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Economic cycles and their synchronization: Spectral analysis of macroeconomic series from Italy, The Netherlands, and the UK

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Abstract: The present work applies several advanced spectral methods ((Ghil, et al., 2002)) to the analysis of macroeconomic fluctuations in Italy, The Netherlands, and the United Kingdom. These methods provide valuable time-and-frequency-domain tools that complement traditional time-domain analysis, and are thus fairly well known by now in the geosciences and life sciences, but not yet widespread in quantitative economics. In particular, they enable the identification and characterization of nonlinear trends and dominant cycles – including seasonal and multi-annual components – that characterize the behavior of each time series. These tools are therewith well adapted to the analysis of short and noisy data, like the macroeconomic time series analyzed herein.

We explore five fundamental indicators of the real aggregate economy – namely gross domestic product (GDP), consumption, fixed investments, exports and imports – in a univariate as well as multivariate setting. A single-channel analysis by means of three independent spectral methods – singular spectrum analysis (SSA), the multi-taper method (MTM), and the maximum-entropy method (MEM) – reveals very similar near-annual cycles, as well as several longer periodicities, in the macroeconomic indicators of all the countries analyzed.

Since each indicator represents different features of an economic system, we combine them to infer if common oscillatory modes are present, either among different indicators within the same country or among the same indicators across different countries. Multichannel-SSA (M-SSA) reinforces the previous results.

The present work concludes with a study of the synchronization of economic fluctuations, which follows a similar study of macroeconomic indicators for the United States ((Groth, Ghil, S., & Dumas, 2009)). Since business cycles are not country-specific phenomena, but show common characteristics across countries, our aim is to uncover hidden global behavior across the European economies (cf. (Mazzi & Savio, 2006)).

Keywords: Economic Cycles; Synchronization; Spectral Analysis; Advanced Time Series Analysis.

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1. Introduction

The nature of aggregate fluctuations is one of the most controversial topics in Macroeconomics: since the first systematic time series analysis on France, England, and the US aggregates ((Juglar, 1862)), a recurrent behavior of economic crises has been hypothesized, with strong interdependence between boom and recession phases. About a century and a half later, the debate on the nature and causes of economic fluctuations is still open and some fundamental issues like the exogenous/endogenous nature of business cycles and their propagation mechanisms are still unsolved ((Slutsky, 1927); (Frisch, 1933); (Kaldor, 1940); (Hicks, 1950); (Goodwin, 1967); (Kydland & Prescott, 1982); (Long & Plosser, 1983); (King & Rebelo, 2000); (Chiarella, Flaschel, & Franke, 2005)).

By the way, it is well acknowledged that business cycles are multi-country phenomena, showing common characteristics across countries ((Woitek, 1996); (Dickerson, Gibson, & Tsakalotos, 1998); (Den Haan & Sumner, 2001); (De Haan, Inklaar, & Sleijpen, 2002); (Süssmuth, 2002); (Stock & Watson, Understanding changes in international business cycle dynamics, 2005); (Mazzi & Savio, 2006)). Though, there is still no accordance about the characterization of comovements, the existence of supranational (e.g. European, G7) cycles, and the determinants of economic synchronization. In fact, both theoretical and empirical contributions suggest contrasting results, partly due to different data and diverging methodologies ((de Haan, Inklaar, & Jong-A-Pin, 2008)). On the one side, some scholars advocate that economic and capital integration encourages the emergence of specialized production structures, so that sector-specific shocks essentially become region-specific ((Krugman, 1993); (Kalemli-Ozcan, Sørensen, & Yosha, 2001)) and countries with similar production patterns experience correlated business cycles ((Imbs, 2004); (Calderon, Chong, & Stein, 2007)). However, this fact is not always verified ((Otto, Voss, & Willard, 2001); (Baxter & Kouparitsas, Determinants of business cycle movement: a robust analysis, 2005)). On the contrary, the removal of trade barriers should intensify synchronization, because of the transmission of demand shocks and knowledge and technological spillovers ((Coe & Helpman, 1995); (Frankel & Rose, 1998)). Empirically, the effect of trade intensities on business cycle comovements is not clear ((Gruben, Koo, & Millis, 2002); (Calderon, Chong, & Stein, 2007)); (Baxter & Kouparitsas, Determinants of business cycle movement: a robust analysis, 2005)). Finally, the impact of monetary and financial integration on synchronization is ambiguous. On the one side, the less asymmetric monetary policies and the more stable exchange rates and trading relations should have a positive impact on synchronization ((Inklaar & De Haan, 2001); (De Haan, Inklaar, & Sleijpen, 2002)); on the other side, the fixed exchange rates should have a negative impact, since eventual asymmetric shocks are now discharged on the real economy ((de Haan, Inklaar, & Jong-A-Pin, 2008)).

Our work is a quantitative inquiry about economic cycles and synchronization by spectral analysis of quarterly macroeconomic indicators (GDP, consumption, fixed investment, export, import) from Italy, the

UK, and The Netherlands. These countries have been selected because they are European economies with different magnitudes and socio-economic characteristics (see section 2).

Our approach is quite innovative in this kind of applications and slightly different from standard macroeconometric analysis, since it basically relies on time-and-frequency-domain methods. These are widely spread in digital signal processing, oceanography, meteorology, and so on, but quite neglected in socio-economic fields. In fact, economic time series are generally short, noisy, and heavy trended, so that classical estimated spectra cannot reveal high frequencies eventually characterizing the data ((Granger & Hatanaka, Spectral Analysis of Economic Time Series, 1964); (Granger, The typical spectral shape of an economic variable, 1966); (Granger, Investigating causal relations by econometric models and cross-spectral methods, 1969)). New developments in spectral estimation techniques help to curb such drawback, allowing useful applications in various economic contexts ((Lisi & Medio, 1997); (Higo & Nakada, 1998); (Atesoglu & Vilasuso, 1999); (Baxter & King, Measuring business cycles: approximate band-pass filters for economic time series, 1999); (A'Hearn & Woitek, 2001); (Süssmuth, 2002); (Aadland, 2005)). Moreover, they support a richer description of multivariate phenomena with respect to standard time-domain methods ((Croux, Forni, & Reichlin, 2001)), which is particularly attractive in business cycles analysis because of their multivariate character.

In the present work we mostly apply Singular Spectrum Analysis (SSA) to the selected indicators, in a univariate as well as multivariate context. SSA is well suited in analyzing short, chaotic[f], and noisy time series, without requiring particular properties of stationarity or ergodicity ((Ghil, et al., 2002)). It is a non parametric technique. Accordingly, it does not require any *a priori* modeling, but it allows a rigorous description, quantification, and extraction of the long, medium, and short term components of the series analyzed ((Iacobucci, 2003)). The univariate framework allows us to investigate the behavior of each indicator separately, extracting the dominant periodic and quasi-periodic oscillations which account for most of the series variability, and comparing the results with similar univariate studies ((Süssmuth, 2002)). On the other hand, the multivariate context allows us to gain deeper insights into the common behavior of business fluctuations, both across countries and across indicators.

The paper is divided into 6 sections: an introduction, a description of the dataset and the methodology, a univariate spectral analysis of the macroeconomic series, an extension to a multivariate spectral analysis, and conclusions.

[f] Evidence of chaos in economic data has not been confirmed, but (Broomhead & King, 1986) demonstrate that SSA works well even in the case of mildly nonlinear processes, as economic series prove to come from ((Brock, Distinguish random and deterministic systems: abridged version, 1986); (Neftci & McNevin, 1986); (Brock & Sayers, Is the business cycle characterized by deterministic chaos?, 1988); (Frank & Stengos, 1988); (Serletis, 1996); (Stanca, Asymmetries and nonlinearities in Italian macroeconomic fluctuations, 1999); (Brock, Whither nonlinear?, 2000)).

