Business Cycle Coherence between the Euro Area and the EU New Member States: a Time-Frequency Analysis

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Abstract[1]

This paper applies time-frequency analysis to study patterns of co-movements between economic cycles in the euro area and some of the new European Union member states. Kalman filtering is used to estimate time-varying spectra of GDP growth series in the analysed countries and coherences between them. The individual spectra of the euro area and NMS exhibit several joint patterns with power mostly concentrated in the low and business cycle frequency ranges, though there is also a degree of heterogeneity. Estimates of coherences between NMS and euro area growth rates point to the strong relationship at frequencies which would be the focus of the joint monetary policy once NMS adopt the euro.

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1. Introduction

Research on the characteristics and causes of business cycles is at the core of macroeconomics. The study of business cycles can be dated back to 1920s (Kitchin, 1923) and the work of Mitchell (1946), Burns and Mitchell (1946) and Kuznets (1958). Already Burns and Mitchell (1946) turned their attention to the question of synchronicity of cycles and this issue has remained central of the large literature, in particular studying synchronicity of cycles between countries (e.g. Morgenstern, 1959; Backus and Kehoe, 1992). This work was often related to the interest in the formation of regional blocks in the world economy, usually identical to trading blocks. Among these, European Union has become the focus of a particularly large body of literature, especially after it started preparations for adopting a common currency.

The theory of Optimal Currency Area (Mundell, 1961; McKinnon, 1963; Kennen, 1969) motivated ever increasing interest in the co-movement of business cycles in Europe, their determinants and evolution over time and the existence or absence of a 'European business cycle'. It is virtually impossible to list all important contributions to this strand of literature. Examples include Artis and Zhang (1997 & 1999), Artis (2003), Altavilla (2004), Reichlin (2005), Camacho et al. (2006), Böwer and Guillemineau (2006), Gayer and Weiss (2006), Giannone and Reichlin (2006). Prospects of the EU enlargement and subsequent enlargement of the euro area stimulated the work on the characteristics of business cycles in new EU Member States (NMS) and synchronicity of business cycles between NMS and countries of the euro area or euro area as a whole. Examples include EFN (2003), Artis et al. (2004), Darvas and Szapary (2004), Benczúr and Rátfai (2005), Eickmeier and Breitung (2006a) and reviews can be found in Fidrmuc and Korhonen (2006), Basten (2006), and de Haan et al. (2005).

2. Approaches to analysis of business cycles' co-movement

Various approaches have been used to study characteristics of individual economic time series and co-movement patterns of pairs or groups of series. This section briefly reviews some of the most commonly used techniques to place the method applied in this paper in a broader perspective.

Analyses of time series behaviour can be broadly classified into two groups: the ones carried in the time domain and the ones in the frequency domain.

Time domain analysis has so far been dominant in business cycle literature. The typical approach has been to analyse correlations between selected indicators of real activity (GDP, industrial production, unemployment rates, etc.) after some filtering or between shocks in these variables identified from a vector autoregression system. The examples – exemplifying the variety of approaches – include Ambler et al. (2004) applying generalised method of moments to estimate correlation coefficients, Blaszkiewicz and Wozniak (2005) calculating correlation of growth rates of selected variables, Frenkel et al. (1999) looking at demand and supply shocks recovered from a structural VAR, Den Haan (2000) suggesting a dynamic correlation measure based on VAR forecast errors at different horizons, Hall and Hondroyiannis (2006) applying an orthogonal GARCH model, allowing for calculating a time varying correlation matrix between the examined countries, Bordo and Helbling (2003) using concordance correlations suggested by Harding and Pagan (2006), Eickmeier and Breitung (2006b) employing a large scale structural dynamic factor model and many other approaches.

The literature applying a frequency domain perspective is somewhat smaller, yet still quite well developed. Croux et al. (2001) suggest a frequency-domain measure of dynamic co-movement which they call 'cohesion'. Ma and Park (2004) apply spectral analysis to identify co-movement patterns of international interest rates.

By their very nature, both time- and frequency-domain analyses have important limitations. Frequency characteristics and periodicity of the series are not captured by time-domain analyses. On the other hand, the work in frequency-domain largely ignores the changes in the character and behaviour of series, as the description is averaged over time. It is very tempting to try to combine the strengths of both approaches by extracting the information on the frequency distribution but allowing for time-variation of spectral characteristics. This is what we attempt to do in this paper.

