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Economic cycles and their synchronization: A survey of spectral properties

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Abstract

The present work applies several advanced spectral methods to the analysis of macroeconomic fluctuations in three countries of the European Union: Italy, The Netherlands, and the United Kingdom. We focus here in particular on singular-spectrum analysis (SSA), which provides valuable spatial and frequency information of multivariate data and that goes far beyond a pure analysis in the time domain. The spectral methods discussed here are well established in the geosciences and life sciences, but not yet widespread in quantitative economics. In particular, they enable one to identify and describe nonlinear trends and dominant cycles — including seasonal and interannual components — that characterize the deterministic behavior of each time series. These tools have already proven their robustness in the application on short and noisy data, and we demonstrate their usefulness in the analysis of the macroeconomic indicators of these three countries.

We explore several fundamental indicators of the countries' real aggregate economy in a univariate, as well as a multivariate setting. Starting with individual single-channel analysis, we are able to identify similar spectral components among the analyzed indicators. Next, we consider combinations of indicators and countries, in order to take different effects of comovements into account. Since business cycles are cross-national phenomena, which show common characteristics across countries, our aim is to uncover hidden global behavior across the European economies. Results are compared with previous findings on the U.S. indicators (Groth et al., 2012). Finally, the analysis is extended to include several indicators from the U.S. economy, in order to examine its influence on the European market.

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1. Introduction

The nature of aggregate fluctuations is one of the most controversial topics in macroeconomics: the first systematic analysis of economic data from France, England, and the United States led Juglar (1862) to hypothesize a recurrent behavior of economic crises, with strong mutual dependence between their expansion and recession phases. About one and a half century later, the debate on the nature and causes of economic fluctuations is still going on, and some fundamental issues like the endogenous vs. the exogenous nature of business cycles and their propagation mechanisms are still open (Kydland and Prescott, 1982; Long and Plosser, 1983; King and Rebelo, 2000; Chiarella et al., 2005).

Although it is widely acknowledged that business cycles are multi-country phenomena, showing common characteristics across countries (Woitek, 1996; Dickerson et al., 1998; Den Haan and Sumner, 2001; Stock and Watson, 2005; Mazzi and Savio, 2006), there is still no agreement on basic issues like the quantification of comovements, the existence of supranational cycles — e.g., European or G7 ones — and the determinants of economic synchronization. For this reason, many theoretical and empirical studies suggest contrasting results, due to different data sets as well as different methodologies.

Concerning the mechanisms of economic synchronization, three main factors have been identified theoretically, but hardly verified by empirical analysis. First of all, some scholars argue that economic and capital integration supports the creation of specialized production structures, due to which sector-specific shocks become region-specific (Krugman, 1993; Kalemli-Ozcan et al., 2001). As a consequence, the business cycles of those countries showing similar production patterns would tend to converge (Imbs, 2004; Calderon et al., 2007); empirical studies (Otto et al., 2001; Baxter and Kouparitsas, 2005), however, are far from buttressing this hypothesis.

Other scholars direct their attention on trade barriers, arguing that their removal enhances synchronization, because of the consequent transmission of shocks in demand and because of knowledge and technological spillovers (Coe and Helpman, 1995; Frankel and Rose, 1998). Still, the effect of trade intensities on business cycle comovements is empirically not clear (Gruben et al., 2002; Calderon et al., 2007; Baxter and Kouparitsas, 2005).

Finally, the impact of monetary and financial integration on synchronization is theoretically ambiguous. On the one hand, monetary policies that are less asymmetric, exchange rates that are more stable, and stronger trading relations should have a positive impact on synchronization (Inklaar and De Haan, 2001; De Haan et al., 2002). On the other hand, the fixed exchange rates could have a negative impact, since asymmetric shocks that may eventually occur cannot be

absorbed by exchange rate adjustments and are discharged on the real economy (De Haan et al., 2008).

The present work attempts to shed further light on supranational synchronization of business cycles, by applying recently developed spectral methods to a set of quarterly macroeconomic indicators — namely gross domestic product (GDP), consumption, fixed investment, export, and import — across three European countries. In the paper's last part, the indicators of the U.S. economy are added to the data set being analyzed, since this economy is strongly associated and possibly coupled with the European ones.

Given that economic time series are rather short, highly volatile, and often nonstationary, classical spectral estimation methods (e.g., the Fourier transform) are limited in their ability to describe the underlying dynamical behavior (Granger and Hatanaka, 1964; Granger, 1966, 1969). New developments in spectral estimation techniques, however, have been shown to successfully overcome these limitations in many cases, and thus allow useful applications in various economic contexts (Lisi and Medio, 1997; Higo and Nakada, 1998; Atesoglu and Vilasuso, 1999; Baxter and King, 1999; A'Hearn and Woitek, 2001; Iacobucci, 2003; Aadland, 2005). Moreover, these advanced spectral methods support a richer description of multivariate phenomena with respect to standard time-domain methods (Croux et al., 2001); this feature is particularly attractive in business cycle analysis.

The multivariate, spectral approach presented in this paper is quite innovative in the field of economic research and extends the classical macroeconomic analysis in the time domain to the frequency domain. Although fully exploited in many fields of research, it has been so far mostly neglected in the analysis of socio-economic problems.

In the present work we propose the application of singular-spectrum analysis (SSA) to investigate multiple indicators, first in a univariate and, more importantly, in a multivariate setting. SSA is well suited for the analysis of short and noisy time series (Vautard et al., 1992; Ghil et al., 2002), like the typical macroeconomic ones. It is a nonparametric decomposition methodology and it does not require any a priori modeling of a time series to be analyzed. SSA allows a systematic description, quantification, and extraction of long-, medium-, and short-term components of the series being analyzed. Univariate SSA allows us to investigate the behavior of each indicator separately, extracting the dominant periodic and quasi-periodic oscillations that account for most of the series variability. On the other hand, the extension to multivariate SSA (M-SSA) gives deeper insights into the common behavior of business fluctuations, both across countries and across indicators.

The paper is divided into six sections: In Section 2, we introduce the data set and pre-processing procedure. In Section 3, we present the methodology of univariate analysis, its multivariate extension, and a crucial significance test. In Section 4, we apply the method to individual time series, and then discuss different combinations thereof in Section 5. Finally, we draw conclusions about the underlying macroeconomic dynamics and its synchronization in Section 6.

2. Data description and pre-processing

Our analysis is based on quarterly national accounts from Italy, the United Kingdom (henceforth UK), and The Netherlands [1]. For each country we analyze GDP at market prices, final consumption expenditure, gross fixed capital formation, exports, and imports of goods and services [2].

