ORIGINAL PAPER

Business cycle characteristics of Mediterranean economies: a secular trend and cycle dynamics perspective

Anna Solms[1] · Bernd Süssmuth[1,2]

Abstract

This study analyzes business cycle characteristics for all 20 major contemporaneous economies bordering the Mediterranean Sea based on annual real gross domestic product series for the period from 1960 to 2019. The region we investigate corresponds to the *Mare Internum* region of the Imperial Roman Empire during the Nerva-Antonine and early Severan dynasty, i.e., at the time of the maximum extent of the Roman Empire around 100 to 200 CE. The covered area encircles the Mediterranean, including economies now belonging to the European Union as well as acceding countries, Turkey, and the Middle East and North African economies. Using a components-deviation-cycle approach, we assess level trends and relative volatility of output. We also quantify the contribution of various factors to the business cycle variability within a region. We find cyclic commonalities and idiosyncrasies are related to ancient and colonial history and to contemporaneous trade relationships. Caliphate and Ottoman Empire membership as well as colonial rule in the twentieth century and contemporaneous Muslim share of population are the most promising predictors of business cycle commonalities in the region.

1 Introduction

Business cycle synchronization and linkages between countries have been studied intensively since Mitchell (1927) and Kuznets (1958), among others, pioneered the field. Especially the creation of the Euro Area (EA) has spurred research

✉ Bernd Süssmuth
suessmuth@wifa.uni-leipzig.de

Anna Solms
annasolms@web.de

[1] Leipzig University, Leipzig, Germany

[2] CESifo, Munich, Germany

on the topic. Business cycle co-movement and linkages are widely recognized as important for economic unionization in the form of free trade areas or currency unions. In particular, this point is made by the well-known Optimal Currency Area (OCA) theory literature (Bayoumi and Eichengreen 1997; Frankel and Rose 1998; Eggoh and Belhadj 2015). The analysis of Europe-Middle East and North Africa (MENA) co-movement is interesting because countries can be distinguished by European Union (EU) membership from the beginning, EU-accession during the observation period, EU membership candidacy, and Non-EU membership. This allows us to study intra- and inter-group commonalities and idiosyncrasies.

In this paper, we revisit and extend the contribution by Süssmuth and Woitek (2004) with an increased number of countries, different filtering methods, and a longer time horizon (from 1960 to 2019) that covers institutional changes as well as exogenous shocks such as the 2008 financial crisis. The aim is to investigate business cycle characteristics for 20 different Mediterranean Economies, including, among others, EU economies like France, Spain, and Greece, Maghreb economies like Tunisia, Algeria, and Morocco, and Mashreq economies like Egypt, West Bank Gaza (WB Gaza) or State of Palestine, and Syria based on annual GDP per capita series.

Analyzed countries are all connected through the Mediterranean Sea. The linkage through the sea provides geographically and historically trading possibilities that might have affected business cycle synchronization between the observed economies. With the integration of some of those countries into a single common currency area during the observation period, the focus is set to the question if there are indications of change in co-movement of cycles, compared to results obtained by Süssmuth and Woitek (2004) several years ago.

First, we sketch the historical roots of the region and review the existing literature to get an overview of previously examined countries and different methods. Subsequently, we describe our methodology. An output stability and volatility analysis helps to identify countries that are relatively more volatile and to classify their respective weight within the analyzed sample: Output series are filtered with seven different detrending devices and spectral analysis is used to identify business cycle characteristics. Consecutively, a non-parametric spatio-temporal framework as well as some correlation analysis serve as validation and rationalization of results obtained in the spectral analysis. Helping the identification of business cycle lengths, the focus is set to two different ranges: the 3- to 5-year range (Kitchin cycle) and the 5 to 10-year range (Juglar cycle), where the latter is generally dominating the spectral density. Finally, we conduct a detailed case study based on the most popular filtering device.

2 Deep historical roots and review of the literature

2.1 Deep historical roots

Recently, Chronopoulos et al. (2021), using high granular light emission data, demonstrate that ancient colonialism shapes the economic geography of the

Mediterranean region to the present day. Geographical areas colonized by ancient civilizations overall show higher population density and economic activity. A civilization that presumably had a lasting impact on still economically relevant notions such as infrastructure and public administration is the Roman Empire.

After Emperor Nero committed suicide, the second part of the first century CE of the Roman Empire was coined by a civil war between rival generals. Victory went to Vespasian who became an Emperor of a new type. As sketched, e.g., in Robinson and Hunter (1942) he reorganized the army and finance on business-like lines. In this era, the government of the Empire grew more systematically. After the death of his son Domitian, it became custom to choose emperors by merit rather than by lineage. A highly prosperous period started, in which Roman officials ruled provinces with justice guided by Emperor Trajan (98 to 117 CE). Law and order prevailed as never before in the *Imperium Romanum*. Europe to the present owes much to the methods that were devised during this period for impartial and efficient public administration. Besides, the Empire gave the Mediterranean region civilization. The influence of Greek culture had transformed the Romans themselves. They were no longer simple farmers like Cincinnatus of old. Magnificent infrastructure was built. Provinces located around the Mediterranean basin were encouraged to build towns with imposing squares, amphitheaters, and public baths. Education spread all across the area. Under Emperor Hadrian (117–187 CE) the height of the Empire's prosperity was reached.

Provinces were either imperial or senatorial (Fig. 1). For the latter, the Roman Senate appointed the governor (*proconsul*) exclusively provided with civic powers. In general, legions were not stationed in these provinces. In contrast, the imperial provinces rather represented the periphery of the Empire inasmuch as they acted as strategically located border provinces.

The Western Roman Empire, spanning from contemporary Croatia in Eastern Europe to the Iberian Peninsula in the South West and on the side of Northern Africa Morocco, Tunisia, Algeria, and the major part of today's Libya, officially ended in 476 CE when Germanic King Odoacer invaded and deposed Emperor Romulus Augustulus. The Eastern Roman Empire, comprising nine contemporary countries on three continents, continued (though more loosely related to Constantinople than to Rome during the *Imperium Romanum* times) on as the Byzantine Empire. The spread of Islam across the MENA area happened largely in three waves: during the life of Mohammad, under the first four Caliphs, and finally under Umayyad Rule which was the basis for the Caliphate. The Caliphate reached its furthest advance in 732 CE comprising eleven modern day Mediterranean economies, where only the southern parts of the Iberian Peninsula became Muslim states, the northern parts remained Christian Spanish kingdoms. At the beginning of the fourteenth century the Ottoman Empire started to spread until it conquered and acquired territories of the Caliphate in their entirety by 1683. However, the latter did no longer include the Andalusian parts of modern Spain as well as Morocco in the West of North Africa. As of 1800, the Ottoman Empire until the end of World War (WW) I was in decline. Nevertheless, the Ottoman Empire comprised five contemporary Mediterranean economies in their entirety

Fig. 1 The Roman Empire during the Nervane-Antonine and early Severan period (around 100 to 200 CE). Light colored areas bordering the Mediterranean Sea (Mare Internum) represent senatorial provinces, while dark grey shaded regions depict imperial provinces; Source: Nacu (2012)

for the whole period of its existence, five for a still substantial part, and two for a somewhat shorter period of its existence.

In the last century, colonial rule through other Mediterranean nations (Spain, France, Italy) or the United Kingdom (U.K.) prevailed across the Mediterranean MENA economies until most of them gained independence around the beginning of the second half of the century.

2.2 Literature review

As regards business cycle characteristics and commonalities across EU and EA economies, there is an ample literature dating back to the seminal contribution by Frankel and Rose (1998). Particularly many studies are devoted to the accession of (new) member states both to the EU and EA. The same applies to cross-country correlated economic performance at the supranational level after the experience of global and area-wide economic shocks such as the 2008 financial crisis and the proceeding European sovereign debt crisis. The EU/EA is the most researched area in this respect. However, there is also a slim, but growing, strand of literature concerned with Arab economies including or focusing on the MENA region. For instance, Eggoh and Belhadj (2015) study business cycle commonalities in the Maghreb area. They note that the Maghreb labeling dates back to the period of French colonialization grouping Algeria, Morocco, and Tunisia. In contrast to the Mashreq economies, the latter belong to the region referred to as *Djazirat al-Maghrib* during the Muslim conquests. In contemporary terms, the Maghreb zone comprises Algeria, Morocco, and Tunisia (also referred to as Maghreb Central) as well as Libya and Mauritania. Apart from the latter, these are all Mediterranean economies and, thus, also in the focus of our study.

The importance of business cycle synchronization within a monetary union arises from the fact that a single-currency area specifically comprises the adoption of a common monetary policy. A high degree of business cycle synchronization thus can be seen as a prerequisite of a "one size fits all" monetary policy to be efficient (Degiannakis et al. 2014). If there exist similar dynamics in business cycles, it will be easier for a central bank to impose stabilizing interventions. Not only does business cycle synchronization impact central bank decisions, but it also has implications on the fiscal policy of a country trying to stabilize possibly adverse effects of monetary policy, which are not suited for every member in the same way (Crowley and Schultz, 2010). Regarding the level of EU/EA business cycle synchronization, the existing literature has not reached a clear-cut consensus, although it is mostly found and agreed on that trade synchronization has positive effects on cyclic co-movement. This consent is even less present in the case of the by far less frequently studied business cycle dynamics of the emerging Arabian economies such as the ones of the Organization of Islamic Cooperation (OIC) member states; see Arshad (2016, p. 57). Arshad (2016), besides Hassan et al. (2010), is one of the few studies that envisions an Islamic Common Market. To highlight a puzzle from this literature, consider Chemingui and Eris (2017) who find for the sub-group of 18 Pan-Arab Free Trade Area (PAFTA) economies—where PAFTA more than quadrupled in members in the last decades since concluded in 1988 (originally comprising only the Maghreb zone excluding Libya)—in their global panel that trade integration among Arab economies is associated with less synchronized business cycles. In contrast, against the backdrop of an endogenous process towards a Maghreb OCA, Eggoh and Behadj (2015) find in their panel of Maghreb economies that trade has positive effects on business cycle co-movement in these countries. However, the effects are, at the same time, "by far below those registered in industrial economies" (p. 567). Similar to Arshad (2016) whose focus is on volatility pass-through, these authors stress the role of strengthened financial and—in contrast, to Arshad (2016)—also trade linkages across all sectors for their result. They ascribe it mostly to economic policy and trade agreements, for which they also provide a historical account in their introduction (pp. 554–555). Their sketch comprises the 1989 Arab Maghreb Union (AMU), the 1997 Greater Arab Free Trade Area (GAFTA), and the 2004 Agadir Agreement as well as several conferences held in their proceedings.

Getting back to the EU/EA context, several studies conclude that the level of synchronization increased during the post-European Exchange Rate Mechanism (ERM) period (Belo, 2001) and increased further in the post-Economic and Monetary Union (EMU) period (Darvas and Szapary 2008). Yet, some studies are pointing to evidence of decreased business cycle synchronization after the introduction of the common currency, implying a higher level of synchronization in the pre-EMU period (Hughes Hallet and Richter 2008; Lee 2012). Next to studies examining the effect of countries joining the EMU, a few research works analyzed the effects of the financial crisis in 2008. Gächter et al. (2012) find that there was a desynchronizing effect on business cycles in the EA together with a contemporaneous increase in dispersion of synchronization levels. Gomez et al. (2017) suggest that especially Greece is subject to a substantial decrease in synchronization levels. Only a few studies have taken up time-dependent measures. Rozmahel (2011) applies the widely used rolling

windows approach to identify temporal changes in synchronization. However, there are some disadvantages of this approach, e.g., the requirement to either set a window span or to lose observations at the start of the observation period. Also, the impact of a shock may not be reflected in consecutive periods that are defined within the window span, leading to so-called "ghost features" (Cerqueira and Martins 2009). Aguiar-Conraria and Soares (2009) use a wavelet transform to examine the evolution of power spectra across time and to study business cycle synchronization across the EA.

In sum, it seems that business cycle synchronization changes over time, indicating that examination within a time-varying environment is sensible. This is why this paper focuses on the estimation of autoregressive spectra as well as contemporaneous *and* lead-lag correlations between the analyzed GDP series. As regards the sensitivity with regard to the region at stake, the literature also suggests to consider deep (historical) roots (e.g., Chronopoulos et al. 2021) besides recent trade and financial integration. This concerns, in particular, the Arab part of the Mediterranean economies in order to rationalize business cycle similarities across economies with an Islamic culture and tradition and a high share of Muslims in the respective population.

3 Data and methodological framework

3.1 Time series

The yearly series used in the analysis is taken from the FRED database and is given as constant annual GDP per capita, evaluated in 2010 USD for 1960 to 2019. Unfortunately, quarterly series and/or series for sub-national entities of countries in our sample is available only for the OECD member sub-group. The main reason for using this measure instead of, for example, industrial production figures is that GDP per capita is the most comprehensive measure of economic activity and thus not limited to the manufacturing sector. The per capita figures abstract from deviations of gross numbers when immigration or demographic change is influencing economic activity throughout the observation period of almost 60 years. The latter is a considerable span and likely sensitive to changes within an economy. Unfortunately, the GDP series from 1960 onwards are not available for all countries equally. Especially for eastern European countries, figures are only available beginning with the 1990s. An overview of data availability for each country is given in Table 1 in the Appendix. As a robustness check, the volatility measures from Table 2 have been recalculated for an artificially shortened sample for the period 1995–2019 (see Table 3 in the Appendix). Results and trends are similar, which makes us confident that missing data are not obscuring our insights.