2. Dataset description and pre-processing

Our analysis is based on the quarterly national accounts of Italy, the UK, and The Netherlands[g]. For each country we analyze GDP at market prices, final consumption expenditure, gross fixed capital formation, exports and imports of goods and services. This choice has been motivated by the attempt to seize the multivariate character of business fluctuations. All series are expressed in constant euros (base year 2000). They are seasonally adjusted and corrected by working days[h].

The series refer to different time spans, covering 54 years for the UK (1955:01 – 2008:04, N=216), 32 years for The Netherlands (1977:01 – 2008:04, N=128), and 28 years for Italy (1981:01 – 2008:01, N=112). The left panel in Fig. Figure 1 shows the raw series and the corresponding Hodrick-Prescott (HP) trends, obtained by applying an HP filter ((Hodrick & Prescott, 1997)) with the recommended smoothing parameter for quarterly time series ($\lambda = 1600$). The whole analysis is performed on the HP residuals, normalized by the trend itself and standardized (right panel). This pre-processing guarantees that multivariate cross-correlations are not distorted by the relative magnitude of the trends.

Figure 1 shows some peculiarities of the dataset. The Netherlands are a small open economy, with relatively low GDP (in absolute values) but very high shares of imports and exports[i]. Consequently, they are more exposed to international shocks with respect to Italy and the UK, whose economy is more closed. More in details, the UK are mostly linked to the US economy, while Germany is the most important commercial partner for Italy[j]. Bilateral trade represents a channel for the diffusion of both international and country-specific shocks, yielding to synchronization among different economic systems.

The UK experiences the most strong fluctuations, as we can observe from its GDP residuals (not shown). This could be mostly due to the flexible structure of its labour market. In fact, the low bargaining power of its trade unions allows more flexible adjustments in both wages and employment, thus determining more rapid responses to both positive and negative shocks, together with more sudden recessions and more pronounced expansions. On the contrary, the high bargaining power of the Italian trade unions causes a more rigid reaction of the entire economy[k]. The Netherlands stand in the middle, showing a labour market structure close to the Scandinavian typology ((Esping-Andersen, 1999)).

[g] The quarterly national accounts are compiled in accordance with the European System of Accounts (ESA95). Data are available from EUROSTAT on the web at http://epp.eurostat.ec.europa.eu/.

[h] EUROSTAT adjusts the series from Italy and the UK following the TRAMO-SEATS procedure for both seasonal and working days corrections ((Maravall, 2005)). EUROSTAT data for the Netherlands are simply seasonally adjusted, so we correct them by working days following the TRAMO-SEATS protocol.

[i] In 2008 the share of imports on GDP is around 28% for Italy, 34% for the UK, and 77% for The Netherlands. The shares of exports are about 28%, 29%, and 84% respectively.

[j] In 2000 the UK exported to the US the 15.4% of its total exports and imported from them the 13.2% of its total imports, while Italy exported the 14.5% to Germany and imported the 17.7% from it (source: our elaborations from (Feenstra, Lipsey, Deng, Ma, & Mo, 2005)).

[k] For instance, Italian Collective Agreements address very complex firing procedures to firms larger than 15 workers. As a consequence, both medium- and large-size firms are discouraged to vary their employment level.

Another important factor is the availability of energetic resources. While the UK and The Netherlands own a direct access to natural energetic sources, Italy is a strong oil net importer. Thus, energetic shocks affect the Italian economy much more strongly than the other two countries, with consequent impacts on its business fluctuations. For example, an enlargement of the HP trend of the Italian GDP would show how the 1973 and 1979 energetic shocks lengthened the Italian recession phase in the early 80s.

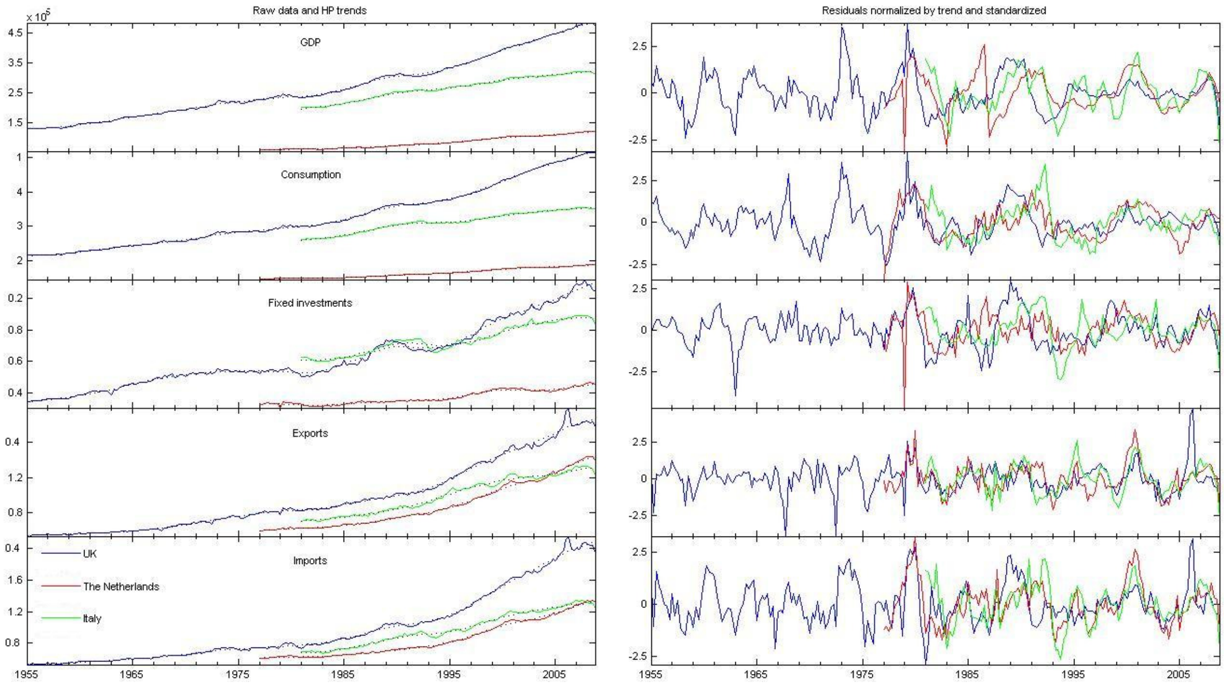

Figure 1 – Time series of GDP, consumption, fixed investments, exports and imports for the UK, Italy, and The Netherlands. Left panel: raw series (expressed in 2000-euros) and Hodrick-Prescott trends (dotted lines); right panel: trend residuals normalized by the trend and standardized. It is quite evident an underlying cyclical structure, which is the subject of our analysis. Source: elaborations from EUROSTAT data.

3. Methodology

Singular Spectrum Analysis (SSA) is a non-parametric spectral method specially designed to get information about the dynamics of non-linear systems without appealing to the equations of the underlying process ((Vautard & Ghil, Singular spectrum analysis in nonlinear dynamics, with applications to paleoclimatic time series, 1989); (Vautard, Yiou, & Ghil, Singular-Spectrum Analysis: a toolkit for short, noisy chaotic signals, 1992); (Allen & Smith, 1996); (Ghil, et al., 2002)). This technique helps to overcome some drawbacks affecting the study of short and noisy discrete time series, i.e. the finite length of the sample and the noisiness, which typically characterize experimental datasets. The goal of SSA is to identify the different components of the analyzed signal (e.g. trends, oscillatory patterns, random noise), rather than fitting a parametric model to the data.

