Business cycle correlation of the CEEC and the Euro area: some methodological controversy

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Abstract. The paper focuses on some methodological features of the business cycle correlation measuring. Particularly, a spurious influence of detrending techniques used when analyzing the classical and growth business cycles is examined in the paper. The results give some evidence of different impact of detrending filters on final measures of correlation since uneven volatility, autocorrelation and other characteristics in detrended time series are produced by the filtering techniques. This might lead to a biased or distorted interpretation of the results when assessing business cycle correlation.

Keywords: business cycle, correlation, detrending, Hodrick-Prescott filter, band-pass filter,

JEL Classification: C18, C82, E32 AMS Classification: 91G70

1 Introduction

During past two decades a vast variety of research papers and analytical studies on business cycle similarity measuring were published in economic literature. The business cycle similarity and convergence was assessed mainly with regards to analyzing the economic and monetary integration processes in Europe. Particularly, business cycles of candidate countries aceeding the Euro zone were analyzed and compared with the member countries' cycles. The characteristic of business cycle similarity and shock asymmetry were defined in a frame on the "New" Optimum Currency Areas Theory [10]. Technically, the classical and growth business cycles have to be identified first in order to apply some measure of similarity. Burns and Mitchell [2] define the classical business cycles as cyclical fluctuations with decline and growth phases in an absolute level of aggregate economic activity of a nation. The growth cycles are considered as fluctuations of cyclical component of analyzed macroeconomic time series around its trend [9]. Accordingly, a selected detrending technique to dissect the cycles and trends in the data time series need to be applied.

The OCA literature provides a general theoretical framework for business cycle similarity assessment [11]. However, the theory does not give a clear recommendation of a concrete method or technique to be applied. Thus a vast variety of detrending and cycle identification method was used in the past literature. Fidrmuc and Korhonen [7] used a meta-analysis of the business cycle correlation between the Euro area and Central and Eastern European countries (CEEC) analyzing 35 selected publications on business cycle synchronization in Europe. In the analysis they compare the datasets, methods including detrending techniques and results of chosen topical papers. Among others they found more conservative and careful estimation results in studies by the central banks comparing to those by research institutions and academia. There is also a lot of econometric and statistical literature dealing with impact of using methods such as filters on resulted time series including business cycles (e.g. [1], [4], [5], [13], [12], [6], and [14])

In our paper we concentrate on the role of detrending techniques and filters in the business cycle correlation analysis. Particularly, we focus on evaluation of spurious impacts of various detrending techniques on macroeconomic time series when estimating the business cycles correlation. The paper is structured as follows. After the introduction the second session describes the data and used methodology. The correlation of business cycles and detrended time series characteristics are compared in the third section. The fourth section concludes.

2 Data and methodology

The monthly data of industrial production in 1994-2011 sourced from IFS IMF is used when analyzing the business cycles. Germany, France, Italy, Spain and Portugal were selected as the representatives of core and peripheral Euro area countries. Czech Republic, Hungary, Poland and Slovakia complete the sample of CEE countries.

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The Hodrick-Prescott filter, Baxter-King band pass filter using for identification of growth cycles and first differencing of logarithms for classical cycles were applied in the analysis.

There is a lack of consensus in economic literature for the classical business cycles identification. The first differencing method is used in studies on classical as well as growth cycle. As Canova [5] points out the first differencing of logarithms is an appropriate method producing stationary time series provided that the trend component represents the random walk process, cyclical component is stationary and both components are not correlated. In addition the unit root of y_i is supposed due to systematic component y_{i-1} , for

$$y_t = y_{t-1} + \mathcal{E}_t \tag{1}$$

For which a trend is defined as $g_t = y_{t-1}$ and $\hat{c}_t = y_t - y_{t-1}$.

The Hoddrick-Prescott filter [8] enables to dissect the stochastic trend and uncorrelated cyclical component in analyzed time series solving the minimum problem

$$\min_{\{g_t\}_{t=1}^T} \sum_{t=1}^T c_t^2 + \lambda \sum_{t=1}^T \left[(g_{t+1} - g_t) - (g_t - g_{t-1}) \right]^2, \ \lambda > 0$$
(2)

We apply the smoothing parameter λ =14400 (monthly data) penalizing the variability in the growth component. The value of smoothing parameter λ can be adjusted according to the business cycle definition. The greater λ the smoother trend identified in the time series.

