Univariate Detrending and Business Cycle Similarity Between the Euro-area and New Members of the EU*

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Abstract

Cyclical decomposition of output is at best uncertain and depends heavily on the method applied. The task of estimating the long-run component of output is an even more dubious exercise for countries experiencing large structural changes, such as transition countries. Despite their deficiencies, however, univariate deternding methods are frequently adopted for both policy oriented and academic research. In this paper we propose a procedure of combining univariate deternding techniques. The procedure is applied for the study of the similarity of the business cycles between the euro-area and eight new members of the EU.

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1. Introduction

The potential or permanent component of output is an important unobserved variable for decision making, policy analysis, and macroeconomic modeling. For instance, sustainability of fiscal positions and monetary policy actions are frequently evaluated in the light of the cyclical position of the economy. Another example from the central bank point of view is the setting of monetary targets and analysis of money demand where the permanent component of the output should be considered instead of the actual one.

Estimation of potential output, though, is very difficult even for developed countries. The troubles are not mainly associated with the complexities of empirical methods, but rather with the mapping of an economic concept of potential output into a plotted time series. There are dozens of methods and models for empirical estimation: some are intended to measure potential output and the output gap, others call their objectives trends and cycles, while the terms permanent and transitory components are also frequently used. The common idea behind these methods is to uncover a component that is likely to persist over the long-run.[1] Problems arise when we want to define in a model to be estimated what the long-run component is. Critiques stemming from properties and economic implications characterize all methods. Those who employ multivariate methods criticize univariate models on the grounds that such methods do not take into account all relevant information. Those who prefer non-structural methods (either univariate or multivariate) criticize structural multivariate approaches on the basis that they impose *a priori* structures for the economy that may be invalid. Univariate modelers usually favor their methods because of simplicity and the absence of a number of *ad hoc* assumptions; several univariate methods, however, make one very important *ad hoc* assumption.

Disagreement on the mapping of the concept into empirical estimates in mature economies renders estimates even more problematic for countries facing deep structural changes, such as transition economies. Although most transition countries had already introduced some market institutions by the end of the 1980s, processes such as democratization, further decentralization, the collapse of COMECON, privatization, comprehensive adoption of market institutions, opening and Western integration changed dramatically these economies. As a natural consequence, standard models

[1] Throughout this paper the terms potential output/trend output/permanent component of output and output gap/cycle/transitory component are regarded as synonymous. Although there is a slight difference among the generally assumed ideas behind these concepts, the same methods were applied to recover all of them. Policy makers and global agencies use the wording potential output and output gap more frequently while academics mostly prefer the other expressions.

might not work for the transition period that covers several years. For example, the considerable downturn in the early years of transition was accompanied by a massive rise in inflation, while inflation contracted during periods of rapid growth in several countries (Figure 1). Issues of structural changes and non-applicability of standard concepts are coupled with poor quality and short databases. Emergence of thousands of enterprises and retail stores, quickly changing product and quality structures posed huge challenges for statistical offices. Many important figures are simply not available for several years and the available data necessary for potential output estimates are mostly at annual frequency. Quarterly national accounts figures started to be published only since the first half of the nineties and were frequently subject to major revisions. The aforementioned drawbacks leave us very cautious when it comes to estimating potential output figures for transition economies.

Despite conceptual and practical concerns, the need for output gap measures led almost all central banks of the new EU members and dozens of academic researchers to estimates some measures using various univariate detrending techniques. A remedy for these applications is provided by Smets-Wouters (2003), who tried to answer the question of why central banks use various filters if modern New-Keynesian micro-founded models predict that appropriate target level of output, which usually corresponds to flexible-price level of output, may be more volatile than actual output. Their answer is that not all shock should affect the target level of output on the one hand, and in practice it is difficult to decide the nature of shocks. In such circumstances the target level of output could be smooth.

One of the most frequently studied issues with the help of estimated output gap figures was business cycle correlation with the euro-area, motivated by optimum currency area considerations. Fidrmuc-Korhonen (2004), for instance, surveyed 31 papers studying this issue. In this paper we adopt various univariate techniques for calculating the cyclical component of GDP and document the dependency of the cyclical correlation with the euro-area on the method selected, for quarterly GDP data in 1993Q1-2003Q4. Hence, our first goal is similar to Canova (1998), who compared the results of ten filters on business cycle properties. Our results will be also similar since we will also document the dependency of results on methods. This raises the question whether there is any use of adopting these filters, since all of them has conceptual weaknesses and one can not select the 'best' among them. However, the need for filters is rather strong from the perspective of both economic policy and academic research as well. Therefore, we propose a procedure that is able to combine various techniques into a single measure. As standard errors, which might be used for deriving weights, are not available for some of the methods, we base our weights on similar but computable statistics, namely on revisions of the output gap for all dates by recursively estimating the models. We will compare our combining procedure to the most widely used one, to principal components analysis.

The rest of paper is structured as follows. Section 2 reviews the concepts of potential output and underlines its limitations for open economies in general and for transition economies in particular. Section 3 introduces the univariate filtering methods we use and describes our procedure of combining methods. Section 4 presents the empirical results, and Section 5 concludes.

2. Concepts of potential output

2.1. Mainstream concepts

Probably the most widely adopted concept of potential output is the level of output that represents a balanced state of the economy. This balanced state is frequently defined as stable inflation. Stable inflation corresponding to a certain level of unemployment is called NAIRU (non-accelerating inflation rate of unemployment) that relates to a certain level of output via the Okun-law. However, NAIRU is not easy to measure because of structural and hysteresis reasons. Partly due to this reason and partly due to theoretical Phillips-curve considerations, there are models that use inflation directly as information about the output gap.[2]

The so-called production function method analyses factor inputs to production. It is usually combined with the concept of NAIRU; thus the potential labor input is taken into account instead of the actual labor input.[3]

Another line of the literature defines potential output as the level of output free of the effect of demand shocks. Demand and supply shocks are frequently studied in the framework of SVARs pioneered by Blanchard–Quah (1989). They estimated a two-variable VAR model for output and unemployment and constrained the parameters the following way. There are two types of shocks: (1) Supply shocks have a transitory effect on unemployment and a permanent effect on output; (2) Demand shocks have a transitory effect on both variables. Behind these constraints there is a model

[2] See, e.g. Kuttner (1994) and Gerlach–Smets (1999).

[3] See Giorno *et al.* (1995) and Denis–McMorrow–Werner (2001). As described in Giorno *et al.* (1995), the OECD Secretariat used the split time trends (= segmented deterministic trends) method with *ad hoc* judgements till the first half or the 1980s, then switched to the production function (PF) approach incorporating a very simple NAWRU model. Principal drawbacks of the segmented trend approach were a key impetus for changing to the PF-approach.

where the permanent shocks can be interpreted as supply shocks while the transitory shocks as demand shocks.[4]

A further class of models assumes that potential output is driven by exogenous productivity shocks that determine long-run growth. Short-run movements in output are due to the behavior of rational agents who react to unexpected productivity shocks by writing off old capacities and rearranging resources to new conditions.

We argue that, in addition to the highlighted conceptual weaknesses of NAIRU and the econometric weaknesses of the SVARs,[5] the assumptions behind these models are rather questionable for open economies in general and for transition countries in particular.

2.2. The transition shock

We argue that standard concepts are incapable of describing transition shocks.

During transition the economy was shocked by enormous relative price changes,[6] which resulted in a structural change in demand. The structure of supply was unable to adjust to this change quickly. Therefore, capacities became redundant while new capacities were established only in a gradual evolutionary process. Meanwhile, excess demand and excess supply existed side by side, and aggregate output decreased because the short-side rule prevailed in each micro-market. Decrease in output brought about unemployment.

It is rather difficult to assign the nature of this shock either to supply or demand. The definition based on the concept of demand as aggregate planned purchases and supply as aggregate planned sales does not help much in finding the answer as it was the structure and not the aggregate amount that differed.

The definition of aggregate excess demand implies that a demand shock would create excess demand in the short run, but does not affect output in the long run. A supply shock related mostly to technical changes would have permanent effects. Generally, supply shocks may have transitory effects as well. A monetary squeeze affects both supply and demand temporarily, as supply is constrained through the credit channel. Similarly, a structural shock may have transitory effects. This has led to the reinterpretation of demand and supply shocks: in several contexts they do not mean changes in planned purchases or planned sales, but only the temporary or permanent nature of

[4] The data induced even Blanchard-Quah (1989) to adopt an atheoretical pre-filter: they detrended the unemployment rate with a broken deterministic trend.

[5] See, for instance, Faust and Leeper (1997), Cooley and Dwyer (1998) and their references.

[6] Due to the transfer to a system of market pricing.

the shock.[7] The question may arise then, whether the recession of the early 1990s in the transition economies was the result of a temporary or a permanent negative shock. On the one hand, the high rate of unemployment that has arisen would suggest that the shock was temporary. On the other hand, it is clear that the persistence of the crisis is longer than the usual excess-demand driven business cycle recessions. If output drops below equilibrium because of a lack of aggregate demand, then it is the speed of price adjustment that determines the length of the impact of the shock. However, if output drops because of a structural mismatch, not only prices have to adjust, but the structure of supply. This is presumably much slower than price adjustment, because it requires the establishment of whole new production cultures. The inertia in this process is too large to be explained by pure construction costs: uncertainties owing to limited information constrain the speed of adjustment decisively.[8]

How long does the effect of a transitory shock last? In practice in finite samples it is difficult to separate shocks which have an autoregressive representation with dominant (inverted) roots that are 1 from those which have roots less than 1. Sometimes it is useful to consider some roots to be 1 even though theory would tell that they are less than 1. In this manner, some shocks that are transitory in theory may be considered as permanent in some models. Although it is true that employment reverts to its natural rate and therefore its fluctuation gives a transitory element to output, the observation period of the transition countries did not render either the quality or the variability of data that would be required for using them as information on this effect. Therefore, in Hungary for example, even though unemployment rose from 0 to 13 percent after the system change in 1990 and then slowly declined to 6 percent (Figure 1), we do not consider the slow decline of unemployment as an important element of a transitory increase in output.

The persistence of unemployment as a result of this structural shock is similar to the phenomenon of hysteresis. The difference is that in the literature on hysteresis the emphasis is on the fact that unemployment erodes the capabilities of the worker, while in the case of a structural shock it is the production environment (structure of capacity, geographic location, and invisible business capital) that erodes and cannot be recovered.

2.3. Open economy considerations

Renouncing unemployment as a source of information may be motivated from another aspect as well. We do not even use information given by inflation data, as the steady fall of inflation in the second half of the 1990s (Figure 1) should not be regarded as the result of a continuously negative

[7] For example, univariate trend-cycle decompositions that we study adopt this interpretation.