3.2 Overview of methods

Lucas (1977) describes business cycles as deviations from a trend. To extract business cycles, the computation of the trend of each series is therefore necessary for

the analysis. Following the seminal work of Burns and Mitchell (1946), the business cycle itself can be viewed as a movement in the time series that exhibits periodicity within a certain range of time.

An approach suited to describe those fluctuations at different frequencies is spectral analysis. If a process is stationary, it has a spectral representation with frequencies $\omega \in [-\pi, \pi]$. The variance or power of the process at $X_t(\omega)$ indicates its influence on the overall movement of X_t (A'Hearn and Woitek, 2001). A first step in the analysis is therefore testing for stationarity. There are several methods to test for this, as for example the Dickey-Fuller test or the Philipps-Perron test. The power of those tests heavily depends on prior knowledge of the series' properties and performance is substantially reduced in presence of autocorrelated errors. Following DeJong et al. (1992), the augmented Dickey-Fuller (ADF) procedure is in this case reasonably well-behaved and suitable for testing annual macroeconomic time series.

Secondly, filtering methods are applied in order to remove the trend component from the series. An ideal filter would remove fluctuations at frequency zero but leave all others untouched. Each of the following methods is sensitive to its respective parameter choice in that it influences the obtained outcomes. For the widely used Hodrick-Prescott (HP) Filter (Hodrick and Prescott 1997), the risk of inducing spurious power when applied to the wrong type of data exists. Nevertheless, it is close to ideal when applied to trend-stationary data and its widespread acceptance in the literature is based on several robustness checks of its de-trending method (Artis and Zhang 1997; Montoya and De Haan 2008). It decomposes the initial series into a trend- and cyclical component, such that the distance between the trend and the original series, as well as the curvature of the trend series, is minimized. The trade-off between both objectives is governed by the parameter λ. Following Hodrick and Prescott (1997), a smoothing weight of a hundred is used in a first step. Additionally, we consider the popular modification of the HP filter by Ravn and Uhlig (2002). It adjusts the filter weight λ to a value of 6.25 in the case of series with annual frequency.

In contrast to the HP filter, which is considered a high pass linear filter that eliminates all frequencies above the applied maximal period, the Baxter-King (BK) filter is a bandpass filter that allows suppression of both the low and the high-frequency trend components (Baxter and King 1999). Following their specification of the filter, which relies on the Business Cycle definition of Burns and Mitchell (1946), the cutoff frequencies of this filter are in the following set to preserve periodicities of between 2 and 10 years.

Another filtering method used here is the one proposed by Christiano and Fitzgerald (1999), henceforth referred to as CF filter, which uses the whole time series for the calculation of each filtered data point. Both the BK and the CF filters are approximations of the ideal infinite bandpass filter. The advantage of the CF filter is that it converges in the long run to the optimal filter so that it outperforms the BK filter. They also argue that their filter is an improvement over the HP filter when quarterly data is examined. As for the BK filter, cutoff frequencies of the CF filter are set to filter out stochastic cycles of smaller than 2 and larger than 10 years. A fifth filtering method applied in this paper is the application of the HP filter in a parallel circuit application (PCA) as proposed by Artis et al.

(2004). Following, among many others, Artis et al. (2004), the approximate BP filter through the PCA is achieved by applying the HP filter twice in order to obtain a smoothed de-trended cycle. First, the parameter λ is set to a high value, so that high-frequency components of the series are preserved. In a second step, a smaller λ is applied so to preserve the trend components. Chosen cutoff frequencies are here set so to preserve cycles between 2 and 10 years, deliberately deviating from the usual selection of restrictions. The choice of parameters presupposes knowledge about the properties of business cycles, as for example the optimal cycle length.

As the underlying definitions of cycles and therefore decisions on behalf of the frequency band are dating back decades ago and there is moreover no consensus in the literature about how long a cycle should be, it might be interesting to extend those boundaries. Since for instance Agresti and Mojon (2001) propose an upper boundary of 10 years for European cycles, preservation of cycles between 2 and 10 years is chosen here. Furthermore, we follow Hamilton (2018) in considering his recently proposed one-sided MA filter adjusted to an annual frequency of observations, i.e., the Hamilton filter (HF) with projection-horizon parameter h set to 2. Given the apparent trade-offs between the filters and even within them, looking at numerous extensions and modifications, a total of seven devices—including log first differences besides the sketched six methods—are implemented to develop our framework to quantify potential cycle lengths. For five out of these seven filtering devices (excluding the PCA and log first differences) an AR(p) Model is estimated for each series individually in comparing the different Information Criteria and subsequently choosing the model with the lowest Akaike Information Criterion (AIC) value. If the comparison suggests a model that leads to a low-order autoregressive model with which it is impossible to detect any cycles, the next lowest order is chosen so to obtain information about cycle dynamics. Based on the respective AR(p) model, the spectral density of the parametric process is calculated. For further detail on the underlying definition of such measured cyclicalities contained in the series see the note to Table 4 in the Appendix.

Following Süssmuth and Woitek (2004), three measures are being calculated in the subsequent part to assess relative volatility and contribution of a time series to the constitution process of an aggregate series: the relative trend level (RTL), the contribution to standard deviation (CTS) and the standardized standard deviation (SSD).

The relative trend level is given by

$$\text{RTL} = \frac{\tau_t(y_i)}{\tau_t(\sum_i^N y_i)}, \tag{1}$$

for all i components at different points in time $t=1,\ldots., T$. It describes the relative share of series i's trend level $\tau_t(y_i)$ to the aggregate series' trend level, with $i=1,\ldots., N$.

Here, the focus is set on the starting point ($t=1=1960$), the midpoint ($t=T_m=1990$) and the endpoint K; ($t=T=2019$).

The standardized standard deviation is a measure of relative volatility and given by

$$\mathrm{SSD} = \frac{\sigma[(y_{i,t} - \tau_t(y_i))]}{\tau_{T_m}}, \tag{2}$$

in other words, it is the standard deviation of a detrended series divided by its mid-trend level value, here the trend level of the year 1990.

Finally, the contribution of the ith series to the aggregate's standard deviation is defined as

$$\mathrm{CTS} = 1 - \frac{\sigma(y^a - y_i^c)}{\sigma(y^a)}, \tag{3}$$

where y_i^c is the business cycle component of series $i = 1, \ldots, N$, that are forming the aggregate series y^a. The CTS is therefore the reduction in the standard deviation of the aggregate, when y_i^c is left out, as a share of the total aggregate's standard deviation.

In order to assess our AR-based spectral density estimates of cyclic commonalities and idiosyncrasies against the backdrop of different degrees of sea access and particularities of ancient and colonial history (Sect. 2.1), we propose a non-parametric spatio-temporal framework. This framework is rather descriptive than inductive or "quasi-experimental" in nature. It is motivated by the recent debate on spatial noise regressions, "p (value) hacking," and problematic causal inference methods with—in particular, historical—economic data; see, among others, Brodeur et al. (2016), Brodeur et al. (2020), and Kelly (2019).

Our alternative approach rests on bivariate kernel density estimates weighting observations i, e.g., estimated period lengths of a business cycle contained in a series of country i, at certain points p_i via a continuous weighting function K. For a number of dimensions d, the respective bandwidth h_j governs the impact of a pair of observations s_{ij} on p_i. It is chosen following the normal reference rule leading to a biweight or quartic kernel K; see, e.g., Härdle (1991):

$$\widehat{f}(p_i) = \frac{1}{nh_1h_2} \sum_{i=1}^{n} \left[\prod_{j=1}^{d} K\left(\frac{p_i - s_{ij}}{h_j} \right) \right].$$

For further detail, in particular, on kernel K, see Note A.1 in the Appendix. As regards the interpretation of three-dimensional (3D) surface and contour plots of bivariate kernel densities, it is straightforward: Following, for instance, Deaton (2019, p. 179), we can—just as we interpret univariate kernel densities as substitutes for histograms—interpret bivariate kernel densities in place of cross-tabulations for joint relative frequencies. In other words, the z-axes in the following 3D plots or alternatively the figures to the contour lines in the 2D contour plots represent joint relative frequencies or empirical joint probabilities for variables p (i.e., estimated dominating business cycle period lengths) and s (any other, e.g., historical variable

as outlined in the text) variables depicted in the 3D surface plots on the respective rear axis.

4 Results

4.1 Findings across filters and some rationalizations

To get a summarizing impression of our spectral analytical findings, Fig. 2 gives an overview of implied periodicities averaged across the seven filtering devices (in years) for all 20 contemporaneous countries of our study. Detailed results on a filter by filter basis are given in Table 4 (with corresponding RTL, SSD, and CTS measures given in Table 5, 6, 7) in the appendix.

The first point to note is that the long period length cycle estimates clearly show more variation across economies of the regions. This does not really come as a surprise as Juglar periodicities are ususally asscoiated with potentially more heterogeneous gross fixed capital formation processes, while Kitchin cycles traditionally are attributed to inventory dynamics. Thus, in the following the focus is on our findings regarding the peak of the estimated spectral density, i.e., on the contained cyclicality with the longer periodicity.

Regarding the belonging to one of the three different continents of the area seems not helpful in predicting national period lengths. Strikingly, however, for the Northern African economies, we find, on average, to either show a clearly above the mean periodicity value of 7.23 years period length (Morocco, Egypt) or a substantially shorter cycle length in years. However, a bivariate kernel density estimate, considering our mean periodicities and a continent categorial, for our 20 economies at stake does not produce a conclusive result for a significant association between the two. The same holds for a categorization in regions that formerly where either imperial or senatorial provinces in the Roman Empire (Fig. 1). Proceeding chronologically with potential historical rationalizations of our results, we might look for a differential of formerly Eastern Roman Empire, comprising nine contemporary countries on three continents, of our sample and the ones that did not belong to the Byzantine Empire. A corresponding quartic kernel density estimate is shown in Fig. 3. As can be seen from the upper schedule of Fig. 3, the three-dimensional joint kernel density clearly is of bi-modal type. However, a closer look at the lower schedule contour plot representation reveals that the Eastern Roman Empire property (right peak) is only more densely centered around a periodicity value of about 7 years than for the remaining economies of the region. The latter (left peak) are more dispersed, in particular, towards business cycle lengths that fall below 7 years. Nevertheless, the center of both peaks of the joint distribution lies at a periodicity that corresponds to the overall implied period length averaged across filters of about 7 years.

As the so-called middle empires, including the Roman, Byzantine, the Caliphate, and the Ottoman Empires lasted almost 2000 years, while the age of European colonization of the Mediterranean MENA area just lasted less than 200 years, it seems logical to next consider the Caliphate era. At its maximum extent, the Caliphate comprised nearly eleven modern day Mediterranean economies. In the following,