Finally the frequency domain band pass filter suggested by Baxter and King [1] was applied in the paper. The assumption drawn from Burns-Mitchell [2] of the suggested filter is the cycle no shorter than 1.5 year and no longer than 8 years. The Baxter-King filter is basically the two-sided symmetric linear filter in a form of a combination of low-pass ad high pass filter passing by the components with periodical fluctuations between 6-32 quarters of the spectrum. The components with fluctuations of higher or lower frequencies are removed by the filter. The authors define the ideal truncation period K=12 for quarterly data and K=36 for monthly data. This implies eliminating of 12 and 36 observations, respectively, at the beginning and the end of the time series [3]. The length of the truncation period improves the equality of resulting time series decomposition but bigger loss of data.

Concerning the methods used the cross-correlation analysis of analyzed countries is applied first. The resultant correlation matrices are compared in case of all three detrending techniques applied in order to point out significant differences in resultant correlation coefficients when using various filters. Next, the business cycle of selected country identified with selected detrending techniques is described and characterized. Finally, the resultant detrended time series approximating the business cycles are analyzed and compared focusing on filters' properties such as autocorrelation, standard deviation and a frequency of turning points in order to examine various effects of selected detrending techniques.

3 Business cycle correlation of CEEC and the Euro area

3.1 Cross correlation

Table 1 includes the cross correlation coefficients with p-values of all selected countries. The coefficients resulted from using the Hedrick-Prescott (HP) and Baxter-King band pass filter (BK) are compared in a cross correlation matrix. Table 2 completes the results obtained with applying the first differencing technique.

	bk_fr	bk_it	bk_de	bk_es	bk_pl	bk_hu	bk_cz	bk_sk	
hp_fr	1	0.7645	0.6945	0.6865	0.511	0.7227	0.5081	0.6671	bk_fr
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
hp_it	0.9054	1	0.8091	0.7133	0.4939	0.7865	0.5733	0.5899	bk_it
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
hp_de	0.9204	0.909	1	0.6265	0.4208	0.8075	0.5488	0.6043	bk_de
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
hp_es	0.8689	0.8738	0.8586	1	0.6061	0.6917	0.4653	0.6401	bk_es

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	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	
hp_pl	0.6087	0.6405	0.5925	0.665	1	0.4694	0.6198	0.4862	bk_pl
	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
hp_hu	0.8599	0.8353	0.8816	0.8416	0.5826	1	0.4436	0.5079	bk_hu
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	(0.0000)	
hp_cz	0.7563	0.7853	0.7728	0.7095	0.6272	0.6805	1	0.4982	bk_cz
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)	
hp_sk	0.6258	0.7121	0.6319	0.6229	0.5917	0.5394	0.682	1	bk_sk
_	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
	hp_fr	hp_it	hp_de	hp_es	hp_pl	hp_hu	hp_cz	hp_sk	

 Table 1 Statistical characteristics of industrial production cycles identified with Hodrick-Prescott and Baxter-King band pass filter; source: author's calculations; p-values in parentheses,

	fd_fr	fd_it	fd_de	fd_es	fd_pl	fd_hu	fd_cz	fd_sk
fd_fr	1							
fd_it	0.4480	1						
	(0.0000)							
fd_de	0.3534	0.3148	1					
	(0.0000)	(0.0000)						
fd_es	0.3121	0.3621	0.1949	1				
	(0.0000)	(0.0000)	(0,0031)					
fd_pl	0.2641	0.2108	0.0835	0.2130	1			
	(0.0001)	(0.0013)	(0.2080)	(0.0012)				
fd_hu	0.2121	0.1573	0.2235	0.1784	0.1136	1		
	(0.0013)	(0.0174)	(0.0007)	(0.0069)	(0.0870)			
fd_cz	0.2077	0.2343	0.1214	0.1799	0.3961	0.2167	1	
	(0.0017)	(0.0004)	(0.0672)	(0.0065)	(0.0000)	(0.0010)		
fd_sk	0.2153	0.2067	0.1337	0.1570	0.4530	0.1254	0.4063	1
	(0.0011)	(0.0017)	(0.0437)	(0.0177)	(0.0000)	(0.0588)	(0.0000)	

Table 2 Statistical characteristics of industrial production cycles identified with first differencing; source: author's calculations; *p*-values in parentheses.