[8] See Stiglitz (1992) for a thorough development of this argument.

output gap. Rather, it might have been the consequence of the larger weight of expectations than inertia in a standard neo-Keynesian Phillips-curve.[9]

However, in an open economy excess demand may simply result in increased imports without any direct effect on inflation. The increased imports may have an impact on future inflation, but the effects may be variable both in lags and magnitude, depending on policies and on capricious business sentiment. In addition to that, during our sample period, inflation was still hit by shocks related to the transition process,[10] so a decomposition of these shocks would face insurmountable difficulties.[11]

3. Empirical methods

3.1. Univariate filtering

We considered various variants of the following univariate filters:

(1) Deterministic trend (DT): The series is detrended using a deterministic trend.[12]

(2) Hodrick-Prescott filter (HP): The filter minimizes the weighted sum of the squared cycle the squared change in the growth rate of the potential output. See Hodrick–Prescott (1997). We used the standard λ=1600 smoothness parameter.

(3) Band-Pass filter (BP): The filter intends to eliminate both high frequency fluctuations (which might be due to measurement errors and noise) and low frequency fluctuations (which rather reflect the long term growth component). The filter's major weakness is that in finite samples only various approximations could be used, see, e.g. Baxter-King (1995) and Christiano–Fitzgerald (2003). We used the later one with 6 and 32 quarters for the cycle range to be passed through.

(4) Beveridge-Nelson decomposition (BN): Time series can be decomposed as the sum of a random walk, a stationary process, and an initial condition. The cycle in this definition is the stationary process resulting from the decomposition. See Beveridge–Nelson (1981). An ARIMA(1,1,0) representation seemed satisfactory for all countries.

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[9] It is well known that under certain parameter values, including a large weight of expectations in the new keynesian Phillips-cure, disinflation can be costless in small macromodels. See Benczúr-Simon-Várpalotai (2002).

[10] For example, hardly quantifiable expectations in the circumstances of a highly uncertain system change, substantial price liberalization, and administered price raises.

[11] This is the reason that Darvas–Simon (2000) developed a model, which makes use of the information that is rendered by the openness of the economy.

[12] Since our sample is rather short, we do not allow for breaks in the trend.

(5) Unobserved components (UC): UC models assume stochastic processes of the unobserved potential output and output gap and estimates them using a state-space representation using the Kalman-filter. See, e.g. Watson (1986) and Harvey (1989). We adopted the local linear trend plus cycle model of Harvey (1989).

(6) Wavelet transformation (WT): WT is a frequency domain technique to decompose time series. See, e.g. Schleicher (2002) and Percival and Walden (2000). We used Daubechies' wavelets with 8 elements and a 3-scale multiresolution scheme.

A general weakness of univariate methods is that they are univariate: they take into consideration neither the consequences of non-zero output gaps, nor structural constraints and limitations of growth. However, as we have argued that standard structural methods for output gap calculations are not applicable for open economies in general and for transition countries in particular, and the results of Smets-Wouters (2003) indicate that even from a New-Keynesian SDGE perspective the use of univariate filtering could be justified.

There are some surveys available on potential output/trend/permanent component measurement. The most wide-ranging survey can be found in Canova (1998), who compare the properties of the cyclical components of US data using seven univariate (Hodrick–Prescott filter, Beveridge–Nelson decomposition, linear trend, segmented trend, first order differencing, unobservable components model, frequency domain masking) and three multivariate (cointegration, common linear trend and multivariate frequency domain) detrending techniques. His conclusion is that, both quantitatively and qualitatively, properties of business cycles vary widely across detrending methods and that alternative detrending filters extract different types of information from the data.

Similar conclusion was reached by some other papers comparing fewer methods. For example, Dupasquier–Guay–St-Amant (1997) focuses on three multivariate methodologies: structural vector autoregression, multivariate Beveridge–Nelson decomposition, and Cochrane's methodology. Due to the deficiencies of univariate filters they apply some of them only for comparison. They arrive to the conclusion that statistical properties of cycles derived from different methods are dissimilar, conclusions regarding certain recessions in the US are different, and also highlight that the confidence intervals of different measures are generally wide. Harvey–Jaeger (1993) compares some univariate models: the structural times series models of Harvey, the Hodrick–Prescott filter, ARIMA modeling (i.e. Beveridge–Nelson decomposition), and the segmented trend approach. They argue that all but the structural times series models suffer from significant deficiencies and make a case for their so called 'structural models', which are univariate unobserved-components techniques. Stock-Watson (1999) studies the Hodrick-Prescott and Band-Pass filter, and argue that the BP filter is preferable from a theoretical point of view, but the BP filter also has weaknesses, since in finite samples only various approximations could be used.

The BN decomposition and many UC models assume that potential output follow random walk. Lippi–Reichlin (1994) and Dupasquier–Guay–St-Amant (1997) criticize this assumption arguing that the random walk model of potential output is inconsistent with the generally accepted view of productivity growth. They argue that technology shocks are likely to be absorbed gradually by the economy because of adjustment costs, learning, and the time-consuming process of investments, for example.

Still, perhaps the most commonly applied filter is the HP filter. Cogley–Nason (1995) directly studied the properties of this filter. They showed that when applied to stationary time series (including trend-eliminated trend-stationary series), the HP filter works as a high-pass filter, that is, suppresses cycles with higher frequencies while letting low frequency cycles go through without change. However, for different stationary series, the HP filter is not a high-pass filter, but suppresses high and low frequency cycles and amplifies business cycle frequencies, therefore creating artificial business cycles. Similar criticism was voiced by Harvey and Jaeger (1993). They showed that the HP filter creates spurious cycles in detrended random walks and I(2) processes, and that the danger of finding large sample cross-correlations between independent but spurious HP cycles is not negligible. Another important weakness of the HP filter is the treatment of sudden structural breaks, as the HP filter smoothes out its effect to previous and subsequent periods. Moreover, the HP filter works as a symmetric two-sided filter in the middle of the sample, but becomes unstable at the end and at the beginning of the sample, although end-point instability is also a weakness of other filters as well. For many filters, it is recommended that three years at both ends of the sample of the filtered series be disregarded.

Hence, the general conclusion emerging from the literature is that all methods have various weaknesses, results can strongly depend on the selected method and are subject to considerable uncertainty. Therefore, there are no firm grounds for selecting a preferred univariate method as all of them are criticized from different aspects. Given disagreements on the appropriate method, we adopted the pragmatic approach to apply several methods and derive a final estimate by combining the results of these methods.

3.2. Combining Methods

We propose a new procedure for combining the results received by various methods. The motivation of our proposal is based on the idea that a method is 'better' if it led to smaller revisions of past inference as new information arrived.[13] In real time there are two possible sources of revision of estimated output gaps from time t to time t+1: (1) At time t+1 the statistical office could revise GDP data for time t or earlier; (2) even without data revision, the adopted filter could lead to different estimation for the output gap up to time t when a new observation for time t+1 is added to the sample. Our proposal takes into account the second source of revision, since it is directly related to the filter.

Our suggestion is to weight the estimates of various methods with weights proportional to the inverse of revisions of the output gap for all dates estimated for recursive samples. That is, first one should filter the series on a sample ending at time k, which is less then the full available sample size, T. Then an additional observation is added and filtering is performed for the one-period extended sample, so we can calculate the revision of potential output estimation for the sample [1,k]. Adding further observations one by one and filtering the series we arrive to several estimation of potential output for all dates. Namely, we will have T-k+1 estimates for $t \leq k$, hence, the number of revisions is T-k. For $k < t < T$, the number of estimations will be T-t+1 and the number of revisions will be T-t. For instance, for t=T-1, there will be only two estimations (for samples [1,T-1] and [1,T]) and one revision, and there will be only one estimation and no revision for the last observation of the available sample.

Formally, the size of revision at a certain date is

$$\begin{aligned}
&REV_t^{(m)} = \frac{1}{l_t}\sum_{s=k+1}^{T}\left|(q_{t,s}^{(m)*} - q_{t,s-1}^{(m)*})\right| = \frac{1}{l_t}\sum_{s=k+1}^{T}\left|(q_t - q_{t,s}^{(m)*}) - (q_t - q_{t,s-1}^{(m)*})\right| \\
&l_t = T - k \quad for\ t \leq k \\
&l_t = T - t \quad for\ k < t < T
\end{aligned} \tag{1}$$

where $REV_t^{(m)}$ is the revision of the m^{th} method for observation t, q_t is the logarithm of actual GDP, $q_{t,s}^{(m)*}$ is the logarithm of potential output revealed by the m^{th} method for observation t in the sample starting at the first observation and ending in s, $s \in [k,...,T]$ and s $\geq t$, k denotes the length of the shortest sample possibly taken into consideration and T is the full sample size. The average revision for the m^{th} method is computed by the average of revisions at all dates:

$$REV^{(m)} = \frac{1}{T-1}\sum_{t=1}^{T-1} REV_t^{(m)} \tag{2}$$

[13] Although the variance of the various output gap estimations could also form the weights in an optimal-weighting framework, for several methods it is rather difficult to derive a confidence band.

The weights we suggest to be used for combining the results of various methods are proportional to the inverse of revisions:

$$w_m = \frac{1 \big/ REV^{(m)}}{\sum_{j=1}^{p} 1 \big/ REV^{(j)}} \tag{3}$$

where w_m denotes the weight of m^{th} method and p is the number of methods taken into account. Thus, the weighted output gap, that we will call as 'consensus I.' output gap is defined as:

$$\hat{c}_t = \sum_{j=1}^{p} w_j \hat{c}_{t,j} \tag{4}$$

where $\hat{c}_t$ is the consensus output gap measure and $\hat{c}_{t,m}$ is the output gap measure of the m^{th} method.

We should draw the attention to one possible drawback of our methodology, namely to variance dependence. The absolute value of revisions could likely be smaller for methods leading to smaller variance of estimated output gaps, which will be confirmed in the empirical section. Hence, our method could give preference for those methods that led to output gaps with smaller variance, although there is nothing in theory that would say anything about the variance of the output gap. We overcome this problem by standardizing the output gaps, hence, calculate (1') instead of (1) as well:

$$REV_t^{(m)} = \frac{1}{l_t} \sum_{s=k+1}^{T} \left| \frac{(q_t - q_{t,s}^{(m)*}) - (q_t - q_{t,s-1}^{(m)*})}{\sigma_{(q_t - q_{t,T}^{(m)*})}} \right| \tag{1'}$$

where $\sigma_{(q_t - q_{t,T}^{(m)*})}$ denotes the standard deviation of the estimated output gap for the full sample (ending at T), and l_t is the same as in (1). Since the difference of two output gap estimations appears in the numerator and their means are anyway close to zero, we do not correct for the means. Substituting (1') into (2) and (3) we arrive at new weights, and using the new weights in (4) we have a new combined output gap measure that we call as 'consensus II.' output gap.