Our study uses the joint time-frequency analysis. Applications of these techniques to economics, while growing in number more recently, are still not very common, partly due to shortness of existing economic time series. In contrast, time-frequency analysis has become popular in several other fields, such as speech and signal recognition or medicine (e.g. Tarvainen, 2006; Zhan and Jardine, 2005; Gu et al., 2000). Some voices are rather sceptical as to the potential of time-frequency analysis in economics (Iacobucci, 2003), while others still view the field as promising (Chen, 1995). An example of an application to finance data is provided by Turhan-Sayan and Sayan (2002). Benati (2006) applies yet another joint time-frequency technique (based on demodulation and pass-band filtering) to study the relation between economic series allowing the relation in question to vary with time. Crowley and Lee (2005) and Crowley et al. (2006) use wavelet analysis to static and dynamic correlations among the euro area member states while Jagrič and Ovin (2004) apply a similar technique to evaluate the synchronisation of the Slovenian economy with the EU. Hughes Hallett and Richter (2004a, 2007) estimate time-varying spectra for selected economies and then calculate time-varying coherences between the US and European business cycles and between selected Central and East European countries and the euro area. Our work closely follows the approach used by Hughes

Hallett and Richter (2004a) applying it to the recent data on economic growth in most new EU member states and the euro area..

Below we describe the notion of time-varying spectra and explain one of the techniques of their construction. This parametric method is based on fitting a Kalman-filter based time-varying autoregressive (AR) model to a series in question and obtaining estimates of momentary spectra from time-varying AR parameters.

3. Methodology

Following Hughes Hallett and Richter (2004a) our analysis is clearly divided in two sections. The first one is devoted to the investigation of individual cycles in the euro area and among NMS. The second one analyses the co-movement in those cycles as measured by the characteristics and time developments of coherences.

3.1 Motivation for the use of time-varying frequency analysis

Spectral analysis can be seen as an equivalent of the covariance analysis in the frequency domain. A full spectrum presents the decomposition of variance and contributions of cycles with different periodicity to the overall dynamics of a process. Usually the whole wide variety of cycles with different frequencies is considered so that the process can be thought of as being a weighted average of contributions from all these cycles.

In the case of the real activity variables, such as GDP it is natural to think of those cycles as business cycles. The traditional business cycle correlation analysis treated the cycle structure invariant throughout the sample which imposed constant weights of specific cycles in determining the movement of a real activity indicator in question. However, in light of evidence of structural breaks in business cycles, it is more appropriate to allow the mode of periodic decompositions to be a function of time. This can enhance spectral analysis of individual-country business cycles as well as enable better detection of co-movements in business cycles across countries and regions.

3.2 Individual spectra

The starting point of our analysis is the investigation of individual cycles in the euro area and in the studied NMS countries. Following the large part of literature and Hughes Hallett and Richter (2004b) in particular, we fit a time-varying AR model to the data[2]. This is achieved by the application of the Kalman filter.

The real activity variable *y* that follows an *AR(p)* process can be represented as:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + \varepsilon_t \ , \qquad (1)$$

where *y* is expressed in terms of deviation from the mean and $\varepsilon_t \approx N(0, H)$.

To obtain time-varying estimates of the AR coefficients we first estimate the model by the forward-pass Kalman filter and then, subsequently process it by the backward-pass fixed-interval smoother. Using the standard notation the AR process of order *p* can be reformulated in a state-space form as follows:

Observation equation: $y_t = Z_t \alpha_t + \varepsilon_t$ (2)

State equation: $\alpha_t = \alpha_{t-1} + \eta_t$ (3)

where

[2] Estimating time varying spectra based on time varying AR model is one of the commonly used parametric approaches to the problem. There exist also different approaches to estimation of time-varying spectra. Among non-parametric techniques, the simplest one is by applying the Short-Time Fourier Transform, i.e. taking a Fourier transform on the moving time-window of data (with a constant length of the window). The wavelet transform is somewhat similar, but the window size is frequency dependent, with narrower windows used for higher frequencies

- ε_t is the zero-mean random walk process with variance H
- $\alpha_t = \left[\alpha_{1t}\ \alpha_{2t}\ \alpha_{3t}\ \ldots\ \alpha_{pt}\right]'$, is the state vector (p x 1) containing AR model coefficients,
- η_t is a (p x 1) vector of serially uncorrelated disturbances with mean zero and covariance matrix Q where the only non-zero elements are on the diagonal and correspond to variances of the elements of the state vector.
- $Z_t = [y_{t-1} \quad y_{t-2} \ldots y_{t-p}]$ is a (1 x p) vector containing lagged values of the observed process y.

For the state-space system defined above the equations of the forward-pass Kalman filter are as follows (e.g. Harvey, 1993, pp. 82-86):

Prediction equations:

$$\begin{aligned} a_{t|t-1} &= a_{t-1} \\ P_{t|t-1} &= P_{t-1} + Q \end{aligned} \tag{4}$$

Correction equations:

$$\begin{aligned} a_t &= a_{t|t-1} + P_{t|t-1} Z_t' \left(Z_t P_{t|t-1} Z_t' + H\right)^{-1} \left(y_t - Z_t a_{t|t-1}\right) \\ P_t &= P_{t|t-1} - P_{t|t-1} Z_t' \left(Z_t P_{t|t-1} Z_t' + H\right)^{-1} Z_t P_{t-1} \end{aligned} \tag{5}$$