The time series refer to the different time intervals of availability: they cover 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, $N = 112$); here N stands for the number of quarters. Figure 1 shows the raw time series and the corresponding trend. The trend has been estimated by the Hodrick-Prescott filter (Hodrick and Prescott, 1997), with the standard smoothing parameter for quarterly time series of $\lambda = 1600$. For normalization purposes, the trend was extracted from the raw time series, the corresponding residuals were divided by the trend, and then the relative residuals were standardized to the same variance. Figure 2 illustrates this pre-processing procedure.

We selected the data from a set of European Union countries that show interesting characteristics, which could affect the features of business cycle propagation. First of all, The Netherlands are a small, wide-open economy, showing relatively small GDP levels but very high shares of imports and exports.[3] Consequently, they are more exposed to international shocks in comparison with Italy and the UK, two economies that are more closed. The UK has the economy that is most strongly linked to that of the United States, while Italy's most important trading partner is Germany.[4] It is well known that bilateral trade represents a channel for the propagation of both international and country-specific shocks, and that it can favor synchronization among different economic systems.

Another significant characteristic of the UK economy is that it experiences the strongest fluctuations in GDP residuals. This is possibly due to the flexible structure of its labor 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, along with more sudden recessions and more pronounced expansions.

On the contrary, the high bargaining power of the Italian trade unions is likely to cause a more rigid reaction of the entire economy[5]. The Dutch econ-

[1] 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/.

[2] All series are expressed in constant year-2000 Euros. They are seasonally adjusted and corrected by working days, following the TRAMO-SEATS procedure (Maravall, 2005).

[3] In 2008, the ratio of imports to GDP was around 28% for Italy, 34% for the UK, and 77% for The Netherlands. The GDP share of exports was about 28%, 29%, and 84%, respectively.

[4] In 2000, the UK exported to the US 15.4% of its total exports and imported from it 13.2% of its total imports, while Italy exported 14.5% of its total to Germany and imported 17.7% from it, as derived from Feenstra et al. (2005).

[5] For instance, Italian Collective Agreements dictate very complex firing procedures for firms that have more than 15 workers. As a consequence, both medium- and large-size firms are discouraged from modifying their employment level.

omy shows a behavior that is intermediate between Italy and the UK, being characterized by a labor market structure close to the Scandinavian typology (Esping-Andersen, 1999).

Finally, another important factor that differentiates among these three economies is the availability of energy resources. While the UK and The Netherlands both have direct access to natural energy sources, Italy is a strong net importer of oil. Thus, energy supply shocks are likely to affect Italy much more strongly than the other two countries, and hence induce larger business fluctuations. As an example, zooming in on the HP trend of the Italian GDP in the 1970s and early '80s illustrates how the 1973 and 1979 energy shocks lengthened the Italian recession phase in the early 1980s (not shown).

3. Methodology

SSA is a non-parametric method of time series analysis that provides insight into the unknown or partially known dynamics of the underlying dynamical system (Vautard and Ghil, 1989; Ghil and Vautard, 1991; Vautard et al., 1992). SSA allows the identification of different components of the analyzed signal — such as trends, oscillatory patterns, random noise — without the explicit need of a parametric model. The next three subsections, i.e. Sections 3.1–3.3, may be skipped, upon a first reading, by the student or researcher more interested in the results than in the methodology. All three subsections are essential, however, for a full understanding of the results.

The starting point of SSA is the Mañé-Takens idea to reconstruct dynamics from a single time series by its time-delayed embedding (Mañé, 1981; Takens, 1981), and then to find a new orthogonal basis for the extended phase space so obtained that describes most of the variance in the original time series by a minimal number of components. As an optimal solution to this optimization problem, Broomhead and King (1986a) proposed the application of principal component analysis (PCA).

In contrast to a classical Fourier decomposition, the new orthogonal basis is data adaptive and not restricted to pure sine and cosine functions. This way, SSA provides a reconstruction of a skeleton of the dynamical system's structure that is formed by a few robust periodic orbits. Even when these simple attractors have lost their stability, they still play a role in the observed patterns and lead to phase- and amplitude-modulated cycles.

3.1. Single-channel SSA

In this section, we start with a brief description of single-channel SSA. Given a time series $\{x(t),\, t = 1, ..., N\}$ of length N, we build an M-dimensional phase space by using M lagged copies of x

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

From this augmented time series $\mathbf{X}$, we estimate the covariance matrix $\mathbf{C} = \mathbf{X}'\mathbf{X}/N$; here $(\cdot)'$ denotes the transpose.

Due to finite-size effects for small N, $\mathbf{C}$ may deviate from symmetry; thus, we use the more accurate Toeplitz approach of Vautard and Ghil (1989), in which the entries c_{ij} of $\mathbf{C}$ are given by

$$c_{ij} = \frac{1}{N-|i-j|} \sum_{t=1}^{N-|i-j|} x(t)x(t+|i-j|). \tag{2}$$

This formula yields constant entries c_{ij} along the (sub- and super)diagonals of $\mathbf{C}$, which depend only on the lag $|i-j|$.

Next, the symmetric covariance matrix is diagonalized

$$\mathbf{\Lambda} = \mathbf{E}'\mathbf{C}\,\mathbf{E} \tag{3}$$

to yield a diagonal matrix $\mathbf{\Lambda}$ of eigenvalues λ_k and an orthogonal matrix $\mathbf{E}$ of eigenvectors. The columns $\mathbf{e}_k$ of $\mathbf{E}$ represent the new M-dimensional coordinate system and λ_k describes the variance of $\mathbf{X}$ in the direction of $\mathbf{e}_k$. Since the eigendecomposition in Eq. (3) is a similarity transformation of $\mathbf{C}$, the variance of the original time series $x(t)$ is preserved in the eigenvalues, which now lie along the main diagonal of $\mathbf{\Lambda}$.

From the largest eigenvalues we get a first impression of the most important part of the signal, which often can be separated from a tail of many small eigenvalues. Further, in order to identify periodic or quasi-periodic behavior in the original signal, Vautard and Ghil (1989) found that nearby eigenvalues at times form a pair, with their variances being nearly equal, while the corresponding eigenvectors have the same period and are in phase quadrature. These so-called "oscillatory pairs" are the analog of sine-and-cosine pairs in Fourier analysis and adapt to the oscillations present in the system.