The concept of SSA is firstly to embed the time series in a sufficiently high dimensional time-delayed embedding ((Mañé, 1981); (Takens, 1981)), and then to find a new orthonormal system which describes most of the time series variance by means of few components only. This new linear system is determined by a principal component analysis ((Broomhead & King, Extracting qualitative dynamics from experimental data, 1986)). In other words, this technique provides a linear decomposition of the time series into a new orthogonal system, where the new coordinate system is given as the principal components in a time-delayed embedding of the time series. With respect to a classical Fourier decomposition, the new orthogonal system is no more restricted to sine and cosine functions, but rather it consists of data-adaptive functions ((Allen & Smith, 1996)). Consequently, the detected oscillations may show amplitude and/or phase modulation. Such flexibility clearly represents a notable advantage when dealing with complex dynamical systems, as in economics.

3.1. Single-channel SSA

This paragraph contains a brief description of univariate SSA. Given a univariate time series $\{x(t), t = 1,...,N\}$, we embed it into an M-dimensional phase space by using M lagged copies of it ((Mañé, 1981); (Takens, 1981)):

$$\mathbf{x} = \begin{pmatrix} x(1) & x(2) & \dots & x(M) \\ x(2) & x(3) & \dots & x(M+1) \\ .. & \dots & \dots & \dots \\ x(N-M+1) & x(N-M+2) & \dots & x(N) \end{pmatrix}.$$

From this new M-dimensional embedded time series we estimate the MxM lag-covariance matrix $\boldsymbol{C}$. It is directly estimated from the data as a Toeplitz matrix with constant diagonals, i.e. its entries c_{ij} depend only on the lag $|i\text{-}j|$ ((Vautard & Ghil, Singular spectrum analysis in nonlinear dynamics, with applications to paleoclimatic time series, 1989)):

$$c_{ij} = \frac{1}{N-|i-j|} \sum_{t=1}^{N-|i-j|} x(t)x(t+|i-j|).$$

The eigenvalues λ_k and eigenvectors $\mathbf{E}_k$ of $\mathbf{C}$ are determined, where $\mathbf{E}_k$ represent the new M-dimensional orthonormal basis and λ_k describes the variance in the direction determined by $\mathbf{E}_k$. The trace $Tr\{\mathbf{C}\}$ gives the total variance of the original series $x(t)$ ((Ghil, et al., 2002)). From the spectrum of eigenvalues, i.e. the sequence of eigenvalues put in descending order, we can distinguish at first sight between the relevant part of the signal and noise by finding a threshold to a "noise floor". In order to identify periodic or quasi-periodic activity in the original signal, (Vautard & Ghil, Singular spectrum analysis in nonlinear dynamics, with applications to paleoclimatic time series, 1989) suggest to adopt such spectrum, since the near-equality of eigenvalue pairs whose eigenvectors are in phase quadrature may be associated with oscillatory patterns ((Ghil & Mo, Intersesonal oscillations in the global atmosphere. Part I: Northern Hemisphere and Tropics, 1991)).

By projecting the embedded time series $\boldsymbol{x}(t)$ onto the k-th eigenvector $\{\mathbf{E}_j^k : 1 \le j \le M\}$, we get the so-called Principal Component (PC) $\mathbf{A}_k$:

$$\mathbf{A}_k(t) = \sum_{j=1}^{M} \mathbf{x}(t+j-1)\mathbf{E}_j^k \text{ with } 1 \le t \le N-M+1 .$$

The PCs, however, are shorter than the original series and do not provide phase information. In order to reconstruct the time series, we are able to study various aspects by restricting to a subset κ of the eigenvectors:

$$\mathbf{R}_\kappa(t) = \frac{1}{M_t} \sum_{k \in \kappa} \sum_{j=L_t}^{U_t} \mathbf{A}_k(t-j+1)\mathbf{E}_j^k ,$$

where (M_t, L_t, U_t) is (t, 1, t) for $1 \le t \le M$; (M, 1, M) for $M \le t \le N-M+1$; ($N-t+1$, $t-N+M$, M) for $N-M+2 \le t \le N$ ((Ghil, et al., 2002)). The $R_\kappa(t)$ are called Reconstructed Components (RCs) and capture the variability associated with the eigenvalues of interest $\{\lambda_k : k \in \kappa\}$. No information is lost during this reconstruction process, since the sum of all individual RCs gives back the original time series ((Ghil, et al., 2002)).

3.2. Multi-channel SSA

Multi-channel SSA (MSSA) is simply the multivariate extension of single-channel SSA ((Broomhead & King, On the qualitative analysis of experimental dynamical systems, 1986b)). It analyses a multivariate set of time series (input channels) with the goal of identifying and extracting the dominant spatio-temporal structures of the underlying stochastic process. In particular, MSSA emphasizes the oscillatory patterns common to most time series in the sample, i.e. the periodicities intrinsic to most channels.

Given an L-channel[I] vector time series $\mathbf{x}(t) = \{x_l(t) : l = 1,\ldots,L, t = 1,\ldots,N\}$ of length N, its $LM \times LM$ grand covariance matrix $\tilde{\mathbf{C}}$ contains all auto-covariances $\boldsymbol{C}_{l,l}$ and cross-covariances $\boldsymbol{C}_{l,l'}$

$$\tilde{\mathbf{C}} = \begin{pmatrix} \mathbf{C}_{1,1} & \mathbf{C}_{1,2} & \cdots & \mathbf{C}_{1,L} \\ \mathbf{C}_{2,1} & \mathbf{C}_{2,2} & \cdots & \mathbf{C}_{2,L} \\ \vdots & \cdots & \mathbf{C}_{l,l} & \vdots \\ \mathbf{C}_{L,1} & \mathbf{C}_{L,2} & \cdots & \mathbf{C}_{L,L} \end{pmatrix},$$

where the entries of each block $\boldsymbol{C}_{l,l'}$ are estimated by

$$\left(\mathbf{C}_{l,l'}\right)_{i,j} = \frac{1}{\tilde{N}} \sum_{t=\min\{1,1+i-j\}}^{\max\{N,N+i-j\}} x_l(t) x_{l'}(t+i-j) ,$$

and $\tilde{N} = \min\{N, N+i-j\} - \max\{1, 1+i-j\} + 1$. Similarly to the univariate case, the grand covariance matrix is diagonalized and the LM eigenpairs $\left(\lambda_k, \tilde{\mathbf{E}}_k\right)$ are obtained by solving the corresponding

[I] Each channel is assumed to be centred and weakly stationary.

eigenvalue problem. In this case, however, MSSA decomposes the spatio-temporal variability of the multivariate dataset into a set of spatial patterns (EOFs) and temporal patterns (PCs). Each MSSA-EOF consists of L consecutive segments of length M $\left(\mathbf{E}_k^l : 1 < l < L; 1 < k < M\right)$, which display spatial structure. They vary from channel to channel, thus allowing to inspect how strongly the corresponding MSSA mode is present in a particular channel with respect to the other ones. On the contrary, the associated MSSA-PCs are obtained by projecting the multivariate time series onto $\mathbf{E}_k^l$:

$$\mathbf{A}_k(t) = \sum_{j=1}^{M}\sum_{l=1}^{L} \mathbf{x}_l(t+j-1)\mathbf{E}_k^l(j), \quad 1 < k < M \;,$$

thus producing single-channel time series.

As in the univariate case, it is possible to reconstruct a detected MSSA mode for each selected channel, but the RCs may differ from channel to channel:

$$\mathbf{R}_k^l(t) = \frac{1}{M_t}\sum_{j=L_t}^{U_t} \mathbf{A}_k(t-j+1)\mathbf{E}_k^l(j), \quad 1 < k < M,\; 1 < l < L \,,$$

thus inspecting how that particular mode influences each time series. Moreover, a single oscillation can be significant for all time series, even if the fraction of variance it accounts for is not the same in all channels. This means that such oscillation is more energetic in a specific input variable rather than in the other ones. Thus, MSSA allows to inspect the spatio-temporal behaviour of each channel with respect to the other ones, rather than the temporal and spatial evolution of the global process only.