The resulting filtered estimates A_t are then subjected to the backward-pass smoothing filter to produce a set of smoothed estimates $A^s{}_t$ of the state vector α_t. The fixed-interval smoothing algorithm was used which consists of a system of recursions starting with the final estimates given by the Kalman filter a_T and P_T as (e.g. Harvey, 1993, p. 87):

$$\begin{aligned} a_t^s &= a_t + P_t^* \left(a_{t+1}^s - a_t\right) \\ P_t^s &= P_t + P_t^* \left(P_{t+1}^s - P_{t+1|t}\right) P_t^{*'} \\ P_t^* &= P_t P_{t+1|t}^{-1} \end{aligned} \tag{6}$$

The unknown variance matrices: H and Q are estimated by the optimisation algorithm *daropt* from the CAPTAIN TOOLBOX developed at Lancaster University (Young et al., 1999)[3].

The Kalman filter yields the set of estimates of the state vector A_t while the smoother produces smoothed estimates $A^s{}_t$. These can be then used to obtain time-varying spectrum of the observed process y. The standard formula for the AR process spectral density using the known AR coefficients is (see formula 4.2, p. 180 in Harvey, 1993):

$$f_Y(\omega) = \frac{1}{2\pi\left|1-\sum_{k=1}^{p}\alpha_k e^{-ik\omega}\right|^2} \quad \text{where } |\,| \text{ denotes the modulus.} \tag{7}$$

Due to the small sample size and ensuing high variability of Kalman filter coefficient estimates A_t (in particular in the beginning of the sample) we decided to rely on the smoothed set of estimates ($A^s{}_t$). The resulting time-varying sample analogue of the true spectrum of y is therefore a function of frequency ω and time t:

$$s_y(\omega,t) = \frac{1}{2\pi\left|1-\sum_{k=1}^{p}a_k^s(t)e^{-ik\omega}\right|^2}, \tag{8}$$

where $a_k^s(t)$ is a backward-pass smoother estimate of an underlying AR coefficient α_k.

3.3 *Coherences*

Coherences can be interpreted as the frequency-domain equivalent of the goodness of fit in the time-domain as measured by R^2. To calculate coherences we first need an estimate of the

[3] See also http://www.es.lancs.ac.uk/cres/captain/.

dynamic model relating the real activity variable in the NMS (*y*) to the real activity indicator in the euro area (*x*). This involves estimating the model with the general form:

$$V(L)_t\, y_t = A(L)_t\, x_t + u_t \tag{9}$$

where $V(L)_t$ and $A(L)_t$ are time-dependent lag structures and y_t and x_t are real activity indicators in the NMS and euro area, respectively. We do this by directly estimating the reduced-form of the model by the Kalman filter by means of the following state-space system:

Observation equation: $y_t = \beta_t x_t + v_t$ (10)

State equation: $\beta_t = \beta_{t-1} + e_t$ (11)

where

- v_t is the zero-mean random walk process with variance σ_v^2
- $\beta_t = \left[\beta_{0t}\ \beta_{1t}\ \ldots\ \beta_{dt}\right]'$ is the state vector, a column vector of the model's coefficients of size *(d+1 x 1)* [4],
- e_t is a vector of serially uncorrelated disturbances with mean zero and covariance matrix *T* where the only non-zero elements are on the diagonal and correspond to variances of the elements of the state vector.
- $x_t = [x_t \quad x_{t-1} \quad x_{t-2} \ldots x_{t-d}]$ is the *(d+1 x 1)* row-vector of lagged values of *x* [5]

Estimates *b* of *β* at each point of time are obtained by applying the analogous procedure of filtering and subsequent smoothing described by sets of equations (5) and (6). This yields the matrix of smoothed model coefficients $B^s{}_t$ that can be used to calculate the gain (as the Fourier transform of the coefficients):

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[4] Or $\left[\beta_{con\,t}\ \beta_{0t}\ \beta_{1t}\ \ldots\ \beta_{dt}\right]'$ if the constant term is included in the model

[5] Or $[x_{con\,t}\ x_t \quad x_{t-1} \quad x_{t-2} \ldots x_{t-d}]$ if the constant term is included in the model

$$\left|B(\omega)\right|_t = \left|\sum_{j=0}^{d} b_j^s e^{-i\omega j}\right| \tag{12}$$

Hughes-Hallett and Richter (2004b) show how coherences K^2 can then be directly obtained from gain and individual spectra by applying the formula:

$$K_t^2 \equiv \left|B(\omega)\right|_t \frac{s_x(\omega)_t}{s_y(\omega)_t} \tag{13}$$

where $s_x(\omega)_t$ and $s_y(\omega)_t$ are individual time-varying spectra of x and y, i.e. the euro area and NMS real activity variables.

4. Data

The subsequent analysis is based on quarterly GDP data for a number of European countries with a focus on new member states of the EU. The source of the data is Eurostat. We rely on seasonally and working days adjusted series at market prices – chain-linked volumes with reference year 2000 (mio_nac_clv2000 in Eurostat mnemonics). These series are available for the euro area and several of NMS starting between first quarter of 1992 to the first quarter of 1995. The analysis reported below is based on data ranging from 1Q1992-1Q1995 till 1Q2007, i.e. 49-61 observations covering up to 15 years (in most instances just above 12 year).

