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Is Europe growing together or growing apart?



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Is Europe Growing Together or Growing Apart?

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Abstract

While it is painfully clear that the 'ever closer' monetary and financial union in the EU has run into serious trouble there has been very little study of the degree to which the countries have become similar or different in their economic growth dynamics. This paper therefore goes beyond the traditional convergence literature to look at their dynamic convergence and explore the path of their changing similarity in the frequency domain. The results show that while a core group of countries may be developing together, there appears to be at least seven identifiable groups of countries with different growth dynamics. Greece appears to be in a class on its own. Business cycles are important but longer-term trends and higher frequency fluctuations all have a role to play in facilitating adjustment. These results provide awkward implications for policy, particularly for those who thought that simply having a union would draw countries closer together (endogenous OCA criteria).

Keywords: Business cycles, growth cycles, frequency domain, wavelet analysis, cluster analysis, euro area, European Union, optimal currency area

JEL Classification: C49, E32

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1 Introduction

Since its inception, the euro area has been an anomaly in the realm of economic policy. It is a single currency area without an effective supranational fiscal policy and no federal or confederal political structure. This has led to significant problems of governance, not only because most member states have had little room to manoeuvre in terms of their own fiscal policy stances, but also because there is little agreement on moving towards a more centralized political arrangement. The European Central Bank (ECB), as effective "protector" of the euro area, has also, until lately, been hamstrung in terms of its ability to assist struggling euro area member states, with the result that the European Union (EU) has had to introduce new emergency assistance programs as well as enlisting the help of the International Monetary Fund (IMF) to cope with the unfolding crisis.

Why is this the case? Obviously the fiscal record of each member state government is a significant factor in the cumulation of public debt of many of the southern euro area member states, but also the usual criteria for whether a currency union is an optimal currency area is also an important factor. Several papers have established that the euro area is not, in the strictest sense of the term, an optimal currency area (see Crowley (2008) for example). Not only is there the forementioned lack of any meaningful supranational fiscal policy in the EU, but also there is not a high degree of labor mobility. Thus the major criteria for being in a single currency area in the European context is inevitably heavily weighted towards that of a high correlation of output movements between the participants of the single currency. This is the starting point for this paper, which explores the nature of the co-movement in growth, not only at traditional business cycle frequencies, but also in terms of all identifiable cycles in growth.

The paper is novel as it not only uses frequency domain techniques to decompose the cycles in growth, but also it then uses cluster analysis to compare these decomposed cycles to see what groupings currently exist in the euro area since the inception of the euro in 1999. What makes frequency domain analysis important in empirical macroeconomic and financial analysis? Simply put, the time horizon and the interrelationships between macroeconomic and financial variables at different time horizons. In time-series analysis we often search (by using different econometric specifications) for the most appropriate "fit" for the time-series data at hand, and thus attempt to better understand the evolution of the series over time and the drivers behind the series. In time-frequency domain we can take this one step further - we can attempt to understand the evolution of the series over

different time horizons and the drivers behind the series at different time horizons. Given the ongoing developments in time-frequency analysis there is a possibility that we might also be able to uncover meaningful sub-series in the data operating at different frequencies.

Section 2 presents a literature review of the economics behind the analysis, then section 3 explains the frequency domain approaches used in this paper. Section 4 shows the results for the discrete wavelet transform, while section 5 shows the results for the continuous wavelet transform. Lastly section 6 employs cluster analysis to identify groupings in the euro area and section 7 concludes.

2 Business cycles in the euro area

2.1 Background

The European Union (EU) business cycle was first proposed as a phenomena by Michael Artis in a series of papers in the late-1990s and early 2000s (see Artis and Zhang (1997), Artis and Zhang (1999), Artis and Zhang (2002), Artis and Zhang (2001), Artis, Marcellino, and Priorietti (2004)), and this led to a number of other authors exploring this issue in some depth (notably Honohan (2000), Crowley (2003), Altavilla (2004) and Giannone and Reichlin (2006) for example) with many more papers published in various outlets. The general conclusion of these papers is that there was an emerging EU business cycle, but that there existed several groups of member states with different business cycle characteristics.

This is an important issue, as given the euro was launched in 1999, and that an EU business cycle exists, how much heterogeneity in business cycle behavior by different member states can be tolerated within a single currency area such as the euro area, without significant problems emerging? Most of the papers cited above use empirical methods which attempt to operationalize the optimum currency area theory (or OCA theory, and originally due to Mundell (1961)), which essentially states the conditions for a single currency area to operate without significant problems emerging in the long term¹.

According to the OCA theory, without offsetting conditions (such as a high degree of labor mobility or fiscal transfers in the face of asymmetric shocks or asynchronous business cycles), the main condition for forming an OCA is that business cycles are relatively synchronous (or in terms of economic shocks, that shocks to the different members of the

¹The OCA theory states that if countries are to adopt a single currency, then business cycle synchronization should be high, but if not, that asymmetric shocks can be absorbed by i) a high degree of labor mobility; ii) fiscal redistributions between the countries; or iii) a high degree of wage flexibility.

currency union are symmetric). This means that business cycle variables need to be moving together through time. This makes sense from a central bank perspective as well, as variables such as output, inflation and unemployment should display similar patterns across the single currency area if the single currency itself is appropriate for all the constituent members. That is, if monetary policy is to be appropriate for all members, then as there is a single interest rate for a monetary union, it implies that any monetary policy changes will also be appropriate for all members.

Of course there is also an ex-post argument which has been made by Frankel and Rose (1997). Simply stated, this argument is that if a country is subject to the monetary policy of a central bank within a currency union which is also a common market, then the flow of factors of production between the constituent members could promote greater synchronicity of business cycles. So for example, if most of the members are in a boom, then with free trade this would also tend to stimulate exports from those member states that are not in a boom, thereby leading to some convergence over time. This is an argument for an ex-post OCA rather than an ex-ante OCA.

2.2 Data

Given the argument above, the main variable for determining the phase of the business cycle (or other cycles for that matter) is the growth in real GDP. So in this paper we use real GDP from the EU's eurostat database from 1998 through until Q1 of 2012, on a quarterly basis. Unlike other studies this therefore allows us to assess cyclical convergence with the euro area measure (here we use a 17 member state measure), and as all GDP values are calculated in terms of real GDPs in euros, we can also assess the cyclical convergence of euro area member states with the rest of the euro area to see if individual member states have converged with the other 16 member states in the currency union.