3.3. Monte Carlo SSA (MC-SSA)

A fundamental step in spectral analysis is the distinction of “interesting” components (signal) from noise. When either the S/N ratio is not sufficiently large or the noise affecting the data is not simply white but “coloured”, the traditional signal extraction approach, based on the identification of gap in the spectrum of eigenvalues between a few important eigenvalues and a remaining noise floor of less important eigenvalues, becomes problematic. Thus, an alternative statistical approach based on Monte Carlo simulation techniques has been proposed (Ghil and Vautard, 1991; Vautard et al. 1992).

In particular, the Monte-Carlo SSA technique (MC-SSA) proposed by Allen (1992) gives the statistical significance of the extracted spectral components by testing the original data set against a red noise null-hypothesis, i.e. against an autoregressive (AR) process of order 1 (Allen and Smith, 1996; Ghil and Yiou, 1996; Ghil and Taricco, 1997) defined as:

$$X(t) = a_1\left[X(t-1) - X_0\right] + \sigma\xi(t) + X_0 \,,$$

where X_0 is the process mean, $a_1$and σ are the constant coefficients to be estimated and ξ is a Gaussian-distributed white noise process with zero mean and unit variance.

Once the model describing the underlying process is assumed, the first step in MC-SSA is to estimate the red-noise coefficients $a_1$and σ by maximum-likelihood criterion. Then, a Monte Carlo ensemble of surrogate data is generated from the estimated model and compared with the real data. More precisely, for each realization of the model a covariance matrix C_R is computed and projected onto the eigenvector basis E_X of the original data, as it follows:

$$\Lambda_R = E_X^t C_R E_X$$

The matrix L_R, not necessarily diagonal, allows to determine the degree of resemblance between the generated surrogates and the original data, by computing the statistical distribution of its diagonal elements. From these distributions we obtained confidence intervals outside which the time series' eigenvalues can be considered significantly different from a generic red noise simulation. Notice that if we can reject the most likely AR(1) process, we can be confident to reject all other red noise processes at the same or higher confidence level (Ghil et al. 2002)

In the multivariate case of M-SSA, we follow the approach of Allen and Robertson (1996). That means we first perform a standard principal component analysis (PCA) on the given L channels in order to obtain L pairwise uncorrelated principal components (PCs). In a next step, we fit on each of these PCs an independent AR(1) process as in the univariate case. Our null hypothesis is therefore that these PCs can be generated by L independent AR(1) processes. We do not directly test the given time series, since they are correlated and a test for independent AR(1) processes is likely to be rejected; even by a simple visual inspection of the data set. An alternative would be that of a vector AR(1) process. However, this model is inappropriate for the test of oscillations, since a vector AR(1) process supports itself oscillations (Principal oscillation patterns, Von Storch et al., 1995).

Having formulated the model in our null hypothesis, we proceed as before in the univariate case; that means we determine the covariance matrix for every realization and project it onto the M-SSA eigenvectors of the PCs in order to assess whether the M-SSA eigenvalues of the PCs exceed the level of variation of the null hypothesis. If this is the case, it holds also for the M-SSA eigenvalues of the original data set x, because the M-SSA eigenvalues of x and the ones of the PCs are the same.

4. Univariate SSA

In this section we extract and reconstruct by SSA[m] the dominant periodicities which mainly characterize the macroeconomic aggregates in our sample. The following section presents the results obtained by a univariate analysis of the residuals of HP detrending, normalized by the trend itself and standardized. This transformation is needed, since raw economic variables are typically characterized by pervasive trends, which clearly determine the shape of their estimated power spectra[n]. In fact, they typically show a large bump at the zero frequency band, which is quickly but smoothly reabsorbed in the neighbouring bands ((Granger, The Typical Spectral Shape of an Economic Variable, 1966)). If detrending procedures fail to remove any possible trend, this shape persists Figure 2 illustrates the issue for the UK quarterly GDP series. After detrending by the HP filter (right panel), the estimated spectrum ((Blackman & Tukey, 1958)) shows three main peaks, respectively associated to periodicities of about 9, 5, and 3 years. This suggests the presence of such (quasi-)periodic components in the analyzed series, effectively confirmed by further analysis.

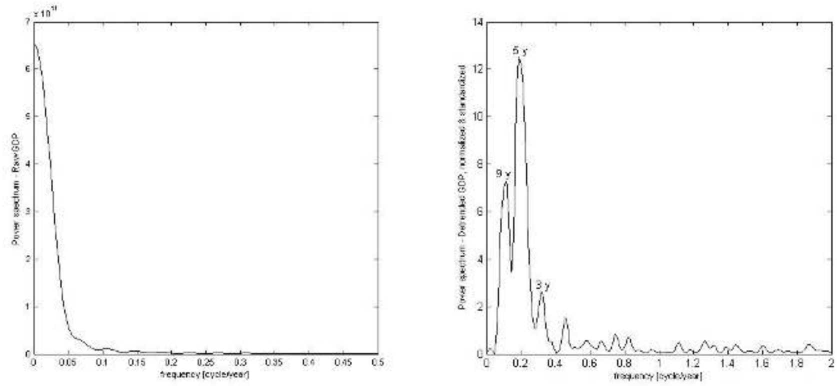

Figure 2 – UK GDP: Blackman-Tukey power spectra for the raw series (left panel) and the transformed HP residuals (right panel) with Hanning window of length M = 100.

As an illustrative application of SSA, we discuss in detail the results of the transformed HP residuals of the UK GDP series. Then, other univariate results are briefly explained.

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[m] We use the freeware software "SSA-MTM Toolkit" developed by the Theoretical Climate Dynamics Group at UCLA (http://www.atmos.ucla.edu/tcd/ssa/).

[n] The power spectrum of a time series describes how its power (or variance) is distributed with frequency. A single line or a finite number of lines in the spectrum indicates that the underlying process is purely periodic or quasi-periodic. On the contrary, a smooth and continuous spectrum reveals an irregular motion, which excites all frequencies in the analyzed band. When an estimated spectrum shows some spectral peaks superimposed on a continuous and wiggly background, it reveals some periodic or quasi-periodic component embedded in a noise background ((Ghil, et al., 2002)).

Section 3 describes how SSA decomposes a time series into its relevant components and the remaining uninformative part. A first step consists in evaluating the eigenvalues of the lag-covariance matrix, which indicate the fraction of the series total variance explained by the corresponding eigenvectors. Figure 3 shows the Monte Carlo singular spectrum of the transformed UK GDP series. Eigenvalues are plotted versus frequency, together with error bars, representing the 95% of the range of variance found in the direction of the corresponding eigenvector in an ensemble of 1000 red noise realizations ((Allen & Smith, 1996)). Hence, the eigenvalues lying outside the corresponding error bars are very unlikely to be due to a red noise process.

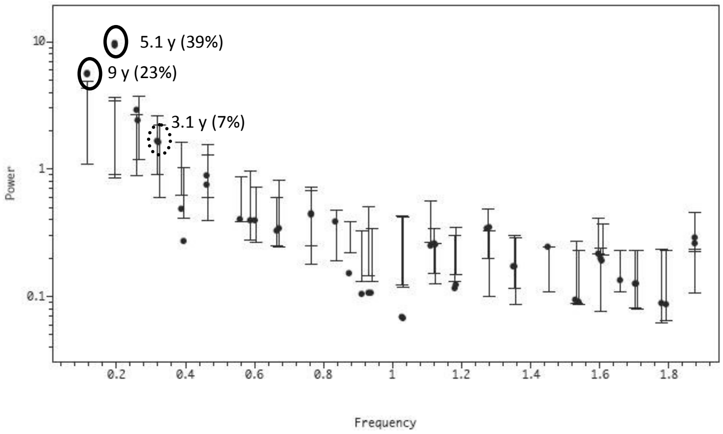

Figure 3 – UK GDP: Monte Carlo singular spectrum of the transformed residual series with M = 50. The dots represent the eigenvalues, while the lower and upper ticks of the error bars represent the 2.5th and 97.5th red noise percentiles. The bold circles indicate the significant eigenvalue pairs (1-2 and 3-4), which correspond to oscillatory behavior of about 5- and 9-year periodicity. The dotted circle indicates an eigenvalue pair (7-8) which is not significantly different from noise.