Fig. 2 Estimated periodicities averaged across seven filtering devices (in years). Long (short) cycle period length refers to the (second) highest peak in the parametrically estimated spectral density. In the stylized map the contour of Malta and WB Gaza miss; corresponding values are given approximately at their corresponding location in the respective map
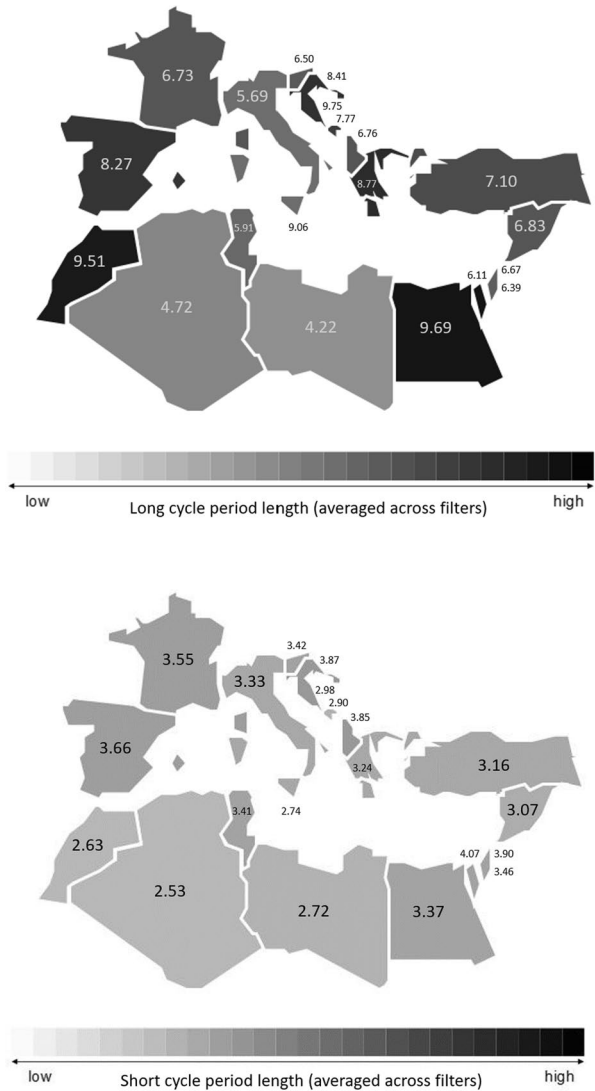
we consider this extreme spread. Note, however, whether today's Spain is ascribed a value of 0.5 or 1 in formerly belonging to the Caliphate does not qualitatively alter our results. As can be seen in the lower panel of Fig. 4, the modern economies formerly belonging to the Caliphate empire obviously show a systematically lower business cycle length than their non-Caliphate counterparts. The peaks in the joint kernel density are not only separate but also shifted downwardly from each other. A relative frequency value of 0.12 is ascribed to the left and right peak of the joint kernel density, respectively. This is an interesting finding and implicitly raises the question whether this feature is sustained also for the Ottoman Empire era.
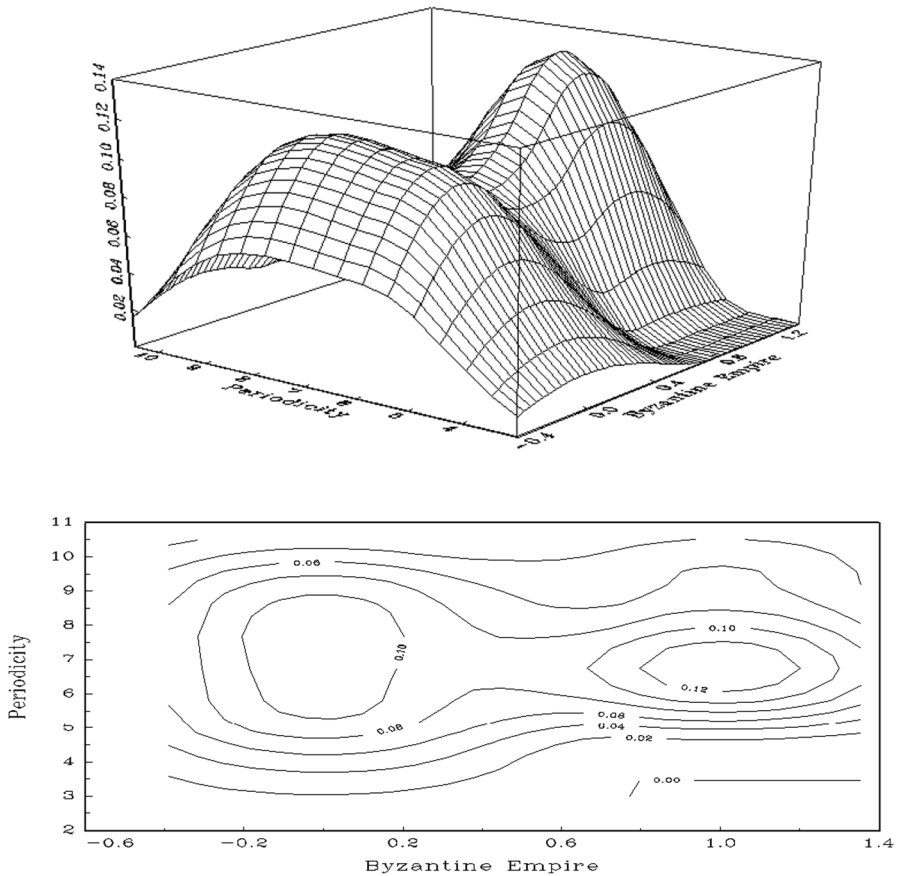
Fig. 3 Kernel density of long cycle periodicity with Byzantine Empire property. Bivariate kernel density estimation (quartic kernel) of average, i.e., arithmetic mean across seven filtering devices, long cycle period length with Byzantine Empire property of the analyzed 20 Mediterranean economies; in the 3D-density representation (upper panel), ordinate values are joint relative frequency values; in the contour plot (lower panel) these correspond to the values ascribed to contour lines

We ascribe territory of the Ottoman Empire that was lost between 1800 and 1877, such as modern day Algeria, a value of 0.5, territory that was lost between 1877 and 1913, such as Tunisia and Egypt, a value of 0.75, and territory that belonged to the Ottoman Empire up to the start of WW I a value of 1, respectively. An even higher relative frequency value of 0.12 (0.16) is ascribed to the left (right) peak of the joint kernel density (Fig. 5). This tells us that 12% of our sample's economies without an Ottoman Empire background show a dominating business cycle period length of about 8 years, while 16% with a long-lived Ottoman Empire affiliation are coined by shorter cycles of roughly 6.5 years. There are also several in-between cases, however, the dichotomy, as already given in Fig. 4 (for the Caliphate property) is fostered and obvious: The peaks in the joint kernel density are now also clearly more profoundly shifted downwardly (in contrast, e.g., to Fig. 3). Thus, the
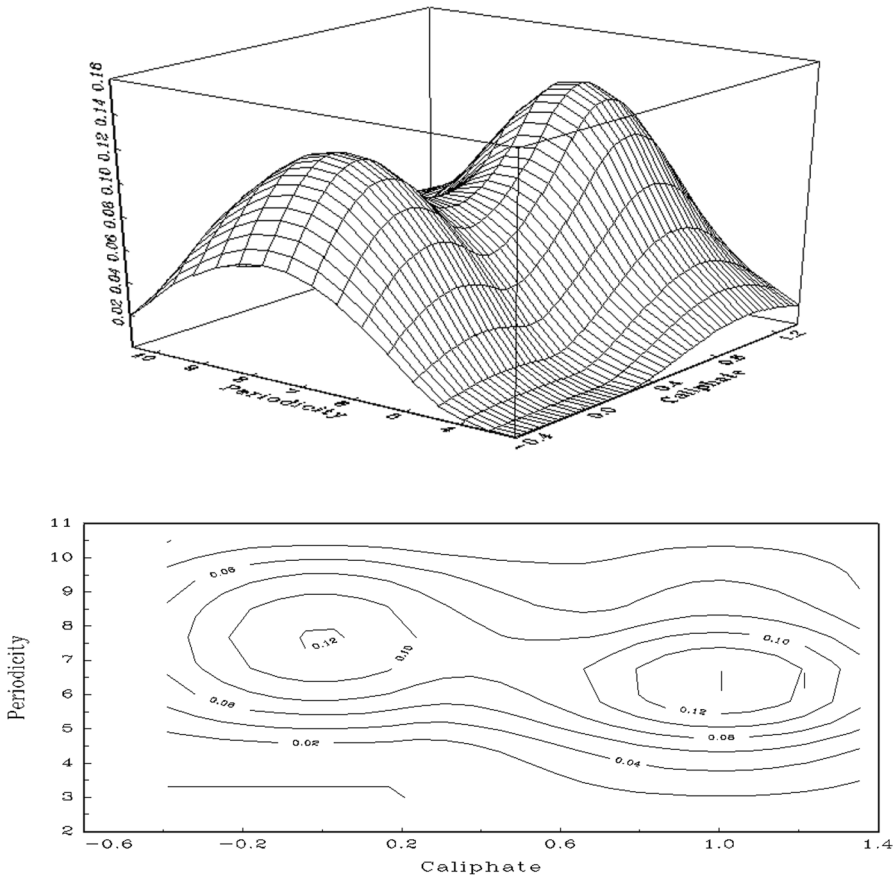
Fig. 4 Kernel density of long cycle periodicity with Caliphate property. Bivariate kernel density estimation (quartic kernel) of average, i.e., arithmetic mean across seven filtering devices, long cycle period length with Caliphate property of the analyzed 20 Mediterranean economies; in the 3D-density representation (upper panel), ordinate values are joint relative frequency values; in the contour plot (lower panel), these correspond to the values ascribed to contour lines

cyclical property differential cannot only be seen as sustained but rather as amplified comparing the Caliphate era with the more recent Ottoman Empire phase.

But does this relationship also carry over to the age of European colonization of the Mediterranean MENA area lasting less than two centuries? By mere eyeballing, our results summarized in Fig. 2 are not suggestive for bi-lateral similarities such as a particulraly striking similarity between the Italian and the Lybian business cycle or the French with the ones of Morocco, Algeria, Tunisia, the Lebanon, and Syria.

All our efforts in establishing such relationships, also considering different shades of control and spells of colonial rule, failed to establish a clear pattern. However, if we use just a binary identifier for a country being either one of the colonizing countries or a country under European colonial rule in the twentieth century, the joint distribution shown in Fig. 6 results. This might be rationalized on grounds of the recent
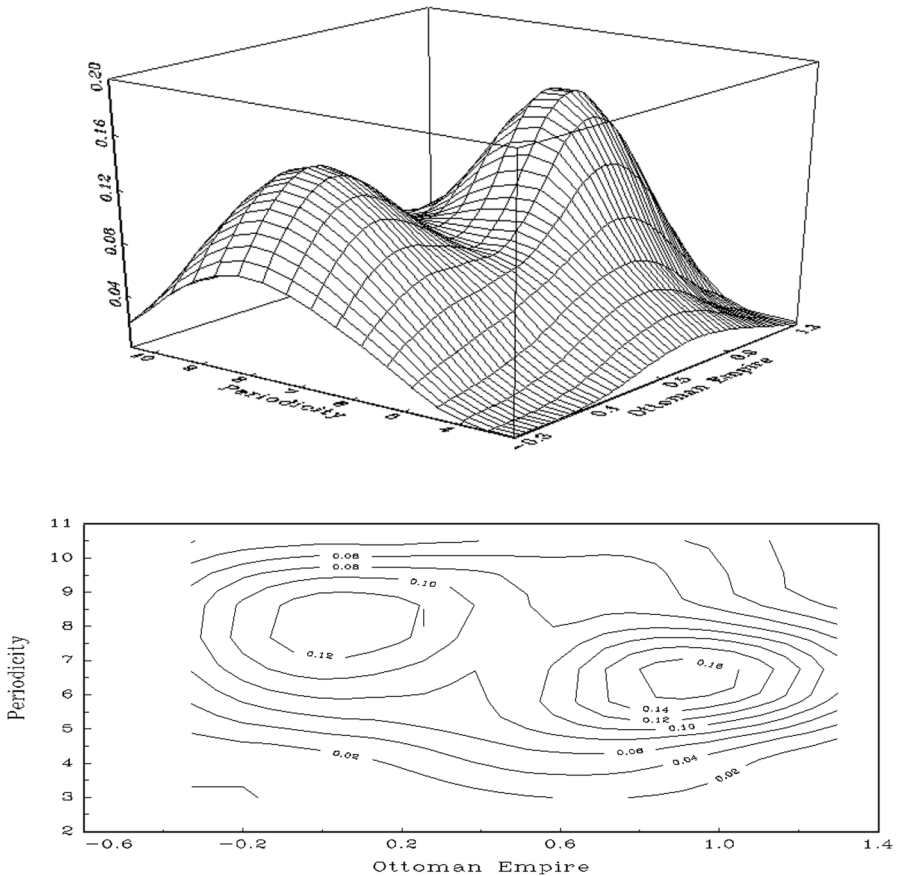
Fig. 5 Kernel density of long cycle periodicity with Ottoman Empire property. Bivariate kernel density estimation (quartic kernel) of average, i.e., arithmetic mean across seven filtering devices, long cycle period length with Ottoman Empire property of the analyzed 20 Mediterranean economies; in the 3D-density representation (upper panel), ordinate values are joint relative frequency values; in the contour plot (lower panel) these correspond to the values ascribed to contour lines

insights by Kleinert et al. (2015). Accordingly, the presence—notably not primarily through trade channels—of foreign affiliates of multinational firms is of paramount importance for business cycle co-movement. It is straightforward to consider former colonialization by their countries of origin, for instance, through missing language and other cultural barriers, as an attractor of such multinationals.