4. Results

Our data covers the period of 1993Q1-2002Q4 and are seasonally adjusted. We study eight new members of the European Union: the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic, and Slovenia. Constant price GDP series are taken from national statistical institutes and the IMF: International Financial Statistics. For three countries, the Czech Republic, Hungary, and Poland, the available official quarterly GDP series start later than 1993: the Czech data start in 1994Q1 and the Hungarian and Polish data start in 1995Q1. For these three countries, quarterly data for 1993-94 were generated with the method of Várpalotai (2003), which uses information from annual GDP figures and supplementary quarterly figures like industrial production and prices. We have tested the sensitivity of results to these generated series by estimating the methods for 1994Q1-2002Q4 in the case of the Czech Republic and for 1995Q1-2002Q4 in the cases of Hungary and Poland and compared these estimates to estimates using the full sample including the generated data for the first one or two years. The results were rather close indicating that the generated data do not induce serious biases. Data for the euro area is taken from the fifth update of the ECB's Area-Wide Model (AWM) for the Euro Area by Fagan, Henry and Mestre (2001).

Table 1 reports the revisions of the five individual methods using percentage point output gaps, the weights based on both the percentage point and standardized output gaps, the revisions of the three combining methods (principal components, consensus I., consensus II.), and results of the principal components analysis for the full sample. Our intention that the revisions could be larger for methods revealing larger variance output gaps proved right, which is also reflected in the difference of derived weights for the percentage point and standardized output gaps.

The 'worst' performer in terms of revisions is the Beveridge-Nelson decomposition[14], having a 6% weight on average of the new EU members and an 8% weight in the euro-area based on standardized output gaps. This is likely due to the fact BN is a parametric method estimated on relatively short samples. The wavelet transformation and the simple deterministic trend seem to be the best both among the new members and in the euro-area, while the HP and BP filters are middle runners.

The distribution of the first eigenvector of the principal component analysis is markedly different from the weights we derived from revisions, since it gives almost 50 percent weights on average to the deterministic trend and almost zero to the BN and WT both in the new members and in the euro-area. Not surprisingly, the revisions of the first principal component are much larger than our revision-based consensus measures.

For a graphical inspection, Figure 3 plots the revisions of the five individual methods and the three combining methods for the nine countries, and Figure 4 plots the results of the three combining methods for the full sample for all countries.

[14] Canova (1998) underlines that problems inherent to ARIMA specifications are carried over to this method. He also states that results of his paper varied considerably with the choice of the lags both in terms of the magnitude of the fluctuations and of the path properties of the data.

Table 2 reports the correlation coefficient between the business cycle of the euro-area and new member states in the full sample period of 1993-2002 and in the first and second 5-year period of this sample. The general conclusion is that different methods reveal rather different conclusions. For example, in the case of the Czech Republic and the full sample, the deterministic trend and the HP-filter indicates significantly negative correlation (-0.44 and -0.27, respectively), while the BP-filter and the wavelet transformation shows significantly positive correlation (0.49 and 0.48, respectively). The table also shows the range of correlation coefficients, which are tend to be quite high, especially in the two 5-year long sub-periods (0.70 and 0.71 on average).

From the perspective of optimum currency union theory not just the level of correlation matters, which, as we have just seen, seems rather different using different methods, but also the change in correlation is important to test whether business cycles became synchronized in time. This is usually called as the test of the 'endogeneity hypothesis of the OCA'. The fourth block of Table 2 reports the change in correlation coefficient from the first to the second sub-period, i.e. the difference between values in the third and the second blocks of the table. The general result, again, is that conclusion on endogeneity depends heavily on the method and the conclusions are rather different across methods. For example, in the case of the Czech Republic, three methods (ST, HP, BP) indicate an increase in correlation about 0.4-0.5, while BN and WT indicates no increase or even decrease. Still, the Czech Republic and Hungary has the most modest range of dispersion in the change of correlation coefficients (0.69 and 0.68, respectively), the dispersion is even larger in the other six countries. The worst case is the Slovak republic, for which the deterministic trend indicates a 1.08 increase in correlation (from -0.69 to 0.39), while the BP filter indicates a 0.59 decline (from 0.40 to -0.19).

To sum up, both the level and the change in correlation coefficients depends heavily on the specific filter adopted.

Among the three combining methods the first principal component and our preferred consensus II measure reveals reasonably similar correlations, which are, anyway, in most cases tend to be different from the simple average correlations of the five individual methods. Continuing the Czech and Slovak example mentioned earlier, cyclical correlation increased by about 0.5-0.6 in both countries based on these two combining procedures. Regarding the level of correlation in the second half of the sample, Slovenia, Poland, Hungary, and Estonia have reached a relatively high level of business cycles synchronization (correlation is in the range of 0.63-0.78). The Czech Republic is less synchronized (0.23); Slovakia is not synchronized, while Latvia and Lithuania seems countercyclical. As for the endogeneity hypothesis, Hungary and Estonia was already synchronized in the first half of the sample and did not improve, but the other two leading countries, Slovenia and Poland, made a strong improvement in synchronization. As already mentioned, the Czech and Slovak Republics improved but most of this improvement simply meant that they moved away from their counter-cyclical position to an acyclical one. In the two remaining Baltic states, Latvia and Lithuania, business cycles became less synchronized in time.

5. Summary

Most of the structural methods for output gap calculations are not applicable for open economies in general and for transition countries in particular. Univariate detrending methods are also burdened with various deficiencies. However, they are frequently used because of the need for detrending from both policy and academic oriented research.

In this paper we have shown that results on business cycle correlation of the new EU members of the euro-area differ substantially across methods, which preclude the possibility of drawing firm conclusions. As all methods have strengths and weaknesses, we suggest combining individual methods in order to derive a single measure of output gaps. Our suggested weights are based on revisions of the output gap for all dates by recursively estimating the models; hence, we suggest giving preference to methods leading to more stable inference. Although in terms of correlation results based of our procedure do not differ much from the results achieved by principal component analysis, our procedure has much smaller revisions and hence we regard it preferable.

Our results indicate that Slovenia, Poland, Hungary, and Estonia have reached a relatively high level of business cycles synchronization with the euro-area by 1998-2002, the Czech Republic is less synchronized, Slovakia is not synchronized, and Latvia and Lithuania are countercyclical.

6. References

Baxter, M. – King, R. G. (1995): Measuring Business Cycles Approximate Band-pass Filters for Economic Time Series, NBER Working Paper Series No. 5022.

Benczúr, P – Simon, A. – Várpalotai, V. (2002): Dezinflációs számítások kisméretű makromodellel, MNB Working Paper No. 2002/4. http://www.mnb.hu/dokumentumok/fuz200204_hu.pdf

Beveridge, S. – Nelson, C. R. (1981): A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the 'Business Cycle', Journal of Monetary Economics 7, pp. 151-174.

Blanchard, O. J. – Quah, D. (1989): The Dynamic Effects of Aggregate Demand and Supply Disturbances, American Economic Review Vol. 79, No. 4, pp. 655-673.

Canova, F. (1998): Detrending and Business Cycle Facts, Journal of Monetary Economics, Vol. 41, pp. 475-512.

Christiano, Lawrence J. —Fitzgerald, Terry J. (2003): The Band Pass Filter, International Economic Review, 44, No. 2., May 2003, pp.435-65.

Cogley, T. – Nason, J. M. (1995): Effects of the Hodrick-Prescott Filter on Trend and Difference Stationary Time Series: Implications for Business Cycle Research, Journal of Economic Dynamics and Control Vol. 19, pp. 253-278

Cooley, Thomas F. – Mark Dwyer (1998): Business Cycle Analysis without Much Theory: A Look at Structural VARs, Journal of Econometrics 83, 57-88.

Darvas, Zs. – Simon, A. (2000): Potential Output and Foreign Trade in Small Open Economies, MNB Working Paper No. 2000/9. http://english.mnb.hu/dokumentumok/fuz2000_09_en.pdf

Daubechies, I (1988): Orthonormal Bases of Compactly Supported Wavelets, Communication on Pure and Applied Mathematics 41: pp. 909-96.

De Masi, Paula R. (1997): IMF Estimates of Potential Output: Theory and Practice, IMF Working Paper No. 97/177.

Denis, C. – McMorrow, K. – Röger Werner (2002): Production function approach to calculating potential growth and output gaps – estimates for the EU Member States and US, Economic Papers No. 176 – September 2002, European Commission.

Dupasquier, C. – Guay, A. – St-Amant, P. (1997): A Comparison of Alternative Methodologies for Estimating Potential Output and the Output Gap, Bank of Canada Working Paper No. 97-5.

Evans, G. – Reichlin, L. (1994): Information, Forecast, and Measurement of the Business Cycle, Journal of Monetary Economics Vol. 33, pp. 233-54.

Fagan, Gabriel — Henry, Jérôme — Mestre, Ricardo (2001): An Area-Wide Model (AWM) for the Euro Area, ECB Working Paper, No. 42.

Faust, J. – Leeper, E.. M. (1997): When Do Long-Run Restrictions Give Reliable Results? Journal of Business & Economic Statistics, Vol. 15, No. 3, pp. 345-353.

Fidrmuc, Jarko — Korhonen, Iikka (2004): Meta-analysis of the business cycle correlation between the euro area and the CEECs: What do we know? And who cares? mimeo.

Gerlach, S. – Smets, F. (1999): Output Gaps and Monetary Policy in the EMU Area, European Economic Review, Vol. 43, pp.801-812.

Giorno, C. – Richardson, P. – Roseveare, Deborah – van den Noord, Paul (1995): Estimating Potential Output, Output Gaps and Structural Budget Balances, OECD Economics Department Working Papers No. 152.

Harvey, A.C. – Jaeger, A. (1993): Detrending, Stylized Facts and the Business Cycle, Journal of Applied Econometrics 8, pp. 231-47.

Harvey, A.C. (1989): Forecasting, Structural Time Series Models, and the Kalman Filter, Cambridge U.K.: Cambridge University Press.

Hodrick, R. J. – Prescott, E. C. (1997): Postwar US Business Cycles: An Empirical Investigation, Journal of Money, Credit, and Banking, Vol. 29, pp. 1-16.

King, R. – Rebelo, S. (1993): Low Filtering and the Business Cycle, Journal of Economic Dynamics and Control 17, pp. 207-231.

Kuttner, K. N. (1994): Estimating Potential Output as a Latent Variable, Journal of Business & Economic Statistics, Vol. 12, No. 3, pp.361-368.

Laxton, D. – Tetlow, R. (1992): A Simple Multivariate Filter for the Measurement of Potential Output, Bank of Canada Technical Report No. 59.

Lippi, M. – Reichlin, L. (1994): Diffusion of Technical Change and the Decomposition of Output into Trend and Cycle, Review of Economic Studies 61, pp. 19-30.

Maddala, G.S. – Kim, I.M. (1996): Structural Change and Unit Roots, Journal of Statistical Planning and Inference, Vol. 49, pp.73-103.