In this particular case, the eigenvalues 1-2 and 3-4 (bold circles) indicate components whose power is significantly different from the simulated red noise. The nearly-equality of these eigenvalue pairs suggests that they potentially represent oscillatory patterns. In fact, first of all they explain more or less the same variance in the series, and secondly the corresponding eigenvectors are nearly in phase quadrature and associated to the same characteristic frequency (result not shown). An estimate of the characteristic frequency reveals that the pair 1-2 is associated with an oscillatory pattern of about 5 years, which explains the 39% of the series total variance, while the pair 3-4 reveals a 9-year oscillation capturing the 23% of the total variance. On the contrary, the pair 7-8 (dotted circle in Figure 3) is associated with a 3-year pattern which cannot be distinguished from a red noise component at the 95% confidence level.

Extending the same univariate exercise to all time series, similar oscillatory patterns are recurrently detected, which satisfy all required features, i.e. nearly-equality of the eigenvalues, phase quadrature of the eigenvectors, and same characteristic frequency. Table 1 summarizes the findings by country and variable, neglecting some uninteresting near-annual behaviour. All results are robust to moderate variations in the window length M[o]. The black dots in the table indicate the patterns which are significantly different from simulated red noise components at the 95% confidence (90% for Italian series).

	9 y	5 y	3 y
UK			
GDP	● (23%)	● (39%)	○ (7%)
Consumption		● (22%)	○ (4%)
Fixed investments		● (35%)	○ (7%)
Exports		● (18%)	● (15%)
Imports		● (25%)	
The Netherlands			
GDP		● (44%)	
Consumption	○ (48%)		○ (3%)
Fixed investments	● (33%)		
Exports		● (38%)	● (9%)
Imports		● (39%)	○ (9%)
Italy			
GDP		● (40%)	○ (20%)
Consumption	● (59%)		● (13%)
Fixed investments		○ (25%)	○ (6%)
Exports		● (45%)	● (16%)
Imports		○ (17%)	● (29%)
Total # of findings	4/15	12/15	12/15

Table 1 – Univariate SSA: summary of results. The dots indicate detected patterns. The black dots indicate the patterns significantly different from simulated red noise components at the 95% confidence (90% for Italian series) in an ensemble of 1000 noise realizations. Partial variances in parentheses.

The table suggests quite homogeneous cyclical behaviour among the indicators of Italy, the UK, and The Netherlands. Notwithstanding the different time spans covered and the peculiarities of each economy, three similar business fluctuations[p] recurrently emerge:

- a longer oscillation of about 9 years, which is hardly detected;
- a medium fluctuation of about 5 years, significantly isolated in quite all series;

[o] The dimension of M is fundamental in determining the spectral resolution, since the larger M, the higher periodicities can be detected. However, excessively large windows make the autocovariance function dominated by statistical error. (Vautard, Yiou, & Ghil, Singular-Spectrum Analysis: a toolkit for short, noisy chaotic signals, 1992) suggest that SSA is typically successful for periods in the range (M/5, M). In our analysis the lag-covariance matrix is estimated directly from the data by the Vautard-Ghil algorithm ((Vautard & Ghil, Singular spectrum analysis in nonlinear dynamics, with applications to paleoclimatic time series, 1989)).

[p] In literature there is no full agreement about the effective extension of business cycles, but it is quite common to consider them the result of an about 2-8 (or 10) years data generating process ((Crivellini, Gallegati, Gallegati, & Palestrini, 2007)).

- a shorter oscillation of about 3 y, which is generally not too powerful and often falls in the noisy floor of the spectrum.

As mentioned above, all these patterns can be isolated from the original series and reconstructed in the time domain by SSA, helping to investigate some features of the data. In particular, the flexibility of the method allows to inspect both amplitude and phase modulation ((Ghil, et al., 2002)).

As an exampleFigure 4 plots the reconstructions of the about 5-year oscillations detected in the GDPs. All patterns are significant against red noise at the 95% confidence and represent the dominant periodicity in the GDP, exhibiting partial variances in the range 39% - 44%. The reconstruction for the UK shows an increase in amplitude (i.e. in the variance of the pattern) in correspondence of the huge energetic shocks in 1973 and 1979. The shorter reconstruction for Italy shows the lengthening of the recession phase and the following stretched reprise in the early Eighties, due to both the energetic shocks and the subsequent counter-shock and dollar depreciation. Contrarily, the 5-year oscillation in exports shows very tiny modulation, revealing a more stable behaviour in the dominant pattern of the indicator (not shown).

The 9-year movement is hardly detected, since most time series are short. In all the UK series some pairing up of the corresponding eigenelements emerges, but the detection of an oscillatory pair is unambiguous just in the case of the GDP. Again, the reconstruction shows an increase in amplitude from the late Seventies to the early Nineties (not shown).

Finally, the 3-year fluctuation is generally less informative in the UK and The Netherlands, with partial variance in the range 3%-15%. On the contrary, its role is significant in all Italian series, particularly in imports and the GDP, as the following multivariate analysis shows Figure 5).

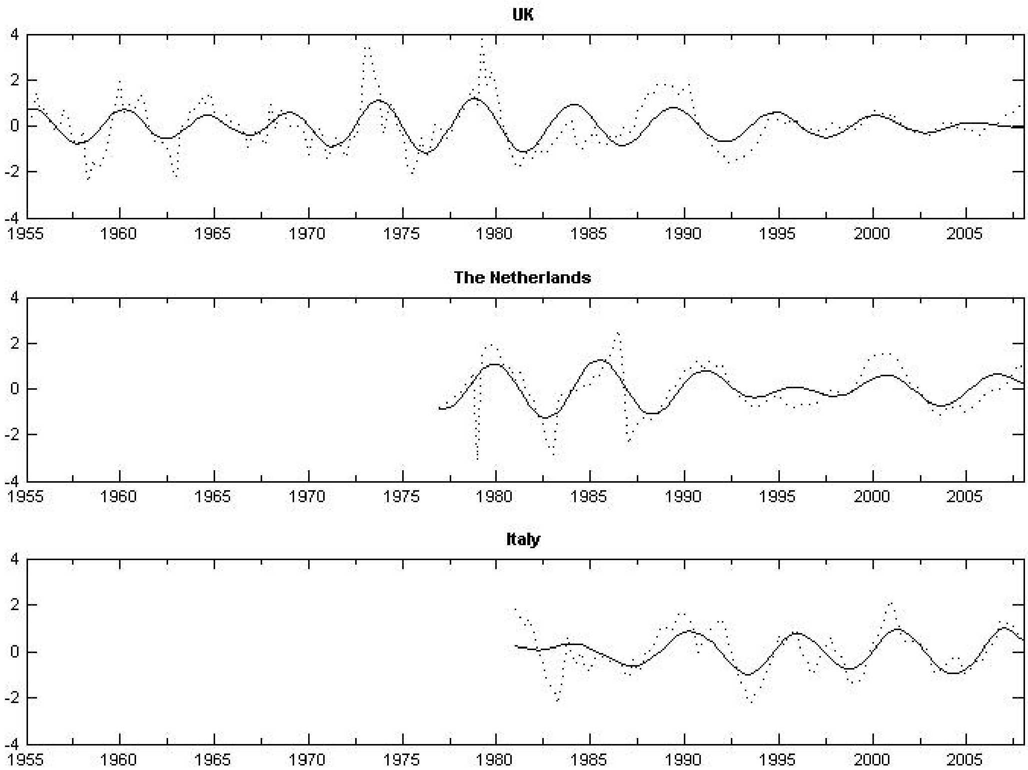

Figure 4 – SSA reconstruction of the 5-year oscillation in GDPs. The pattern is represented by the first two eigenpairs in each series, explaining the 39% of the total variance for the UK, the 44% for The Netherlands, and the 40% for Italy. *M* = 50, 45, 34, respectively.