Such a period is arguably rather short for carrying out a spectral analysis of economic series, particularly where spectra are allowed to vary with time. Still, this limitation can hardly be overcome.

The GDP series are clearly nonstationary and following the standard procedure, as e.g. in Hughes Hallett and Richter (2004a), we work with growth rates rather than levels (we use first differences of logarithms of GDP levels). This is further standardised by subtracting the average value over the entire sample, an operation that does not affect the spectra in any respect.

5. Analysis of individual spectra

The first step in calculating time-varying spectra consists of fitting a time varying AR model to the data. This requires a determination of the model's lag length. The task is by no means trivial even in applications where one works with very long times series (compared to the ones typically found in economics), such as in medical applications (see discussion e.g. in Juntunen and Kaipio, 1999). The AR model order selection in our application is based on the set of statistical criteria: Schwartz's Bayesian Criterion, Akaike's Final Prediction Error, as well as finite sample criterion proposed by Broersen (2000) and implemented by the software Broersen (2002) with an additional condition that resulting models are stationary. In practice, apart from considering information from the statistical criteria a visual inspection was carried out with the aim of investigating sample estimates of the spectra emerging from AR models of different lag order. This resulted in the choice of AR models of order ranging from 2 to 8.

Before turning to the analysis of individual spectra it may be useful to briefly review existing evidence on spectral properties of economic variables. Levy and Dezhbakhsh (2003) analyse spectral shapes of output levels in 58 countries testing a hypothesis formulated by Granger (1966). They find that majority of the series have high power at very low frequencies, gradually declining with an increase in frequency. For some countries, a (smaller) local peak is also evident somewhere in the region of the so-called business cycle frequencies, corresponding to cycles of between 3 and 8 years.

Time varying spectra for the euro area and seven NMS are shown in Figure 1. The three dimensional plots of spectra show the results starting from the 5^{th} year of the sample. Dropping the first four years from the plot (not from the calculations) is motivated by the fact that estimated

AR coefficients are typically quite volatile in the beginning of each sample and thus estimates of the spectra are subject to very wide error margins.

The literature has typically assumed an indicative division of the frequencies interval into three distinct groups: long-run frequency band, corresponding to cycles longer than 8 years or so, business cycle frequency band, with cycles between around 3 and 8 years and a short-run frequency band for cycles shorter than around 3 years (Prescott, 1986; Levy and Dezhbakhsh, 2003). This division, while arguably simplistic, may offer a useful framework for the analysis. Since we use quarterly data, the long-run band would correspond to frequencies between 0 and 0.2, the business cycle band would lie between frequencies of 0.2 and 0.5, while frequencies between 0.5 and π correspond to short-run cycles.

Visual inspection of plots in figure 1 allows for inferring several potentially interesting conclusions. First, in line with what could be expected for growth rate data (see e.g. Hamilton, 1994), most of the power is concentrated at business cycle frequencies. There is also substantial power in the long-run frequency band for a number of countries. The spectra are gradually declining in the short-run frequencies, with smaller local power maxima in a few countries indicating an importance of some short-term cycles lasting of up to a few quarters.

It is also worth noting that one does not observe sharp changes in the spectral shape over time, such as shifts in the concentration of power between frequencies, although some changes do take place – particularly in the low frequency range. This contrasts to some extent with the findings of Hughes Hallett and Richter (2004a, 2007). This is partly explained by the slightly different approach to estimating the time-varying coefficients of the underlying AR models, where our use of fixed interval smoothing implies more stable estimated AR coefficients and therefore a more stable spectrum over time. Given the uncertainty surrounding particular point estimates of the spectra we believe that our approach using the smoothed AR parameters is more likely to provide a good description of underlying trends in the data. Moreover, as pointed out by Gustafsson et al. (1993) quick changes in the lower frequency sections of the spectra cannot really be meaningfully interpreted.

The spectral shape of the euro area economic growth rate is similar to the one reported by Hughes Hallett and Richter (2004a). The power is concentrated in the low (particularly after 2001) and business cycle (particularly until 2001) frequency ranges. A second, much smaller, local maximum indicates some role of the cycles lasting just above 2 quarters.

Czech Republic and Latvia are characterised by the apparent importance of very long cycles, lasing more than 8-10 years. Cycles shorter than around 5 years do not appear to be playing any important role in these countries. Estonia has a somewhat similar spectral shape of its GDP growth rate. The difference is that the whole business frequency range is still quite important there and also there is indication of the more important role played by cycles lasting just below 3 quarters.