By projecting the time series $x(t)$ onto each of the M eigenvectors $\mathbf{e}_k$, we get the M principal components (PCs),

$$a_k(t) = \sum_{j=1}^{M} x(t+j-1)\mathbf{e}_k(j), \tag{4}$$

with $1 \le t \le N-M+1$. The PCs are the projections of x onto the new basis; in this case, the window width is M. For this reason, PCs exhibit no exact phase information.

We are able, however, to study various aspects of the time series that belong to the direction $\mathbf{e}_k$ by computing its reconstructed component (RC),

$$r_k(t) = \frac{1}{M_t} \sum_{j=L_t}^{U_t} a_k(t-j+1)\mathbf{e}_k(j), \tag{5}$$

where $(M_t, L_t, U_t) = (M, 1, M)$ for $M \le t \le N-M+1$; for either end interval they are given in (Ghil et al., 2002). No information is lost during this reconstruction process, since the sum of all individual RCs, $x(t) = \sum_{k=1}^{M} r_k(t)$, gives the original time series (Vautard et al., 1992).

3.2. Multi-channel SSA

Multivariate SSA (M-SSA) is the extension of SSA to multivariate time series (Broomhead and King, 1986b). It simultaneously analyses multiple channels in order to identify and extract dominant spatio-temporal structures of the underlying dynamics. In particular, M-SSA helps to extract oscillatory patterns that are common to the time series at hand, even if they account for different fractions of variance in each of the time series.

Given an L-channel vector time series $\mathbf{x}(t) = \{x_l(t) : l = 1, ..., L;\ t = 1, ..., N\}$ of length N, its $LM \times LM$ grand covariance matrix $\widetilde{\mathbf{C}}$ has the form

$$\begin{pmatrix} \mathbf{C}_{1,1} & \mathbf{C}_{1,2} & \dots & \mathbf{C}_{1,L} \\ \mathbf{C}_{2,1} & \mathbf{C}_{2,2} & \dots & \mathbf{C}_{2,L} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{C}_{L,1} & \mathbf{C}_{L,2} & \dots & \mathbf{C}_{L,L} \end{pmatrix}. \tag{6}$$

Each block $\mathbf{C}_{l,l'}$ is a covariance matrix between channels l and l' and is estimated by

$$\left(\mathbf{C}_{l,l'}\right)_{i,j} = \frac{1}{\tilde{N}} \sum_{t=\min\{1,1+i-j\}}^{\max\{N,N+i-j\}} x_l(t) x_{l'}(t+i-j), \tag{7}$$

where $\tilde{N} = \min\{N, N+i-j\} - \max\{1, 1+i-j\} + 1$ depends on the range of summation.

As in the univariate case, the grand covariance matrix is diagonalized into a set of LM eigenpairs $\{\lambda_k, \mathbf{e}_k\}$, $k = 1 \dots LM$. In contrast to the univariate case, M-SSA eigenvectors describe temporal as well as "spatial" correlations of the multivariate data set, where the L-dimensional space here is that of the vectors $\mathbf{x}(t)$. Each eigenvector $\mathbf{e}_k$ of length LM consists of L consecutive segments of length M, denoted by $\mathbf{e}_k = \{e_k^l(j) : l = 1 \dots L;\ j = 1 \dots M\}$. Each segment is associated with an individual channel, and it describes the participation of that channel in a particular mode.

As in the univariate case, the corresponding PCs are obtained by projecting the multivariate time series onto the eigenvectors

$$a_k(t) = \sum_{l=1}^{L} \sum_{j=1}^{M} x_l(t+j-1) e_k^l(j). \tag{8}$$

This projection yields LM PCs of reduced length $N - M + 1$. Finally, it is possible to reconstruct that part of channel l that correspond to eigenvector $\mathbf{e}_k$ by means of the RCs

$$r_k^l(t) = \frac{1}{M_t} \sum_{j=L_t}^{U_t} a_k(t-j+1) e_k^l(j), \tag{9}$$

with $k = 1, \dots, LM$. The RCs have the same length N as the time series, with the latter being completely reconstructed by the sum of all its RCs, $x_l(t) = \sum_{k=1}^{LM} r_k^l(t)$.

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3.3. Monte-Carlo SSA significance test

A critical step in all forms of spectral analysis is the distinction of significant oscillations from random fluctuations. The classical signal extraction approach, based on the identification of a gap in the spectrum of eigenvalues, has several limitations: when either the signal-to-noise ratio decreases or the random fluctuations correlate, a separation into a few large eigenvalues and a remaining noise floor becomes meaningless.

Thus, Allen and Smith (1996) have proposed a more stringent test; this test relies on a more sophisticated null hypothesis, which takes the possibility of spurious oscillations into account. Based on a Monte-Carlo simulation technique, the extracted spectral components are tested against a red-noise hypothesis, i.e. an autoregressive process of order 1, AR(1),

$$X(t) = a_1 \left[X\left(t-1\right) - X_0\right] + \sigma\xi(t) + X_0; \tag{10}$$

here X_0 is the process mean and ξ a normally distributed white-noise process with zero mean and unit variance.

Once the coefficients a_1 and σ are estimated from the time series, an ensemble of surrogate time series is generated from the AR(1) process and compared with the real data. In practice, this requires one to estimate the covariance matrix $\mathbf{C}_R$ for each AR(1) realization and to project $\mathbf{C}_R$ onto the eigenvectors $\mathbf{E}$ of the original data

$$\mathbf{\Lambda}_R = \mathbf{E}'\mathbf{C}_R\mathbf{E}. \tag{11}$$

Since Eq. (11) is not the eigendecomposition of the surrogate covariance matrix $\mathbf{C}_R$, the matrix $\mathbf{\Lambda}_R$ is not necessarily diagonal, as it is in Eq. (3). In fact, this projection allows one to determine the degree of resemblance between the surrogates generated by the test and the original data by computing statistics on the diagonal elements. From the ensemble distribution of λ_R along the diagonal, we are able to obtain significance intervals outside which the time series' eigenvalues can be considered to be significantly different from an AR(1) process in Eq. (10). Note that a rejection of the most likely AR(1) process leads to a rejection of all other red-noise processes, at the same or at an even higher level of significance (Ghil et al., 2002).

