

Measuring Co-movements in the Euro Area Using a Non Stationary Factor Model

By C. Bruneau,¹ O. de Bandt² and A. Flageollet³

Abstract

The paper investigates to what extent business cycles co-move in the four largest euro area economies, using a large-scale database of non-stationary series for the euro area over the 1980:Q1 to 2003:Q4 period. We apply the methodology proposed by Bai (2004) and Bai and Ng (2004) to construct a coincident indicator of the euro area business cycle, based on the first common factor estimated from a dynamic factor analysis on the level of the variables. The indicator appears to be significantly close, from a statistical point of view, to the level of the euro area GDP in the most recent period. We also show that national developments are increasingly correlated to the indicator at the business cycle frequencies. We finally suggest a decomposition of GDP growth along the different stationary and non stationary factors.

Keywords: factor models, non stationary panel data techniques, euro area business cycles

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¹ University Paris X, cbruneau@u-paris10.fr

² Banque de France, corresponding author : Banque de France, 46-1405 DAMEP, 39 rue Croix des Petits Champs, 75049 Paris Cedex 01 France; e-mail: olivier.debandt@banque-france.fr

³ University Paris X, alexisflageollet@yahoo.fr

1. Introduction

The objective of the paper is to investigate to what extent business cycles co-move in the four largest euro area countries, namely Germany, France Italy and Spain, using a large database for the euro area on the 1980Q1 to 2003Q4 period. We construct a Business Cycle Index (BCI) to which the cycles in the four countries are compared, in order to determine how important are common versus specific shocks, and to determine whether individual countries' business cycles have become more correlated within the euro area.

In the lines of previous research that analysed cyclical movements on the basis of a large number of economic series (see e.g. the National Bureau of Economic Research in the US), we construct a Business Cycle Indicator (BCI) from a large database.

We refer to the most recent literature using dynamic factor models, as recently developed by Bai & Ng (2004) and Bai (2004) extending previous results from the stationary case (Stock & Watson, 1998, Forni et al., 2001) to the non-stationary case, for which inference is proved to be complete, thanks to the large panel and time dimensions. Moreover, it turns out that we are in the proper case where factors can be extracted from the series in level.

We identify a small set of common factors to explain the fluctuations of GDP at business cycle frequencies in the countries under study and suggest a useful decomposition for each of the GDP series -taken in levels- into three parts: a common persistent part, a common transitory one and an idiosyncratic one. Each of them can be filtered in order to keep the business cycle frequencies only.

The real benefit of the application of the Bai and Ng (2004) methodology appears for the construction of a BCI from the first factor. We derive confidence bands around the first factor in order to verify that it is close to the euro area GDP. We show that the correlation of the cyclical components of the four countries with the indicator has increased since 1992, indicating higher correlation of business cycle components and convergence among the countries.

The paper is organized as follows. In section 2 we extract the common factors from the database in level. In section 3, we construct our euro area indicator and interpret it. In section 4 we decompose GDP business cycles in three components.

2. Extracting Factors from a Large-Scale Database

In order to extract common trends from a large panel of non-stationary macroeconomic variables for the euro area, we rely on the PANIC (Panel Analysis of Non-stationarity in the Idiosyncratic and Common Components) procedure, developed by Bai and Ng (2004), hereafter BN2004. In the non stationary case, the estimation procedure is fairly the same as in the more common stationary case (Stock and Watson, 1998) and remains simple.