Poland, Hungary, and Lithuania are all characterised by the dominance of the business cycle frequency. In Poland, one could observe the gradual increase of the role of the relatively short cycles lasting around 4 years in the recent period, although the speed of changes in the low frequency band of the spectra appears rather high to allow for strong interpretations. In Hungary and Lithuania, the length of the dominant cycles appears to be even shorter, at just above 3 years. In all three countries one also observes the second – weaker – local maximum indicating the importance of cycles lasting between 2 and 3 quarters.

Slovenia differs from other analysed countries in that shorter cycles appear to be playing a much more important role with relatively low power concentrated on business cycle and low frequency ranges. The dominant cycle lasts just above 2 quarters, with another local maximum at cycles lasting around 1 year. This result is similar to what Hughes Hallett and Richter (2004a) have found for Germany.

We do not report result for Slovakia, Romania and Bulgaria. In the case of Slovakia, we could not fit a time-varying AR model to the country growth rates that would represent a stationary process irrespective of the model order. This illustrates the limits to the proposed parametric approach. In the case of Bulgaria and Romania available time series were too short to carry a meaningful analysis.

Overall, while spectral analysis of individual series reveals similarities in some broad features, there is also significant variation between the countries. Thus, studying the measures of co-movements between cycles is important. The results are reported in the following section.

Figure 1. Time-varying spectra for the GDP growth in the euro area and selected NMS