Data is transposed into log annual change data, and then correlated in raw form below in table ?? for euro area member states, table 2 for non-euro area EU member states, and table 4 for non-EU countries. For euro area member states, the obvious outliers are both Greece and Portugal, while for those member states outside the euro area, the two member states with particularly high correlations being Denmark, Sweden and the UK. For those countries outside the EU, rather unsurprisingly (given its location) only Switzerland has a high correlation with the euro area.

Member state	BEL	GER	EST	FRA	GRE	IRE	ITA	LUX	NET	AUS	POR	SLO	FIN	SPA
Correlation	0.895	0.806	0.824	0.924	0.370	0.792	0.938	0.839	0.891	0.931	0.366	0.818	0.930	0.830

Table 1: Real GDP correlations for euro area member states

Member state	BUL	CZR	DEN	CYP	LAT	LIT	HUN	MAL	ROM	SLV	CRO	SWE	UK
Correlation	0.600	0.628	0.875	0.700	0.788	0.776	0.778	0.565	0.707	0.509	0.751	0.872	0.862

Table 2: Real GDP correlations for non-euro area member states

Member state	NOR	SWI	ICE
Correlation	0.622	0.813	0.573

Table 3: Real GDP correlations for non-EU countries

3 Wavelet Analysis

The method employed in this paper to analyze cyclical convergence with the euro area is wavelet analysis. There are two types of wavelet analysis, namely discrete wavelet analysis, which operates as a filter bank to extract cycles within different ranges, and continuous wavelet analysis, which operates like spectral analysis to extract cycles over the whole range of frequencies. The discrete wavelet method operates in the time domain while the continuous wavelet method operates in the frequency domain.

3.1 Discrete wavelet (MODWT) analysis

In short, discrete wavelet analysis uses wavelet filters to extract cycles at different frequencies from the data under consideration: it uses a given discrete function which is passed through the series and convolved with the data to yield a coefficient, otherwise known as a "crystal". In the basic approach (the discrete wavelet transform or DWT) these crystals will be increasingly sparse for lower frequency cycles if the wavelet function is passed down the series over consecutive data spans. So another way of obtaining crystals corresponding to all data points in each frequency range is to pass the wavelet function down the series data observation by data observation. This is the basis of the maximal overlap discrete wavelet transform (MODWT), and this is the technique used here.

In mathematical terms, consider a double sequence of functions:

$$\psi(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{1}$$

where s is a sequence of scales, where scale here corresponds to a particular frequency range. The term $\frac{1}{\sqrt{s}}$ ensures that the norm of the wavelet function $\psi(\cdot)$ is equal to one. The function $\psi(\cdot)$ is then centered at u with scale s . In the language of wavelets, the energy of $\psi(\cdot)$ is concentrated in a neighbourhood of u with size proportional to s , so that as s increases the length of support in terms of t increases. For example, when $u = 0$, the support of $\psi(\cdot)$ for $s = 1$ is $[d, -d]$ where $2d$ denotes the initial total width (pre-scaling) which is also known as the "tap" of the wavelet). As s is increased, the support widens to $[sd, -sd]$. Dilation (i.e. changing the scale) is particularly useful in the time domain, as the choice of scale indicates the "stretching" used to represent any given variable or signal. A broad support wavelet yields information on variable or signal variations on a large scale, whereas a small support wavelet yields information on signal variations on a small scale. As projections are orthogonal, wavelets at a given scale are not affected by

features of a signal at scales that require narrower support. Lastly, if a wavelet is shifted on the time line, this is referred to as translation or shift of u . Any series $x(t)$ can be built up as a sequence of projections onto two different sets of wavelet functions, one used to capture trend movements and cycles beyond the scale limit imposed by the researcher (the "father" wavelet) and another used to capture deviations from mean for cycles at different frequencies (the "mother" wavelets). Wavelet functions are therefore indexed by both j , the scale, and k , the number of translations of the wavelet, where k is often assumed to be dyadic. As shown in Bruce and Gao (1996), the wavelet coefficients can be approximated given by the integrals for father and mother wavelets as:

$$s_{J,k} \approx \int x(t)\phi_{J,k}(t)dt \quad (2)$$

$$d_{j,k} \approx \int x(t)\psi_{j,k}(t)dt \quad (3)$$

respectively, where $j = 1, 2, \dots, J$ such that J is the maximum scale sustainable with the data to hand, then a multiresolution representation of the signal $x(t)$ is can be given by:

$$x(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \dots + \sum_k d_{1,k}\psi_{1,k}(t) \quad (4)$$

where the basis functions $\phi_{J,k}(t)$ and $\psi_{J,k}(t)$ are assumed to be orthogonal, that is:

$$\begin{aligned} \int \phi_{J,k}(t)\phi_{J,k'}(t) &= \delta_{k,k'} \\ \int \psi_{J,k}(t)\phi_{J,k'}(t) &= 0 \\ \int \psi_{J,k}(t)\psi_{J',k'}(t) &= \delta_{k,k'}\delta_{j,j'} \end{aligned} \quad (5)$$

where $\delta_{i,j} = 1$ if $i = j$ and $\delta_{i,j} = 0$ if $i \neq j$. The multiresolution decomposition (MRD) of the variable or signal $x(t)$ is then given by the set of crystals:

$$\{s_J, d_J, d_{J-1}, \dots, d_1\} \quad (6)$$

The interpretation of the MRD using the DWT is of interest as it relates to the frequency at which activity in the time series occurs². For example with a quarterly time series table 4 shows the frequencies captured by each scale crystal:

Note that as quarterly data is used in this study, to capture the conventional business cycle length scale crystals need to be obtained for 5 scales. This requires at least 64

²One of the issues with spectral time-frequency analysis is the Heisenberg uncertainty principle, which states that the more certainty that is attached to the measurement of one dimension (- frequency, for example), the less certainty can be attached to the other dimension (- here the time location).

Scale crystals	Quarterly frequency resolution
d1	2-4=6m-1yr
d2	4-8=1-2yrs
d3	8-16=2-4yrs
d4	16-32=4-8yrs
d5	32-64=8-16yrs
d6	64-128=16-32yrs
d7	etc

Table 4: Frequency interpretation of MRD scale levels

observations, but to properly resolve at the longest frequency it would help to have 128 observations, and as we have at least 214 observations for all 8 series this is easily accomplished, and hence we use 6 crystals here even though resolution for the d6 crystal is not high. It should be noted that if conventional business cycles are usually assumed to range from 12 quarters (3 years) to 32 quarters (8 years), then crystal d4 together with the d3 crystal should contain the business cycle.

The variance decomposition for all series considered in this paper calculated based on:

$$E_j^d = \frac{1}{E^d} \sum_{k=1}^{\frac{n}{2^j}} d_{j,k}^2 \quad (7)$$

where $E^d = \sum_j E_j^d$. represents the energy in the detail crystals E_j^d .