Percival, D. B. – Walden, A. T. (2000): Wavelet Methods for Time Series Analysis, Cambridge University Press.

Quah, D. (1992): The Relative Importance of Permanent and Transitory Components: Identification and Some Theoretical Bounds, Econometrica 60, pp. 107-18.

Schleicher, C. (2002): An Introduction to Wavelets for Economists, Bank of Canada, Working Paper No. 2002-3.

Smets, Frank — Wouters, Raf (2003): Output gaps: Theory versus practice, paper presented at the ASSA Meetings in Washington, D.C, January 2003.

Stiglitz, J.E. (1992): Capital Markets and Economic Fluctuations in Capitalist Economies, European Economic Review 36, 269-306.

Stock, James H. — Mark O. W. Watson (1999): Business Cycle Fluctuations in US Macroeconomic Time Series, in Handbook of Macroeconomics, Vol. 1., Edited by J.B. Taylor and M. Woodford, Elseiver Science B.V., pp. 3-64.

Várpalotai, V. (2003): Numerikus módszer gazdasági adatok visszabecslésére (Numerical method for backward projection of macroeconomic data) MNB Working Paper 2003/2. http://english.mnb.hu/module.asp?id=125&did=1853

Watson, M.W. (1986): Univariate Detrending Methods with Stochastic Trends, Journal of Monetary Economics 18, pp. 49-75.

Figure 1 Inflation and unemployment rate, 1993Q1-2002Q4

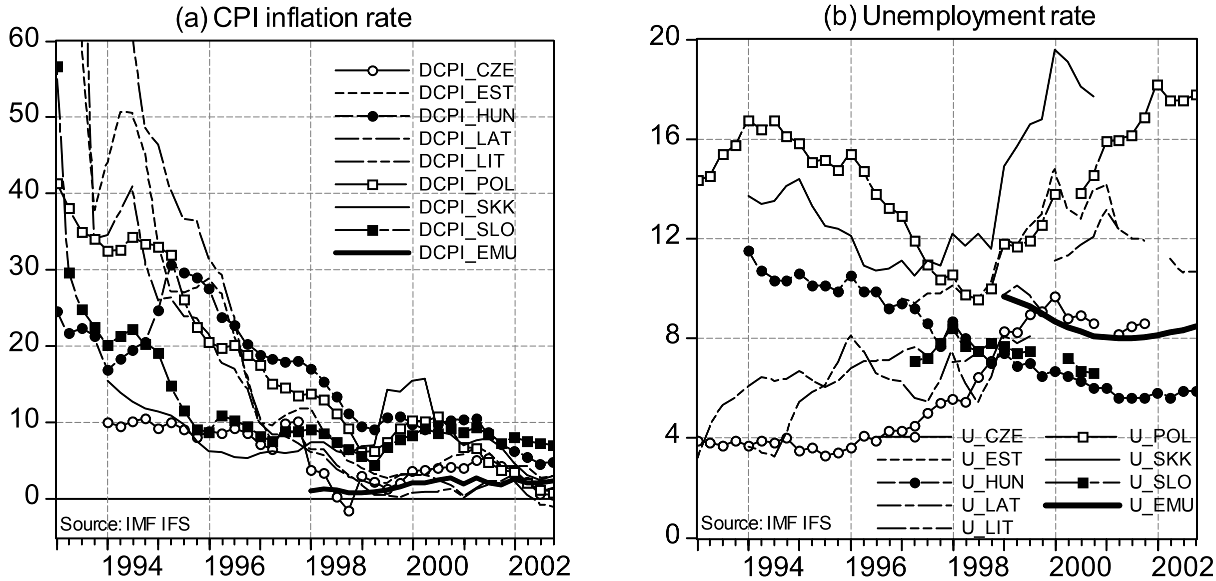


Figure 2 GDP of acceding countries and the Euro-area (seasonally adjusted logarithmic values), 1993Q1-2002Q4

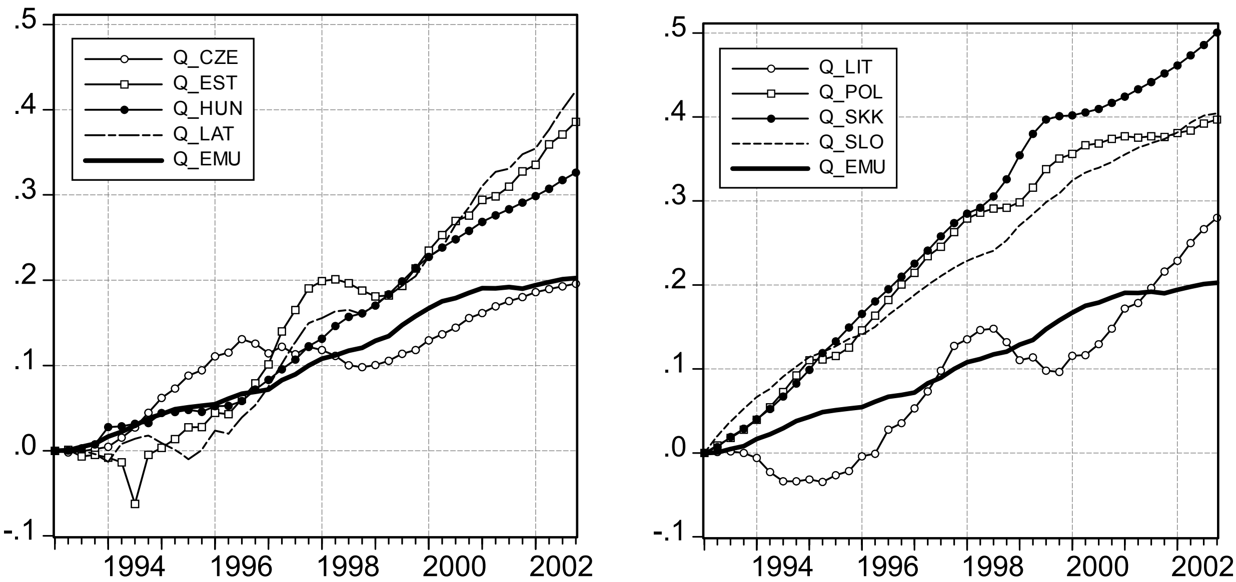
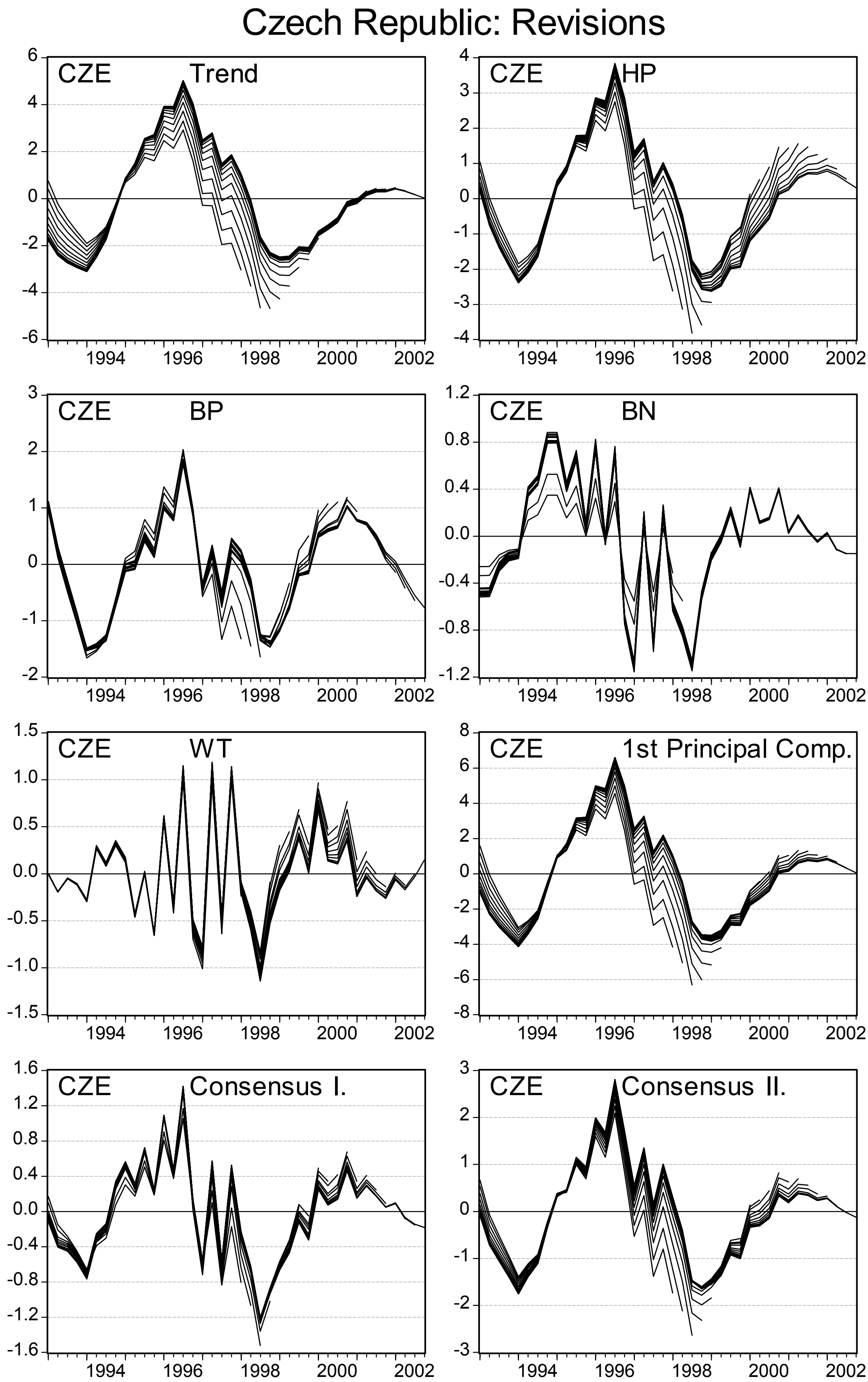
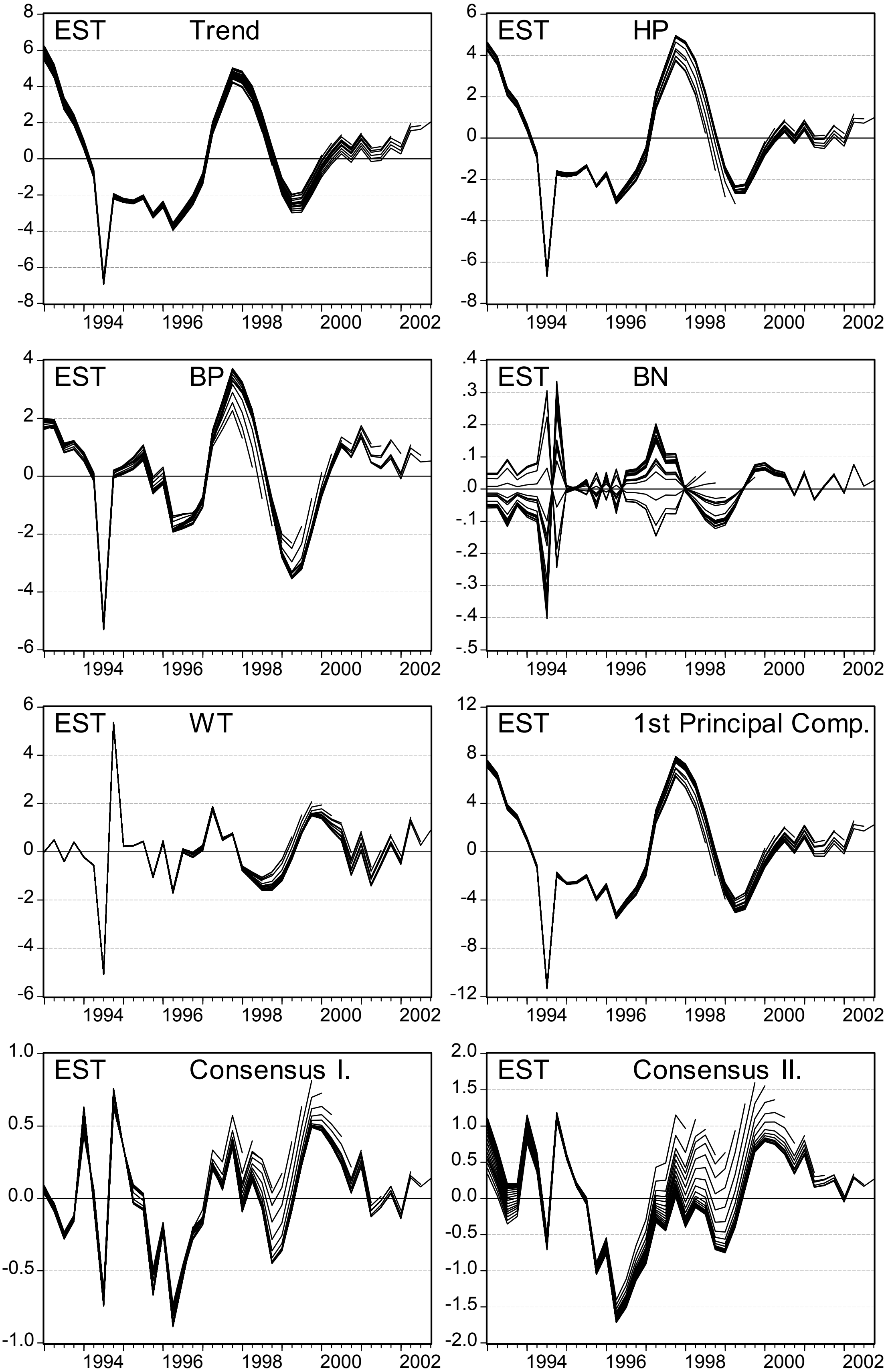