In the case of a multivariate data set, we follow the approach of Allen and Robertson (1996). Since the presence of cross-correlations would reduce the power of the test, if not included in the null hypothesis, we first have to find a rotation that transforms the L channels to pairwise uncorrelated ones. This rotation can be simply achieved by a classical PCA, to which end we are able to test the invariant set of eigenvalues against L independent AR(1) processes. This avoids the test against a vector AR(1) process, which may itself support oscillations, the so-called principal oscillation patterns, or POPs (Penland, 1989; Von Storch, 1995). Having thus formulated the model in the null hypothesis, we proceed as in the univariate case: we first determine the covariance matrix for every realization and then project it onto the M-SSA eigenvectors of the rotated PCs. Finally, we test whether the M-SSA eigenvalues of the PCs exceed a preset significance level.

4. Individual analysis of macroeconomic indicators

In this section, we perform a univariate SSA analysis of all the indicators discussed in Section 2. To do so, we use the pre-processed data shown in Fig. 2 and the SSA-MTM spectral toolkit developed at UCLA, which is available as freeware at http://www.atmos.ucla.edu/tcd/ssa/.

The pre-processing is of the essence for the spectral analysis, since raw economic variables are typically characterized by a pervasive trend that dominates the shape of the power spectral estimate. This is reflected in a high peak at zero frequency, which is scattered into the neighboring frequency bands due to leakage effects (Granger, 1966). Figure 3 illustrates this effect on the GDP of the UK. After removing the trend with the help of the HP filter, the power spectral density (PSD) estimates in Fig. 3 reveal three distinct peaks, associated with periodicities at about 9, 5, and 3 years. These spectral peaks suggest the presence of roughly periodic components in the analyzed series, whose robustness remains to be confirmed by further statistical tests.

In the next step, we carry out an SSA analysis of the trend residuals of the UK GDP. Figure 4 shows the spectrum of eigenvalues (filled circles) assigned to a frequency scale on the abscissa[6].

The error bars represent the 2.5% and 97.5% quantiles of variance from an ensemble of 1000 red noise realizations (cf. Section 3.3). Hence, it is very unlikely that the eigenvalues lying outside the corresponding error bars are consistent with the hypothesis of random fluctuations generated by a red-noise process. In the case of the UK GDP, the eigenvalues 1–2 and 3–4 (filled circles) have more power than can be explained by simple red noise. The near-equality of the two eigenvalues in each of these two pairs — in their size, as well as in the frequency of the associated eigenmodes — suggests further that they represent oscillatory pairs (Ghil et al., 2002).

Figure 4 indicates that the eigenvalue pair 1–2 is associated with a frequency of approximately 5 years, which captures 39% of the variance in the detrended and normalized time series. The pair 3–4 can be attributed to a 9-year oscillation, which describes 23% of the variance. Hence, almost two-thirds of the variance is associated with the first four PCs of our SSA analysis. A possible 3-year oscillation in the PSD estimation of Fig. 3 can be identified with the eigenvalue pair 7–8, but Fig. 4 shows that it cannot be distinguished from an AR(1) process at the 95% confidence level. Finally, note the oscillatory pair at a 1-year periodicity, which clearly lies below the expected variance level. This can be attributed to the elimination of the seasonal behavior in our pre-processing (cf. Section 2).

This comparison between the classical PSD estimation of Fig. 3 and the SSA estimates in Fig. 4 illustrates the capability of SSA to automatically identify

[6]Plotting the eigenvalues against their rank, as originally proposed by Vautard and Ghil (1989), is more useful in distinguishing between signal and noise. In identifying and statistically testing for oscillatory modes, as we do here, it is more informative to plot the eigenvalues versus the associated frequency of the corresponding eigenvectors (cf. Allen and Smith, 1996).

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Table 1: Univariate SSA analysis. Oscillations significant at the 95% level are indicated by filled circles, with their partial variances in parentheses; open circles indicate the presence of oscillations at a lower significance level.

	9 yrs	5 yrs	3 yrs
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 FINDINGS	4/15	12/15	12/15

oscillations and to capture the statistically significant dynamical behavior by using just a few components. This parsimonious description of the time series by SSA substantially simplifies the comparison of multiple indicators. On each time series of the —mgdata set, we perform a separate SSA analysis, identifying oscillatory pairs, and testing for their significance by means of Monte Carlo SSA. Table 1 summarizes the findings for each indicator within each country, where filled circles indicate oscillations that are significant at a 95% confidence level, while the open circles indicate that an oscillatory pair is present, but at a lower confidence level.

The results in Table 1 suggest a remarkable homogeneity in cyclical behavior among the indicators of Italy, the UK, and the Netherlands. Despite the different structures of each country's economic system and the different observational spans, the complex picture of the macroeconomic indicators can be reduced to three components [7]:

- a long-term mode of about 9 years, in a few times series;

[7] In the literature there is no complete agreement on the effective duration of business cycles, but it is quite common to consider them as the result of a generating process of about 2–8, or possibly 10 years (Crivellini et al., 2007).

- an intermediate 5-year oscillation, in nearly all indicators; and
- a faster oscillation of about 3 years, accounting for a small fraction of the total variance.

As already mentioned at the beginning of Section 3, a few robust periodic orbits can generate phase- and amplitude-modulated oscillations in the observed time series. This behavior can be reconstructed, to some extent, by using the RCs. As an example, in Fig. 5 we reconstruct the 5-year oscillation in the GDP of the three countries. All the patterns in Figs. 5(a,b,c) are significant against a red-noise hypothesis and represent a large fraction of the GDP variance.

The reconstruction of the UK GDP describes an increase in the amplitude of this 5-year mode due to huge energetic shocks in 1973 and 1979. The reconstruction of Italian GDP shows the lengthening of the recession phase and the following stretched recovery in the early 1980's due to energetic shocks, the subsequent counter-shock and the dollar depreciation. The 5-year oscillation in exports, however, is much more weakly modulated, thus suggesting a stabler behavior (not shown).

The 9-year oscillation is less significant in our fairly short data set[8]. In all the UK indicators, some pairing of the corresponding eigenelements emerges, but this oscillatory pair is unambiguously significant only in the case of the GDP. Again, the reconstruction of this mode exhibits an increase in amplitude from the late 1970s to the early '90s (not shown).

Finally, the 3-year oscillation is generally less pronounced in the UK and The Netherlands; its partial variance there lies in the range of 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; see Section 5.1.

5. Composite analysis of multiple indicators

In the previous section, we have focused on separate SSA analyses of individual indicators for single countries, and found a remarkable agreement in their spectral properties. This striking simplicity in the rather complex picture of economic behavior for three very diverse Europran countries remains to be verified by a composite analysis of multiple indicators and countries. The detection of similar oscillatory patterns across the univariate series points to the presence of similar dynamics, but it does not suffice in order to draw conclusions about their coupling. The inclusion of cross-correlations into the analysis of business cycles, though, will help draw such conclusions.