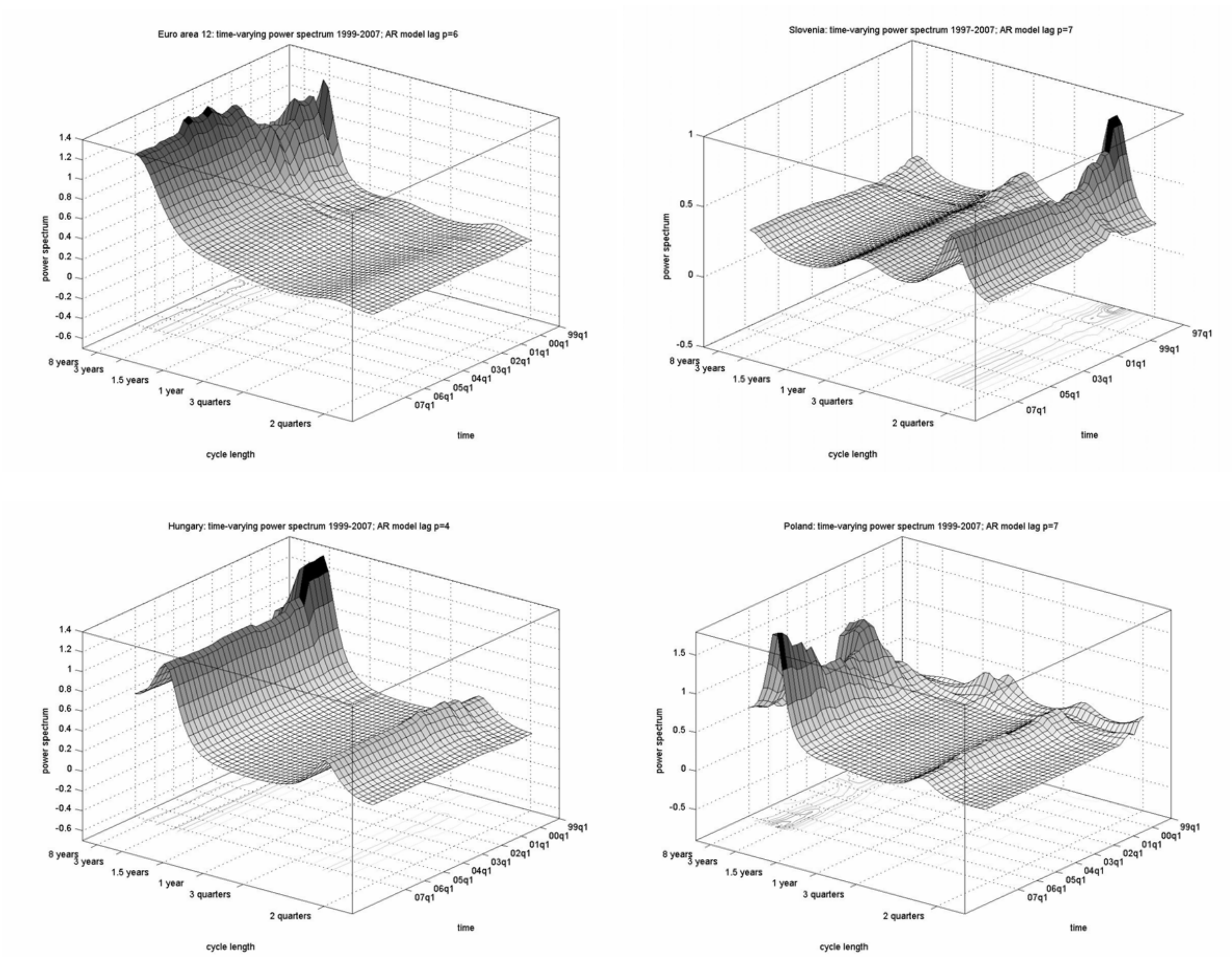
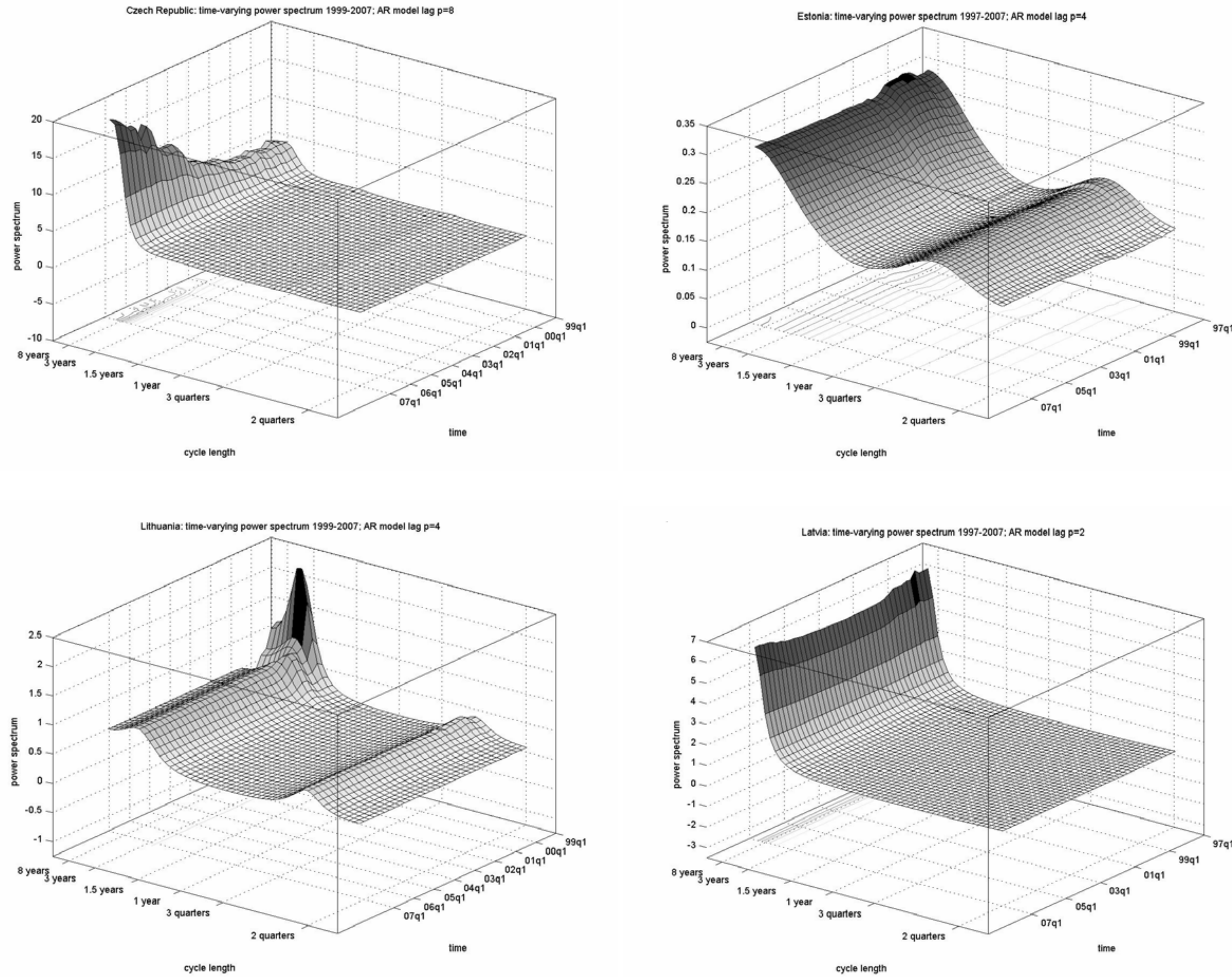


Figure 1. Time-varying spectra for the GDP growth in the euro area and selected NMS (continued)



6. Analysis of coherences

Figure 2 plots the estimates of the time-varying coherences between GDP growth series in the euro area and in seven NMS. These estimates have been obtained from the model defined in equation (9) above with between 3 and 10 lags. Coherences can give us an indication whether cycles in economic activity in NMS are closely related to the euro area cycles and if so, at which frequencies.

For the majority of countries the coherence at low and business cycle frequencies (i.e. for periods lasting above 3 years) appear relatively low. This implies a weak relation between long run trends in the euro area on the one side and NMS on the other during the analysed period (1995-2007). This may come as not particularly surprising given that during this period most of the NMS have first been recovering from the transitional decline in economic activity in early 1990s. and later embarked on the strong growth path, which was only weakly related to developments in the euro area. Our results on the weak coherence at the low frequency end of the spectrum are broadly in line with what Hughes Hallett and Richter (2007) find for Hungary and Poland relative to the euro area.