2.1 The model

We start from a database of 220 quarterly macroeconomic series for all euro area countries, including national accounts, industrial production, employment, prices and wages, share prices and interest rates. The series form a $N \times T$ matrix called X . The BN2004 model is the following, where the N individual (non stationary) series in the panel ($i = 1, \dots, N$) and the r common factors ($k = 1, \dots, r$) are noted X_{it} and F_{kt} , respectively:

$$X_{it} = c_i + \beta_i t + \sum_{k=1}^r \lambda_{ik} F_{kt} + e_{it} \quad (1)$$

$$\Delta F_t = \alpha + \sum_{j=0}^{\infty} C_j u_{t-j} \quad (2)$$

$$e_{it} = \rho_i e_{it-1} + \sum_{j=0}^{\infty} D_{ij} \varepsilon_{it-j} \quad (3)$$

The ε_{it} 's are white noises which may be (weakly) cross-correlated. The model allows r_0 stationary factors and r_1 common trends with $r = r_0 + r_1$. The idiosyncratic component e_{it} is I(1) if $\rho_i = 1$, and stationary if $\rho_i < 1$.

The factors and the idiosyncratic components may be either I(1) or I(0) and can even be integrated at different order.

2.2 Estimation and test procedures

When the residuals e_{it} are I(0), it is possible to get consistent estimates of the factors and loadings F_{kt} and λ_{ik} respectively (Bai, 2004, hereafter B2004).

When it is not the case – the e_{it} 's are I(1) – another procedure need to be implemented and BN2004 propose to run the principal component analysis on the first differenced series, specified as:

$$\Delta X_{it} = \beta_i + \sum_{k=1}^r \delta_i' \Delta F_{kt} + e_{it} \quad (4)$$

Consistent estimates of F_{kt} and e_{it} from (1) are thus obtained for $t=2, \dots, T$ and $i=1, \dots, N$ as:

$$F_{kt} = \sum_{s=2}^t \Delta F_{ks} \quad (5)$$

$$e_{it} = \sum_{s=2}^t \Delta e_{is} \quad (6)$$

where r , the number of common factors, is identified by using the information criteria PC2 and IC2 proposed by BN2004. We find that r is equal to 5.

Next, it is possible to identify the source of non stationarity of the series. For that purpose, one first focuses on the idiosyncratic components e_{it} . We run therefore standard univariate ADF test for each idiosyncratic component but implement a pooled test procedure, in order to increase the power of the test:

$$H_0 : \forall i, \{d_{i0} = 1\}$$

$$H_1 : \exists i / \{d_{i0} < 1\}$$

$$\text{where } e_{it} = d_{i0} e_{it-1} + \sum_{j=1}^p d_{ij} \Delta e_{it-j} + \xi_{it}$$

Pooling is achieved for $N \rightarrow \infty$ provided that the e_i 's are independent for different i . With $p_{e_i}^c$ the p-value associated with $\text{ADF}(e_i)$ as obtained by simulations, the test statistics is:

$$p_e^c = \frac{-2 \sum_{i=1}^N \log p_{e_i}^c - 2N}{\sqrt{4N}} \quad (7)$$

which, asymptotically, is proved to be normally distributed (Choi, 2002).

In our study, the idiosyncratic components e_i can be considered as stationary according to a low p-value (0.00) of the pooled statistic (3.13). Thus, according to B2004, it is possible and more efficient to extract the factors directly from the series in level.

The number of common trends is identified by using modified variants MQ of Stock and Watson's Q statistics (1988). According to these statistics, we find that r_1 , the number of non stationary common factors, is equal to 3.

Confidence intervals can be computed around any (true) underlying factor (or any linear combination of the factors) at each date t . For example, B2004 proves that, without cross-correlations between the idiosyncratic components, or, after correction, (provided that $N/T^3 \rightarrow 0$):

$$\frac{\sqrt{N}(\delta' F_t - Y_t)}{\sqrt{\delta' V_{NT}^{-1} \left(\frac{1}{N} \sum_{i=1}^N e_{it}^2 \lambda_i \lambda_i' \right) V_{NT}^{-1} \delta}} \xrightarrow{N,T} N(0,1) \quad (8)$$

where e_{it} is the estimated residual $e_{it} = X_{it} - \lambda' F_t$ and V_{NT} is a diagonal matrix consisting of the first r largest eigenvalues of XX'/T^2N ; δ , the parameter which rescales F_t towards Y_t , the euro area GDP series, is such that:

$$Y_t = \delta' F_t + error \quad (9)$$

One should mention that, in our case, we find that the first non-stationary factor contributes to each of the 220 series with an almost constant loading. The first factor can therefore be identified as the steady state growth rate of the euro area. From a Real Business Cycle point of view, three non stationary factors may be surprising but additional persistent demand shocks may have been at work in the recent history of the euro area. Factor 2 is associated with price developments, while factor 3 is strongly correlated with interest rates, in particular in Germany, a natural result, given the dominant role of that country in interest rate setting in the first part of the sample period. The fourth and fifth (stationary) factors are associated with transitory supply and demand shocks.

3. Constructing a coincident indicator for the euro area

In the lines of the literature on BCIs derived from factor models, we now use the first common factor to construct a new coincident indicator of the euro area GDP.

The first factor, as an (almost) equally weighted linear combination of the 220 series, is a good candidate for a Business Cycle Index, in the lines, for example, of the US Conference Board index.

Figure 1 displays the first factor together with the expansion/recession periods derived from "classical business cycle" analysis in the line of Harding and Pagan (2002). It appears that indeed the 1993 recession and the early 2000 slowdown are well captured by the indicator.

[Insert Figure 1]

In Figure 1, we also test, more precisely, using equation (8) and (9), whether the euro area GDP, GDP_{euro} , is close to a linear combination of the non stationary factors, and more precisely of the first factor. One observes that the euro area GDP (solid line) is close to the 99% confidence band around the first factor (dashed lines). The correspondence between the first factor and euro area GDP is increasing over time from 1992 onwards.

4. The Source of Business Cycle Fluctuations

We now study the sources of business cycle fluctuations in the euro area. For that purpose, we apply the Christiano and Fitzgerald (1999) filter which is a linear filter that removes the highest and lowest frequencies, and we only keep the business cycle frequencies. We decompose GDP in the various countries into the common and the idiosyncratic components. We end up measuring the contribution to the business cycle from (1) common non-stationary factors, (2) common stationary factors, (3) idiosyncratic components.

For each GDP-variable X_i of country i , CX_{it} , CF_{kt} and CE_{it} are the Christiano and Fitzgerald cyclical components of, respectively, X_i , the factors, F_k and the idiosyncratic component e_i . Since the filter is linear and the factor loadings are constant over time, each GDP series can be decomposed according to:

$$CX_{it} = \sigma_{X_i} \left(\sum_{k=1}^5 \lambda_{ik} CF_{kt} + CE_{it} \right) \quad (10)$$

with σ_{X_i} a scaling factor.

Furthermore, in computing the contribution of each common or idiosyncratic component $y_{it} \in \{ \phi_{ikt} = \sigma_{X_i} \lambda_{ik} CF_{kt}, \xi_{it} = \sigma_{X_i} CE_{it} \}$ to the cyclical part CX_{it} of X_{it} , we only take into account the influence of y_{it} when y_{it} and X_{it} have the same sign. Accordingly, the contribution $A_{ikt}(y)$ is characterized, after normalization, as:

$$A_{ikt}(y) = \frac{1_{\text{sign}(y_{it})} y_{it}}{\sum_{k=1}^5 1_{\text{sign}(\phi_{ikt})} \phi_{ikt} + 1_{\text{sign}(\xi_{it})} \xi_{it}} \quad (11)$$

$1_{\text{sign}(y_{it})} = 1$ if y_{it} and X_{it} have the same sign and $1_{\text{sign}(y_{it})} = 0$ otherwise.

Figure 2 displays for the four countries the cumulative contribution of each common factors and the idiosyncratic component to the cyclical part of the corresponding GDP. It is worth emphasizing that the first non stationary factor is generally the main source of the common cyclical variation with the exception of Germany, where the third factor has a more significant contribution than in the other countries.