In practice, this inclusion requires one to combine multiple time series into a single M-SSA, including the cross-correlations into the analysis. In doing so, we consider three different configurations: we combine (a) all indicators from a single country; (b) the same indicator across all countries; and (c) all

[8]Note that the chance of not being significant increases with the period length.

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Table 2: Country-based M-SSA results. Oscillations significant at the 95% level are marked as filled circles.

	9 yrs	5 yrs	3 yrs
UK	•	•	
The Netherlands		•	•
Italy		•	•

available indicators from all countries into a single M-SSA analysis. We refer to these three configurations as "country-based," "indicator-based," and "global" analysis, respectively. This hierarchy of configurations allows us to gradually investigate the existence of oscillations from smaller to larger scales, and to identify phenomena on a local as well as on a global scale.

This hierarchical approach helps in particular to avoid an increase in the number of false positive detections (type II error) in the significance analysis of the eigenvalues: with an increasing number of channels and a decreasing length of observations, discrepancies between the null-hypothesis model and the data at hand become more likely. For this reason, we focus in the following M-SSA analysis only on those oscillations that have already been identified in the univariate SSA (see Table 1).

5.1. Country-based analysis

In this section, we combine all economic indicators for each country into a single M-SSA analysis. This allows one to understand regional dynamics at the country level. The most highly significant oscillations are summarized in Table 2. As in the univariate analyses, the 5-year oscillation is clearly shared by all three countries, while the highest frequencies are well established in the Italian macroeconomic time series, and the 9-year component prevails in the UK.

These similar patterns are an evidence of common features in the dynamics of industrialized economies (Blanchard and Watson, 1987; Stanca, 1999; Stock and Watson, 2002, 2005). This intuition of commonality is further strengthened by the remarkable correspondence between our empirical findings and the theoretical predictions of a non-equilibrium dynamic model [NEDyM: Hallegatte et al. (2008)] that introduces investment dynamics and non-equilibrium effects into a Solow (1956) growth model.

NEDyM exhibits endogenous business cycles of 5–6 years in duration, as well as near-annual fluctuations. The 5–6-year periodicity emerges in profits, production, and employment, consistently with the well-known mean business cycle period (Zarnowitz, 1985; King and Watson, 1996; Kontolemis, 1997). In addition, NEDyM exhibits the characteristic seesaw shape of business cycles, with short recessions and substantially longer recoveries, as well as several stylized facts of the business cycle in terms of lead-lag relationships between indicators. On the other hand, the detailed numerical calibration of NEDyM to the actual history of macroeconomic indicators of major economies is still necessary, in order to further consolidate its credibility.

Table 3: Indicator-based M-SSA results. Oscillations significant at the 95% level are marked as filled circles.

	9 yrs	5 yrs	3 yrs
GDP	•	•	•
Consumption	•		•
Fixed investments	•	•	•
Exports		•	•
Imports	•		•

5.2. Indicator-based analysis

This section is devoted to the cross-country comparison of each indicator over the common, nearly three-decade–long time span of (1981:01–2008:04). The results are summarized in Table 3 and help us uncover indicator-specific behavior.

It is interesting to notice that the significant 9-year RCs (see Section 3) display similar amplitudes across countries, but different phasing, with the UK leading. The agreement in amplitude, on the one hand, can be attributed to the configuration of international interdependencies, with the U.S. economy influencing most strongly that of the UK, but also the other two; this commonality also appears in the global analysis (Section 5.3). The differences in phasing, on the other hand, including the UK lead, can be attributed to to each country's peculiarities, with both Italy and The Netherlands being more linked to Germany and France than to the U.S.

The 5- and 3-year periodicities show good cross-country agreement, especially concerning exports and imports. The latter agreement confirms the role of trade as a transnational transmission mechanism of business cycle dynamics.

5.3. Global analysis

In this subsection we combine all given time series into a single M-SSA analysis and focus on the dynamics that dominate the economic behavior on the broadest scale covered by our data sets. Since Groth et al. (2012) have already discussed the presence of a 5-year oscillatory mode in the U.S. economy, we extend here the analysis to the U.S. economy. Doing so will allow us to assess possible links between oscillatory modes in the economies of the European Union and of the U.S.

The quarterly data set for the U.S. macroeconomic indicators is provided by the Bureau of Economic Analysis (BEA; see `http://www.bea.gov`) and all monetary variables are in constant 2005 dollars. Like for the European data, we first non-dimensionalize the trend residuals by dividing them by the long-term trend, and then standardize the relative residuals.

As was the case, at least in part, for the individual SSA analyses of subsets of the three EU countries or five indicators in the two previous subsections (see again Tables 2 and 3), the eigenvalue spectrum in Fig. 6 clearly shows three oscillatory pairs, each significant above the 95% level, with the previously

detected period lengths of approximately 9, 5, and 3 years. The sum of the variances captured by these three pairs is 27 + 19 + 7 = 53% of the variance in the total data set of the five indicators times the four countries, including now the U.S.

The longest period of 9 years is just barely significant at the 95% level, confirming the finding that this oscillation is hard to detect in the single time series (Table 1). It is especially the short overlap in time span, from 1981 to 2008, in this global M-SSA analysis that complicates the distinction between random fluctuations and deterministic oscillations at this period length.

On the other hand, the 5- and 3-year oscillations can be identified more often in the single-channel SSA and the corresponding eigenvalues in Fig. 6 rise well above the 95% level of significance. Hence, it is highly unlikely that these oscillations can be attributed to random fluctuations, even in the barely three decades of data available at this time.

Next, we reconstruct the temporal behavior that corresponds to these three oscillatory pairs. The reconstruction with a few RCs allows a streamlined view of the rather complex behavior of multiple countries and their indicators. It thus helps separate common behavior from single shocks. As a consequence, the behavior seen in Fig. 7 is indeed rather homogeneous across all four countries and their five indicators .

It is quite remarkable that the U.S. economy reveals the most coherent within-country behavior over the whole interval of observation (Fig. 7(d)), and that all its indicators behave quite similarly, in both amplitude and phase. For the three EU countries, the amplitude modulation in time is still fairly consistent for each country separately, but the phases are more variable, from indicator to indicator for the same country as well as across countries.

The UK is fairly strongly linked to the U.S. during the '90s (Fig. 7(a)), but it shows a more erratic behavior recently, probably due to its stronger European integration in the last two decades. On the other hand, The Netherlands and Italy are generally more closely linked over the entire data span, and their macroeconomic behavior is quite similar. In the '90s, both countries clearly lag behind the U.S. and the UK, while in recent times this delay has been reduced.