Apart from the case of Slovenia all other six coherence estimates are characterised by relatively strong links between euro are and NMS cycles lasting between around 4 and 6-7 quarters. At these cycles coherence estimates are at its global or at least local peaks. The strength of this relationship remains broadly constant over time with some gradual changes such as a slow shift of the maximum coherence estimate in Hungary towards slightly longer cycles. Such a cycle length correspond to the one of maximum impact of monetary policy shocks on output in these countries (see e.g. discussion in Paczynski, 2005, Jarocinski, 2005). While this cannot be directly taken as an indication that after joining the euro area NMS would react to joint monetary policy similarly to the rest of the euro area (it may well be that the relation between cycles changes after this event) it does nevertheless provide some support for the view that economic cycles in NMS exhibit a substantial degree of similarity to the euro area at a cycle length on which monetary policy is typically focused.

7. Conclusions

We have used the Kalman filter to extract time-varying spectral properties of GDP growth rates in NMS and the euro are and to estimate the coherences between these series. The analysis of individual spectra has confirmed the existence of several common features such as concentration of power in the low and business cycle frequency ranges (i.e. for cycles lasting above around 3 years). Beyond this, there is also substantial heterogeneity between estimated spectral properties of individual series, similarly to what has been found elsewhere in the literature.

The estimated coherences between GDP growth series in the euro area and NMS economies enable observing the structure of the relationship between the series, i.e. frequencies at which the relationship is the strongest and frequencies characterized by a weaker link as well as its evolution over time. The results suggest a relatively weak relationship as far as longer cycles (lasting 3 years and more) are concerned. In almost all analysed countries the maximum strength of the relationship was identified for economic cycles lasting between 4 and 7 quarters. Importantly, this range broadly coincides with the typical horizon of monetary policy. In other words, the results could be seen as providing some support to the view that NMS economies have already achieved substantial convergence with the euro area in the sphere which is most important from the perspective of effects of a common monetary policy on economies of the (future enlarged) euro area.

Figure 2. Time-varying coherences between GDP growth in the euro area and selected NMS