Comparing the results in both tables one might conclude that the Euro zone member countries reveal higher cross correlation than the CEE countries. Using he HP filter all countries seem to share a kind of European business cycle since all correlation coefficients higher than 0.5 with high statistical significance. Even the CEE countries such as the Czech Republic and Hungary show business cycles highly correlated to Germany as a benchmark for the Euro zone average. Results in case of using the BK filter are very similar to those of HP filter. Apart from few exceptions the cross correlation confirms highly similar cycles in the whole analyzed period of 1994-2011. However, the situation is dramatically different in case of applying the first differencing technique. All cross correlation coefficients are significantly lower than those of using HP and BK filters. The resultant coefficients even give an evidence of uncorrelated cycles with high statistical significance. Let's recall that first differencing of logarithm of the macroeconomic data implies an approximation of the growth rates, which is commonly used in studies on economic integration. Since the underlying OCA theory does not provide a clear methodological recommendation on a concrete business cycle identification results. Accordingly, the final interpretation of numerical results such as business cycle correlation might be spurious without consideration of different methodological properties.

3.2 Detrending techniques influence

To shed some light on the rationale of a significantly different correlation results obtained when using various filters we now focus on selected statistical properties of applied detrending techniques. The Figure 1 shows the detrended time series when using first differencing, Hodrick-Prescott and Baxter-King filters.

The first differencing technique produces cycles of lower volatile time series measured with standard deviation and more frequent turning points. HP and BK filters generate rather smoother cycles. This is more obvious when using quarterly data of GDP which has less strength in the higher frequencies of the spectra. In our paper we use monthly data of industrial production, which produce frequent turning points in the detrended time series.



Figure 1 First differencing, Hodrick-Prescott and Baxter-King filters comparison: the case of Czech industrial production cycles

Variable	Obs	Mean	Std. Dev.	Min	Max	r(1)	r(2)	r(3)	Turning Points
hp_fr	157	0.003586	0.02298	-0.08286	0.07448	0.803804	0.749725	0.666813	26
hp_it	157	0.005904	0.032947	-0.0882	0.108008	0.880411	0.811609	0.747069	21
hp_de	157	0.00698	0.036678	-0.12421	0.103172	0.869236	0.802636	0.752651	22
hp_es	157	0.004852	0.034588	-0.0835	0.105498	0.885731	0.827801	0.774792	13
hp_pl	157	0.005332	0.042725	-0.09055	0.13098	0.546223	0.598242	0.638061	41
hp_hu	157	0.005939	0.050413	-0.12889	0.131484	0.854477	0.774666	0.72127	22
hp_cz	157	0.006613	0.045914	-0.11313	0.127965	0.784187	0.703349	0.59827	27
hp_sk	157	0.005796	0.055276	-0.16623	0.179847	0.742889	0.669494	0.58775	33
fd_fr	157	-3.6E-05	0.012765	-0.04502	0.037134	-0.31887	0.177753	0.094873	90
fd_it	157	-0.00095	0.014455	-0.04922	0.038412	-0.13731	0.14536	0.225021	88
fd_de	157	0.000901	0.015565	-0.07873	0.03011	-0.07068	0.083816	0.254739	89
fd_es	157	0.000213	0.01552	-0.04134	0.063776	-0.23481	0.107721	0.205314	91
fd_pl	157	0.004727	0.040152	-0.13158	0.12687	-0.56217	0.0071	0.3808	109
fd_hu	157	0.004749	0.025346	-0.12142	0.064458	-0.23306	0.080036	0.040149	81