Finally, to quantify the participation of each country and of its indicators in the three global oscillatory modes, we analyze the variance of the corresponding RCs for each time series separately (Fig. 8). The 9-yr oscillatory mode is strongest in the European countries, where it clearly dominates consumption. In the U.S. market, the importance of this mode is clearly quite limited, except for the exports. This match between EU consumption and U.S. exports points to an obvious link between the two markets.

The second oscillatory mode, with a period length of five years, has quite a different behavior from one country to another. In the case of the UK, this mode has nearly the same energy for all aggregates, whereas for the Netherlands and Italy, the energy varies substantially from one indicator to another. This difference is in particular interesting insofar as the U.S. economy is concerned, since the business cycle there is dominated by a 5-year oscillatory mode (Groth et al., 2012). In this context, Fig. 8 supports a closer connection of the UK as

a whole to the U.S. economy.

For the Netherlands and Italy, the picture is more complex since both countries are known to be more strongly linked to the European market. The consumption, for example, in both these countries shows a much weaker contribution of the 5-year oscillations, although their stronger participation in the exports supports a link to the U.S. market.

The third pair, with a period length of three years, exhibits overall smaller variance, in agreement with the univariate SSA analyses. The picture for the 3-year mode in Fig. 8 is less informative and we are not able to associate this mode either to any particular country or to a particular indicator. Other market mechanisms that we have not taken into account in the present analysis may play a role and it would be certainly of interest to extend the analysis to several additional countries with sufficiently long macroeconomic records.

6. Summary and concluding remarks

In this paper, we have carried out a frequency- and time-domain analysis of macroeconomic fluctuations in three European countries, namely Italy, The Netherlands, and the United Kingdom (UK). For each country, five fundamental indicators of the real aggregate economy — GDP, consumption, fixed investments, exports and imports — have been considered in order to describe several aspects of the economic behavior of these countries, separately as well as together. Despite the peculiarities of each individual economy, the results obtained from both uni- and multivariate investigations by singular spectrum analysis (SSA) suggest the presence of quite a homogeneous multi-cyclical behavior among the countries and indicators.

We have demonstrated that multivariate SSA (M-SSA) clearly goes beyond a simple analysis of cross-correlations and offers the reconstruction of a robust "skeleton" of the underlying dynamics. In this context, M-SSA helps identify different market mechanisms, with their distinct characteristic time scales, and reduce the complex behavior of the system to a few robust oscillatory modes.

Such modes have been attributed, in other contexts, to the existence of weakly unstable periodic orbits in the system's phase space (Ghil et al., 2002). Albeit unstable, this type of closed orbits, also called limit cycles in dynamical systems theory, influence the system's behavior and play an important role in the synchronization process between the irregular evolutions of several macroeconomic indicators within a country and between the economies of several countries. Hence, these orbits leave their imprint in the economic system's trajectories — i.e. in the observed time series of indicators — and it is of special interest to identify and reconstruct them for a set of different indicators and countries.

In the present work, we have identified three main oscillatory modes in the macroeconomic evolution of these three EU countries: (a) a low-frequency oscillation of about 9 years, which is statistically significant at the 95% level only in some of the time series in our data sets; (b) a 5-year oscillation that is clearly dominant in all three countries; and (c) a 3-year oscillation, which shows less

energy and is especially present in Italy and The Netherlands. Our analysis has further been extended to the U.S. economy and, in agreement with the findings of Groth et al. (2012), the pervasive character of the 5-year oscillatory mode in the EU countries we had analyzed could indeed be attributed to its prevalence in the U.S. economy.

Finally, the statistical results in this paper support the predictions made by Hallegatte et al. (2008), using the simple non-equilibrium dynamic model NEDyM, namely the presence of an endogenous business cycle with a period of roughly 5–6 years. The model's 5–6-year periodicity is shared by all the indicators examined here, and it is consistent with the mean business cycle period found by several authors (Zarnowitz, 1985; King and Watson, 1996; Kontolemis, 1997).

This agreement between NEDyM and the time-series analyses here is quite encouraging. Further detailed numerical calibration of NEDyM to the actual history of macroeconomic indicators of major economies is necessary, though, in order to consolidate our confidence in the model's predictve power.

To conclude, M-SSA provides a self-consistent and robust way of analyzing spatio-temporal behavior across countries and economic aggregates, where space is understood here in the sense of the phase space of the aggregates. This conclusion is especially in line with the U.S. National Bureau of Economic Research (NBER) understanding of business cycles, namely that a recession is a significant decline in economic activity spread across the economy, i.e. not one that is limited to GDP alone. In a multivariate framework, we have shown that the inclusion of more and more time series into M-SSA gives consistent results and helps extract oscillatory modes that are shared across different economies.

In future work, it is certainly of interest to extend the present analyses to several additional countries with sufficiently long aggregate records. Doing so would enable one to study shared mechanisms and synchronization effects on a global market.

7. Acknowledgments

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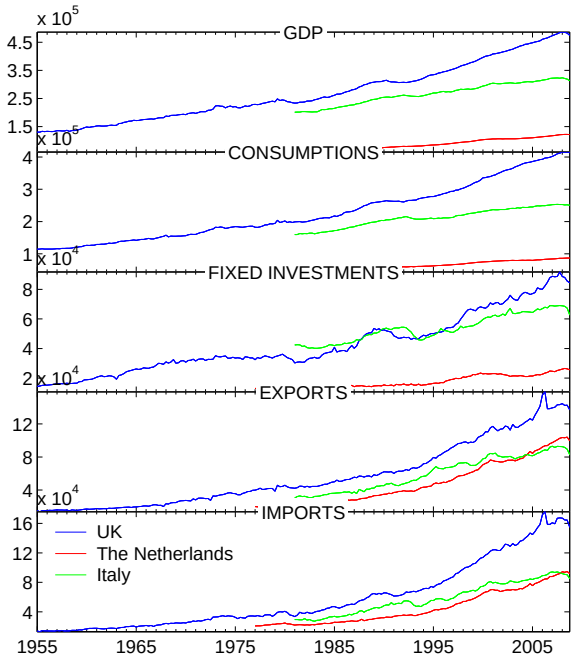


Figure 1: Time series of gross domestic product (GDP), consumption, fixed investments, exports and imports for the United Kingdom (UK, blue curve), The Netherlands (green curve), and Italy (red curve). These raw series are based on EUROSTAT data and expressed in constant, year-2000 Euros. See text and http://epp.eurostat.ec.europa.eu/ for details.