Although extremely popular due to its intuitive approach, the DWT suffers from two drawbacks: dyadic length requirements for the series to be transformed and the fact that the DWT is non-shift invariant. In order to address these two drawbacks, the maximal-overlap DWT (MODWT)³ was originally introduced by Shensa (1992) and a phase-corrected version was added and found superior to other methods of frequency decomposition⁴ by Walden and Cristan (1998). The MODWT gives up the orthogonality property of the DWT to gain other features, given in Percival and Mofjeld (1997) as the ability to handle any sample size

³As Percival and Walden (2000) note, the MODWT is also commonly referred to by various other names in the wavelet literature such as non-decimated DWT, time-invariant DWT, undecimated DWT, translation-invariant DWT and stationary DWT. The term "maximal overlap" comes from its relationship with the literature on the Allan variance (the variation of time-keeping by atomic clocks) - see Greenhall (1991).

⁴The MODWT was found superior to both the cosine packet transform and the short-time Fourier transform.

regardless of whether the series is dyadic or not, increased resolution at coarser scales as the MODWT oversamples the data, translation-invariance, and more asymptotically efficient wavelet variance estimator than the DWT.

Both Gençay, Selçuk, and Whicher (2001) and Percival and Walden (2000) give a thorough and accessible description of the MODWT using matrix algebra. Crowley (2007) also provides a good "intuitive" introduction to wavelets, written specifically for economists, and references the (limited) contributions made by economists using discrete wavelet analysis⁵. The first real usage of wavelet analysis in economics was by James Ramsey (NYU) and can be found in Ramsey and Lampart (1997), and the first application of wavelets to economic growth (in the form of industrial production) was by Gallegati and Gallegati (2007) and in the form of GDP in a working paper by Crowley and Lee (2005) and then more recently in a published article by Yogo (2008).

3.2 Continuous wavelet (CWT) analysis

One of the problems with discrete wavelet analysis is that there is no widely-available technique currently available that allows time-varying analysis of correlations (although Crowley and Lee (2005) use an approximation by applying dynamic correlation analysis to analyze how the crystal wavelet correlations change over time with European growth data). So in this section we apply continuous wavelet (CWT) analysis to produce spectral-type measures of association so as to evaluate how the relationships uncovered in the previous section change over time.

Continuous wavelet transforms (CWTs), rather than looking at a range of frequencies to increase the time resolution, have the ability to look at greater frequency resolution. This is equivalent to temporal narrow-band filtering. Perhaps the best introduction into the theoretical CWT literature can be found in Lau and Weng (1995), Holschneider (1995) and Chiann and Morettin (1998), while Torrence and Compo (1998) probably provides the most illuminating examples of empirical applications to time series from meteorology and the atmospheric sciences.

In brief, a representation of a covariance stationary process in terms of its frequency components can be made using Cramer's representation, as follows:

$$x_t = \mu + \int_{-\pi}^{\pi} e^{i\omega t} z(\omega) d\omega \quad (8)$$

⁵These can also be accessed online at:

http://faculty.tamucc.edu/pcrowley/Research/frequency_domain_economics.html

where $i = \sqrt{-1}$, μ is the mean of the process, ω is measured in radians and $z(\omega)d\omega$ represents a complex orthogonal increment processes with variance $f_x(\omega)$, where it can be shown that:

$$f_x(\omega) = \frac{1}{2\pi} \left(\gamma(0) + 2 \sum_{\tau=1}^{\infty} \gamma(\tau) \cos(\omega\tau) \right) \quad (9)$$

where $\gamma(\tau)$ is the autocorrelation function. $f_x(\omega)$ is also known as the spectrum of a series as it defines a series of orthogonal periodic functions which essentially represent a decomposition of the variance into an infinite sum of waves of different frequencies. Given a large value of $f_x(\omega_i)$, say at a particular value of ω_i , $\hat{\omega}_i$, this implies that frequency $\hat{\omega}_i$ is a particularly important component of the series.

Given a time series $x(t)$ and an analysing wavelet function $\psi(\theta)$, then the continuous wavelet transformation (CWT) is given by:

$$W(t, s) = \int_{-\infty}^{\infty} \frac{d\tau}{s^{\frac{1}{2}}} \psi^* \left(\frac{\tau - t}{s} \right) x(\tau) \quad (10)$$

For an easier computation making use of FFT algorithms this can be rewritten in Fourier space. For a discrete numerical evaluation we get:

$$W_k(s) = \sum_{k=0}^N s^{\frac{1}{2}} \hat{x}_t \hat{\psi}^*(s\omega_k) e^{i\omega_k t \partial t} \quad (11)$$

where \hat{x}_k is the discrete Fourier transform of x_t :

$$\hat{x}_k = \frac{1}{(N+1)} \sum_{k=0}^N x_t \exp \left\{ \frac{-2\pi i k t}{N+1} \right\} \quad (12)$$

Here we use a Morlet wavelet, which is defined as:

$$\psi(\theta) = e^{i\omega\pi} e^{-\frac{\pi^2}{2}} \quad (13)$$

This is a symmetric wavelet, and is widely used in CWT analysis in the wavelet literature. Given our analysis above, it is also then possible to calculate conventional spectral measures, such as the spectral power:

$$WPS(t, s) = E\{W(t, s)W(t, s)^*\} \quad (14)$$

where $*$ represents the complex conjugate. The wavelet power spectra measures the strength of cycles at various frequencies - it is the analogue measure of energy for a DWT or variance in a time series context⁶.

With two variables, x and y , it is also possible to derive and empirically estimate the cross wavelet power spectrum:

$$WCS^{xy}(t, s) = E\{W^x(t, s)W^y(t, s)^*\} \quad (15)$$

This gives rise to other multivariate spectral measures such as the coherence (which essentially normalizes the cross wavelet spectrum):

$$WCO^{xy}(t, s) = \frac{|WCS^{xy}(t, s)|}{[WPS^x(t, s)WPS^y(t, s)^*]^{\frac{1}{2}}} \quad (16)$$

which can also be measured as the magnitude squared coherence, being simply $[WCO^{xy}(t, s)]^2$. As wavelet analysis essentially identifies cycles in the data, if such cycles are detected then the phasing, $\Phi(s)$, between the cycles can also be calculated from:

$$WCS^{xy}(t, s) = |WCS^{xy}(t, s)| e^{i\Phi(s)} \quad (17)$$

When plotting the coherence and phase, the arch drawn in the plot shows the "cone of influence"⁷, so points outside the one are to be interpreted as being less reliable than those placed within the cone (because of fitting wavelets to fluctuations at the end of the series).