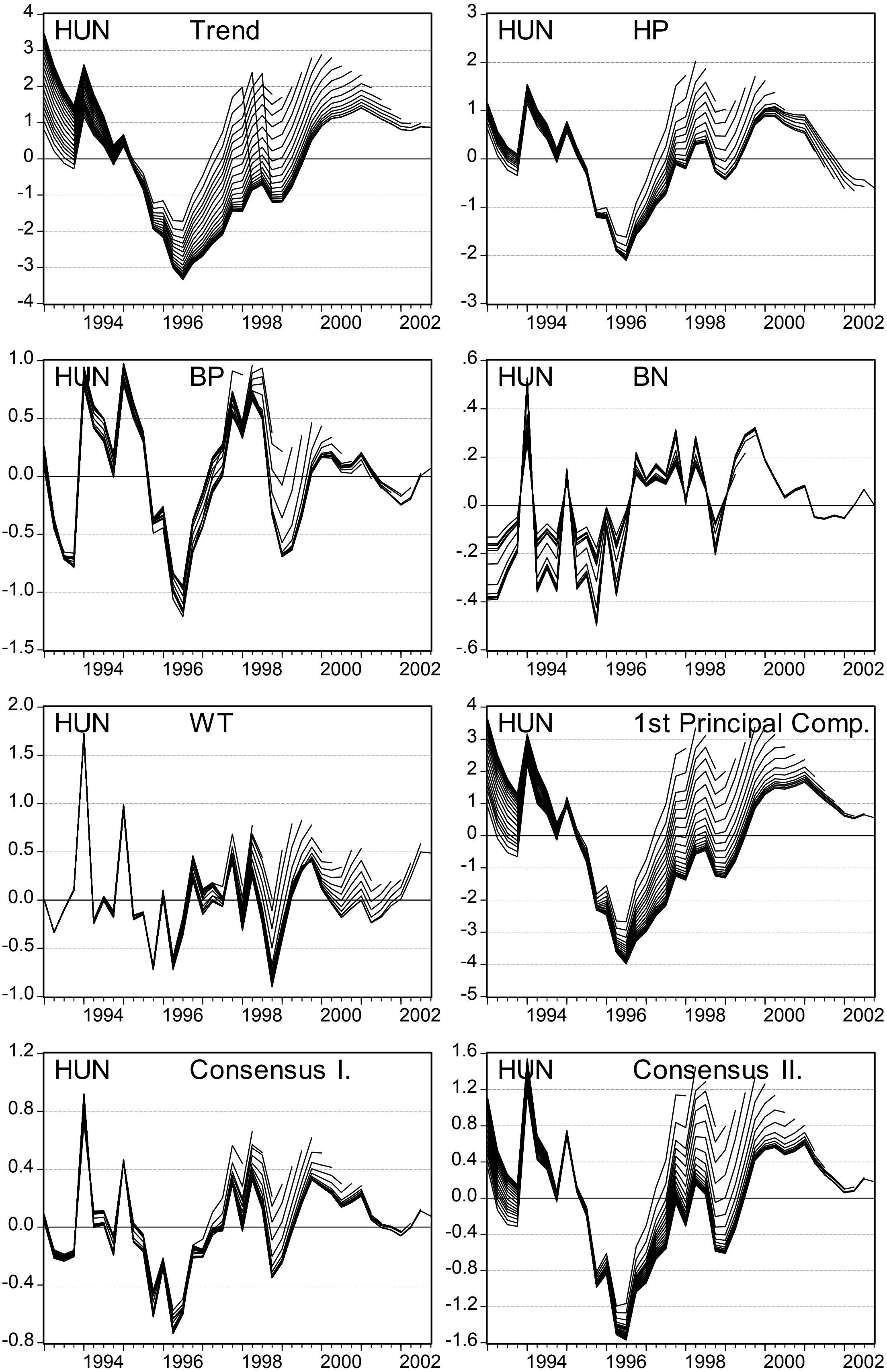
Figure 3 Revisions (estimations for recursive samples)