Again, our finding of earlier centuries, i.e., for the long-lived Ottoman Empire ranging from the late 13th to the inter-war period of the twentieth century, is confirmed for the era of European colonial rule in the twentieth century. Although, the peaks of the joint distributions, i.e., in particular, the first peak representing mostly the European economies that were neither colonized nor colonizing, are not as profoundly differing as in the case of the (less polar) Ottoman Empire variable,
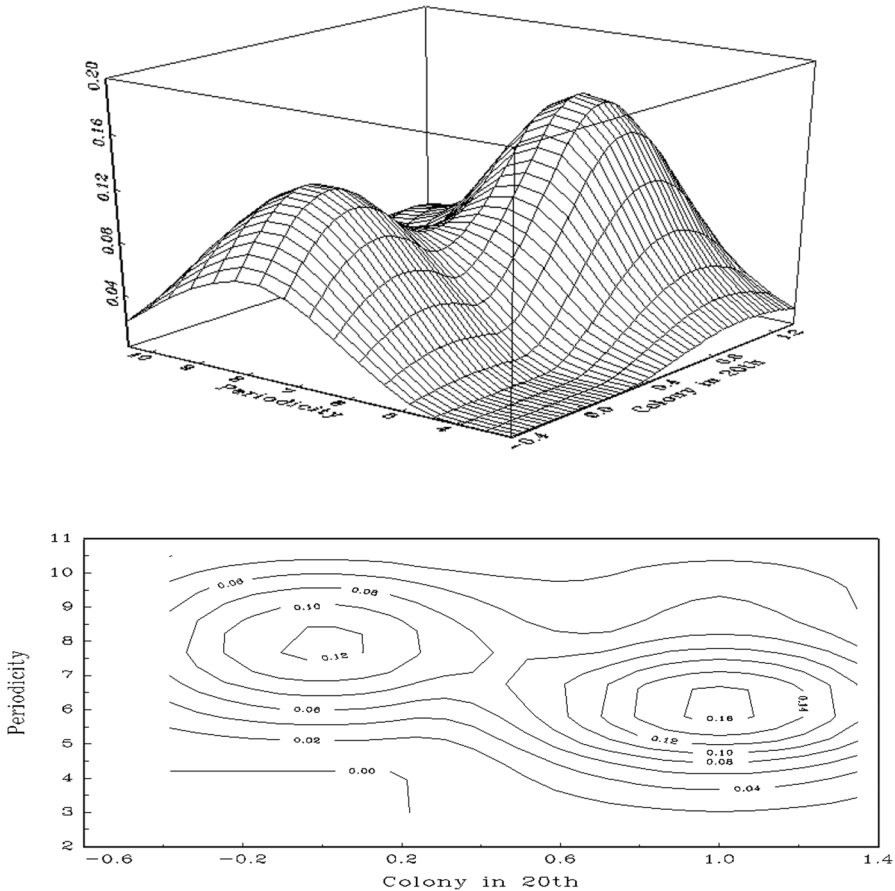
Fig. 6 Kernel density of long cycle periodicity with European colony in twentieth century property. Bivariate kernel density estimation (quartic kernel) of average, i.e., arithmetic mean across seven filtering devices, long cycle period length with European colony—active or passive, i.e., colonializing or colonialized—in the twentieth century property of the analyzed 20 Mediterranean economies; in the 3D-density representation (upper panel), ordinate values are joint relative frequency values; in the contour plot (lower panel) these correspond to the values ascribed to contour lines

a clear-cut differential results. Overall, our results so far allow the cautious interpretation that, indeed, historical circumstances, even from several centuries in the past, seem to have a long shadow in shaping modern business cycle dynamics of the region. The two spatio-temporal denisties concerned with the Caliphate and Ottoman empire affiliation (Figs. 4 and 5), might be seen as instrumenting a modern-day outcome: the respective major religion in these countries nowadays. In the contemporary Mediterranean economies of our sample, the average confessional population share attributable to the Islam is 49.96%, to Christianity 38.16%, and to Judaism 4.36%, respectively. The average atheist share is 6.28%. Interestingly, the

contemporary Islamic population share generates a resulting bivariate density very close to Fig. 4 and, particularly, to Fig. 5 (Ottoman empire affiliation); see Fig. 7. Now the bi-modality comes out even more profound. The respective smoothed modal value of Islamic population share between 0 and one fifth attracts 16% and the one between about four fifth and 100% attracts 14% of probability mass, respectively. The first of these modes corresponds to the longer business cycle periodicity of about 8 years, the second to the shorter one of about 6.5 years. Note, in the case of the (three-categorial) quasi-continuous Ottoman Empire property, the first modal value (no empire affiliation) attracts 12%, the second (longest possible empire affiliation) 16%, respectively. The corresponding periodicity on the ordinate is equivalent.
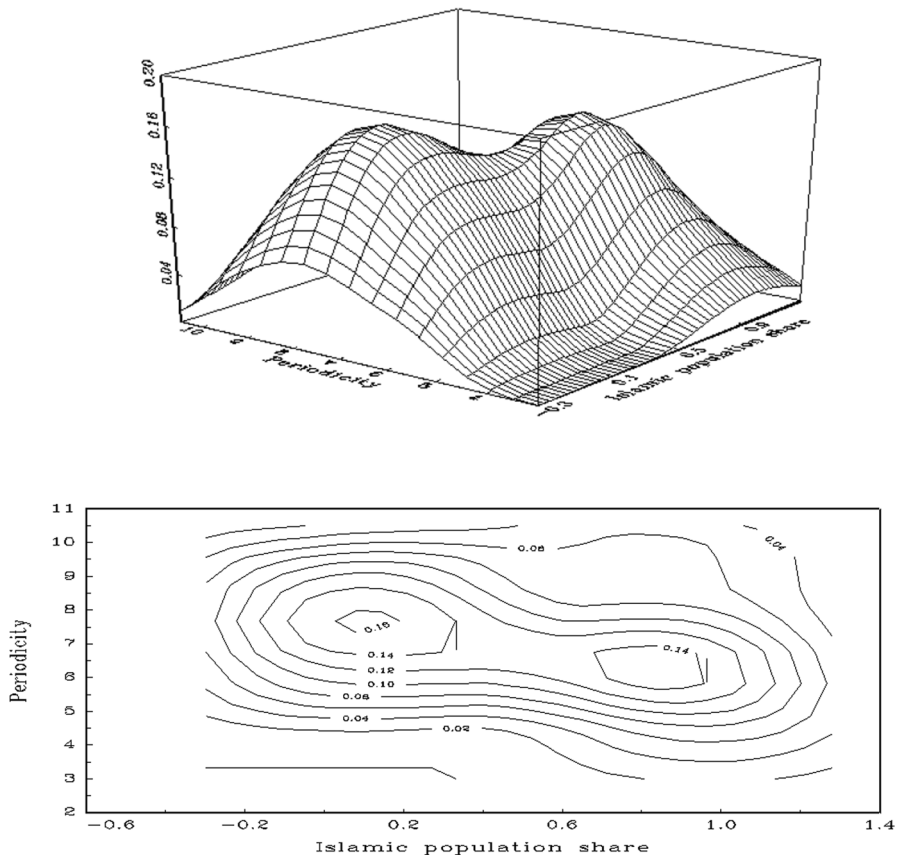
Fig. 7 Kernel density of long cycle periodicity with Islamic population share. Bivariate kernel density estimation (quartic kernel) of average, i.e., arithmetic mean across seven filtering devices, long cycle period length with Islamic population share (data sources: CIA World Factbook, U.S. Department of State, ARDA: Association of Religion Data Archives, Pew Research Center, ACN: Aid to the Church in Need) of the analyzed 20 Mediterranean economies; in the 3D-density representation (upper panel), ordinate values are joint relative frequency values; in the contour plot (lower panel) these correspond to the values ascribed to contour lines

The other religious affiliations and the atheist population shares as well as relative shares of affiliations do not identify any plausible associations with the length of dominating business cycles in the GDP series.

Relying analogously on quartic kernel joint density estimates, we also analyzed different degrees of sea access. For the latter, we considered, among others, coastline in kilometers (km) as well as coast to area ratio (in m/km^2) each from two different sources, i.e. the CIA World Factbook and the World Resources Institute, respectively. Corresponding joint kernel density distributions do not identify any meaningful relationship between differential access to the Mediterranean Sea and the length as the most salient feature of the respective business cycle. As GDP in per capita is underlying our business cycle periodicity estimates, the ratio of coastline (km) to inhabitants (100 K) might be seen as more adequate. A corresponding kernel density, however, does analogously not reveal any plausible relationship. See Figure 8 in the Appendix. This might be due to Greece and Croatia with comparatively high three-digit values of this ratio (129.83 and 139.30) representing upperbound outliers and biasing the bivariate distribution. Considering geopolitically important ports, as in Gawellek et al. (2022), or average distance of highly intensive production sites, as measured, e.g., by remote sensing light intensity data, to the coast could be promising approaches in this regard. However, this goes beyond the scope of the present study.

4.2 Findings for the most popular filter: a detailed case

Results of our output, stability, and volatility measures' calculations for the HP (100) filter are shown in Table 2. The RTL measure is computed for three different points in time, namely the start, the end, and with $t = 1990$ roughly the midpoint of the observation period.

All EU15 countries in the sample, namely France, Spain, Italy, and Greece lost in weight with respect to the relative trend level, whereas the countries that have been part of the 2004 enlargement of the EU, that is to say, Slovenia, Croatia, and Malta, have gained in weight. For Croatia, this tendency is taken from the shortened sample calculations for later periods as of the aforementioned issue with missing data for the defined time frame.

If the EU25 countries are excluded from the sample, Israel loses the most in weight by about 25% between 1960 and 2019, but still has, with a measure of 0.346, the highest share of the estimated subsample in terms of RTL. For the whole sample, France has the highest RTL numbers throughout the period, as it also has the highest GDP per capita numbers among the analyzed economies.

The CTS figures imply that for the whole sample, Lebanon and WB Gaza are contributing the most in standard deviation terms to the aggregate cycle. Among the EU25 countries, the highest contribution to standard deviation is given by the CTS measures of Croatia and Greece. Excluding the EU25 countries, WB Gaza is still showing the highest (negative) CTS figure, suggesting that its economy is evolving countercyclically. Lebanon is with a slightly less value of -0.351 following in

terms of high CTS terms, indicating again a rather countercyclical development of its economy to the aggregate business cycle component from the subsample. The reason for the countercyclical movement of the economy of Montenegro, as well as for smaller but also negative CTS numbers of Albania and Bosnia and Herzegovina could be that all of those countries are membership candidates for the EU and have one-sidedly already implemented the Euro or operate with a currency pegged to the Euro, being therefore partly influenced by European Central Bank decisions. The finding of procyclical movement of EU membership candidates' business cycles with respect to EU countries' GDP fluctuations is also confirmed by our correlation analysis below.

The most fluctuating country in SSD terms with a value of 0.119 is Lebanon, which can mostly be assigned to constant political instabilities like a 16 years lasting civil war until 1990 and in the aftermath the threat of a spillover of the Syrian Civil War, as well as various severe clashes between pro-government and opposition militias. Subsequently, Lebanon has been suffering a serious economic crisis with being the first country in the MENA group that saw inflation rates exceeding 50% for 30 consecutive days.

There might be objections to the obtained results as the data used in the analysis is partly missing. Especially GDP series of Eastern European countries are only available from the mid-90 s, that is, when Yugoslavia was dissolved and countries like Slovenia, Montenegro, Bosnia and Herzegovina, and Croatia became independent. For Syria, GDP series are only available between 1960 and 2007, which is why it is left out in the robustness analysis. Similarly, the series of Libya and Montenegro are also only available from 1999 and 1997, respectively, which is why they are left out in the shortened sample as well. Regardless, the reduced sample comprises in total 17 countries over an observation period of 24 years. Results of the three volatility measures are given in Table 3 in the Appendix.

When comparing the RTL measures with the full sample, trends in the minimized sample are pointing in the same direction. Within the EU countries, France, Italy, Greece, and Spain lost in weight, whereas countries that have joined the EU as part of the 2004 EU enlargement, that is Slovenia, Croatia, and Malta, have gained in terms of their relative trend level.

Comparing the mid-and end-RTL values from the full sample with the two RTL values calculated in the shortened sample, the magnitude of those numbers throughout the observed countries is similar, confirming the robustness of the full sample RTL weights.

When looking at the CTS figures, the values of the reduced sample are throughout the sample smaller than those of the full sample. For some countries, the difference between the samples is considerable, as in the case of WB Gaza and Lebanon the CTS values are almost 30% less negative than in the full sample. When looking at the calculation of the CTS, one reason for this might be found in that the standard deviation of the aggregate might be higher in the shortened sample. It intuitively can be explained by an increased weight of several shocks happening within the shorter time horizon as the aftermath of the dissolution of Yugoslavia, the 2008 financial crisis, and severe wars in the eastern Mediterranean countries.

The value of the standard deviation in the short sample is with 4594.64 higher than that of the longer sample with a value of 4477.29, thus confirming the intuition and therefore giving further confidence of using the long sample without biasing the outcomes. Looking at the SSD terms, there are only small deviations between the reduced and the full sample. In the full sample, the mid-term trend-level was evaluated at $t = 1990$, in the short sample the mid-trend level was evaluated at $t = 2005$. The highest deviation between both samples of around 5% is for Lebanon, which shows in the short sample an SSD term of 0.057 and in the longer sample of 0.119. Taking this together, it looks like the results obtained in the longer time horizon are robust and not severely biased as a result of missing data of single countries. As this paper explicitly wants to analyze all countries bordering the Mediterranean Sea over a continued period, this robustness analysis gives the confidence to use the given data despite the initial objections.

Tables 8, 9, 10 illustrate a correlation analysis, following the approach of Kydland and Prescott (1990). The GDP series of each country is filtered with the Hodrick-Prescott Filter and a smoothing weight of 100. The values in each row are indicating the estimated correlation coefficients that have been computed with ordinary least squares (OLS) for the lags − 1, 0, and + 1 after the filtered series has been standardized. The standard errors are given in parentheses and are corrected for heteroskedasticity and autocorrelation, according to the proposition of Newey and West (1987).