4 DWT Results

4.1 MODWT Results

Here we show a selection of the MODWT results for various member states and countries. In figure 1 the decomposition of euro area growth is shown. The first series shown in the stackplot (d1) is the finest detail crystal, and relates to fluctuations at a 2 to 4 quarter frequency, while the d2 crystal shows the 1 to 2 year cycles etc. The downturn in 2008-9 is clearly shown as a major downturn in all crystals, but since then each crystal rebounded, and then differing dynamics are shown at different frequencies, with for example the d3

⁶These are not shown in this paper, but the plots can be obtained from the corresponding author upon request.

⁷This indicates the central area of the graph where the full length wavelets are applied to the data, so are free of any bias resulting from the use of boundary coefficients to enable wavelet application.

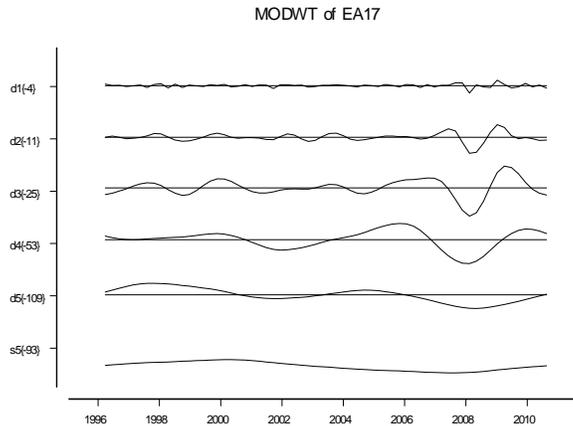


Figure 1: MODWT of euro area growth

crystal (the 2-4 year cycles) now indicating a downturn again, whereas the d5 crystal (8-16 year) crystal clearly shows that a rebound is under way at those frequencies. This is hardly surprising, as fluctuations at different frequencies clearly interact within the growth dynamic, with the general direction indicated by the longer cycles.

The next MODWT stackplot (figure ?? shows the decomposition for Germany, as another illustrative example. Here, once again, the obvious feature is the downturn at the end of the last decade. But in this instance, there is hardly anything remaining in the wavelet "smooth" - which implies that all the fluctuations in growth are captured by the first 5 crystals (- in other words up to a frequency of roughly 16 years).

In figure 3, the Netherlands has a rather different growth dynamic, showing a downturn in longer cycles in 2002, but then roughly the same features as the euro area for the remainder of the period.

In figure 4, Italy's stackplot shows a lot more volatility at medium time horizons, but once again shows roughly the same growth dynamics as the euro area.

In figure 5, Greece's MODWT shows very high volatility at nearly all time horizons, and although the data span doesn't go to 2011, the downturn at the end of the decade was quite severe.

In the case of Ireland in figure 6, once again there is considerable volatility in shorter cycles, but also a longer cycle detected in the wavelet smooth.

In figure 7, the stackplot for Portugal shows considerable volatility at all frequencies, with notable cyclical activity after the major recession at the end of the last decade.