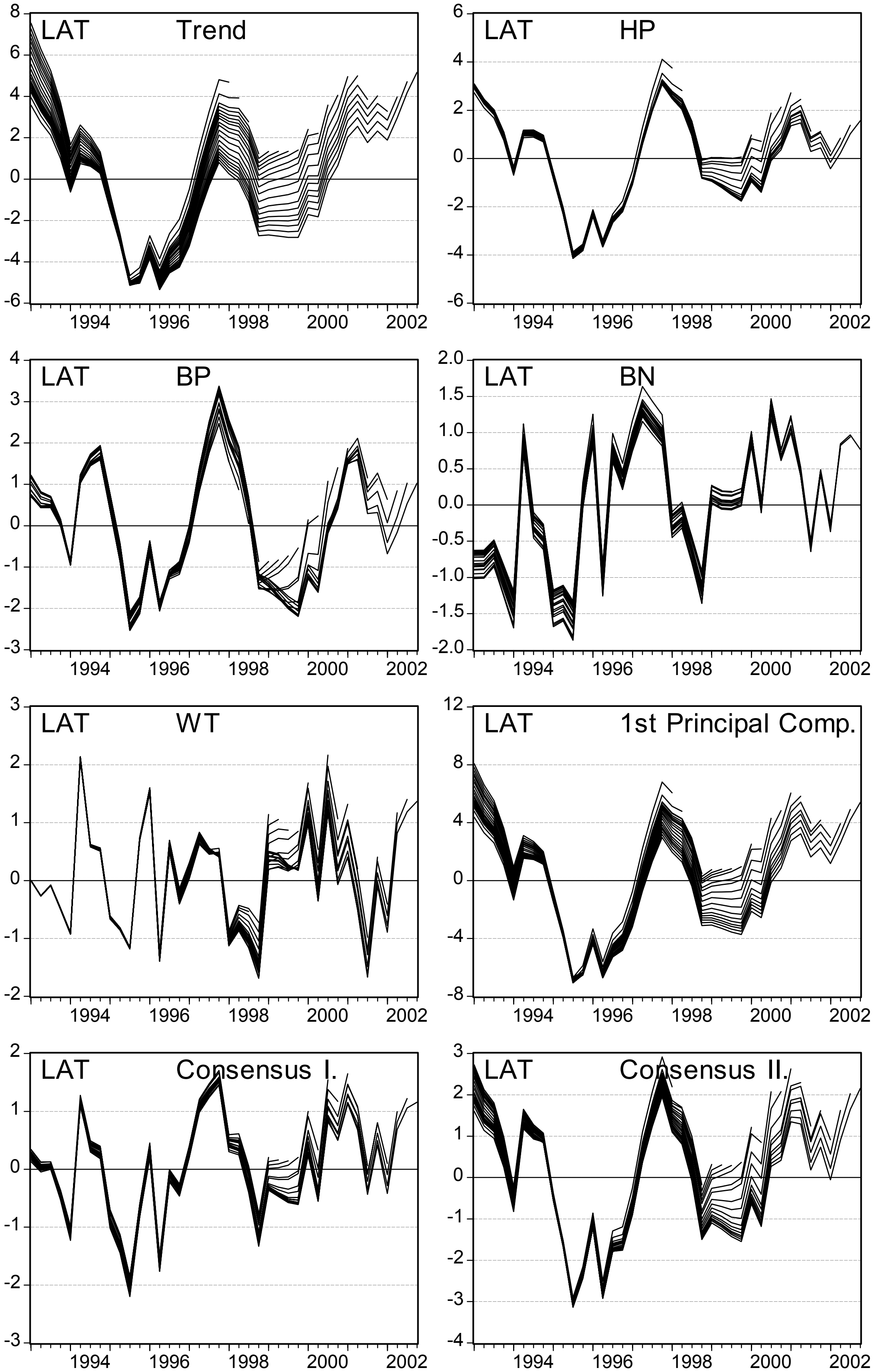
Estonia: Revisions



Hungary: Revisions



Latvia: Revisions



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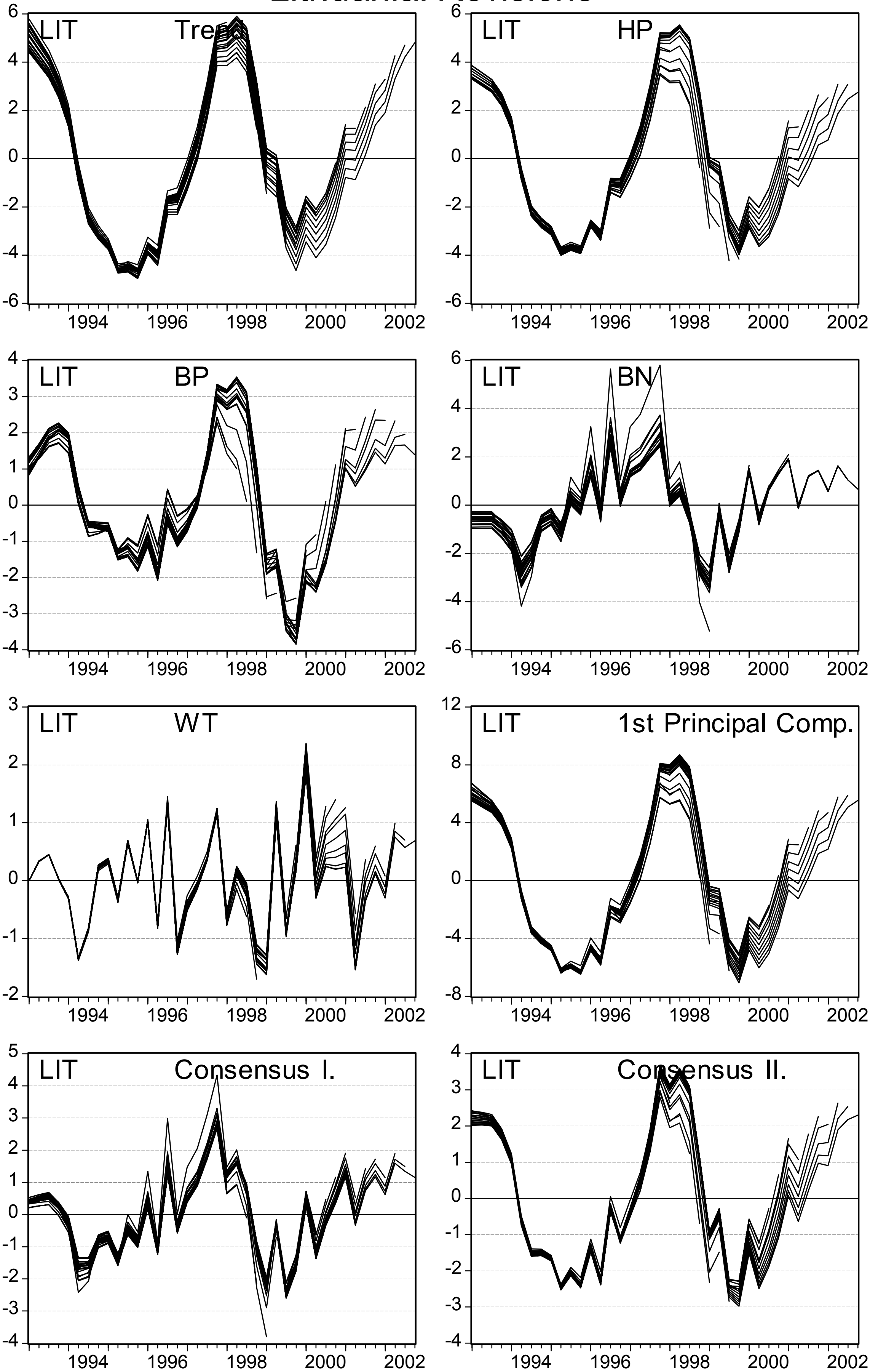
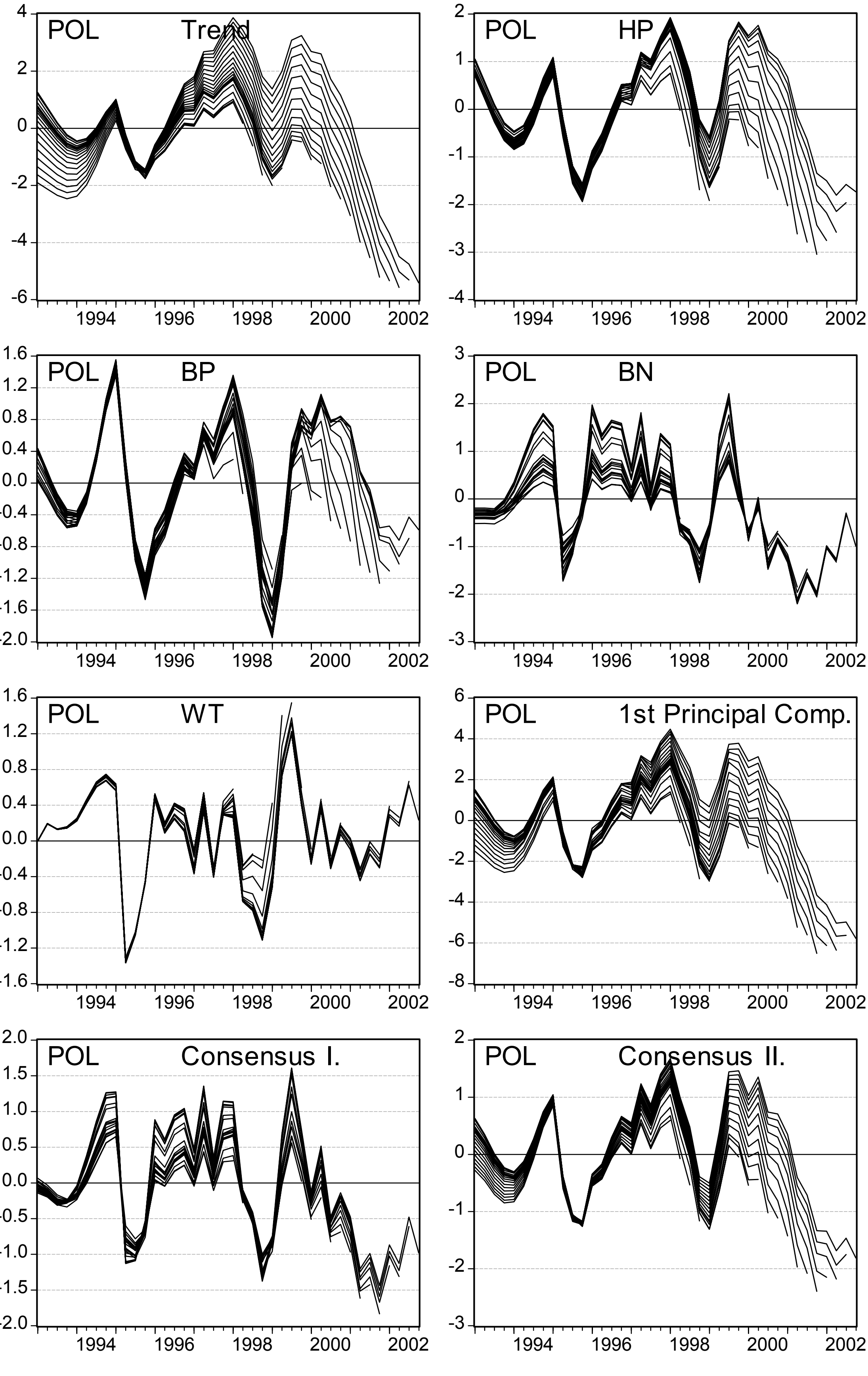
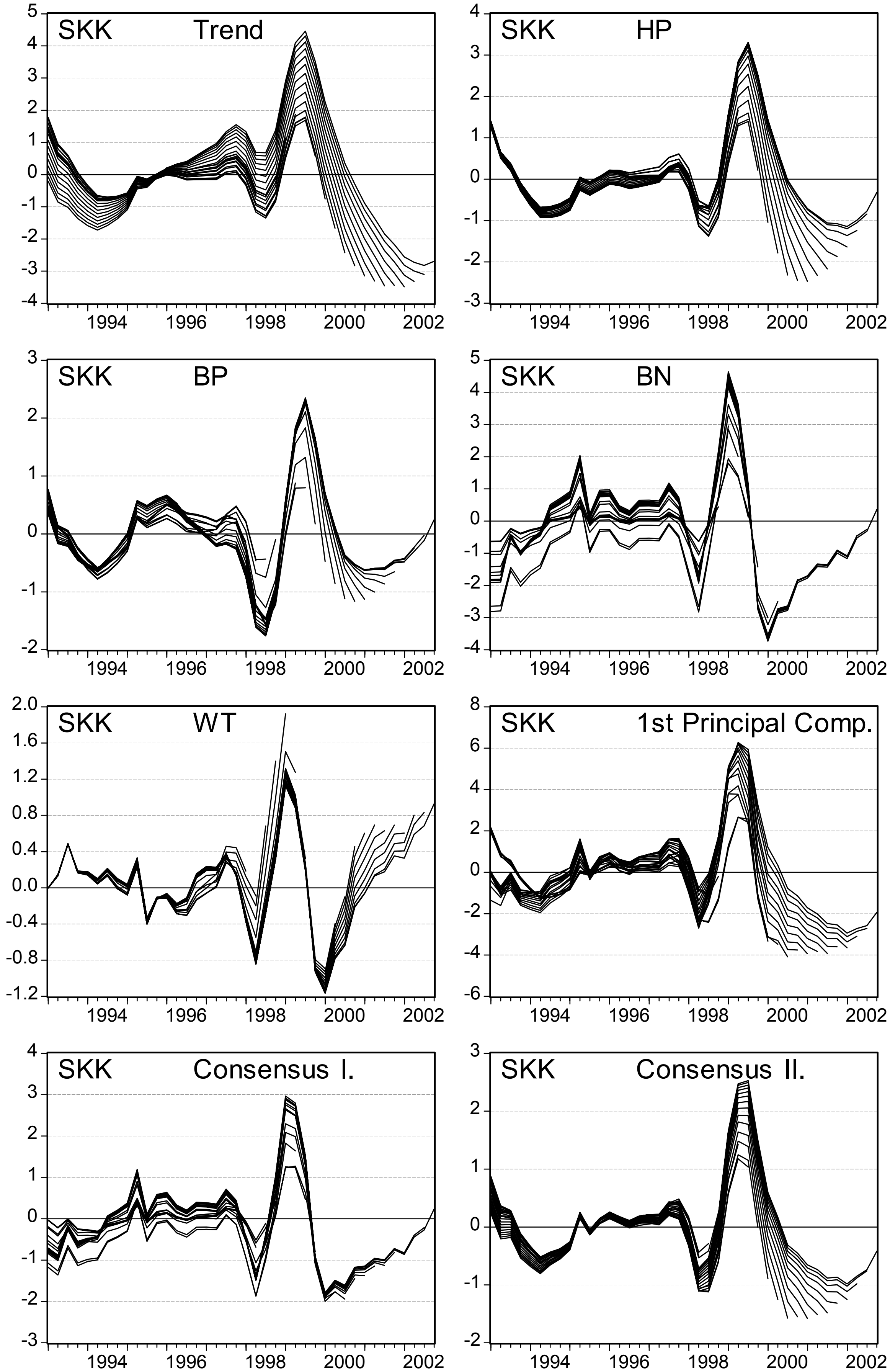