Table 8 in the Appendix displays the contemporaneous co-movement of the different GDP per capita series with each other. The statistics in this column are the correlation coefficients of the analyzed series and the numbers given in parentheses are the estimated standard deviations. A positive value of the correlation coefficient suggests a pro-cyclical movement of the analyzed series; a negative value signals a countercyclical movement of the cyclical component of the respective GDP series. If the value is close to one, the series are highly correlated. Contrary, if the value is close to zero the two series can be interpreted as uncorrelated with each other. Tables 9, 10 also display correlation coefficients, but the series have here been shifted forward (Table 9 in the Appendix) and backward (Table 10 in the Appendix). The coefficients displayed in the columns therefore indicate whether there is a phase shift in the movement of the series with respect to the respective series valued at time t given in each row. If for a GDP series the correlation coefficient with, e.g., France is higher in Table 9, this would mean this series lags the cycle of France by 1 year. Correspondingly, if the coefficient of the series is highest in Table 10, it would mean the series leads the cycle of France.

Looking at Table 8, it seems that the relation between business cycles of the EU countries in the observed samples is contemporaneously pro-cyclical. Furthermore, the correlation between most of the EU countries is highly significant. Coefficients close to one indicate that those series are highly correlated with each other. The only exception here is Malta, which shows with values between 0.05 and 0.42 no high correlation with its neighboring EU countries. The relation between EU members and Eastern Mediterranean Economies, namely WB Gaza, Lebanon, and Syria, is on the other hand contemporaneously countercyclical as indicated by mostly negative

correlations. The cycles of the EU Membership candidates, which are Albania, Montenegro, and Bosnia and Herzegovina, are contemporaneously pro-cyclical. The reason for this pro-cyclical movement of their GDP series can be an indicator, as mentioned above, of their efforts in fulfilling the accession criteria of EU membership candidates. Israel is not showing a significant correlation with any of the EU countries, which is in line with the results of Süssmuth and Woitek (2004), and can be explained by Israel's stronger trade links to the USA, relative to European countries (Süssmuth and Woitek 2004). Inspecting the North African countries, the cycle of Egypt is procyclically leading the cycles of the EU countries, with an exception to the cycles of France and Malta, with correlation coefficients ranging between 0.40 and 0.69. The other North African countries do not show much correlation with European business cycles. There have been several free trade agreements set in place but trade integration between North African countries and EU members still needs to be improved significantly in order to approach gradual convergence of per capita income and living standards.

5 Conclusion

In line with several analyses focusing on European business cycle synchronization, spectral analysis of Mediterranean economies has shown that the cycle structure of EU members is similar with dominant cycles in the range of the long Juglar cycle (7 to 11 years).

The first part of our analysis, resting on a non-parametric spatio-temporal framework, has demonstrated that Byzantine, Caliphate, and Ottoman Empire membership as well as colonial rule in the twentieth century are the most promising predictors of business cycle commonalities in the region. We also find this dichotomy in business cycle characteristics to carry over to the contemporary Islamic population share of Mediterranean economies.

Moreover, we have shown that cycle characteristics of EU membership candidates like Bosnia and Herzegovina, Montenegro, and Albania are in line with those of the EU countries, which can be used as an argument of those favoring an accession of the respective candidates. Looking at the southern Mediterranean countries of our sample, estimated averaged periodicities are still considerably lower than those of the EU countries, and for Algeria and Libya ranging within the Kitchin-cycle (3 to 5 years), for Tunisia and Morocco a little bit higher yet still below the average. This finding is in line with the results of Süssmuth and Woitek (2004). It suggests that there has not been a lot of convergence between European and MENA business cycles within the last decades. Looking at trading activities, the shift from European trade relations to trade between MENA countries and especially China might be an explanation. The initial notion of results being sensitive to different filtering methods can be confirmed when looking at the outcomes and their respective standard deviations. The separate filtering methods used in the analysis can thus be seen as a promising way to identifying differentials in business cycle lengths. Taking the output volatility analysis into account, countries that have joined the EU have gained in weight with respect to the relative trend levels while countries that have been part of the EU15 countries have

lost in weight over the observation period. Not surprisingly, Lebanon and WB Gaza show the highest standardized volatility and contribution to standard deviation terms of business cycle dynamics in the region. This can be seen as an expression of lasting political instabilities, economic crises, and wars.

Correlation analysis of GDP per capita series has revealed that European business cycles are highly correlated with each other and contemporaneously pro-cyclical. Again, EU membership candidates show similar relations with EU countries, indicated by positive contemporaneous correlation coefficients. Except for Libya, which is pro-cyclically leading the cycles of the EU countries, the other North African economies are not significantly correlated with the considered EU members, confirming the results of the preceding spectral analysis. Again in line with the results of Süssmuth and Woitek (2004), Israel does not show much correlation with any of the EU countries' business cycle dynamics. It might be rationalized by its relatively stronger trade links with the US.

The analysis of different business cycle characteristics indicates that EU membership, EU accession, and even the prospect of joining the EU has an influence on GDP per capita fluctuations over the years. It also indicates that there is scope for convergence of EU countries' business cycle convergence, especially, with the Northern African countries, which can be achieved through intensified trade.

As with the creation of the EMU, the power of common monetary policy was delegated to one supranational institution: the European Central Bank. Through this delegation, asynchronous business cycle dynamics can impose further difficulties on stabilization policies. Consequently, the results for the European countries that signal business cycle synchronization are especially relevant against the backdrop of recent crises and an advisable concerted economic and monetary policy action. For the Arabian MENA economies our finding of clear-cut business cycle commonalities due to the historical fact and extent of belonging to the middle empires—in particular, the Caliphate and Ottoman Empire—lasting almost 2000 years generally supports the vision of a Mediterranean Islamic Common Market.

Appendix

Note A.1

The most straightforward way to think of a bivariate kernel estimator is to consider the naïve or rectangular kernel estimator (Deaton 2019, p. 178): "Suppose that we have two variables x_1 and x_2 and that we have drawn a standard scatter diagram of one against the other. To construct the density at the point (x_1,x_2) we count the fraction of the sample in, not a band, but a box around the point. lf the area around the point is a square with side h, which is the immediate generalization of an interval of width h in the unidimensional case, then the rectangular kernel estimator is:"

Table 1 Data coverage for sample observations

Country	GDP availability	Country (cont'ed)	GDP availability (cont'ed)
Italy	1960	Lebanon	1988
France	1960	Bosnia	1994
Greece	1960	Montenegro	1997
Spain	1960	Albania	1980
Slovenia	1990	Egypt	1960
Croatia	1995	Morocco	1966
Malta	1970	Algeria	1960
Turkey	1960	WB Gaza	1994
Libya	1999	Syria	1960–2007
Tunisia	1965	Israel	1960

Table 2 Output stability and volatility (HP100, 1960–2019)

	Start = 1960	RTL Mid = 1990	End = 2019	Start = 1960	RTL(*) Mid = 1990	End = 2019	CTS	CTS(*)	SSD
France	0.244	0.190	0.142				0.073		0.014
Italy	0.213	0.182	0.113				0.085		0.018
Greece	0.115	0.115	0.073				0.141		0.049
Spain	0.148	0.130	0.106				0.105		0.030
Slovenia	/	0.082	0.086				− 0.140		0.063
Croatia	/	/	0.051				− 0.177		/
Malta	/	0.071	0.095				− 0.045		0.037
Turkey	0.060	0.040	0.051	0.206	0.153	0.152	0.005	− 0.009	0.043
Syria	0.012	0.007	/	0.040	0.028	/	0.148	0.040	0.051
WB Gaza	/	/	0.010	/	/	0.030	− 0.298	− 0.355	/
Israel	0.173	0.126	0.115	0.596	0.489	0.346	0.019	0.072	0.024
Algeria	0.040	0.021	0.016	0.138	0.082	0.047	0.002	0.001	0.035
Morocco	/	0.010	0.011	/	0.039	0.034	− 0.053	− 0.054	0.025
Egypt	0.012	0.009	0.010	0.040	0.035	0.029	0.002	0.009	0.026
Albania	/	0.010	0.017	/	0.039	0.051	− 0.194	− 0.193	0.079
Libya	/	/	0.022	/	/	0.067	− 0.214	− 0.084	/
Tunisia	/	0.013	0.014	/	0.052	0.044	− 0.039	− 0.028	0.024
Lebanon	/	0.024	0.020	/	0.091	0.060	− 0.311	− 0.351	0.119
Bosnia and Herzegovina	/	/	0.020	/	/	0.061	− 0.271	− 0.323	/
Montenegro	/	/	**0.027**	/	/	**0.082**	**− 0.283**	**− 0.344**	/

(1) (*) indicates $\sum_i^N y_i$, excluding the EU25 countries.

(2) RTL refers to the relative share of each series' trend to the aggregate trend level: $RTL = \dfrac{\tau_t(y_i)}{\tau_t\left(\sum_i^N y_i\right)}$

(3) CTS refers to the contribution of series i to the aggregate's standard deviation: $CTS = 1 - \dfrac{\sigma(y^{a^{-i}})}{\sigma(y^a)}$

(4) SSD refers to the standard deviation of each detrended series divided by its mid-trend level value: $SSD = \dfrac{\sigma[(y_{t,i} - \tau_t(y_i))]}{\tau_{T_m}}$

Table 3 Output stability and volatility (HP100, 1995–2019)

	RTL Start = 1995	End = 2019	CTS	SSD
France	0.169	0.150	0.080	0.012
Italy	0.164	0.119	0.129	0.019
Greece	0.098	0.077	0.231	0.048
Spain	0.119	0.111	0.158	0.027
Slovenia	0.075	0.091	0.170	0.037
Croatia	0.043	0.054	0.104	0.042
Malta	0.739	0.100	0.034	0.023
Turkey	0.037	0.053	0.016	0.042
WB Gaza	0.010	0.010	− 0.005	0.075
Israel	0.125	0.121	0.024	0.016
Algeria	0.016	0.016	0.001	0.016
Morocco	0.009	0.012	− 0.001	0.016
Egypt	0.008	0.010	0.004	0.023
Albania	0.008	0.018	0.005	0.030
Tunisia	0.012	0.015	0.003	0.016
Lebanon	0.027	0.021	− 0.020	0.057
Bosnia and Herzegovina	0.007	0.021	0.022	0.046

(1) RTL refers to the relative share of each series' trend to the aggregate trend level: $\text{RTL} = \frac{\tau_t(y_i)}{\tau_t\left(\sum_i^N y_i\right)}$

(2) CTS refers to the contribution of series i to the aggregate's standard deviation: $\text{CTS} = 1 - \frac{\sigma\left(y^a - y_i^c\right)}{\sigma(y^a)}$

(3) SSD refers to the standard deviation of each detrended series divided by its mid-trend level value: $\text{SSD} = \frac{\sigma[(y_{i,t} - \tau_t(y_i))]}{\tau_{T_m}}$

Table 4 Periodocities across filtering devices (Long = long cycle; short = short cycle)

Countries	HP (100)	BK	CF	PCA	HP (6.25)	HF	D Log	Mean long	Mean short	Var long	SD long	Var short	SD long
France	9.08	4.92	7.87; 3.69	6.94	7.37; 3.58	7.37; 3.37	3.58	6.73	3.55	2.98	1.73	0.02	0.13
Italy	9.83	4.54	5.36; 3.28	6.21	4.54	5.9; 3.37	3.47	5.69	3.33	3.59	1.89	0.00	0.05
Spain	13.11	6.94	5.36; 3.47	8.43	8.43; 3.93	11.8; 3.58	3.81	8.27	3.66	9.44	3.07	0.04	0.20
Greece	13.11; 3.37	9.08. 3.19	6.56; 3.19	8.43; 3.47	7.87; 3.03	11.8; 3.19	3.19	8.58	3.24	9.26	3.04	0.02	0.14
Slovenia	9.83	4.92	5.62. 3.37	5.90	4.92	10.73; 3.47	3.58	6.50	3.42	6.23	2.50	0.00	0.05
Malta	10.73.2.68	7.87; 2.74	2.56; 5.13	8.42; 2.81	6.94; 2.62	9.83; 3.10	14.75; 2.68	9.10	2.74	12.07	3.47	0.03	0.16
Croatia	11.8	5.9	5.13; 3.19	6.21	5.62	7.37	16.86; 4.54 2.62	8.41	3.87	16.24	4.03	0.46	0.68
Israel	9.83; 3.47	4.21	5.62; 3.28	6.56; 3.69	6.94; 3.47	7.37; 3.37	4.21	6.39	3.46	3.32	1.82	0.02	0.14
Turkey	8.43. 2.81	7.37; 3.10	6.56; 3.03	7.87; 3.47	7.37; 3.10	8.43; 3.47	3.69	7.10	3.16	2.31	1.52	0.06	0.24
Syria	13.11; 2.81	3.47	5.62; 3.03	4.54	3.47	14.75; 3.37	2.81	6.83	3.07	21.09	4.59	0.05	0.23
Algeria	4.91	4.72	5.13; 3.10	4.92	4.92: 2.14	4.07	4.37; 2.36	4.72	2.53	0.12	0.34	0.17	0.41
Tunisia	9.08	4.92	6.21; 3.28	6.94; 3.58	6.56; 3.37	4.07	3.58	5.91	3.41	3.06	1.75	0.02	0.13
Morocco	11.8. 2.46	2.62; 8.43	2.68; 6.21	8.43; 2.62	2.62; 7.87	13.11; 2.74	2.68; 10.73	9.51	2.63	5.09	2.26	0.01	0.08
Lebanon	4.21; 8.43	7.87	5.13; 3.58	4.37	4.54	11.80	4.54	6.67	3.90	6.80	2.61	0.10	0.32
WB Gaza	6.94	5.62	6.21; 4.07	5.90	6.56	5.36	6.21	6.11	4.07	0.25	0.50	0.00	0.00
Montenegro	10.73; 3.19	4.54	5.36; 2.95	6.21	3.69	13.11	2.56; 10.73	7.77	2.90	11.62	3.41	0.07	0.26
Bosnia	9.01; 3.03	11.8; 2.88	6.21; 2.88	8.43; 3.03	7.87; 2.81	11.8; 3.03	13.11; 3.19	9.75	2.98	5.50	2.34	0.01	0.12
Albania	7.87	6.9; 3.37	6.56; 3.28	6.94; 3.58	6.56; 3.28	6.21; 3.19	6.21; 3.10	6.76	3.85	0.28	0.53	0.32	0.57
Libya	8.43; 2.62	3.03	4.72; 2.81	3.69	3.03	3.93	2.68	4.22	2.72	3.36	1.83	0.01	0.10
Egypt	10.73	7.87	6.21; 3.37	9.08	8.43	14.75	10.73	9.69	3.37	6.45	2.54	0.00	0.00
Average								7.23	3.29				

The spectral density is calculated from Fourier transforms of the coefficients of AR(p) models that have been adjusted to the filtered series as described in Sect. 3.2. If the respective table entry displays one figure only, this corresponds to a single global maximum of the parametric model's spectral density, i.e., a dominating cycle of the corresponding period length contained in the series. If there are two values shown separated by a semicolon, there are two local maxima in the spectral density corresponding to two contained cycles with corresponding frequencies/period lengths, where the respective first one dominates the dynamics, i.e., attracts relatively more spectral mass.