These similar patterns are an evidence of common features in the dynamics of industrialized economies (cf. e.g. (Blanchard & Watson, 1987); (Stanca, Are business cycles all alike? Evidence from long-run international data, 1999); (Stock & Watson, Has the business cycle changed and why?, 2002); (Stock & Watson, Understanding changes in international business cycle dynamics, 2005)).

This intuition is further strengthen by the remarkable correspondence between our empirical findings and the theoretical predictions in NEDyM ((Hallegatte, Ghil, Dumas, & Hourcade, 2008)), a non-equilibrium dynamic model introducing investment dynamics and non-equilibrium effects into a Solow growth model, hence focusing on the effects of both institutional and technological inertia on the economic system. From simulations, NEDyM exhibits both endogenous business cycles of a few years in duration and some near-annual fluctuations. In particular, a 5/6-year periodicity emerges in profits, production, and employment, consistently with the mean business cycle period ((Zarnowitz, 1985); (King & Watson, 1996); (Kontolemis, 1997). However, further coupled theoretical-empirical research is necessary on such issue. In fact, so far NEDyM calibration is quite poor, but further agreements between empirical and simulated results could provide a substantial validation.

5. Multivariate SSA

In the previous section we have extracted typical oscillations that we can find in the individual countries and their different aggregates. In order to verify these univariate results and to see if these oscillations are linked, we now analyze the given time series by multivariate SSA (M-SSA).

The multivariate analysis is performed on two levels. On the first level we first analyze each country and its aggregates in a separate M-SSA. This is what we call “country based” analysis (Sec. 5.1). Next, we combine the same aggregates of all countries into a M-SSA and refer to this as “variable based” analysis (Sec. 5.2). Finally, we combine all aggregates into a single “global” M-SSA analysis (Sec. 5.3). This hierarchy allows us to investigate the existence of oscillatory modes pervading the whole (national) economies, as well as some regular behavior within particular indicators. Prior to M-SSA all trend residuals are standardized, say normalized to standard deviation one.

5.1. Country-based analysis

This section analyses all economic indicators by country, thus revealing the cyclical behaviour common to all indicators within a national economy. The main results are summarized in Table 2 and confirm the detection of the same oscillatory modes which dominate the univariate analysis.

	OSCILLATORY MODES		
COUNTRY	**9 y**	**5 y**	**3 y**
UK	×	×	
The Netherlands		×	×
Italy		×	×

Table 2 – MSSA: country-based results.

As in the previous case, the higher frequencies are not well established except for Italy, while the 9-year component prevails in the UK only. This finding strengthens the univariate analysis, which detects the 9-year pattern in an ambiguous form in all the UK indicators. As mentioned, the multivariate analysis detects the spatio-temporal patterns common to all channels, even when they do not dominate the single channels.

On the contrary, the 5-year oscillation is clearly shared by all countries. Moreover, there is generally a good agreement in amplitude and phase among the reconstructions of the shared periodicities. As an example, the left panel of Figure 5 shows the good agreement among the reconstructions of the 5-year oscillation in the UK indicators, while the right panel shows the 3-year pattern characterizing the Italian aggregates, as stressed by the univariate analysis too. Notice the clear lagging behaviour in the exports record with respect to all the other indicators.

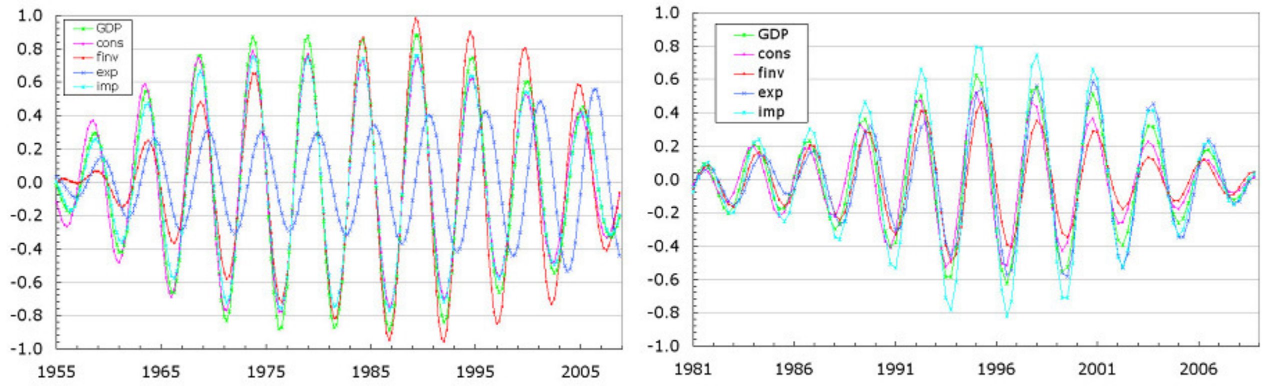

Figure 5 – MSSA: reconstruction of the 5-year pattern in the UK series (left panel) and the 3-year pattern in Italian indicators (right panel).

5.2. Variable-based analysis

This section is devoted to the comparison of each macroeconomic indicator in Italy, the UK, and The Netherlands, over the common time span (1981:01-2008:04). The results summarized in Table 3 turn out to be strongly in line with the previous findings, thus strengthening the evidence of common business fluctuations among the three countries.

	OSCILLATORY MODES		
INDICATOR	**9 y**	**5 y**	**3 y**
GDP	×	×	×
Consumption	×		×
Fixed investments	×	×	×
Exports		×	×
Imports	×		×

Table 3 – Multivariate SSA: variable-based results.

In particular, the 9- and 5-year patterns are alternatively detected, while the 3-year component is common to all variables and it is clearly more energetic in the Italian and Dutch indicators. Moreover, the 9-year reconstructions display almost similar amplitudes in all countries, but different phasing, with the UK leading. This phenomenon can be essentially imputed to two factors: on the one side the different international interdependencies, and on the other side the specific peculiarities of each economic system. In fact, the UK is highly influenced by the US, while both Italy and the Netherlands are more related to Germany and France. Moreover, the UK economy is generally more reactive to both external and internal shocks, being characterized by a flexible labour market which allows quite rapid adjustments. On the contrary, the two continental countries show lagged and more synchronized reactions.

Looking to the higher frequencies domain, the 5- and 3-year ciclicities show a global agreement among countries, especially concerning exports and imports (Figure 6). In a certain sense, this finding suggests a special role for trade as transmission mechanism of cyclical fluctuations across nations.