Poland: Revisions



Slovakia: Revisions



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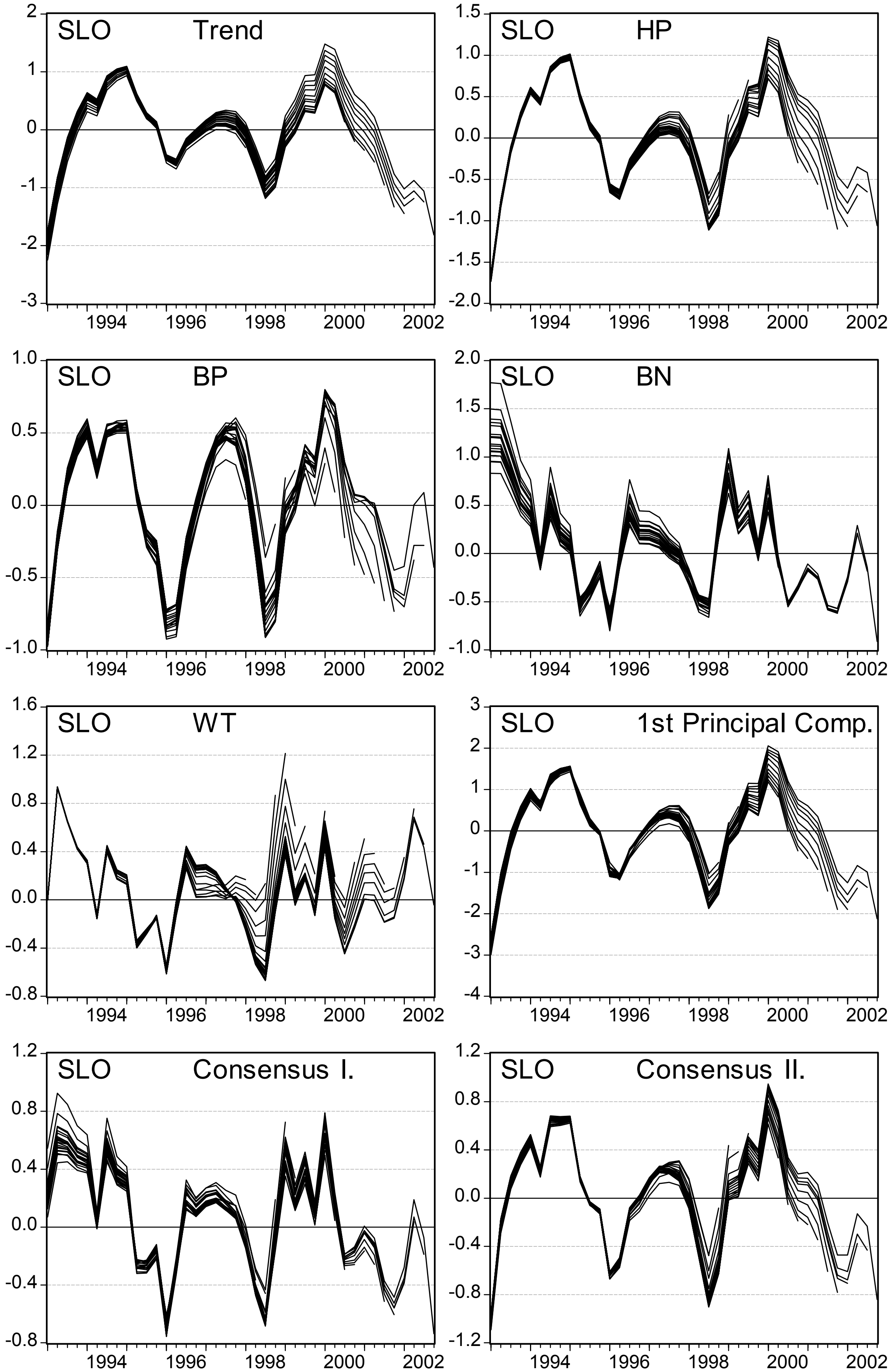