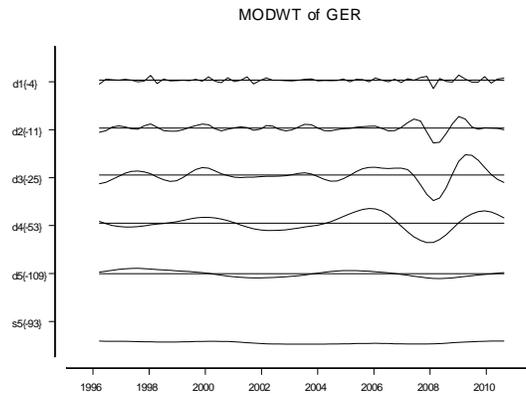


Figure 2: MODWT for Germany

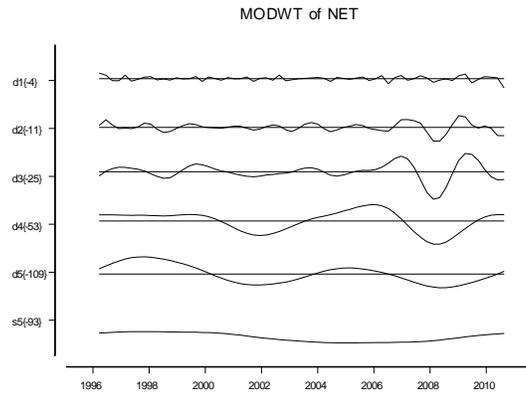


Figure 3: MODWT for NET

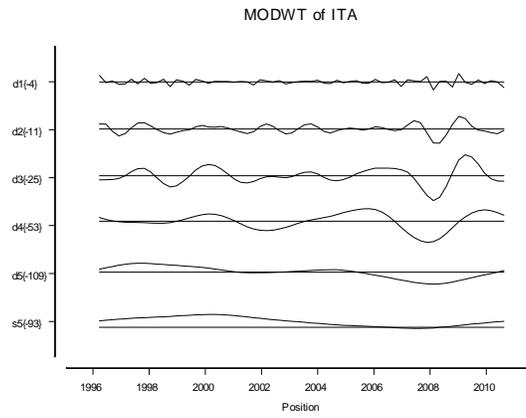


Figure 4: MODWT for ITA

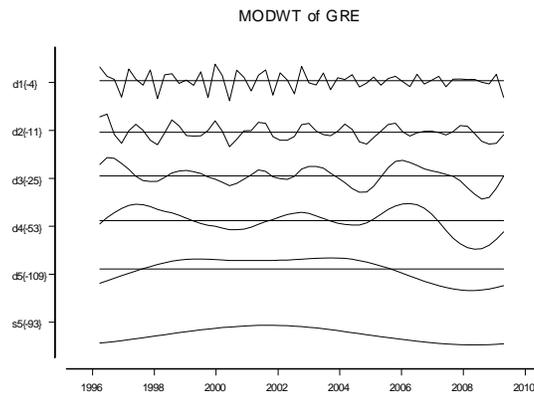


Figure 5: MODWT for GRE

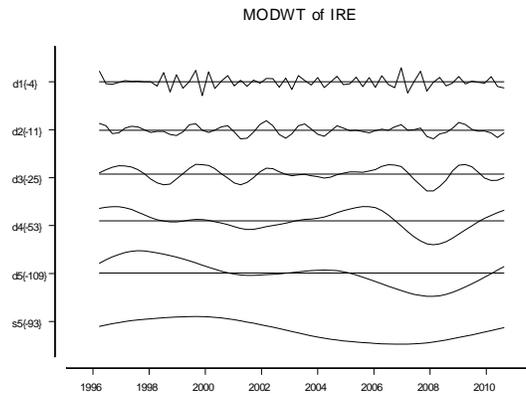


Figure 6: MODWT for IRE

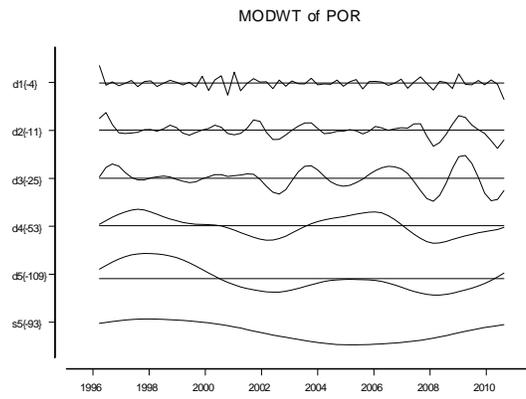


Figure 7: MODWT for POR

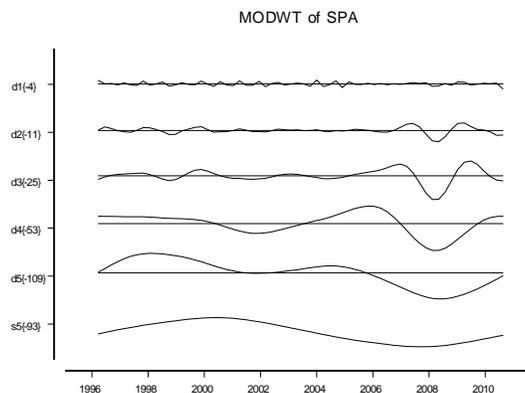


Figure 8: MODWT for SPA

In figure 8, the MODWT for Spain shows that longer cycles seem to have dominated the growth dynamic, with higher frequencies contributing much less to growth than in other southern EU member states.

4.2 Wavelet Correlations

In this section, we report on correlations of individual member state crystals against those obtained for the EU17 aggregate. In figure 9 the correlations for each crystal are plotted (- only the correlations for d1 to d4 are plotted, as there aren't enough cycles for d5 correlations to yield accurate results). 95% confidence intervals are also shown, which then allows for some statistical inference as to whether the correlations are significantly different from zero. In the case of Belgium, all correlations are significant.

In figure 10 the correlations for Bulgaria are shown, and they are clearly negative for longer cycles.

In figure 11 the wavelet correlations are shown. Here all are significant, except for the longest cycles at the 4 to 8 year cycle frequency.

For Finland, shown in figure 12, the correlations are all high and significant. Similar patterns are also observed for Germany and France, so these are not shown here.

In figure 13, the wavelet correlations for Greece are shown. It is clear that there are no frequencies at which the correlation of growth dynamics are significantly different from zero, and in fact at longer cycles which typically encompass the business cycle, the correlation is approximately zero.

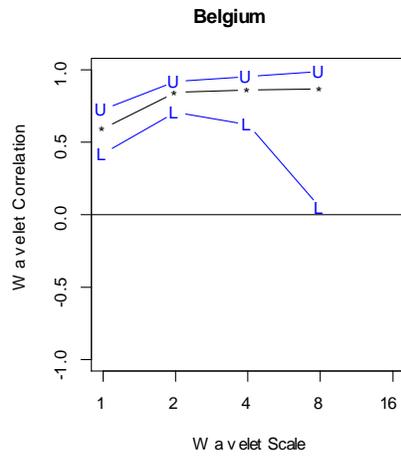


Figure 9: Wavelet Correlations for BEL

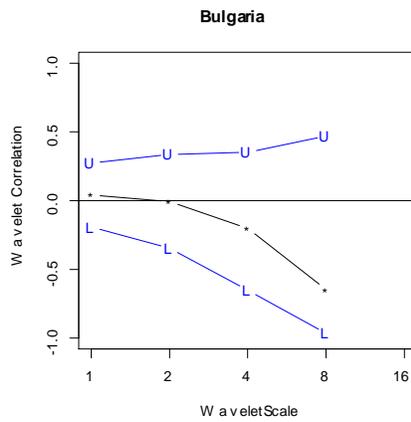


Figure 10: Wavelet Correlation for BUL

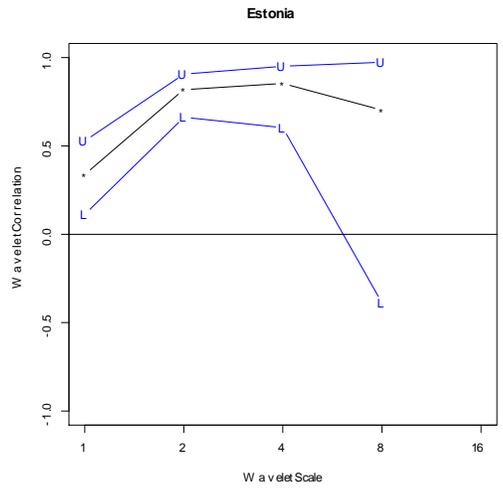


Figure 11: Wavelet Correlations for Estonia

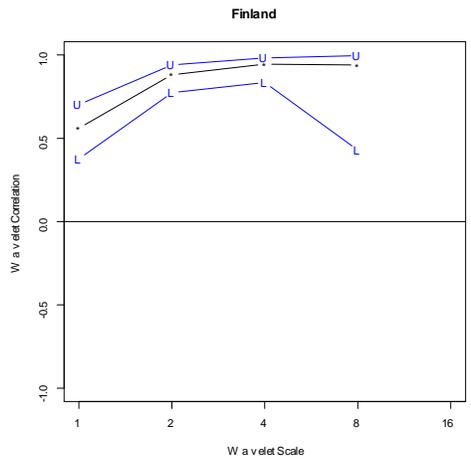


Figure 12: Wavelet Correlation for FIN

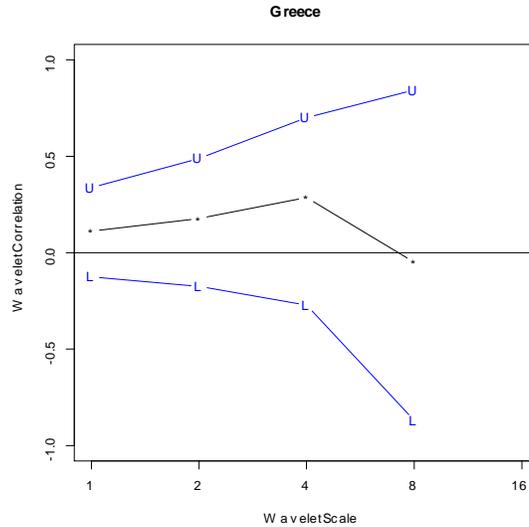


Figure 13: MODWT for GRE

Figure 14 shows the wavelet correlations for Ireland, and in this case the correlations are all significant except for the correlations at high frequencies.

