135)**	**(2.374)**	**(0.704)**	**(2.963)**	**(3.855)**	**(0.925)**	**(2.637)**	**(3.290)**
ΔIP_{t-1}	**-0.702**	**-0.764**	**-0.801**	**-0.717**	**-0.441**	**-0.572**	**-0.721**	**-0.802**	**-0.850**	**-0.441**	**-0.124**	**-0.796**	**-0.610**	**-0.699**	**-0.413**	**-0.662**
	(-4.345)	**(-7.542)**	**(-6.564)**	**(-8.441)**	**(-2.258)**	**(-5.413)**	**(-3.966)**	**(-8.255)**	**(-6.808)**	**(-3.216)**	**(-0.744)**	**(-7.217)**	**(-4.082)**	**(-7.768)**	**(-3.400)**	**(-6.771)**
ΔIP_{t-2}	-0.482	-0.482	-0.565	-0.565	-0.205	-0.205	-0.366	-0.366	-0.424	-0.424	-0.527	-0.527	-0.402	-0.402	-0.419	-0.419
	(-5.368)	(-5.368)	(-7.545)	(-7.545)	(-1.862)	(-1.862)	(-3.910)	(-3.910)	(-4.338)	(-4.338)	(-5.276)	(-5.276)	(-4.868)	(-4.868)	(-5.097)	(-5.097)
ΔIP_{t-3}					0.049	0.049					-0.347	-0.347				
					(0.526)	(0.526)					(-3.509)	(-3.509)				
ΔIP_{t-4}											-0.334	-0.334				
											(-3.781)	(-3.781)				
Steady state	0.0072	0.0062	0.0039	0.0027	0.0096	0.0024	0.0088	0.0041	0.0067	0.0034	0.0032	0.0083	0.0100	0.0017	0.0093	0.0076
R-sq	0.5242		0.5958		0.4170		0.5380		0.4211		0.4020		0.5165		0.4770	
LL	1729.37															
Linearity Bootstrap p-value	0.040															
Transition Variable	$\Delta_{12}IP_{t-6}^{EURO}$				Reg 2 when $\Delta_{12}IP_{t-6}^{EURO} > 0.00401$ Reg 1 when $\Delta_{12}IP_{t-6}^{EURO} \leq 0.00401$											
Threshold	0.00401 (0.00322, 0.00500)															

Note: Estimation period 1999:5-2004:11; First regime labeled Reg 1 ("slow growth regime") applies to 34% of sample and second regime labeled Reg 2 ("high growth regime") applies to 66% of sample; values in parentheses are t-rations; Steady state is estimated unconditional (local) mean; linearity tests whether threshold effect on constants is significant; values in parenthesis next to threshold form the 95% confidence interval; LL is value of log likelihood function

Appendix 10. Correlation Matrix of Residuals from Threshold SUR Specification 2

	HU	SI	PL	CZ	SK	LT	LV	EE
HU	1	0.29	0.34	0.22	0.18	0.25	0.29	0.33
SI		1	0.32	0.44	0.11	-0.23	0.13	0.57
PL			1	0.49	0.10	-0.04	0.52	0.35
CZ				1	0.01	-0.01	0.28	0.32
SK					1	0.22	0.22	0.42
LT						1	0.26	0.03
LV							1	0.56
EE								1

Working Papers of Eesti Pank 2005

Nr 1
Janika Alloja
Tööjõupakkumine Eestis

No 2
Marit Hinnosaar, Hannes Kaadu, Lenno Uusküla
Estimating the Equilibrium Exchange Rate of the Estonian Kroon

No 3
Lenno Uusküla, Peeter Luikmel, Jana Kask
Critical Levels of Debt?

No 4
Janek Uiboupin
Short-term Effects of Foreign Bank Entry on Bank Performance in Selected CEE Countries

No 5
Rasmus Kattai, John Lewis
Hooverism, Hyperstabilisation of Halfway-House? Describing Fiscal Policy in Central and Eastern European EU Members

No 6
Andres Vesilind, Toivo Kuus
Application of Investment Models in Foreign Exchange Reserve Management in Eesti Pank

No 7
Aurelijus Dabušinskas
Money and Prices in Estonia

No 8
Kadri Männasoo, David G. Mayes
Investigating the Early Signals of Banking Sector Vulnerabilities in Central and Eastern European Emerging Markets

No 9
Ott-Siim Toomet
Does an Increase in Unemployment Income Lead to Longer Unemployment Spells? Evidence Using Danish Unemployment Assistance Data

No 10
Danny Pitzel, Lenno Uusküla
The Effect of Financial Depth on Monetary Transmission

No 11
Priit Vahter
Which Firms Benefit More From Inward Foreign Direct Investment?

No 12
Rasmus Kattai
EMMA – a Quarterly Model of the Estonian Economy

No 13
Priit Vahter, Jaan Masso
Home versus Host Country Effects of FDI: Searching for New Evidence of Productivity Spillovers