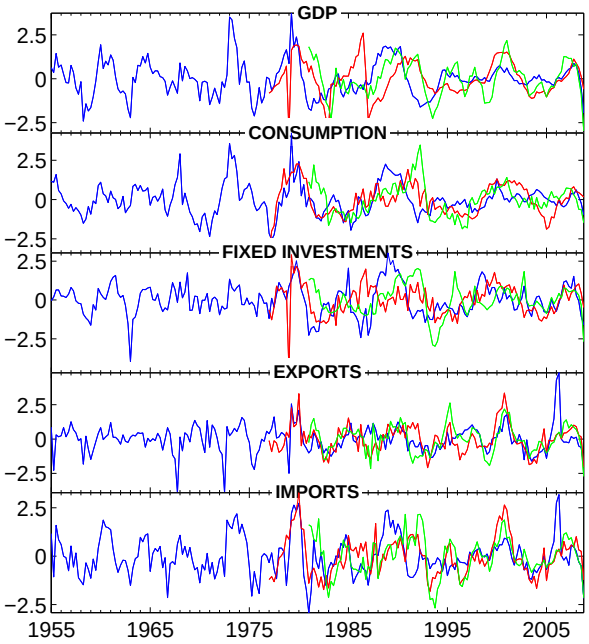


Figure 2: Same time series as in Fig. 1, but pre-processed to extract the trend and normalize the residuals so obtained. The underlying cyclical structure is visually apparent, and it is the subject of the following analysis. Same color convention as in Fig. 1 and in subsequent figures.

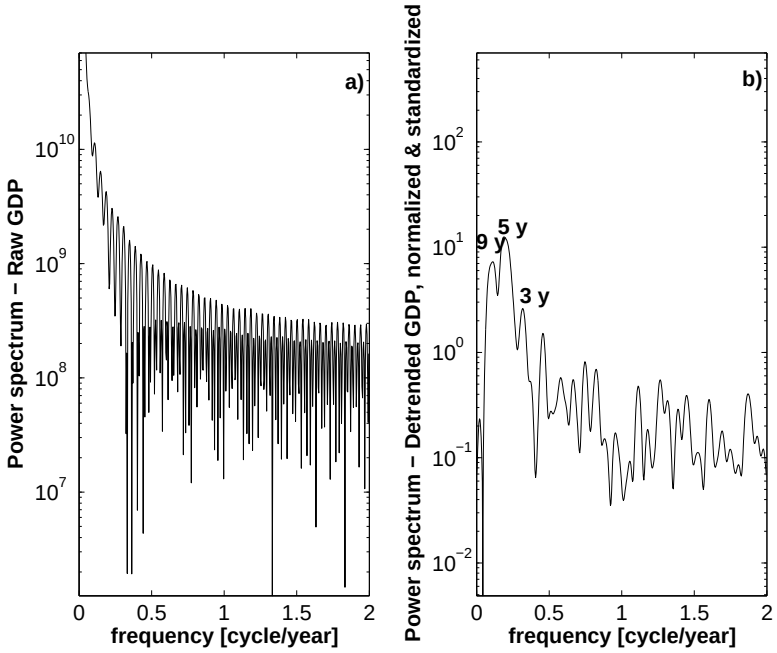


Figure 3: Power spectral density (PSD) estimate for the GDP of the UK. *Panel (a)* PSD estimate for the raw data; *panel (b)* PSD estimate for the pre-processed trend residuals. PSD estimation was carried out by the Blackman-Tuckey algorithm with a Hanning window of $M = 100$ quarters (Blackman and Tukey, 1958).

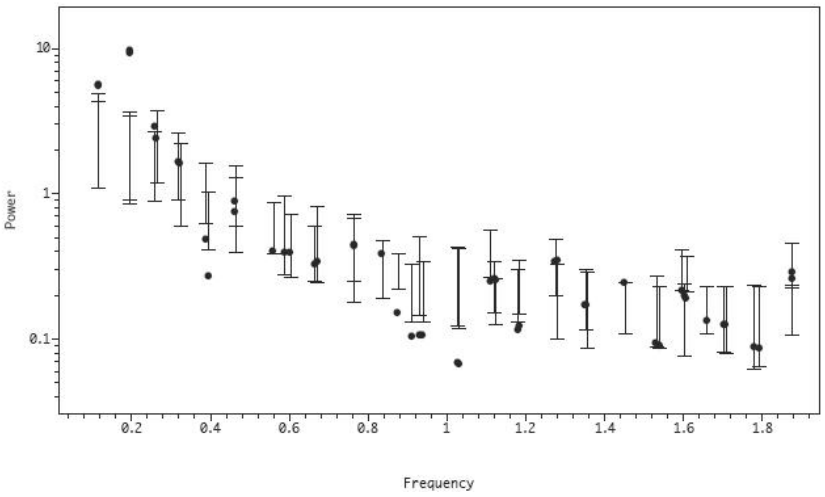


Figure 4: SSA analysis of the UK GDP: Monte Carlo singular spectrum of the transformed residual series with $M = 50$. The filled circles represent the eigenvalues, while the lower and upper ticks of the error bars represent the 2.5% and 97.5% red noise percentiles.

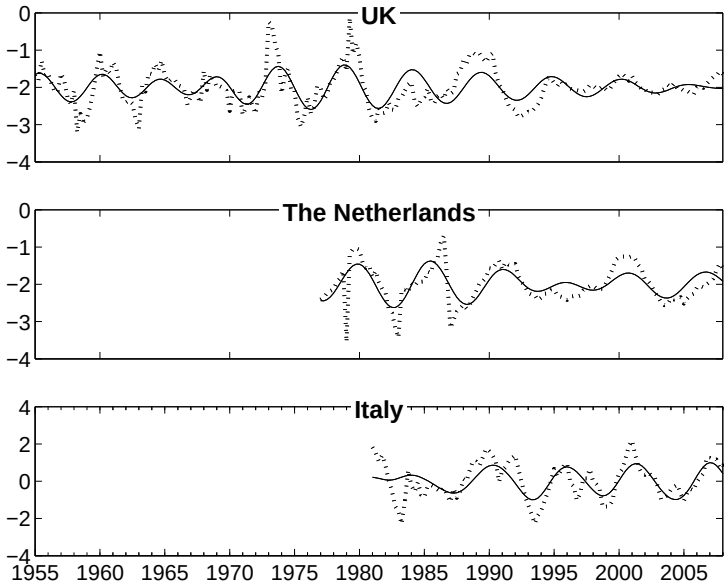


Figure 5: SSA reconstruction of the 5-year oscillation in the GDP time series of the three countries under study (solid line). This oscillation is represented by the first two eigenpairs in each series, and it captures 39% of the total variance for the UK, 44% for The Netherlands, and 40% for Italy. The window widths are $M = 50$, 45, and 34 quarters, respectively. The dotted curve in each panel is the same as the corresponding one in the first panel of Fig. 2.