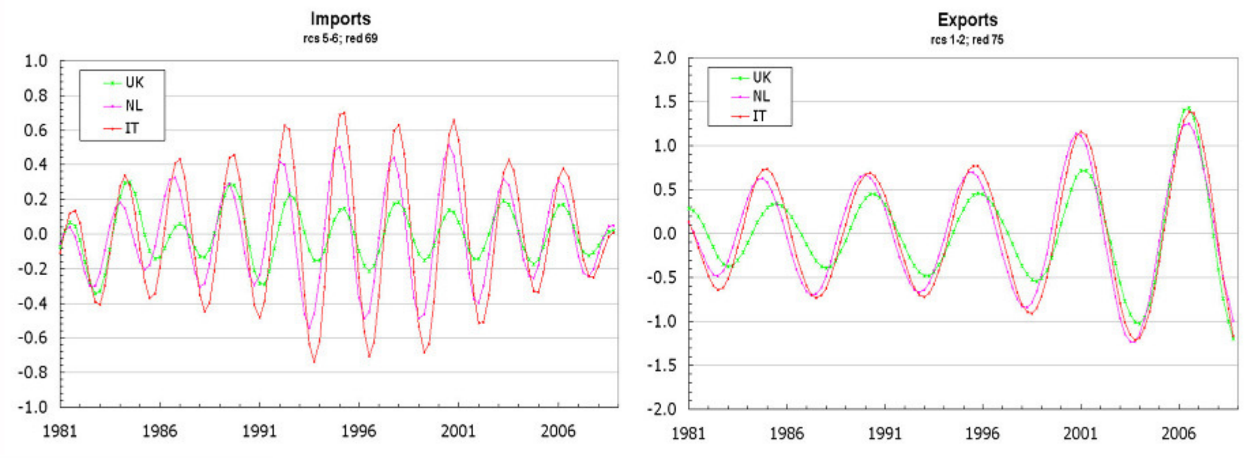

Figure 6 – MSSA: reconstruction of the 3-year pattern in imports (left panel) and of the 5-year pattern in exports (right panel).

5.3. Global Analysis

In this part we combine all given time series into a single M-SSA. This allows us to extract dynamical behavior in the full phase space spanned by all countries and their aggregates.

First of all we consider the spectrum of eigenvalues in order to get a first idea of global oscillatory modes (Figure 7).

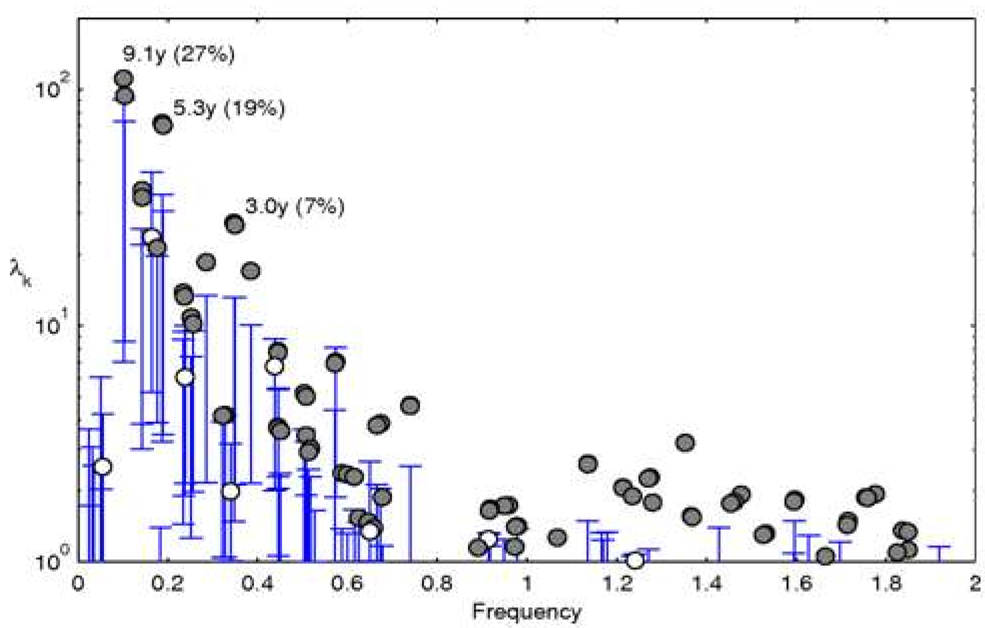

Figure 7 – Spectrum of eigenvalues from a global M-SSA of all 15 time series with M=50. The error bars indicate the 2.5% and 97.% percentiles of 1000 surrogate time series.

In good agreement with the previous findings, we identify again three significant oscillatory pairs with a period length of approximately 9.1 years, 5.3 years, and 3.0 years. This particular picture with window length M=50 suggest also the presence of other significant eigenvalues. However, a test with multiple values for the window length (M=20, 30, 40, 60) confirms only these three pairs as stable and significant. The longest period of 9.1 years is only weakly significant with eigenvalues slightly above the level of significance. This confirms the finding that this oscillation is hard to find in the different time series (see again Table 1). A problem is the short common time span from 1981 to 2008 that we have to restrict to in M-SSA and is likely to find this oscillation by chance in the surrogate time series. The both other much shorter oscillations, however, can be found more frequent in the individual time series; hence, the corresponding eigenvalues in Fig. 1 are more exposed above their level of significance. These oscillations of period length 5.3 year and 3.0 years can be less likely attributed to short observations of red noise.

In a next step we reconstruct that part of the time series that corresponds to the 5.3 year oscillatory pair (Fig. 8).

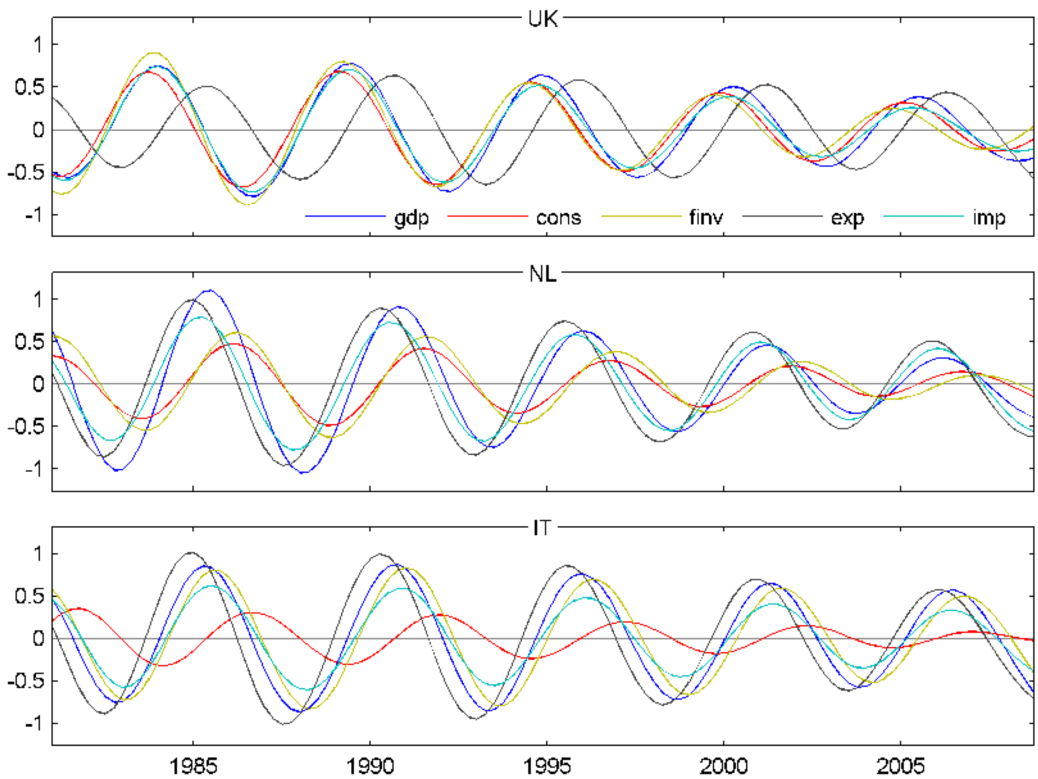

Figure 8: Reconstructions with 5.3-year oscillatory pair RCs 3-4

We see that the reconstruction shows very similar properties to that of the SSA and M-SSA results in the previous sections: The Netherlands GDP, for example, lags behind the UK GDP what we have already seen in Fig. 4. UK exports lag behind UK GDP, and all other aggregates of the UK have only small delay. This agrees very well with the country based analysis of the UK in Fig. 5. UK exports are behind the exports of the Netherlands and Italy at the beginning and get more synchronized at the end. This finding agrees very well with a variable based analysis of all export time series (Fig. 6). These agreements show very well that a global M-SSA provides results that are consistent with individual SSAs or M-SSAs. It is the advantage of a global M-SSA that we are able to extract this information in a single step. Furthermore, if we take more aggregates into account, the analysis is less sensitive to outliers in a single aggregate.