This is contrasted with wavelet correlations for Italy in figure 15, where correlations are all highly significant. The wavelet correlations for the Netherlands are virtually identical to those of Italy.

In figure 16, wavelet correlations for Latvia are all significant for higher frequency cycles, but for the long cycle (4 to 8 years), the correlation is not significantly different from zero. Similar plots are obtained for Slovenia and Lithuania.

For the UK, figure 17 shows a similar pattern for wavelet correlations as per the CEE countries, with the long cycle not significantly different from zero in correlation.

For Norway, a non-EU country, the wavelet correlation plot shown in figure 18 indicates that the correlation is not significantly different from zero for short cycles (2-4Q) and for long cycles (4-8 years). A similar plot is obtained for Iceland, but for Switzerland the plot reverts back to significant correlations at all frequencies.

5 CWT Results

In this section the results using the Continuous Wavelet Transform are presented. As per the method, there are 2 different plots for the cross spectral analysis - one for the coherence,

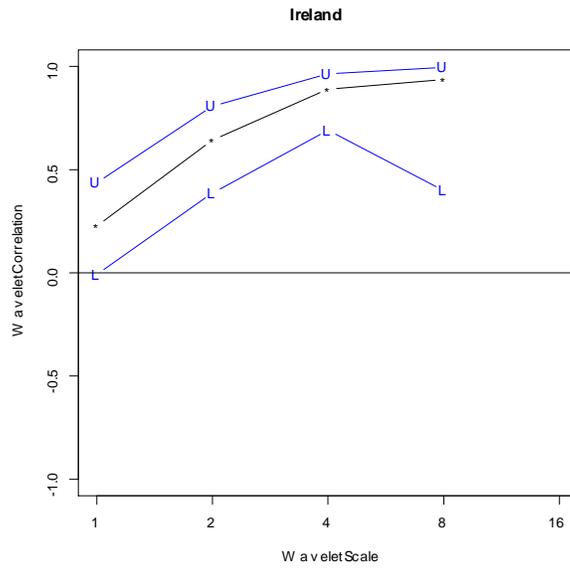


Figure 14: Wavelet Correlations for IRE

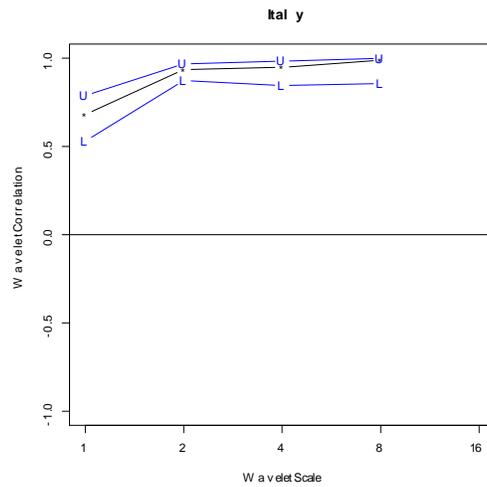


Figure 15: Wavelet Correlations for ITA

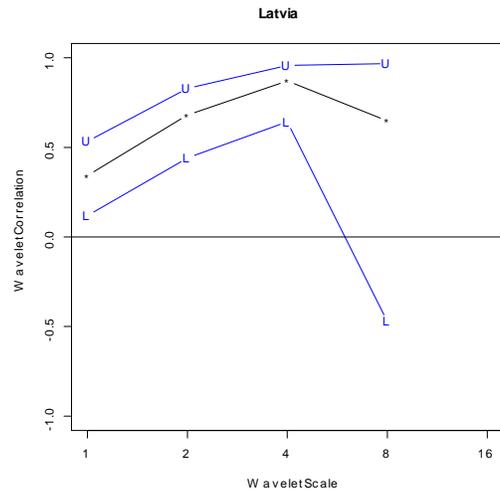


Figure 16: Wavelet Correlations for LAT

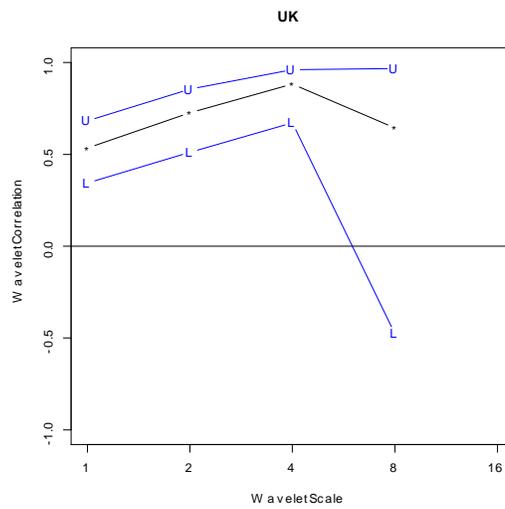


Figure 17: Wavelet Correlation for the UK

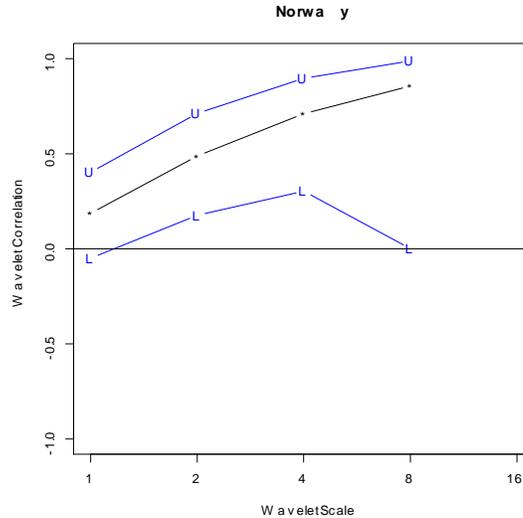


Figure 18: Wavelet Correlation for NOR

which is the equivalent of correlation for the frequency domain, and the phase, which shows how synchronized the cycle is with the euro area cycle at each frequency. In figure 19, the top color plot shows the coherence by frequency, with red areas showing particularly high coherence. Beyond a fairly high frequency, cycles have been highly coherent and coherence increased between 2003 and 2007 at mid-range frequencies so that now nearly all frequencies are highly coherent with euro area cycles. In the lower plot, the phases are all well synchronized with euro area cycles at all frequencies, with a slight lead or lag from time to time at lower frequencies.