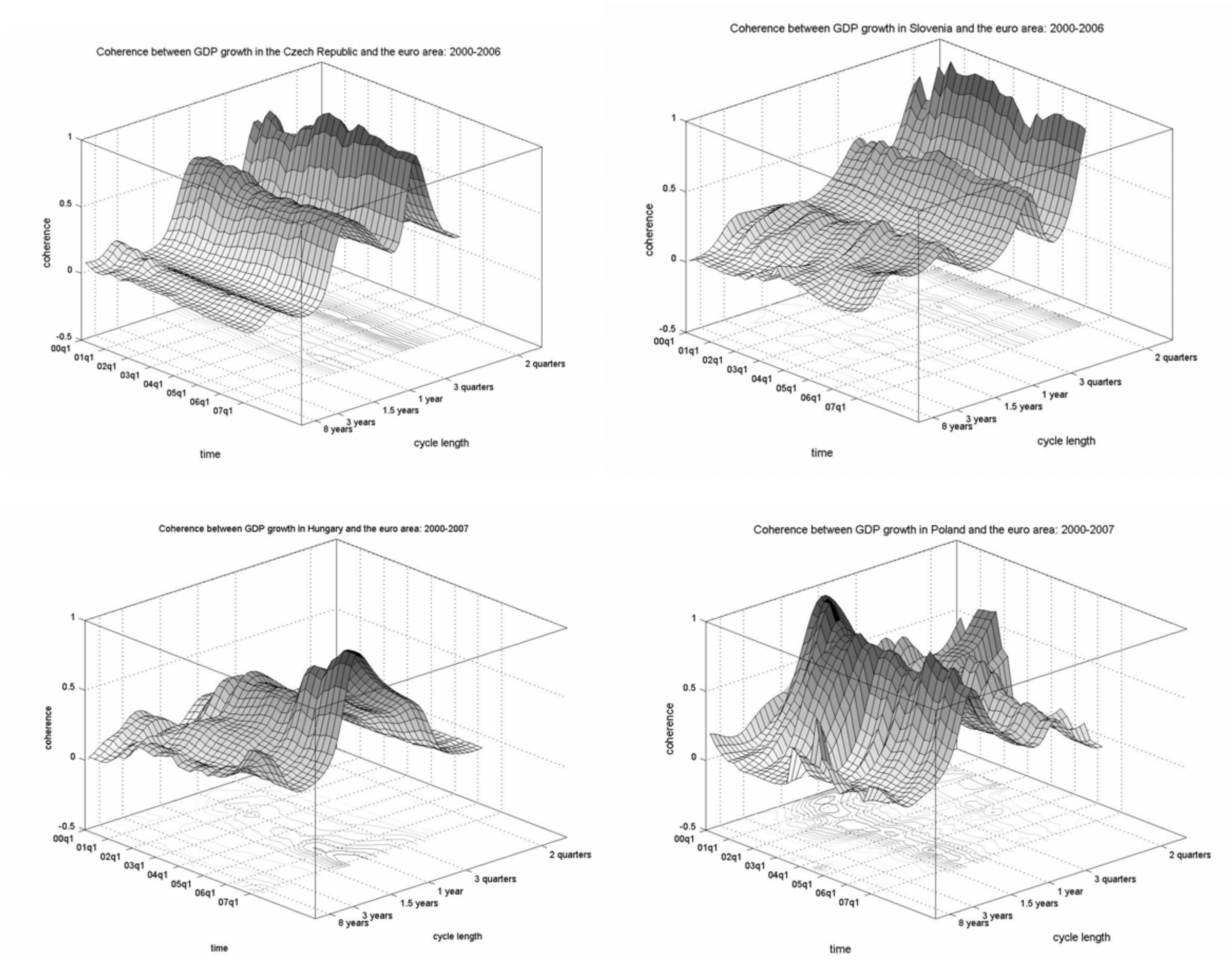
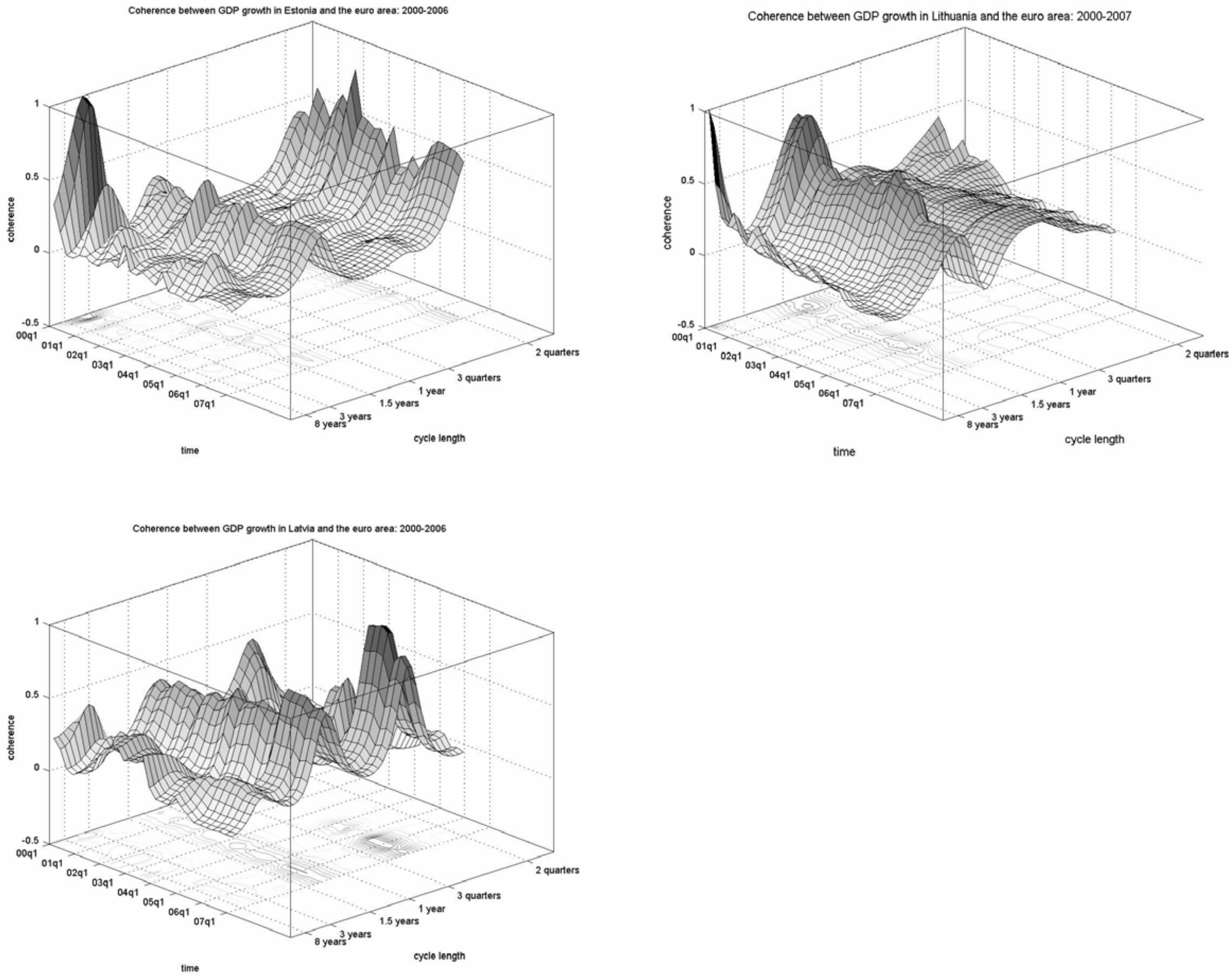


Figure 2. Time-varying coherences between GDP growth in the euro area and selected NMS (continued)



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