Euro-area: Revisions

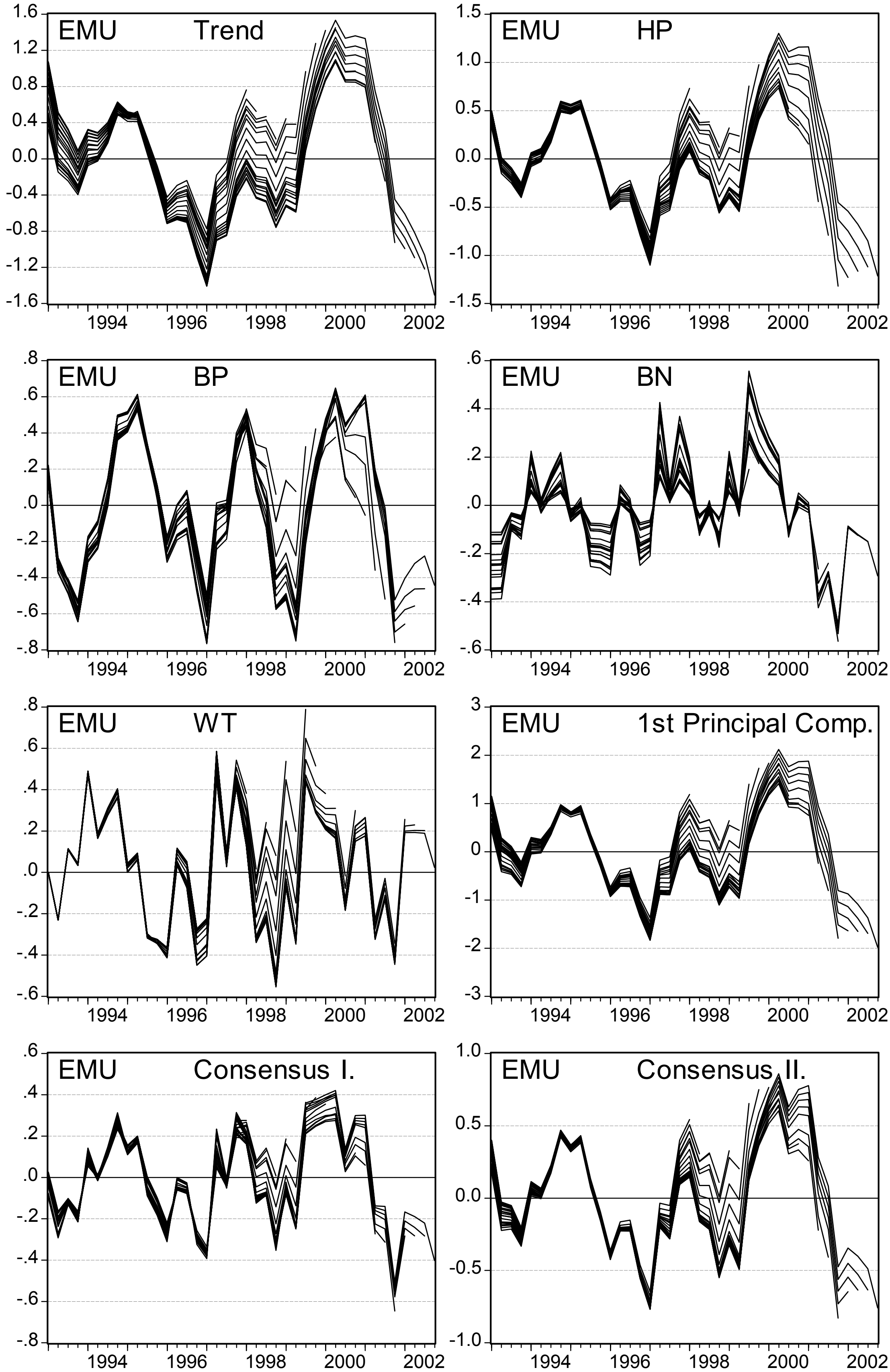

Figure 4 Combined Business Cycles, 1993Q1-2002Q4

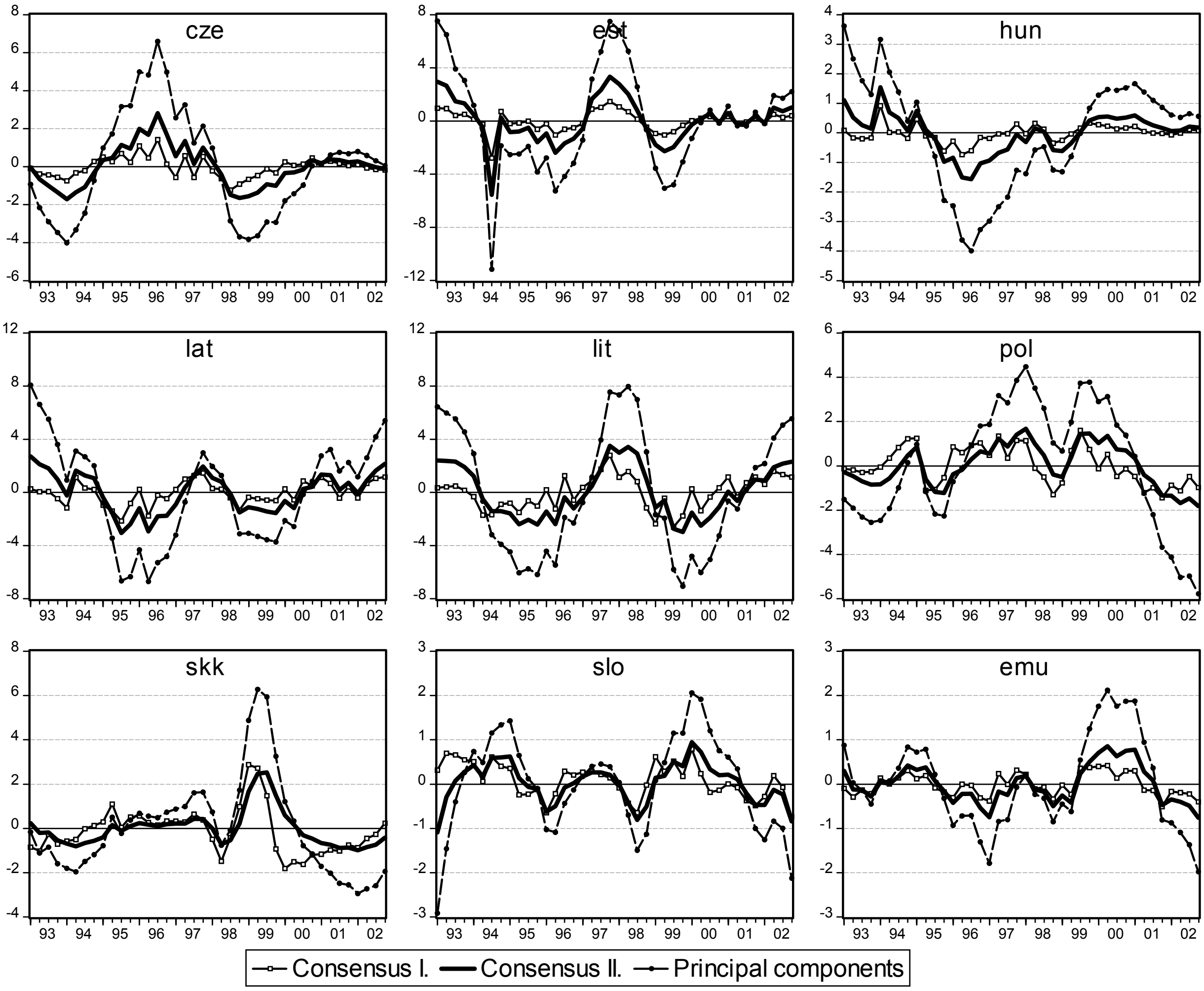

Table 1: Revisions, weights, and principal component analysis

Revisions of percentage point output gaps*

	cze	est	hun	lat	lit	pol	skk	slo	**Average of New Members**	emu
Time	0.084	0.095	0.116	0.237	0.199	0.226	0.160	0.061	**0.147**	0.062
HP	0.089	0.071	0.061	0.091	0.185	0.137	0.095	0.054	**0.098**	0.065
BP	0.033	0.086	0.025	0.112	0.125	0.084	0.055	0.050	**0.071**	0.037
BN	0.020	0.008	0.009	0.051	0.166	0.085	0.142	0.048	**0.066**	0.015
WT	0.019	0.045	0.033	0.054	0.049	0.019	0.037	0.028	**0.035**	0.014
1st Principal C.	0.111	0.129	0.114	0.254	0.288	0.270	0.239	0.089	**0.187**	0.091
Consensus I.	0.018	0.015	0.014	0.055	0.111	0.059	0.073	0.034	**0.047**	0.018
Consensus II.	0.040	0.040	0.038	0.103	0.116	0.096	0.063	0.034	**0.066**	0.036

Weights based on revisions of percentage point output gaps**

	cze	est	hun	lat	lit	pol	skk	slo	**Average of New Members**	emu
Time	8%	6%	4%	7%	11%	5%	9%	15%	**8%**	8%
HP	7%	8%	8%	18%	12%	8%	15%	17%	**12%**	8%
BP	19%	6%	20%	14%	18%	14%	26%	18%	**17%**	14%
BN	32%	68%	53%	31%	13%	13%	10%	19%	**30%**	34%
WT	34%	12%	15%	30%	46%	59%	39%	32%	**33%**	36%
	100%	100%	100%	100%	100%	100%	100%	100%	**100%**	100%

Weights based on revisions of standardized output gaps***

	cze	est	hun	lat	lit	pol	skk	slo	**Average of New Members**	emu
Time	56%	21%	23%	21%	25%	17%	22%	28%	**27%**	22%
HP	20%	11%	23%	30%	23%	13%	21%	26%	**21%**	18%
BP	15%	2%	29%	19%	21%	14%	27%	18%	**18%**	19%
BN	7%	3%	6%	5%	7%	13%	4%	3%	**6%**	8%
WT	2%	63%	20%	25%	24%	43%	25%	26%	**28%**	34%
	100%	100%	100%	100%	100%	100%	100%	100%	**100%**	100%

Results of the principal components analysis (for the full sample of 1993Q1-2002Q4)

	cze	est	hun	lat	lit	pol	skk	slo	**Average of New Members**	emu
Variance Prop.	89%	85%	86%	81%	86%	76%	59%	69%	**79%**	84%
First Eigenvector										
Time	0.78	0.68	0.90	0.85	0.71	0.91	0.79	0.73	**0.79**	0.73
HP	0.59	0.60	0.42	0.44	0.60	0.35	0.42	0.59	**0.50**	0.62
BP	0.20	0.41	0.08	0.28	0.36	0.13	0.23	0.34	**0.26**	0.27
BN	0.03	0.01	0.00	0.02	0.06	0.18	0.38	0.03	**0.09**	0.07
WT	0.03	0.10	0.06	0.03	0.02	0.01	0.02	0.00	**0.03**	0.06
SUM	1.64	1.80	1.46	1.62	1.75	1.59	1.85	1.69	**1.67**	1.76
%-distribution										
Time	48%	38%	62%	53%	41%	57%	43%	43%	**48%**	42%
HP	36%	33%	29%	27%	34%	22%	23%	35%	**30%**	35%
BP	12%	23%	6%	17%	20%	8%	13%	20%	**15%**	15%
BN	2%	0%	0%	1%	3%	11%	21%	2%	**5%**	4%
WT	2%	5%	4%	2%	1%	1%	1%	0%	**2%**	4%
SUM	100%	100%	100%	100%	100%	100%	100%	100%	**100%**	100%

* Revisions are calculated from equations (1) and (2).

** Weights are calculated from equation (3) using equations (1) and (2).

** Weights are calculated from equation (3) using equations (1') and (2).

Table 2: Correlation of business cycles between the euro-area and new EU members based on different detrending methods

1993:1-2002:4

	cze	est	hun	lat	lit	pol	skk	slo	**average**
ST	-0.44	-0.03	0.54	0.10	-0.37	0.28	0.19	0.55	**0.10**
HP (1600)	-0.27	-0.11	0.73	0.02	-0.47	0.54	0.17	0.64	**0.16**
BP (6-32)	0.49	0.30	0.54	0.21	-0.21	0.73	-0.05	0.32	**0.29**
BN (arima110)	0.18	0.16	0.44	0.09	-0.18	0.51	0.11	0.22	**0.19**
WT (d83)	0.48	0.28	0.40	0.21	0.07	0.53	-0.06	0.31	**0.28**
range	*0.94*	*0.41*	*0.33*	*0.19*	*0.54*	*0.45*	*0.25*	*0.42*	***0.44***
average	*0.09*	*0.12*	*0.53*	*0.13*	*-0.23*	*0.52*	*0.07*	*0.41*	***0.20***
principal comp.	-0.29	0.55	0.54	0.05	-0.41	0.35	0.01	0.59	**0.17**
consensus I.	0.20	0.47	0.41	0.04	-0.23	0.46	-0.18	0.34	**0.19**
consensus II.	-0.09	0.56	0.53	0.04	-0.38	0.49	0.02	0.55	**0.21**

1993:1-1997:4

	cze	est	hun	lat	lit	pol	skk	slo	**average**
ST	-0.66	0.20	0.83	0.62	0.18	-0.62	-0.69	-0.09	**-0.03**
HP (1600)	-0.45	-0.08	0.74	0.21	-0.19	-0.03	-0.14	0.29	**0.04**
BP (6-32)	0.25	0.04	0.49	0.05	-0.35	0.44	0.40	0.02	**0.17**
BN (arima110)	0.27	0.24	0.45	0.24	0.16	0.40	0.38	-0.19	**0.24**
WT (d83)	0.46	0.14	0.36	0.06	-0.05	0.36	0.36	0.19	**0.23**
range	*1.13*	*0.32*	*0.47*	*0.57*	*0.53*	*1.06*	*1.09*	*0.48*	***0.70***
average	*-0.03*	*0.11*	*0.57*	*0.24*	*-0.05*	*0.11*	*0.06*	*0.04*	***0.13***
principal comp.	-0.50	0.72	0.72	0.43	-0.01	-0.42	-0.51	0.12	**0.07**
consensus I.	0.18	0.44	0.40	0.14	0.00	0.28	0.22	0.10	**0.22**
consensus II.	-0.32	0.65	0.62	0.30	-0.03	-0.07	-0.36	0.20	**0.12**

1998:1-2002:4

	cze	est	hun	lat	lit	pol	skk	slo	**average**
ST	-0.22	-0.35	0.35	-0.42	-0.81	0.60	0.39	0.89	**0.05**
HP (1600)	-0.06	-0.19	0.95	-0.23	-0.69	0.76	0.21	0.86	**0.20**
BP (6-32)	0.76	0.54	0.67	0.36	-0.12	0.91	-0.19	0.60	**0.44**
BN (arima110)	0.10	0.05	0.65	-0.11	-0.48	0.76	0.02	0.63	**0.20**
WT (d83)	0.52	0.58	0.52	0.36	0.18	0.68	-0.20	0.40	**0.38**
range	*0.98*	*0.93*	*0.60*	*0.78*	*0.99*	*0.31*	*0.59*	*0.49*	***0.71***
average	*0.22*	*0.13*	*0.63*	*-0.01*	*-0.38*	*0.74*	*0.04*	*0.68*	***0.26***
principal comp.	-0.05	0.55	0.55	-0.33	-0.71	0.62	0.11	0.87	**0.20**
consensus I.	0.30	0.59	0.58	-0.08	-0.40	0.69	-0.29	0.55	**0.24**
consensus II.	0.23	0.63	0.66	-0.20	-0.63	0.72	0.08	0.78	**0.28**

Change in correlation from 1993-97 to 1998-02

	cze	est	hun	lat	lit	pol	skk	slo	**average**
ST	0.44	-0.55	-0.47	-1.04	-0.99	1.21	1.08	0.99	**0.08**
HP (1600)	0.40	-0.11	0.21	-0.44	-0.49	0.79	0.34	0.57	**0.16**
BP (6-32)	0.51	0.50	0.18	0.31	0.22	0.47	-0.59	0.57	**0.27**
BN (arima110)	-0.17	-0.19	0.21	-0.35	-0.64	0.36	-0.36	0.82	**-0.04**
WT (d83)	0.06	0.44	0.16	0.30	0.23	0.32	-0.56	0.21	**0.15**
range	*0.69*	*1.05*	*0.68*	*1.35*	*1.22*	*0.89*	*1.67*	*0.78*	***1.04***
average	*0.25*	*0.02*	*0.06*	*-0.24*	*-0.33*	*0.63*	*-0.02*	*0.63*	***0.12***
principal comp.	0.45	-0.17	-0.17	-0.76	-0.69	1.04	0.62	0.75	**0.13**
consensus I.	0.12	0.15	0.18	-0.22	-0.40	0.41	-0.52	0.45	**0.02**
consensus II.	0.56	-0.03	0.03	-0.50	-0.60	0.80	0.45	0.58	**0.16**