The eigenvalues in Fig. 7 give us an average picture of the total variance of oscillations across all time series. With the RCs in Fig. 8, however, we have direct access to the presence of such oscillatory modes in each of the time series. The amplitude of the RC of consumption in the Netherlands (Fig. 8), for example, is clearly below all other aggregates, hence this 5.3-year oscillatory mode seems to be less important in the dynamical behavior. To quantify the importance of the RCs in the reconstruction of each of the time series,

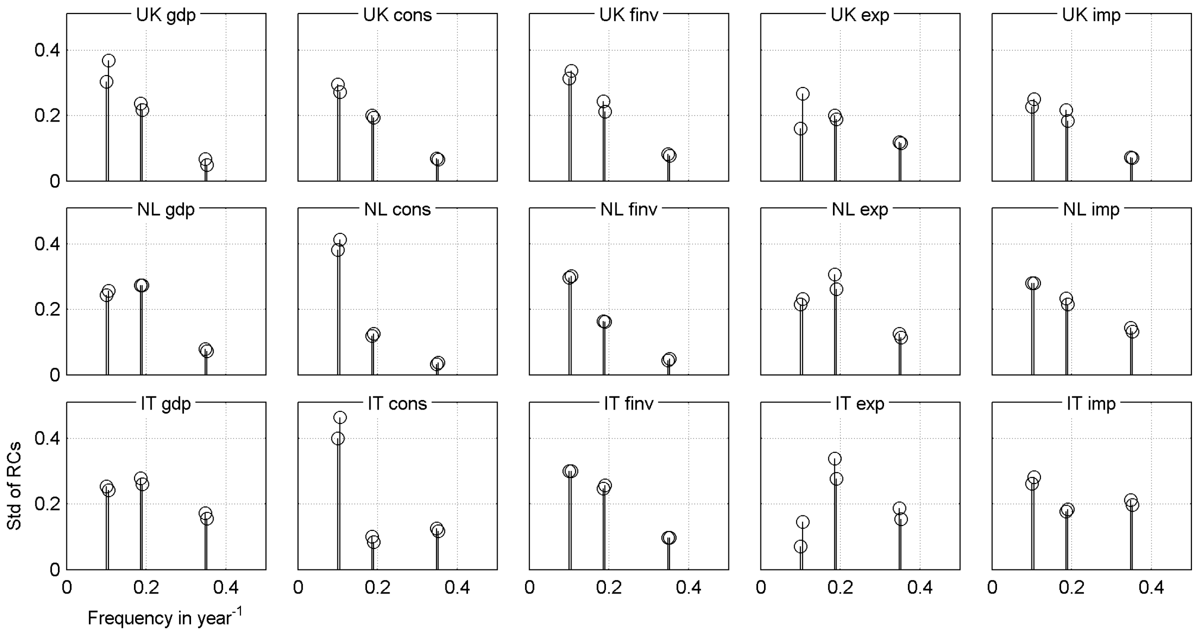

Figure 9: Standard deviation of the RCs as a measurement of energy. The plot shows the RCs that correspond to significant oscillatory pairs, namely RCs 1-2, 3-4, and 7-8 vs. their dominant frequency.

we simply use the standard deviation of the RCs as a measurement for the energy (Fig. 9).

In this analysis we restrict to the three significant oscillatory pairs, namely RCs 1-2, 3-4, and 7-8. The first pair, which is linked to a period length of 9.1 years, is present in almost all time series. However, as we have already seen from the Monte-Carlo test in Fig. 7, this large amplitude can be mainly attributed to the detrending procedure and fairly well explained by the null hypothesis of red noise. The second oscillatory pair with a period length of 5.3 years, and which is much more significant, has quite different behavior between the countries. For the UK, this oscillations has nearly the same energy along all aggregates. For the Netherlands and Italy, the energy varies. This apparent difference is interesting, with respect to the U.S..

This business cycle behavior of this economy is also dominated by a 5.3-year oscillatory mode (Groth et al., 2011), and Fig. 9 supports the closer connection of the UK to the U.S.. In contrast to this, the other both countries are known to be stronger linked to European countries, and the consumption, for example, shows a much weak presence of a 5.3-year oscillations. Furthermore, a stronger presence in the exports of the Netherlands and Italy supports a stronger link to the U.S. The third pair with a period length of 3.0 years is, in agreement with the univariate SSA, generally not very powerful, and especially present in Italy (see again Table 1). Here, other market mechanisms that we have not taken into account could play a role and it would be certainly of interest to extend the analysis to more countries.

6. Concluding remarks

6.1. Overall summary

In this paper we analyse macroeconomic fluctuations in three European countries, namely Italy, The Netherlands, and the United Kingdom. For each country, five fundamental indicators of the real aggregate economy (GDP, consumption, fixed investments, exports and imports) are analyzed by means of advanced spectral methods. The results obtained from both uni- and multivariate analysis suggest the presence of a quite homogeneous cyclical behaviour among the indicators of the three countries, notwithstanding the peculiarities of each economy.

In particular, three main common oscillatory movements are revealed: a low-frequency oscillation of about 9 y, hardly detected and not clearly distinguishable from the noise background; a 5.3 y fluctuation clearly shared in all countries, but dominating the U.K. economy; and a weak 3 y oscillation mainly characterizing the Italian aggregates. Notice that the oscillation characterizing U.K. agrees in character with the 5.3 y oscillatory mode detected in the U.S. economy by Groth et al. (2011): the closer connection of the U.K. and the U.S. economy is thus supported. In contrast, Italy and The Netherlands turn out to be more linked to European countries.

Finally, the lack of an underlying economic model in our empirical work could be somehow compensated by comparing our results with simulations based on NEDyM, the non-equilibrium dynamic model by (Hallegatte, Ghil, Dumas, & Hourcade, 2008) (Hallegatte, Ghil, Dumas, & Hourcade, 2008), which predicts both endogenous business cycles of a few years in duration and near-annual periodicities. From one side, a periodicity of about 5.4, consistent with the mean business cycle period is detected. On the other side, a near-annual cycle arises from labour market, dynamics and it is related to the Goodwin cycle.

So far this model unfortunately provides a quite poor calibration, but the eventual agreement between empirical results and the model stylized facts could perhaps afford a validation.

6.2. Discussion and future work

We have demonstrated that M-SSA clearly goes beyond a simple analysis of cross-correlations and offers a reconstruction of a “skeleton” of the underlying dynamics. M-SSA helps to identify different market mechanisms with its different characteristic time scales. In particular, M-SSA is able to detect oscillatory modes that can be attributed to unstable periodic orbits (UPOs), and which leave their imprint on the system's observed time series. Such UPOs are road posts on the way from simple to complex dynamics, and play an important role in the synchronization process of different economic systems.

Instead of processing and analyzing each time series separately, M-SSA provides a global analysis, and allows a consequent and robust analysis of shared mechanisms. This is especially in line with the NBER's understanding of business cycles, namely that “a recession is a significant decline in economic activity spread across the economy”.

We have shown that the inclusion of more and more time series into M-SSA gives consistent results and does not introduce spurious correlations. This is an important validation for a global M-SSA and that it does not lead to wrong interpretations of relationships. Therefore, it is certainly of interest to extend the analysis to many countries and to study shared mechanisms and synchronization effects.

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