Table 5 Relative trend level (RTL) by filtering device

Countries	RTL																					
	HP100			HP6.25			CF			BK			HF			Mean			
	1963	1990	2016	1963	1990	2016	1963	1990	2016	1963	1990	2016	1963	1990	2016	1963	1990	2016	2016
France	0.281	0.227	0.144	0.282	0.238	0.144	0.276	0.238	0.144	0.282	0.234	0.144	0.268	0.223	0.145	0.278	0.232	0.144	0.000
Italy	0.245	0.217	0.118	0.246	0.227	0.117	0.243	0.230	0.117	0.246	0.224	0.117	0.244	0.213	0.117	0.245	0.222	0.117	0.000
Spain	0.182	0.155	0.106	0.184	0.164	0.106	0.182	0.167	0.106	0.183	0.162	0.106	0.174	0.155	0.104	0.181	0.161	0.106	0.001
Greece	0.153	0.136	0.077	0.152	0.143	0.076	0.150	0.145	0.076	0.152	0.141	0.076	0.162	0.139	0.078	0.154	0.141	0.077	0.001
Slovenia			0.085			0.084			0.084			0.084			0.083	0.000	0.000	0.084	0.001
Malta		0.075	0.090		0.078	0.091		0.079	0.092		0.077	0.091		0.073	0.090	0.000	0.076	0.091	0.001
Croatia			0.050			0.050			0.050			0.050			0.048	0.000	0.000	0.050	0.001
Israel			0.114			0.115			0.115			0.115			0.117	0.000	0.000	0.115	0.001
Turkey	0.066	0.047	0.048	0.066	0.049	0.049	0.065	0.049	0.049	0.066	0.049	0.048	0.060	0.048	0.049	0.065	0.048	0.049	0.000
Syria	0.012	0.009		0.013	0.008		0.013	0.008		0.013	0.008		0.012	0.009		0.013	0.008	0.000	0.000
Algeria	0.041	0.025	0.016	0.040	0.026	0.016	0.039	0.026	0.016	0.040	0.026	0.016	0.041	0.026	0.016	0.040	0.026	0.016	0.000
Tunisia		0.016	0.015		0.016	0.015		0.017	0.015		0.016	0.015		0.016	0.015	0.000	0.016	0.015	0.000
Morocco		0.012	0.011		0.013	0.011		0.013	0.011		0.013	0.011		0.012	0.011	0.000	0.013	0.011	0.000
Lebanon		0.028	0.022		0.027	0.022		0.027	0.021			0.022			0.022	0.000	0.027	0.022	0.000
WB Gaza			0.010			0.010			0.010			0.010			0.010	0.000	0.000	0.010	0.000
Montenegro			0.026			0.026			0.026			0.026			0.026	0.000	0.000	0.026	0.000
Bosnia			0.019			0.019			0.019			0.019			0.018	0.000	0.000	0.019	0.000
Albania		0.012	0.016		0.013	0.016		0.012	0.016		0.012	0.016		0.014	0.016	0.000	0.013	0.016	0.000
Libya			0.025			0.022			0.022			0.023			0.027	0.000	0.000	0.024	0.002
Egypt	0.012	0.011	0.009	0.013	0.011	0.009	0.012	0.011	0.009	0.013	0.011	0.009	0.012	0.011	0.009	0.012	0.011	0.009	0.000

Table 6 Standardized standard deviation (SSD) by filtering device

	SSD						
	HP100	HP6.25	BK	CF	HF	Mean	Standard deviation
Countries							
France	0.014	0.009	0.009	0.011	0.021	0.0128	0.004489989
Italy	0.018	0.011	0.012	0.011	0.03	0.0164	0.007282857
Spain	0.03	0.012	0.123	0.008	0.035	0.0416	0.041974278
Greece	0.049	0.021	0.022	0.017	0.056	0.033	0.016161683
Slovenia						0	0
Malta	0.047	0.029	0.029	0.026	0.069	0.04	0.016297239
Croatia						0	0
Israel						0	0
Turkey	0.043	0.031	0.029	0.03	0.066	0.0398	0.014048487
Syria	0.051	0.034	0.035	0.035	0.072	0.0454	0.014732277
Algeria	0.035	0.027	0.021	0.028	0.048	0.0318	0.009239048
Tunisia	0.024	0.017	0.018	0.017	0.043	0.0238	0.009947864
Morocco	0.025	0.018	0.019	0.028	0.033	0.0246	0.005607138
Lebanon	0.119	0.087				0.103	0.127159349
WB Gaza						0	0
Montenegro						0	0
Bosnia						0	0
Albania	0.079	0.05	0.052	0.054	0.123	0.0716	0.027774809
Libya						0	0
Egypt	0.026	0.013	0.012	0.01	0.032	0.0186	0.008754427

Table 7 Relative trend level (CTS) by filtering device

Countries	CTS							
	HP100	HP 6.25	BK	CF	HF	DHP	Mean	Standard deviation
France	0.02	0.021	0.021	0.02	0.025	0.024	0.02183	0.001950783
Italy	0.034	0.03	0.03	0.029	0.037	0.032	0.032	0.002768875
Spain	0.029	0.021	0.208	0.016	0.03	0.025	0.05483	0.068662014
Greece	0.046	0.022	0.021	0	0.035	0.03	0.02567	0.014220486
Slovenia	0.073	−0.002	0.364	−0.162	0.286	0.034	0.09883	0.177208368
Malta	−0.078	−0.079	−0.09	−0.075	−0.082	−0.081	−0.0808	0.004669642
Croatia	0.04	−0.031	0.317	−0.181	0.252	0.003	0.06667	0.169635557
Israel	0.011	−0.022	0.334	−0.163	0.241	0.01	0.0685	0.167708825
Turkey	0.005	0.009	0.006	0.002	0.001	0.009	0.00533	0.003091206
Syria	−0.011	−0.073	−0.059	−0.075	−0.033	−0.077	−0.0547	0.024641879
Algeria	0.001	0.002	0.002	0.002	−0.001	0.001	0.00117	0.001067187
Tunisia	−0.044	−0.045	−0.05	−0.046	−0.044	−0.045	−0.0457	0.002054805
Morocco	−0.055	−0.056	−0.063	−0.056	−0.055	−0.055	−0.0567	0.002867442
Lebanon	−0.368	−0.375	−0.438	−0.365	−0.37	−0.378	−0.3823	0.02526306
WB Gaza	−0.297	−0.392	0.294	−0.436	0.234	−0.309	−0.151	0.297723585
Montenegro	0.078	0.311	0.281	0.326	0.247	0.271	0.25233	0.082117125
Bosnia	−0.284	−0.393	0.305	−0.433	0.242	−0.305	−0.1447	0.300454471
Albania	−0.212	−0.217	−0.252	−0.215	−0.215	−0.215	−0.221	0.013940349
Libya	0.152	0.344	0.322	0.439	0.284	0.301	0.307	0.085252566
Egypt	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0

Table 8 Contemporaneous correlation between Mediterranean countries

	ITA_t	GRE_t	ESP_t	MAL_t	HRV_t	SLO_t	TUR_t	DZA_t	ALB_t	MNE_t	BIH_t	EGY_t	LBY_t	MAR_t	TUN_t	SYR_t	PSE_t	ISR_t	LBN_t
France	0.83*** (0.10)	0.51*** (0.13)	0.76*** (0.12)	0.42* (0.16)	0.51** (0.22)	0.64*** (0.09)	0.06 (0.21)	0.10 (0.13)	0.09 (0.18)	0.30 (0.29)	0.50* (0.26)	0.05 (0.17)	0.16 (0.31)	0.08 (0.16)	0.02 (0.16)	−0.07 (0.18)	−0.13 (0.13)	0.37 (0.17)	−0.55 (0.14)
Italy		0.60*** (0.14)	0.81*** (0.07)	0.38 * (0.13)	0.74*** (0.20)	0.79*** (0.16)	0.02 (0.21)	0.05 (0.11)	0.22 (0.17)	0.45* (0.32)	0.45 (0.33)	0.15 (0.17)	0.20 (0.41)	0.08 (0.13)	−0.06 (0.164)	0.17 (0.12)	−0.31** (0.13)	0.18 (0.12)	−0.39*** (0.15)
Greece			0.73*** (0.13)	0.22 (0.19)	0.87*** (0.11)	0.85*** (0.21)	0.00 (0.19)	0.21* (0.11)	0.17 (0.17)	0.60** (0.33)	0.39 (0.39)	0.23 (0.18)	0.54** (0.37)	0.10 (0.12)	0.33* (0.19)	0.21 (0.09)	−0.25 (0.26)	−0.12 (0.12)	−0.25 (0.21)
Spain				0.37 (0.19)	0.75*** (021)	0.79*** (0.17)	0.08 (0.18)	0.08 (0.12)	0.11 (0.17)	0.39 (0.35)	0.52 (0.37)	0.06 (0.17)	0.29 (0.28)	0.08 (0.16)	0.04 (0.16)	0.05 (0.14)	−0.31** (0.18)	−0.02 (0.15)	−0.45*** (0.17)
Malta					0.05 (0.23)	0.17* (0.13)	−0.05 (0.12)	0.07 (0.16)	−0.09 (0.16)	−0.13 (0.16)	0.32* (0.19)	0.02 (0.16)	−0.04 (0.21)	−0.12 (0.14)	0.01 (0.14)	−0.19 (0.17)	−0.36 (0.21)	0.21 (0.17)	−0.35* (0.13)
Croatia						0.92*** (0.05)	0.23 (0.14)	0.21 (0.37)	0.27 (0.37)	0.74*** (0.19)	0.37 (0.31)	0.21 (0.18)	0.46 (0.32)	0.03 (0.21)	0.19 (0.23)	0.41* (0.28)	−0.26 (0.18)	−0.05 (0.14)	−0.28* (0.18)
Slovenia							0.18 (0.13)	0.09 (0.26)	0.41*** (0.15)	0.78*** (0.24)	0.45* (0.28)	0.43** (0.15)	0.43 (0.33)	−0.03 (0.13)	0.35 (0.22)	0.43* (0.25)	−0.14 (0.15)	0.21 (0.13)	−0.16*** (0.21)
Turkey								0.14 (0.09)	−0.21 (0.17)	0.31* (0.25)	0.21** (0.17)	−0.35*** (0.13)	−0.09 (0.30)	0.11 (0.12)	−0.07 (0.19)	−0.14 (0.14)	0.37** (0.19)	0.34* (0.12)	−0.16 (0.30)
Algeria									0.19* (0.07)	−0.18 (0.16)	0.06 (0.20)	−0.02 (0.12)	−0.03 (0.11)	0.03 (0.08)	0.15 (0.09)	−0.15 (0.19)	0.02 (0.10)	−0.35 (0.11)	−0.52*** (0.11)
Albania										0.24 (0.18)	0.05 (0.16)	0.50*** (0.09)	0.37 (0.20)	0.08 (0.14)	−0.06 (0.20)	0.16** (0.17)	−0.20 (0.08)	0.09 (0.16)	−0.17 (0.27)
Montenegro											0.58*** (0.27)	0.52*** (0.12)	0.39 (0.34)	0.28 (0.25)	0.44 (0.21)	0.56*** (0.22)	0.10 (0.19)	0.37** (0.18)	0.23 (0.20)
Bosnia												0.37* (0.14)	0.27* (0.15)	−0.08 (0.25)	0.31* (0.17)	0.12 (0.54)	0.16 (0.20)	0.42 (0.19)	−0.11 (0.20)
Egypt													0.37 (0.41)	0.08 (0.13)	0.44** (0.17)	0.42 (0.98)	0.08 (0.12)	0.40 (0.18)	0.33 (0.33)
Libya														−0.02 (0.28)	0.60*** (0.16)	0.09* (0.22)	0.00 (0.15)	−0.01 (0.15)	0.07 (0.27)