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fd_cz	157	0.002482	0.028886	-0.08162	0.077813	-0.31769	0.106423	0.026169	75
fd_sk	157	0.003056	0.037486	-0.16809	0.125571	-0.40684	0.086709	0.138359	98
bk_fr	157	0.000648	0.009455	-0.01988	0.036833	0.900354	0.698133	0.485087	27
bk_it	157	0.000282	0.014976	-0.04358	0.05082	0.885511	0.682071	0.460684	17
bk_de	157	0.001103	0.015824	-0.05534	0.074079	0.862272	0.632629	0.401136	19
bk_es	157	-0.0005	0.011101	-0.04244	0.037015	0.858594	0.590537	0.314767	26
bk_pl	157	-0.00032	0.018296	-0.05226	0.049488	0.874419	0.593139	0.286072	21
bk_hu	157	0.000438	0.01985	-0.07291	0.070847	0.853719	0.580257	0.302516	24
bk_cz	157	0.000475	0.022351	-0.04989	0.055034	0.852671	0.530043	0.178718	23
bk_sk	157	0.000388	0.027297	-0.08906	0.094131	0.865441	0.578016	0.25625	19

 Table 3 Statistical characteristics of industrial production cycles identified with the chosen techniques, source:

 author's calculations

The table 3 summarizes selected properties of detrended time series of monthly industrial production in 1996-2008. The analyzed time series is six years shorter since the Baxter-King band pass filter needs three years (truncation period) to be cut off at the beginning and the end of the analysed time period. The analyzed properties include selected descriptive statistics, autocorrelation measures and also number of turning points at the detrended time series. The monthly data of industrial production does not allow detecting the lowest standard deviation in case of first differencing as suggested in Baxter-King [1]. The measures of autocorrelation and number of turning points provide evidence of different properties of selected filters. The Hodrick-Prescott and Baxter-King band pass filter reveal remarkably higher correlation than first differencing technique. In addition, the number of turning points is 3-5 times higher when using first differencing the HP and BK filters. On the contrary HP and BK filters produce time series with very comparable number of turning points.

As suggested in Baxter-King [1] first differencing emphasises high frequencies and down weights low frequencies of the time series spectra. This implies lower correlation and autocorrelation in detrended time series when using first differencing. HP and BK filters work as band pass filters. HP filter acts as a high-pass filter which leaves components of higher frequencies in the time series whereas the BK-BP removes them. The correlation and autocorrelation measures are higher when using quarterly and monthly data of GDP and other aggregate activity indicators that do not have much of high frequencies in the spectra. Also volatility measured with standard deviation is higher than in case of first differencing in case of quarterly data. Using monthly data of industrial production our results confirm those of Baxter-King [1]. Standard deviation of cycles when using first differencing is not significantly lower than of the other filters. This might be the impact of using monthly data since Baxter-King [1] also found comparable standard deviations in time series when using monthly data of inflation rate and other selected indicators.

4 Conclusion

In our paper we intended to provide some evidence of an influence of selected detrending techniques on business cycle correlation measuring. Three selected detrending techniques were applied to identify cycles of monthly industrial production in selected EU countries including the CEEC. The results of business cycles cross correlation show significant differences when using band pass filters and first differencing. Whereas business cycle correlation identified with using Hodrick-Prescott and Baxter-King band pas filters are highly correlated, cycles detrended with first differencing are uncorrelated. This might imply spurious interpretation when assessing the business cycle similarity from OCA theory perspective. Analysis of selected statistical properties of filtered time series show significant differences in measures of autocorrelation and number of turning points. First differencing rather smoother cycles in terms of significantly lower number of turning points. Band pass filters produce rather smoother cycles in terms of significantly lower number of turning points. Band pass filters are succorrelation measures. All three filters emphasize and down weight dissimilar frequencies of the time series spectra. The results also indicate potentially different properties of filtering techniques when using quarterly and monthly data. Since there is a lack of consensus on business cycle identification technique in the literature, the assessment of business cycle similarity might lead to inappropriate interpretation due to uneven impact of chosen filters. Accordingly, our recommendations are aimed at careful interpretation of results with respect to applied methodology.

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