[Insert Figure 2]

The results from Figure 2 are also summarised in Table 1, which provides the average contribution of the different factors for various sample periods. We observe that for all countries, the contribution of factor 1, our BCI, to the GDP business cycle is increasing over time. According to column 1, it

rose from 46 to 63% in France between the 1980-1992 period and the 1993-2003 period, from 39 to 49% in Germany and from 41 to 58% in Spain (Italy is quasi-stable, from 36 to 35%, before increasing to 51% during the 2000-2003 period). At the same time, the idiosyncratic part of the national business cycle has generally significantly decreased since the 1990s (see contribution in last column). It dropped from 36 to 18% in France between the 1980-1992 period and the 1993-2003 period, from 41 to 20% in Germany and from 37 to 3% in Spain. The reduction occurred in the years 2000 in Italy. Overall, this is in favour of the idea of increasing convergence among the four countries. Taking into account the common trend co-movements appears therefore decisive to characterize the business cycle and the European convergence process.

[Insert Table 1]

Conclusion

In the paper we apply a large-scale factor model recently developed by B2004 and BN2004 to extract common stationary and non-stationary factors in the euro area. We find that the euro area economies share three common non-stationary factors. The first factor is close to the euro area GDP in the second part of the sample. It is used to build a coincident indicator of the euro area that constitutes a benchmark to which the largest countries appear to have converged.

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Table 1: Contribution of the Different Factors to National GDP at Business Cycle Frequency

	%	<i>Fact 1</i>	<i>Fact 2</i>	<i>Fact3</i>	<i>Fact 4</i>	<i>Fact 5</i>	<i>Idiosyncratic</i>
France	1980-1992	29	1	7	0	27	36
	1993-2003	46	6	15	0	15	18
	2000-2003	63	5	16	0	5	12
	2003	63	2	17	0	1	16
Germany	1980-1992	19	0	27	2	11	41
	1993-2003	39	0	37	2	2	20
	2000-2003	49	1	36	3	3	9
	2003	52	0	41	1	3	3
Italy	1980-1992	36	0	14	8	2	40
	1993-2003	35	0	13	5	0	47
	2000-2003	51	0	14	2	0	33
	2003	76	0	22	2	0	0
Spain	1980-1992	41	5	12	0	5	37
	1993-2003	58	12	20	0	7	3
	2000-2003	71	9	17	0	1	3
	2003	76	4	20	0	0	0

Figure 1: Euro Area GDP and Confidence Interval around Factor 1 (in logarithms)

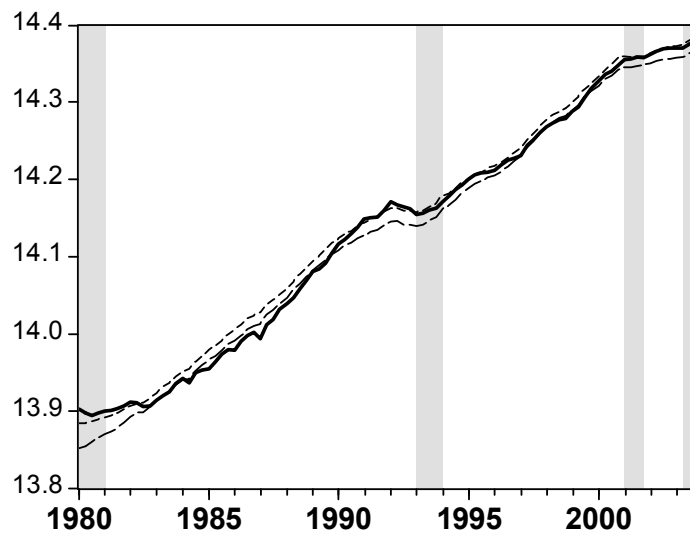


Figure 2: Contribution to Concordance of Business Cycles (GDP at business cycle frequency)