Table 8 (continued)

	ITA_t	GRE_t	ESP_t	MAL_t	HRV_t	SLO_t	TUR_t	DZA_t	ALB_t	MNE_t	BIH_t	EGY_t	LBY_t	MAR_t	TUN_t	SYR_t	PSE_t	ISR_t	LBN_t
Morocco															−0.04	0.01	0.03	0.03	0.12
															(0.14)	(0.18)	(0.16)	(0.13)	(0.17)
Tunisia																0.28**	0.24	0.38	0.37**
																(0.14)	(0.18)	(0.14)	(0.18)
Syria																	0.14	0.04*	0.52***
																	(0.11)	(0.12)	(0.17)
WB																			
Gaza																		0.36	0.30
																		(0.19)	(0.24)
Israel																			0.24**
																			(0.19)

Notes: Numbers in each column display correlation coefficients. Standard errors are given in parentheses and corrected for autocorrelation and heteroskedasticity

*$p < 0.10$

**$p < 0.05$

***$p < 0.01$

Table 9 Lead-lag relationship between Mediterranean economies

	ITA$_{t+1}$	GRE$_{t+1}$	ESP$_{t+1}$	MAL$_{t+1}$	HRV$_{t+1}$	SLO$_{t+1}$	TUR$_{t+1}$	DZA$_{t+1}$	ALB$_{t+1}$	MNE$_{t+1}$	BIH$_{t+1}$	EGY$_{t+1}$	LBY$_{t+1}$	MAR$_{t+1}$	TUN$_{t+1}$	SYR$_{t+1}$	PSE$_{t+1}$	ISR$_{t+1}$	LBN$_{t+1}$
France	0.46*** (0.10)	0.46*** (0.11)	0.58*** (0.12)	0.29 (0.16)	0.45*** (0.17)	0.49*** (0.12)	− 0.25 (0.16)	0.02 (0.12)	− 0.09 (0.21)	0.15 (0.37)	0.31 (0.32)	0.04 (0.17)	0.34 (0.25)	− 0.03 (0.16)	0.24 (0.15)	− 0.09 (0.16)	− 0.42*** (0.08)	0.00 (0.15)	− 0.37*** (0.13)
Italy		0.51*** (0.15)	0.57*** (0.11)	0.13 (0.15)	0.66*** (0.17)	0.62*** (0.16)	− 0.22 (0.15)	− 0.06 (0.13)	0.12 (0.22)	0.37 (0.35)	0.34 (0.31)	0.18 (0.20)	0.40 (0.43)	0.10 (0.13)	0.11 (0.19)	0.17 (0.14)	− 0.36*** (0.09)	− 0.10 (0.12)	− 0.25** (0.11)
Greece			0.59*** (0.13)	0.02 (0.18)	0.73*** (0.15)	0.76*** (0.20)	− 0.19 (0.21)	0.05 (0.11)	0.23 (0.24)	0.61*** (0.30)	0.28 (0.35)	0.40* (0.23)	0.45 (0.50)	0.05 (0.12)	0.44** (0.20)	0.49 (0.10)	− 0.09 (0.21)	− 0.08 (0.10)	0.03 (0.26)
Spain				0.21 (0.15)	0.75*** (0.18)	0.75*** (0.20)	− 0.15 (0.16)	0.03 (0.12)	0.06 (0.25)	0.41 (0.37)	0.36 (0.37)	0.20 (0.20)	0.44 (0.38)	0.11 (0.13)	0.16 (0.18)	0.23 (0.13)	− 0.38*** (0.10)	− 0.14* (0.12)	− 0.21 (0.16)
Malta					0.30 (0.26)	0.24 (0.20)	− 0.43*** (0.12)	− 0.03 (0.13)	− 0.06 (0.14)	− 0.06 (0.20)	0.19** (0.18)	0.06 (0.15)	− 0.11 (0.13)	− 0.14 (0.13)	− 0.05 (0.14)	0.03 (0.21)	− 0.53 (0.16)	− 0.29 (0.11)	− 0.28 (0.13)
Croatia						0.75*** (0.08)	− 0.07 (0.18)	0.04 (0.32)	0.46 (0.45)	0.71*** (0.14)	0.38* (0.28)	0.51** (0.18)	0.60* (0.33)	0.18 (0.28)	0.50* (0.20)	0.56* (0.25)	0.00 (0.13)	− 0.10 (0.12)	0.13 (0.24)
Slovenia							− 0.29 (0.14)	− 0.15 (0.25)	0.65 (0.34)	0.63*** (0.19)	0.39* (0.21)	0.69*** (0.15)	0.54 (0.32)	0.16 (0.19)	0.53* (0.19)	0.54* (0.26)	− 0.09 (0.10)	0.04 (0.12)	0.24 (0.22)
Turkey								0.07 (0.10)	− 0.16 (0.15)	0.47** (0.24)	0.39** (0.25)	− 0.07 (0.20)	0.26 (0.30)	0.30*** (0.11)	0.11 (0.19)	− 0.18 (0.10)	0.36** (0.21)	0.37 (0.16)	− 0.08 (0.28)
Algeria									0.07 (0.10)	0.15 (0.15)	0.23 (0.21)	0.03 (0.10)	0.22 (0.12)	0.10 (0.07)	0.12 (0.15)	− 0.10* (0.12)	0.08 (0.14)	− 0.09 (0.13)	− 0.26 (0.15)
Albania										0.06 (010)	0.16 (0.23)	0.42*** (0.11)	0.16 (0.17)	0.35** (0.13)	− 0.03 (0.16)	0.05*** (0.17)	− 0.22 (0.12)	− 0.01 (0.14)	− 0.11 (0.26)
Montenegro											0.36*** (0.14)	0.72*** (0.10)	0.40 (0.24)	0.29 (0.27)	0.59*** (0.14)	0.53 (0.31)	0.32** (0.12)	0.15 (0.20)	0.57*** (0.18)
Bosnia												0.50*** (0.13)	0.26* (0.14)	− 0.17 (0.25)	0.31** (0.12)	0.11** (0.40)	0.13 (0.25)	0.15 (0.28)	− 0.06 (0.23)
Egypt													− 0.01 (0.37)	0.11 (0.13)	0.23 (0.13)	0.24*** (0.11)	0.00 (0.15)	0.22 (0.14)	0.41 (0.34)

Table 9 (continued)

	ITA$_{t+1}$	GRE$_{t+1}$	ESP$_{t+1}$	MAL$_{t+1}$	HRV$_{t+1}$	SLO$_{t+1}$	TUR$_{t+1}$	DZA$_{t+1}$	ALB$_{t+1}$	MNE$_{t+1}$	BIH$_{t+1}$	EGY$_{t+1}$	LBY$_{t+1}$	MAR$_{t+1}$	TUN$_{t+1}$	SYR$_{t+1}$	PSE$_{t+1}$	ISR$_{t+1}$	LBN$_{t+1}$
Libya														0.28	0.41***	0.45	−0.01	0.24**	0.30*
														(0.20)	(0.09)	(0.25)	(0.19)	(0.09)	(0.20)
Morocco															0.14	−0.10	0.29**	−0.05	−0.08
															(0.11)	(0.15)	(0.13)	(0.13)	(0.25)
Tunisia																0.35	0.11	0.29	0.57***
																(0.19)	(0.12)	(0.15)	(0.18)
Syria																	0.39**	0.20	0.29
																	(0.08)	(0.14)	(0.21)
WB Gaza																		0.75*	0.18
																		(0.25)	(0.27)
Israel																			0.24
																			(0.22)

Notes: Numbers in each column display correlation coefficients. Standard errors are given in parentheses and corrected for autocorrelation and heteroskedasticity

*$p < 0.10$

**$p < 0.05$

***$p < 0.01$

Table 10 Lead-lag relationship between Mediterranean business cycles

	ITA$_{t-1}$	GRE$_{t-1}$	ESP$_{t-1}$	MAL$_{t-1}$	HRV$_{t-1}$	SLO$_{t-1}$	TUR$_{t-1}$	DZA$_{t-1}$	ALB$_{t-1}$	MNE$_{t-1}$	BIH$_{t-1}$	EGY$_{t-1}$	LBY$_{t-1}$	MAR$_{t-1}$	TUN$_{t-1}$	SYR$_{t-1}$	PSE$_{t-1}$	ISR$_{t-1}$	LBN$_{t-1}$
France	0.55*** (0.12)	0.40* (0.21)	0.58*** (0.13)	0.30** (0.13)	0.21 (0.32)	0.24 (0.30)	0.20 (0.13)	0.10 (0.13)	0.17 (018)	−0.06 (0.23)	0.47** (0.19)	−0.10 (0.17)	0.14 (0.19)	0.11 (0.15)	−0.12 (0.15)	−0.07 (0.14)	0.19 (0.18)	0.10 (0.16)	−0.46** (0.20)
Italy		0.54** (0.22)	0.65*** (0.14)	0.37* (0.17)	0.40 (0.40)	0.41* (0.35)	0.10 (0.17)	0.14 (0.12)	0.24** (0.11)	0.02 (0.30)	0.36 (0.28)	−0.03 (0.16)	0.19 (0.16)	0.01 (0.14)	−0.11 (0.12)	−0.00 (0.09)	−0.08 (0.19)	−0.05 (0.12)	−0.39** (0.24)
Greece			0.70*** (0.14)	0.31 (0.19)	0.80*** (0.19)	0.69*** (0.19)	0.28 (0.19)	0.27* (0.15)	0.09 (0.12)	0.33 (0.34)	0.33 (0.37)	−0.14 (0.18)	0.41** (0.28)	0.06 (0.12)	0.09 (0.16)	−0.07 (0.09)	−0.29* (0.20)	−0.21 (0.13)	−0.47* (0.31)
Spain				0.34 (0.23)	0.47* (0.31)	0.46*** (0.24)	0.24 (0.17)	0.13 (0.14)	0.14 (0.14)	0.05 (0.26)	0.48** (0.27)	−0.21 (0.14)	0.18 (0.20)	0.03 (0.17)	−0.10 (0.13)	−0.22** (0.13)	−0.13 (0.22)	−0.07 (0.15)	−0.58*** (0.25)
Malta					−0.27 (0.21)	−0.10 (0.14)	0.02 (0.09)	0.05 (0.21)	−0.14 (0.21)	−0.43 (0.19)	0.25 (0.21)	−0.17 (0.16)	−0.18 (0.32)	−0.04 (0.13)	−0.04 (0.15)	−0.33** (0.11)	0.09 (0.26)	0.13 (0.13)	−0.36 (0.18)
Croatia						0.64*** (0.20)	0.32 (0.17)	0.43* (0.34)	0.05 (0.22)	0.27 (0.21)	0.14 (0.25)	−0.21 (0.14)	0.30* (0.18)	−0.17 (0.18)	−0.06 (0.15)	0.09 (0.26)	−0.35* (0.17)	−0.20 (0.13)	−0.56*** (0.25)
Slovenia							0.38 (0.17)	0.37** (0.26)	0.00 (0.12)	0.40** (0.18)	0.28 (0.20)	−0.06 (0.12)	0.37* (0.20)	−0.10 (0.13)	0.13 (0.19)	0.14 (0.23)	−0.09 (0.14)	−0.01 (0.11)	−0.45*** (0.16)
Turkey								0.09 (0.11)	−0.15 (0.18)	−0.28 (0.32)	−0.36 (0.22)	−0.50*** (0.13)	−0.11 (0.30)	0.10 (0.14)	−0.27* (0.15)	−0.10 (0.15)	0.23 (0.18)	−0.28 (0.16)	−0.22 (0.21)
Algeria									0.20 (0.11)	−0.40* (0.13)	−0.11 (0.16)	−0.06 (0.11)	−0.21 (0.10)	0.01 (0.10)	−0.05 (0.11)	−0.04 (0.10)	−0.26** (0.06)	−0.57 (0.12)	−0.43* (0.15)
Albania										0.54** (0.13)	0.07 (0.19)	0.41*** (0.08)	0.49 (0.19)	−0.17 (0.20)	0.08 (0.16)	0.31 (0.20)	0.00 (0.05)	0.13 (0.16)	0.18 (0.16)
Montenegro											0.26 (0.31)	0.09 (0.10)	0.55** (0.20)	0.00 (0.26)	0.32* (0.14)	0.30 (0.37)	−0.01 (0.23)	0.11 (0.18)	−0.05 (0.29)
Bosnia												0.04 (0.13)	0.27** (0.11)	−0.22 (0.13)	0.06 (0.12)	0.02 (0.54)	0.20 (0.13)	0.24* (0.16)	−0.21 (0.28)

Table 10 (continued)