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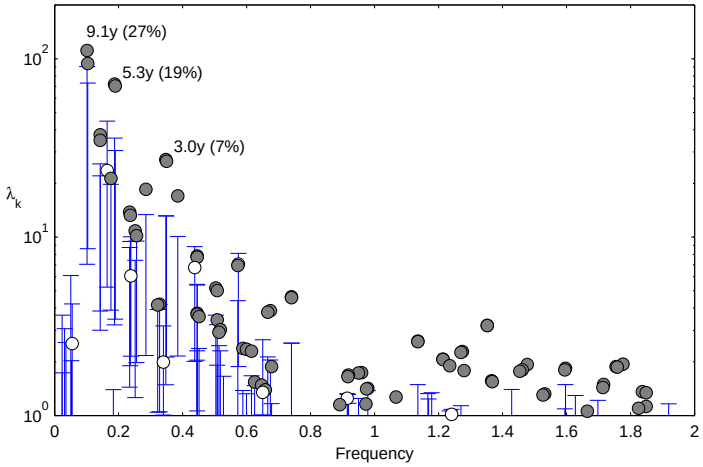


Figure 6: Eigenvalue spectrum from a global M-SSA of all 20 time series — from (4 countries) $\times$ (5 indicators) — with $M = 50$. The error bars indicate the 2.5% and 97.5% percentiles of 1000 surrogate time series, while the numbers in parentheses indicate the variance captured by the pairs of eigenvalues in question.

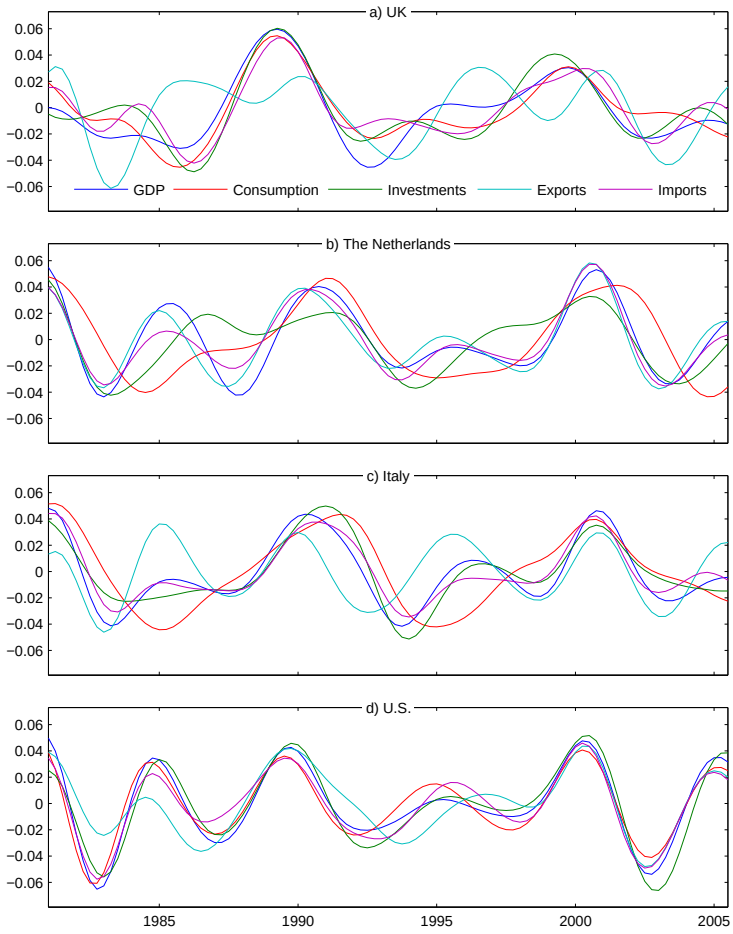


Figure 7: Further results of the global M-SSA analysis in Fig. 6 — reconstructed behavior of the 20 indicators, grouped by countries, using RCs 1–2, 3–4, and 7–8, which belong to the three significant oscillatory pairs of period length 9, 5, and 3 years, respectively. (a) The UK, (b) The Netherlands, (c) Italy, and (d) the U.S.; indicators for each country identified by the five colors shown in the legend of panel (a).

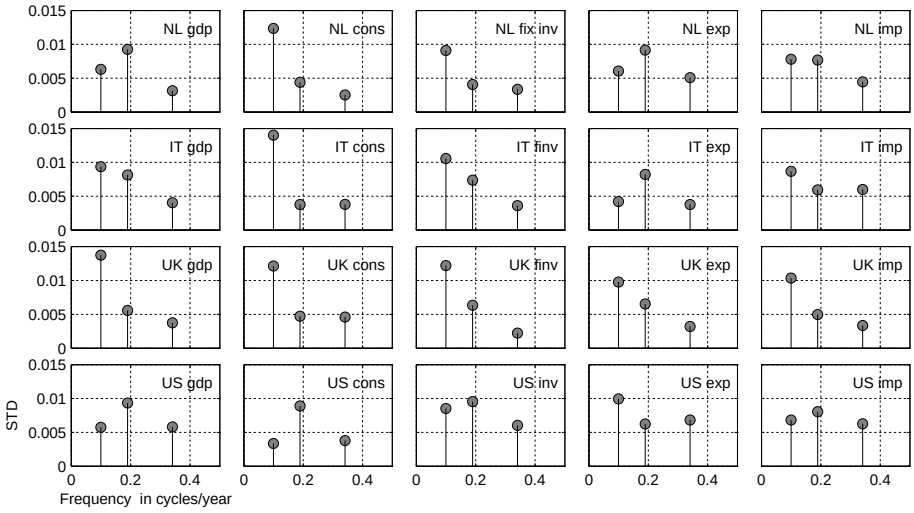


Figure 8: Standard deviation of the RCs as a measure of participation strength. The plot shows the RCs that correspond to the highly significant oscillatory pairs — namely RCs 1-2, 3-4, and 7-8 — vs. their dominant frequency.