In figure 20 the cross spectral plots for Denmark are shown. Here the coherence increases from just covering lower frequency cycles to covering nearly all cycles by 2003. In terms of the phasing of these cycles, they are all virtually in phase with the euro area cycles.

Figure 21 shows the cross spectral plots for Finland. Here the coherent cycles were clearly only at lower frequencies when the country joined the euro area, but through time the significant coherency coverage has extended to higher frequency cycles, but only recently there has been a re-emergence of dynamics at very high frequencies that are not coherent with euro area cycles. Once again in terms of the phase plot, all cycles appear to be almost always in phase.

The contrast for these member states with a member state like Greece is quite instructive. In this case the coherence plot shows that only at longer cycles has there been any

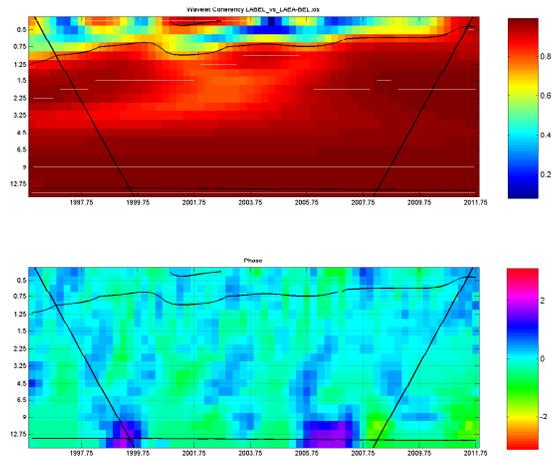


Figure 19: Cross Spectral Plots for BEL

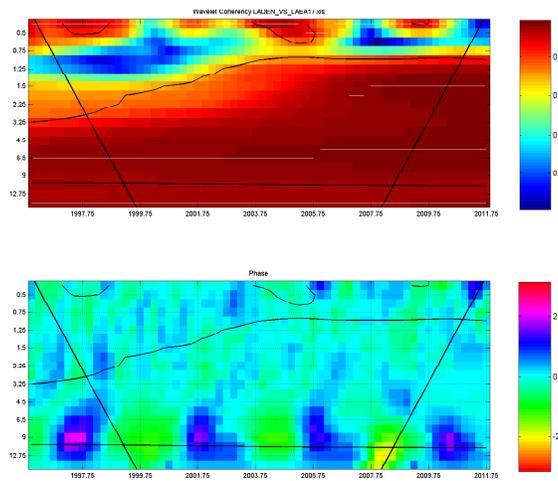


Figure 20: Cross Spectral Plots for DEN

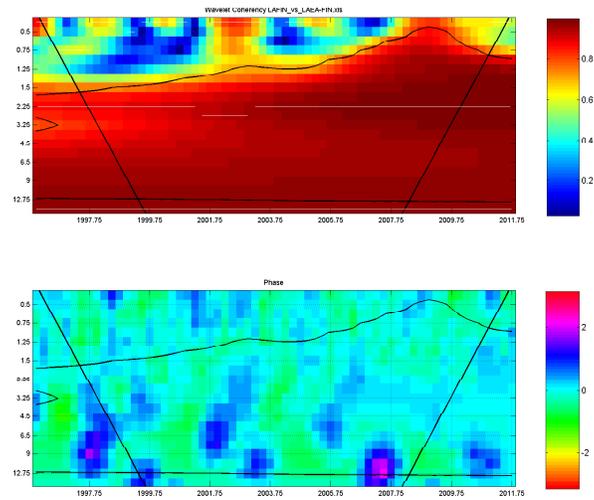


Figure 21: Cross Spectral Plots for FIN

high levels of coherence and at none of these cycle frequencies are the coherences significant. On the other hand up until recently the phasing appears to be relatively synchronized.

In the case of Italy, the plot is once again similar to that of Finland and Belgium shown above. Figure 23 shows that the coherence of cycles with the euro area are mostly significant and coverage has been increasing over time from lower frequency cycles to now higher frequency cycles as well. The phasing is mostly synchronous, except that occasionally longer cycles in Italy tend to lag those of the euro area (- these are the yellow patches)

For some member states, the change that takes place in growth dynamics is clear. In the case of Portugal, growth dynamics clearly changed in the early 2000s, when the euro was introduced, when clearly the coherence at the longer cycle becomes significant, and then in 2004 when this is joined by cycles at higher frequencies, which then see coherence rising to significant levels. Portugal's plot though in figure 24 is interesting as the coherence at longer cycles, although high, is not significant. Once again though, the phasing is highly synchronized with the euro area.

6 Cluster Analysis

Given the analysis undertaken above, it is instructive to see if there any groupings among the countries in terms of the cyclical growth activity at different frequencies. To do this,