	ITA$_{t-1}$	GRE$_{t-1}$	ESP$_{t-1}$	MAL$_{t-1}$	HRV$_{t-1}$	SLO$_{t-1}$	TUR$_{t-1}$	DZA$_{t-1}$	ALB$_{t-1}$	MNE$_{t-1}$	BIH$_{t-1}$	EGY$_{t-1}$	LBY$_{t-1}$	MAR$_{t-1}$	TUN$_{t-1}$	SYR$_{t-1}$	PSE$_{t-1}$	ISR$_{t-1}$	LBN$_{t-1}$
Egypt													0.50	0.05	0.50***	0.46	0.24	0.37	0.22
													(0.43)	(0.14)	(0.17)	(0.11)	(0.18)	(0.17)	(0.25)
Libya														0.05	−0.08	0.24*	0.05	−0.04	−0.26
														(0.21)	(0.29)	(0.24)	(0.06)	(0.08)	(0.21)
Morocco															−0.02	−0.00	−0.04	0.04	−0.09
															(0.13)	(0.20)	(0.22)	(0.09)	(0.23)
Tunisia																0.17	0.29**	0.23	0.05
																(0.11)	(0.12)	(0.08)	(0.16)
Syria																	−0.12	−0.19	0.34
																	(0.19)	(0.12)	(0.22)
WB Gaza																		−0.08	0.35***
																		(0.16)	(0.20)
Israel																			0.23
																			(0.19)

Notes: Numbers in each column display correlation coefficients. Standard errors are given in parentheses and corrected for autocorrelation and heteroskedasticity

*$p < 0.10$

**$p < 0.05$

***$p < 0.01$
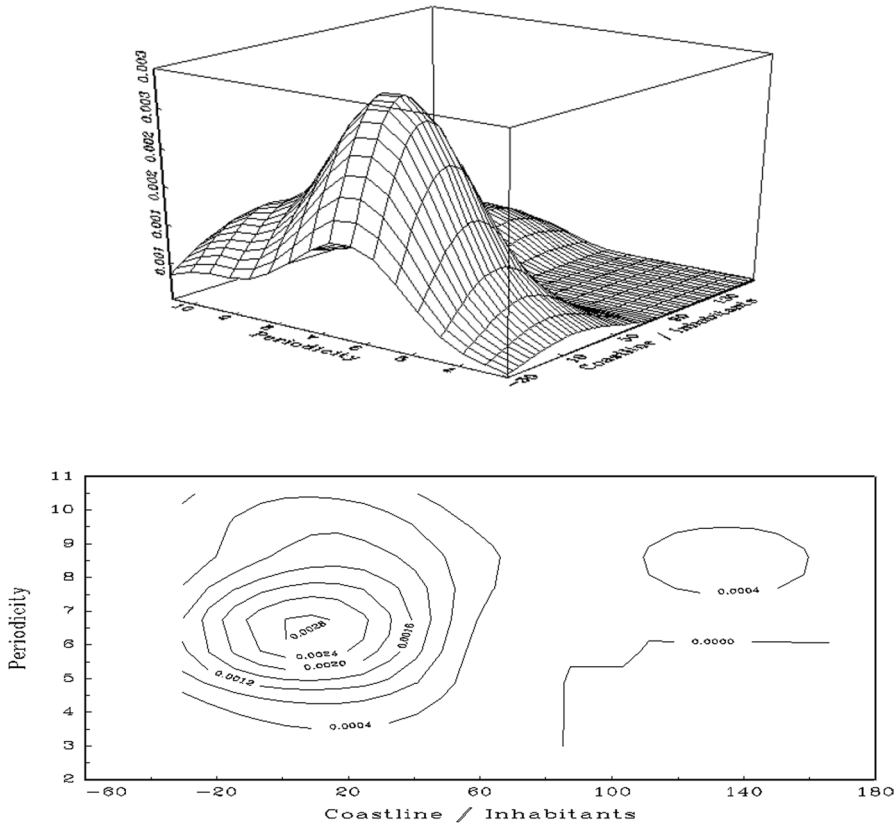
Fig. 8 Kernel density of long cycle periodicity with coastline (km) to inhabitants (100 K) ratio. *Notes:* Bivariate kernel density estimation (quartic kernel) of average, i.e., arithmetic mean across seven filtering devices, long cycle period length with coastline (in km) to inhabitants (in 100 K) ratio for year 2020 (data source: CIA World Factbook); ordinate values are joint relative frequency values; in the contour plot (lower panel) these correspond to the values ascribed to contour lines

$$\tilde{f}(x_1, x_2) = \frac{1}{Nh^2} \sum_{i=1}^{N} \left[1\left(-\frac{1}{2} \leq \frac{x_{1i} - x_1}{h} \leq \frac{1}{2}\right) 1\left(-\frac{1}{2} \leq \frac{x_{2i} - x_2}{h} \leq \frac{1}{2}\right) \right].$$

Note, function $1(\bullet)$ denotes what is referred to as an indicator function. The kernel product inside the rectangular parentheses indicates whether the point is or is not in the square around (x_1, x_2) and the division by h^2 instead of just h is required because we are now counting fraction of sample per unit area rather than interval, and the area of each square is h^2. In general, the generic indicator function needs to be replaced by a bivariate kernel that gives greater weights to observations closer to (x_1, x_2). Also the bandwidth h needs not to be universal in both dimensions. Deaton (2019, p. 178) puts this the following way: "if the variance of x_1 is much larger than that of x_2 it makes more sense to use rectangles instead of squares, or ellipses instead of circles, and to make the axes larger in the direction of x_1."

The quartic kernel that is used here is

$$K(z_1, z_2) = (3/\pi)(1 - z_1^2 - z_2^2)1(z_1^2 + z_2^2 \leq 1),$$

where (z_1, z_2) are just the z-transforms, that is, the standard normal(ized) analogues, of (x_1, x_2).

Declarations

Ethical Statements Herewith, the authors declare that we have no relevant or material financial interests that relate to the research described in this paper. We approve the ethical standards of the publisher. This article does not contain any studies with human participants or animals performed by any of the authors. Thus, necessity for informed consent does not apply.

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

A'Hearn B, Woitek U (2001) More international evidence on the historical properties of business cycles. J Monet Econ 47:299–319

Agresti A, Mojon B (2001) Some stylized facts on the Euro Area business cycle, European Central Bank (ECB) Working Paper Series, No. 95, Frankfurt aM, Germany. https://www.ecb.europa.eu//pub/pdf/scpwps/ecbwp095.pdf. Accessed 29 May 2022

Aguiar-Conraria L, Soares MJ (2009) Business cycle synchronization across the Euro-Area: a wavelet analysis, NIPE Working Paper Series, No. 8, Universidado De Minho, Portugal. https://citeseerx.ist.psu.edu/viewdoc/download?. Accessed 29 May 2022

Arshad S (2016) The vicissitudes of stock markets and business cycles: focusing on the OIC region. Macroeconomics and Finance in Emerging Markets Economies 9:56–74

Artis M, Zhang W (1997) International business cycle and the ERM: Is there a European business cycle? Int J Financ Econ 2:1–16

Artis M, Marcellino M, Proietti T (2004) Dating business cycles: A methodological contribution with an application to the Euro Area. Oxford Bull Econ and Stats 66:537–565

Baxter M, King RG (1999) Measuring Business Cycles. Approximate Band-Pass Filters for Economic Time Series, Review of Economics and Statistics 81:575–593

Bayoumi T, Eichengreen B (1997) Ever closer to heaven? An Optimum-Currency-Area Index for European Countries, European Economic Review 41:761–770

Belo F (2001) Some facts about the cyclical convergence in the euro zone, Banco De Portugal Working Paper, No. 7-01, Lissabon, Portugal. https://www.bportugal.pt/sites/default/files/anexos/papers/wp200107.pdf. Accessed 29 May 2022

Brodeur A, Lé M, Sangnier M, Zylberberg Y (2016) Star wars: The empirics strike back, American Economic Journal. Appl Econ 8:1–32

Brodeur A, Cook N, Heyes A (2020) Methods matter: p-hacking and publication bias in causal analysis in economics. American Economic Review 110:3634–3660

Burns AF, Mitchell WC (1946) Measuring business cycles. MA, National Bureau of Economic Research, Cambridge

Cerqueira PA, Martins R (2009) Measuring the determinants of business cycle synchronization using a panel approach. Econ Lett 102:106–108

Chemingui M, Eris M (2017) Trade integration and business cycle synchronization: evidence from the experience of Arab countries, Economic and Social Commission for Western Asia (ESCWA) EDID Working Paper: United Nations, No. 5, Beirut, Lebanon. https://archive.unescwa.org/sites/www.unescwa.org/files/page_attachments/l1700404.pdf. Accessed 29 May 2022

Christiano LJ, Fitzgerald T (1999) The Band Pass Filter, NBER Working Paper No. 7257, National Bureau of Economic Research, Cambridge, MA, USA. http://www.nber.org/papers/w7257.pdf. Accessed 29 May 2022

Chronopoulos DK, Kampanelis S, Oto-Peralías D, Wilson JOS (2021) Ancient colonialism and the economic geography of the Mediterranean. J Econ Geogr 21:717–759

Crowley PM and Schultz A (2010). Measuring the intermittent synchronicity of macroeconomic growth in Europe, ACES American Consortium on European Union Studies Working Paper, No. 2010.1

Darvas Z, Szapary G (2008) Business cycle synchronization in the enlarged EU. Open Econ Rev 19:1–19

Deaton, A. (2019). The analysis of household surveys. A microeconometric approach to development policy, re-issue edition, Washington, DC: World Bank

Degiannakis S, Duffy D, Filis G (2014) Business cycle synchronization in EU: a time-varying approach. Scott J Polit Econ 614:348–370

DeJong DN, Nankervis JC, Savin NE, Whiteman CH (1992) The power problems of unit root test in time series with autoregressive errors. J Econom 53:323–343

Eggoh J, Belhadj A (2015) Business cycles in the Maghreb: Does trade matter? J Econ Integr 30:553–576

Frankel J, Rose A (1998) The endogeneity of the optimum currency area criteria. Economic Journal 108:1009–1025

Gächter M, Riedl A, Ritzberger-Gruenwald D (2012) Business cycle synchronization in the Euro Area and the impact of the financial crisis. Monetary Policy & the Economy 2:33–60

Gawellek B, Lyu J, Süssmuth B (2022) Geo-politics and the impact of China's outward investment on developing countries: evidence from the Great Recession. Emerg Mark Rev 48(100815):1–24

Gomez DM, Ferrari HJ, Ortega GJ, Torgler B (2017), Synchronization and diversity in business cycles: a network analysis of the European Union. Appl Econ 49:972–986

Hamilton JD (2018) Why you should never use the Hodrick-Prescott Filter. Rev Econ Stat 100:831–884

Härdle WK (1991) Smoothing techniques. Springer, Berlin

Hassan MK, Sanchez BA, Hussain ME (2010) Economic performance of the OIC countries and the prospect of an Islamic common market. J Econ Coop Dev 31:65–121

Hodrick R, Prescott E (1997) Postwar U.S. business cycles: an empirical investigation. J Money, Credit, Bank 29:1–16

Hughes Hallett A, Richter C (2008) Have the Eurozone economies converged on a common European cycle? IEEP 5:71–101

Kelly M (2019) The standard errors of persistence, Centre for Economic Policy Research, CEPR Discussion Paper, No. 13783

Kleinert J, Martin J, Toubal F (2015) The few leading the many: foreign affiliates and business cycle comovement. Am Econ J Macroecon 7:134–159

Kuznets S (1958) Long swings in the growth of population and in related economic variables. Proc Am Philos Soc 102:25–57

Kydland FE, Prescott EC (1990) Business cycles: real facts and a monetary myth. Fed Reserve Bank Minneap Q Rev 14(Spring):3–18

Lee J (2012) Measuring business cycle comovements in Europe: evidence from a dynamic factor model with time-varying parameters. Econ Lett 115:438–440

Lucas RE Jr (1977) Understanding business cycles, Carnegie-Rochester Conference Series on Public Policy. Amsterdam. 5: 7–29

Mitchell WC (1927) Business cycles: the problem and its setting. NBER Books, Cambridge, MA, National Bureau of Economic Research

Montoya LA, De Haan J (2008) Regional business cycle synchronization in Europe? IEEP 5:123–137

Nacu A (2012) Roman empire in 117 CE, world history encyclopedia. Last modified April 26, 2012. https://www.worldhistory.org/image/266/roman-empire-in-117-ce/. Accessed 29 May 2022

Newey WK, West KD (1987) A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55:703–708

Ravn MO, Uhlig H (2002) On adjusting the Hodrick-Prescott filter for the frequency of observations. Rev Econ Stat 84:371–376

Robinson CE, Hunter PG (1942) Roma. Cambridge University Press, Cambridge

Rozmahel P (2011). Real convergence trends in central and eastern European countries towards Eurozone: time-varying correlation approach. Silesian University Working Paper Series (Acta academica karviniensia), Silesian University School of Business Administration, Karvina/Opava, Czech Republic. https://aak.slu.cz/pdfs/aak/2011/02/15.pdf. Accesssed 29 May 2022

Süssmuth B, Woitek U (2004) Business cycles and comovement in Mediterranean economies : a national and areawide perspective. Emerg Mark Financ Trade 40:7–27