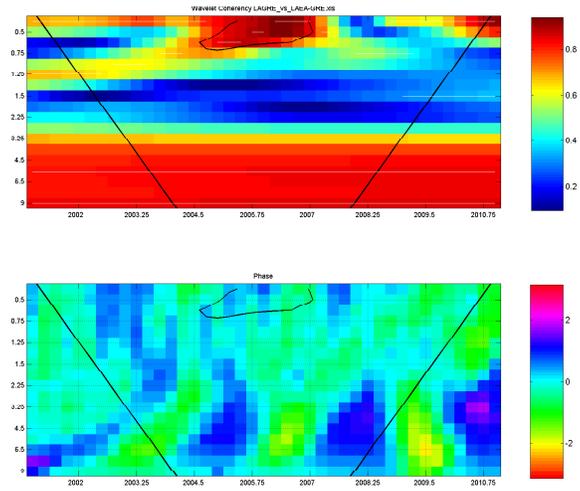


Figure 22: Cross Spectral Plots for GRE

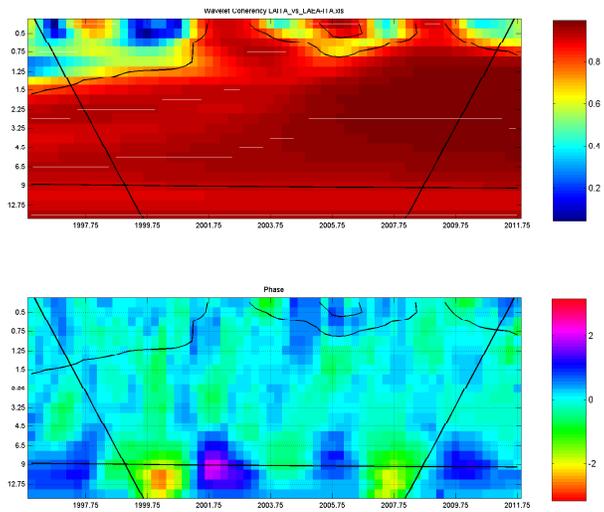


Figure 23: Cross Spectral Plots for ITA

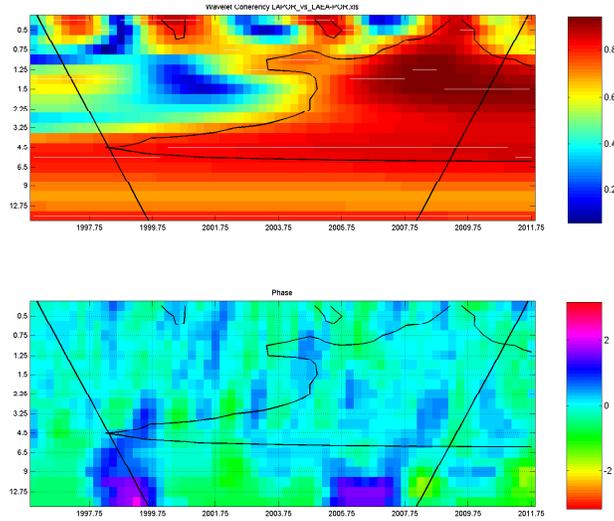


Figure 24: Cross Spectral Plots for POR

the wavelet correlation results from the discrete wavelet analysis are compiled as a dataset, and then cluster analysis is applied to this dataset. Cluster analysis originated from a study by Anderson (1935), and then algorithms were developed to divide objects into meaningful groups based on separation algorithms that look at various metrics (such as Euclidean distance). These algorithms and different clustering techniques are described in Hartigan (1975) and Anderberg (1993).

In terms of the techniques we use two different methods for clustering, notably:

- a) hierarchical clustering; and
- b) fuzzy clustering

In this study we do two different exercises in relation to the wavelet correlation dataset:

- i) unweighted correlations; and
- ii) correlations weighted by variance of EU17 crystals.

Given the above, there are 4 different sets of results and these are listed below:

- a) i) Cophentic correlation indicates $R=0.912$ with $N=7$ so good clustering;

- a) ii) Indeterminate so no result;
- b) i) 10 clusters with relatively little fuzziness; and
- b) ii) 12 clusters with moderate fuzziness

For the cluster exercise a) i) we obtain the following results in terms of membership groups:

- 1 BEL, GER, SPA, FRA, ITA, NET, AUS, SLO, FIN, SWE, SWI
- 2 EST, LAT, LIT, HUN, UKM
- 3 DEN, IRE, CYP, LUX, POR, SLV, NOR
- 4 BUL
- 5 GRE
- 6 CZR
- 7 ICE

Table 5: Unweighted hierarchical clustering

Here the groupings are well separated and clearly put the euro area into 4 distinct groupings - a core grouping, another grouping with Ireland, Luxembourg and Portugal, Estonia in a separate group and Greece in a separate group. What is noticeable here is that the expected member states are outside the core grouping, but that Italy and Spain, two member states that are usually grouped with Ireland, Portugal and Greece, are grouped within the core grouping.

For the cluster exercise in b) i), using the fuzzy cluster approach (which essentially assigns probabilities to member states/countries being in specific groups), the cluster groupings are as follows:

- 1 BEL, SPA, AUS, SLO, FIN, SWE, SWI
- 2 IRE, LUX, POR, SLV
- 3 GER, FRA, ITA, NET
- 4 LIT, HUN, UKM
- 5 BUL, GRE
- 6 CYP, NOR
- 7 EST, LAT
- 8 Rest single clusters

Table 6: Unweighted fuzzy clustering

Here the groupings are somewhat different to those of the a) i) clustering exercise. Here the core splits into two different groupings, one (cluster 3) with the 3 large euro area

members (Germany, France and Italy), and with most of the smaller euro area members falling into either a cluster containing Ireland, Portugal and Luxembourg (cluster 2), or a cluster containing Belgium, Spain, Austria, the Slovak Republic and Finland (cluster 1). Greece and Estonia fall into separate clusters.

For the cluster exercise in b) ii), the correlations are weighted by the importance of each crystal in accounting for the variance of the actual euro area growth variable. Here, interestingly the Germany falls into a different group from France and Italy, and also the Baltic States now form a separate cluster together with the UK. Ireland, Greece, and Portugal fall into separate clusters, with Spain and Italy falling once again into the biggest cluster (cluster 1)

- 1 SPA, FRA, ITA, NET, AUS
- 2 CYP, POR
- 3 EST, LAT, LIT, UKM
- 4 IRE, LUX, SLV
- 5 BEL, GER, SWE
- 6 DEN, SLO, FIN, SWI
- 7 Rest single clusters

Table 7: Weighted fuzzy clustering

7 Conclusions

In this paper, two types of wavelet analysis are used to analyze economic growth patterns in the euro area. This is an important issue, as given that the OCA theory is a valid approach to assessing whether a group of countries forms a currency union, the most important variable in assessing this is the pattern of economic growth. In addition, the data used in this study allows some assessment of whether the euro area is more a currency union ex-post rather than ex-ante.

Discrete wavelet analysis produces correlations for each member state against the growth of the rest of the euro area within specific frequency ranges. The results show similar patterns of growth during the downturn at the end of last decade, but differing cycles at different frequencies for many of the member states, particularly for some of those outside the euro area, but also for certain member states within the euro area. Once the variables have been decomposed into separate frequency cyclical components, then these are correlated against those of the euro area, with a test of statistical significance conducted for each

correlation.

Because discrete wavelet analysis does not look at the dynamics of economic growth over time, we next use continuous wavelet analysis to produce a wavelet analog to cross spectral analysis to see what is happening to individual cycles at different frequencies over time. Once again a test of significance is conducted to test whether the coherence of the cycles is significant.

The results indicate that with both the discrete wavelet analysis and the continuous wavelet analysis, correlations in growth are higher at lower frequencies, but that correlations at higher frequencies have been increasing over time. For certain member states, notably Greece, there appears, perhaps not unsurprisingly, to be a divergence rather than a convergence in the dynamics of economic growth.

Lastly, see if this approach suggest particular groupings, we use cluster analysis to see if the euro area member states fall into specific groupings. One of the results here is that there is not consistent grouping that forms, but there are some patterns that emerge: a hard core of member states still exists, and there appears to be approximately three groupings of member states within the euro area, but Greece definitely is not part of any of these groupings.

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